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The Skills Road

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Abbreviations and Acronyms

ALMP	Active Labor Market Programs
BEEPS	Business Environment and Enterprise Performance Surveys
BNPP	Bank Netherlands Partnership Program
ECD	Early Childhood Development
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

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The report analyzed a unique survey that was implemented jointly by a team from the World Bank and the German Society for International Cooperation (GIZ). The survey 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, led by Joost de Laat. The cognitive and non-cognitive skills scores were constructed by Carly Tubbs (Consultant, New York University) and Louise Bahry (Consultant, University of Massachusetts Amherst).

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Overview

In light of the relative political stability and strong economic growth in Tajikistan since 1997, the government has set ambitious development targets for 2020: to double GDP, to significantly reduce poverty, and to expand the middle class.[1] In recent years, sustained high economic growth rates have sharply reduced poverty rates, from 47 percent in 2009 to about 36 percent in 2012. However, to achieve Tajikistan's 2020 development goals more needs to be done. Generating more productive employment is arguably the most critical challenge.

This report addresses a fundamental question facing policy makers in Tajikistan: is the current level of worker skills hindering employment outcomes? To answer this question, the study relies on a unique household survey—the first 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, of job seekers, and of 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 focusing on the determinants of economic growth and the determinants of employment outcomes.[2] It also builds on a qualitative study on economic mobility, jobs, and gender.[3]

The main finding of the report is that skills gaps hinder labor market outcomes in Tajikistan. There is a significant demand for skills in the Tajik economy, as evidenced by substantial positive labor market returns to both cognitive and non-cognitive skills. Yet, considerable skills gaps persist. Inactive individuals in Tajikistan have significantly lower cognitive and non-cognitive skills than employed individuals. Additionally, a large share of employers reports shortages of adequately skilled individuals in the workforce.

While skills are developed during different stages in the life cycle and a host of actors are involved—families, the education system, and employers play a central role. Tajikistan's education system has a mixed record in skill formation. 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 and non-cognitive skills across workers within educational attainment categories, which means that there are too many low performers in each educational attainment level.

To meet the expected growing demand for higher-order skills in the workplace, policy makers should therefore address skill formation across the life cycle: from conception to preschool (or early

[1] World Bank (2014b).

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

[3] World Bank (forthcoming).

childhood development [ECD] more generally), in general education, in higher education, and while part of the workforce. At all levels of education and training, a broader focus on cognitive and non-cognitive skill formation is crucial to ensure that skills are valued in the current and future labor market. A comprehensive skills development strategy is required that improves the quality and relevance of education and training systems to ensure that they build market-valued skills.

The Skills Toward Employability and Productivity (STEP) Framework can provide the government with a set of policy goals to enhance skills for employability in Tajikistan and outside Tajikistan, where so many Tajik workers find productive employment each year. The STEP framework brings together research-based evidence and practical experience from diverse areas—from research on the determinants of early childhood development and learning outcomes to policy experience in the reforming of vocational and technical education systems and labor markets.[4] In Tajikistan, policy makers can boost employment outcomes through a more skilled workforce by focusing on the following five policy goals:

- Getting children off to the right start by expanding access to quality ECD programs—including nutrition, preschool—which are critical to ensuring that all children acquire the cognitive and non-cognitive skills that are conducive to high productivity and flexibility in the labor market.
- Ensuring that all students learn by modernizing the curricula and improving teaching quality, in order to strengthen the link between educational attainment and cognitive and non-cognitive skills.
- Building job-relevant skills that employers demand by implementing selective active labor market programs, focused particularly on expanding employment opportunities for labor market discouraged and the female population, and incentivizing firms to provide on-the-job training.
- Encouraging entrepreneurship and innovation by managing the expansion of higher education, focusing on quality assurance, selection, and information provision, to ensure that higher education graduates possess market-valued skills and to ensure that investments in higher education pay off.
- Matching the supply of skills with employer demand by improving labor market information systems, in order to make labor markets more efficient by alleviating current constraints in the job search and skill signaling process.

To reach the above findings and policy goals, the report presents analysis of: (a) key labor market outcomes; (b) the returns to skills in the labor market and their use in the workplace; and (c) the formation of skills, with a particular emphasis on whether the education system imparts the cognitive and non-cognitive skills needed to successfully participate in the labor market. The key findings of the three areas analyzed in the report are summarized below.

[4] Valerio et al. (2014).

Labor Market Outcomes

Tajikistan faces important challenges in meeting its rapidly changing labor market needs. First, despite the fact that overall job creation has kept pace with population growth, formal sector job creation has been insufficient. Second, productivity has risen significantly, but wage growth has outstripped productivity increases raising concerns about competiveness. Third, jobs are distributed unevenly. In particular, female employment rates of only 25 percent are far lower than those observed in OECD countries. A large share (over 15 percent) of the young population in Tajikistan is labor market discouraged—meaning that they are not looking for a job because they do not believe they can find one and almost one-in-three young men migrate abroad for employment purposes.

At the same time, Tajikistan's economy is undergoing significant structural changes—specifically, it is shifting away from agriculture and industry toward services. Nonetheless, job quality remains an important challenge. A sizable portion of the working population is engaged in the informal sector (60 percent), and the vast majority of workers perform repetitive tasks and they do not learn new things on the job. Finally, weak labor market systems hinder the effectiveness of job searches and skills signaling, limiting the extent to which the supply of skills are effectively matched with employer demand in Tajikistan.

Skills and Employability

As in many other parts of the world, there is an increasing demand for "new economy" skills in Tajikistan. New economy skills are higher-order analytical and organizational skills, including non-routine cognitive analytical and interpersonal skills. Although there are competing explanations for this observed trend—including technology advances and globalization—it is clear that Tajikistan is in the beginning stages of modernizing its economy and is experiencing a growing demand for new economy skills.

Workers' skills consist of cognitive, non-cognitive (social and behavioral), and technical skills. This study focuses on foundational cognitive and non-cognitive skills more thoroughly. Cognitive skills capture the ability to use logical, intuitive, and critical thinking as well as skills such as problem solving, verbal ability, and numeracy. These skills are the basis for the formation of technical and job-specific skill acquisition later in life. The cognitive skills measured in this report include memory, literacy, and numeracy skills (for more details, see Appendix B: Constructing Cognitive Skills Scores Methods for Scale Development and Scoring). 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 (for more details, see Appendix C: Constructing Non-Cognitive Skills Scores Methods for Scale Development and Scoring).

Beyond educational attainment alone, both cognitive and non-cognitive skills are important factors for employability in Tajikistan. Individuals with better skills are not only more likely to be employed, but they also typically have more desirable jobs—those in the formal sector with labor law protections and access to some benefits in case of termination. Skills valued in the Tajik labor market include not only cognitive skills such as literacy and numeracy alongside technical skills, but also non-cognitive skills such as an individual's attitude in the workplace and decision making skills. In addition, higher skilled individuals use their skills more frequently on the job. For example, workers with higher numeracy skills are more likely to use math on the job. And, workers with a better workplace attitude are more likely to supervise others' work.

Skill Formation over the Life Cycle

The importance of skills for employment outcomes is clear, yet the skill-formation track record of Tajikistan's education and training system is mixed. While skills are developed during different stages in the life cycle and a host of actors are involved—for example, families play a central role—the education and training system plays a key role in skill formation of both the current and future workforce. Although the education system in Tajikistan provides universal access to general education, skills gaps are likely to emerge at early ages given the low coverage of early childhood development (ECD). Because the foundations of cognitive and behavioral skills are formed earlier on in life, the early childhood period is critical in the development of these skills. Furthermore, at the tertiary level, higher education completion rates have been consistently strong while the completion of vocational degrees has diminished in recent years. Upon entering the workforce, few workers continue to develop their skills through on-the-job training.

Aside from access issues, quality concerns across all levels of education and training further contribute to the observed gaps in the level and relevance of skills. On the one hand, workers with higher educational attainment generally have higher cognitive and non-cognitive skills. On the other hand, there is great variation in skill levels across workers, to the extent that the level of cognitive and non-cognitive skills often varies widely despite identical educational attainment levels. In particular, there are individuals in the sample who have completed higher education but have a lower cognitive ability than individuals with less than secondary education. These results raise questions about the quality and selection at various levels in the education system, most notably in higher education institutions. In addition, the variation in non-cognitive skills may result from disparities in the extent to which non-cognitive skills are taught in schools and the quality of such teaching—although, admittedly, families and communities play a central role in the early development of non-cognitive skills in children.

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

The World Bank/German Society for International Cooperation (GIZ) *Tajikistan Jobs, Skills, and Migration Survey* is one of three household surveys conducted in Central Asia in 2013—the other countries covered are the Kyrgyz Republic and Uzbekistan.[+] Conducted from July to September 2013, the survey collects comprehensive information not typically captured by traditional household surveys and is representative at the national, regional (Oblast), and urban/rural levels.

Two distinct instruments are employed in the survey: a core questionnaire and a skills questionnaire. The sample size of the core questionnaire is 3,300 households with a total of 20,142 individuals. Depending on the household, one or two individuals per household were randomly selected to partake in the skills questionnaire. The second skills questionnaire sample consists of 4,892 individuals. Qualitative testing and pilots helped fine-tune the questionnaires and organize the modules in order to administer the survey efficiently and consistently.

1. Core questionnaire*

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

2. Skills questionnaire*

The skills questionnaire contains detailed modules on labor and work expectations, migration and preparation for migration, language skills, and technical skill training. A unique aspect of the survey is the battery of cognitive and non-cognitive questions which helps to test a respondent's ability. The 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 the Kyrgyz Republic," 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 Labor Market Outcomes

This section presents an overview of Tajikistan's labor market outcomes and attempts to answer three fundamental questions that shed light on the country's ability to meet the evolving labor market demand. The questions addressed are:

(1) Has job creation in Tajikistan kept pace with population growth?
(2) What do we know about job quality in Tajikistan?
(3) Are workers in Tajikistan able to find jobs that match their skills with employers' needs?

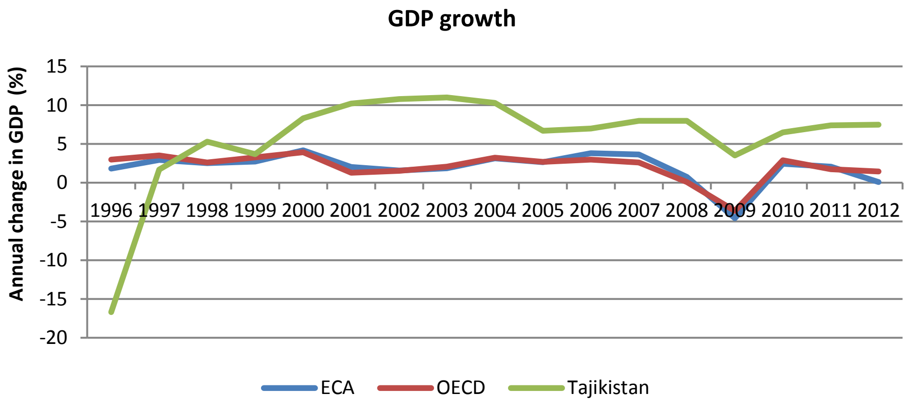
As further explained below, Tajikistan faces important challenges in meeting its rapidly changing labor market needs—five key areas are currently shaping labor market outcomes. First, despite the fact that job creation has kept pace with population growth, formal sector job creation has lagged behind. Moreover, there is a weak link between economic growth and employment opportunities. Second, jobs are distributed unevenly—in particular, female employment rates are far lower than those observed in OECD countries. Third, Tajikistan's economy is undergoing significant structural changes—specifically, it is shifting away from agriculture and industry toward services. Fourth, job quality is an important challenge; a sizable portion of the working population is engaged in the informal sector (60 percent), performs repetitive tasks (82 percent), and does not frequently learn new things on the job (57 percent). And fifth, weak labor market systems hinder the effectiveness of job searches and skills signaling. Overall, these challenges have resulted in high labor market discouragement levels and exceptionally high international migration rates. To improve labor market outcomes in Tajikistan, the government will need to revamp the education and training systems to meet the challenges of a modernizing economy. In addition to the results presented in the main body of the report, Appendix E: Summary Tables contains more detailed results on labor market outcomes.

1.1 Although total job creation has kept pace with population growth, formal sector job growth has lagged behind

Economic growth rates in Tajikistan have been among the highest in the world in recent years—growing at an average annual rate of nearly 8 percent in the last decade. As such, Tajikistan's economy has outpaced its peers in Europe and Central Asia (ECA) as well as the OECD countries (
Figure 1). This dynamic was driven in part by "catch-up" growth following the slump experienced during the early stages of transition in the 1990s. Remittances have also played an increasingly important role, with remittance inflows rising from a relatively low base in 2000 to 46 percent of GDP by 2008. In addition, government stabilization policies, growing exports of aluminum and cotton, and gradual government reforms further propelled the economic boom experienced since the early 2000s.[5]

[5] World Bank (2010b).

Figure 1: GDP growth in Tajikistan has outpaced other ECA and OECD countries in the last decade, 1996–2012



Source: Authors' calculations using the World Bank World Development Indicators, 2013.

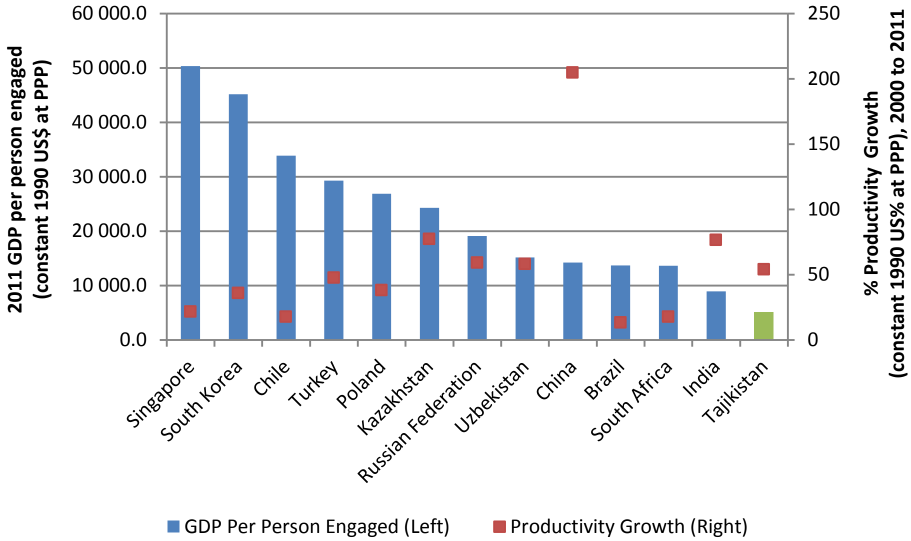
Total job creation has kept pace with population growth, though too many of these jobs were created in the informal sector. Labor demand from both the formal and informal sectors has grown at an average rate of 2.84 percent per year since 1996, while the working-age population has grown at an equivalent rate of 2.8 percent per year. Hence, nearly 1 million additional jobs have been created in the last decade. Since 2006, the Tajikistan's population has increased by 17 percent, while formal employment rose by only 10 percent.[6] In other words, formal sector employment did not keep pace with population growth, and hence, informal sector job growth made up for the shortfall. However, the rate of job creation vis-à-vis population growth is only one of many factors affecting employment outcomes—as explained in the next section, also important are job quality and labor market discouragement, which can be push factors for migration.

Although productivity has grown considerably, Tajikistan continues to lag behind other countries. Productivity in Tajikistan has grown by more than 50 percent between 2000 and 2011 (approximately 4 percent per year), outperforming many comparator countries including Brazil, Chile, Poland, and Turkey(Figure 2). However, in a separate analysis conducted, there are concerns about the rise of real wages in Tajikistan by almost 300 percent since 2005, while labor productivity only increased by 32 percent during the same period.[7] This is potentially important because while poverty reduction may follow from wage growth, increases much larger than productivity growth may hamper sustainable job creation and reduce Tajikistan's competitiveness, unless sizable total factor productivity gains materialize.

[6] World Bank (2014b).

[7] Ibid.

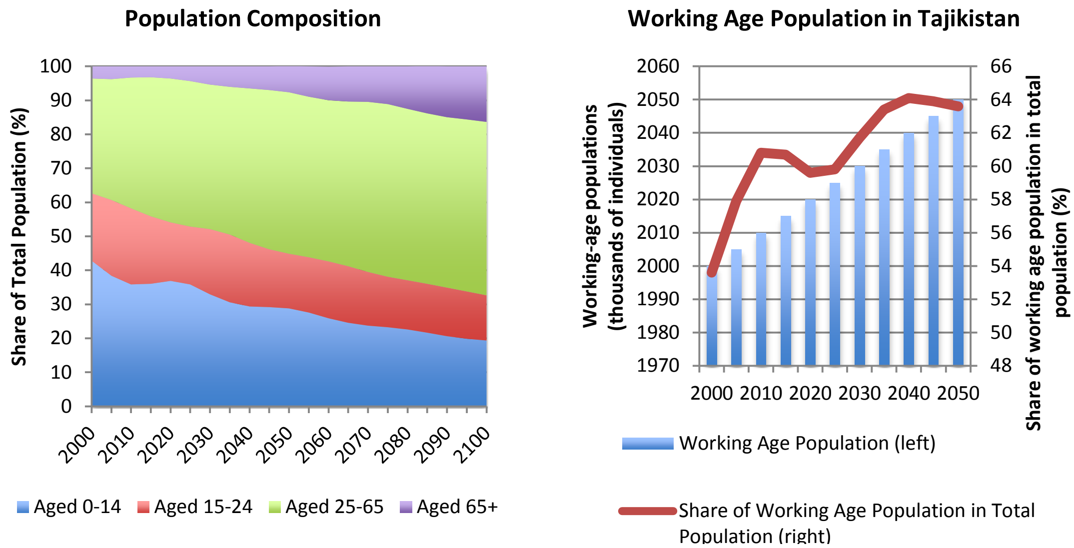
Figure 2: Productivity levels are low but are growing, 2000–2011



Source: International Labour Organization, Key Indicators of the Labour Market (KILM), 2013.

Tajikistan's favorable demographics present an opportunity for continued economic growth, especially if the future labor force is well trained. The demographics favor Tajikistan in that the youth bulge is significant; approximately 55 percent of the population is under 25 years of age. As young adults reach working age, Tajikistan's dependency ratio is projected to decrease. The share of the working-age population will rise from 54 percent in 2000 to roughly 65 percent in 2050. Unlike many other countries in ECA, this window of opportunity is projected to remain open for several decades. The share of elderly (over 65 year of age) in the population is currently very low (3.3 percent), and while the population of Tajikistan is expected to age, the share of elderly in the population will reach close to 15 percent in 2100—lower than in most other countries in ECA. Importantly, however, Tajikistan will only be able to take full advantage of its youth bulge if those young adults are absorbed into the labor market and are productive in the labor force.

Figure 3: Tajikistan's working age population is projected to increase in the next decades, 2000–2011



Source: Authors' calculations using United Nations, World Population Prospects, 2012 revision.

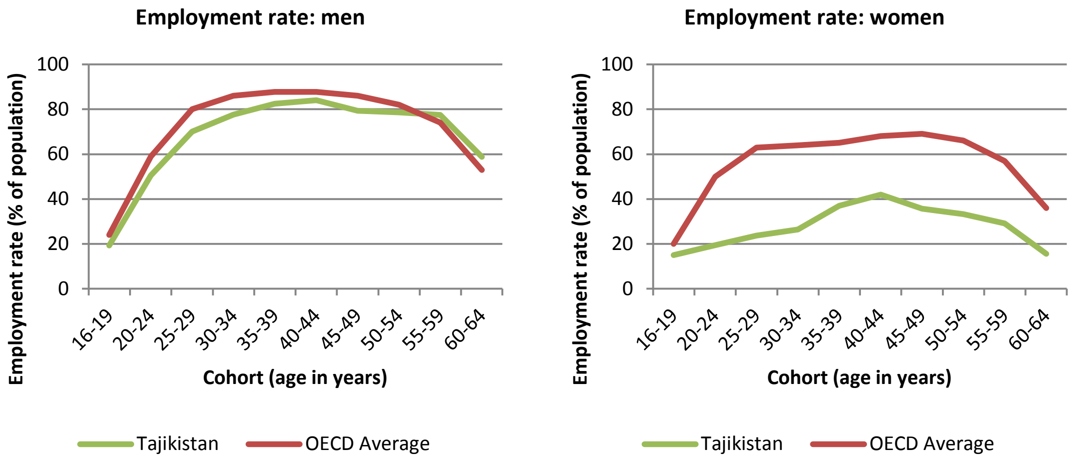
1.2 Jobs are distributed unevenly and labor market discouragement is high

Male employment rates in Tajikistan are similar to those seen in OECD countries, but employment rates among women are far lower. Figure 4 shows that male employment rates in Tajikistan are relatively high and just below those in OECD countries. Female employment rates, on the other hand, are considerably lower than male employment rates and are also lower than female employment rates in OECD countries. A recent qualitative study finds that caring for children is the main obstacle for women to participate in the labor market,[8] particularly among 20- to 34-year-old adults, whose employment rates are 35 percentage points below the OECD average. While the gap is smaller among women between the ages of 35 and 44, it is still significant at 25 percentage points below the average OECD rate. If Tajikistan's female employment rates were on par with those of OECD countries, there would be 700,000 more women contributing to the Tajik economy today.[9]

[8] World Bank (forthcoming).

[9] Author's calculations, based on the World Bank World Development Indicators, 2013.

Figure 4: While male employment rates mirror OECD employment rates, female employment rates are considerably lower than male employment rates, 2013



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

Another important factor affecting employment outcomes in Tajikistan is labor market discouragement—a considerable share of the population feels discouraged from seeking work, especially youth. Discouraged workers are defined as persons who are not in the labor force and are available to work but are no longer looking for a job because they do not believe they will find one.[10] The share of discouraged workers is particularly high among young men and women—approximately one in six men and one in ten women aged 20–24 are too discouraged to look for employment. By comparison, the average share of discouraged workers among the young labor force (aged 15–24) was just 0.5 percent in OECD countries in 2012 (Figure 5). Hence, Tajikistan is not been able to absorb youth who reach working age into the labor market, limiting the extent to which the country has been able to turn the youth bulge into a demographic dividend.

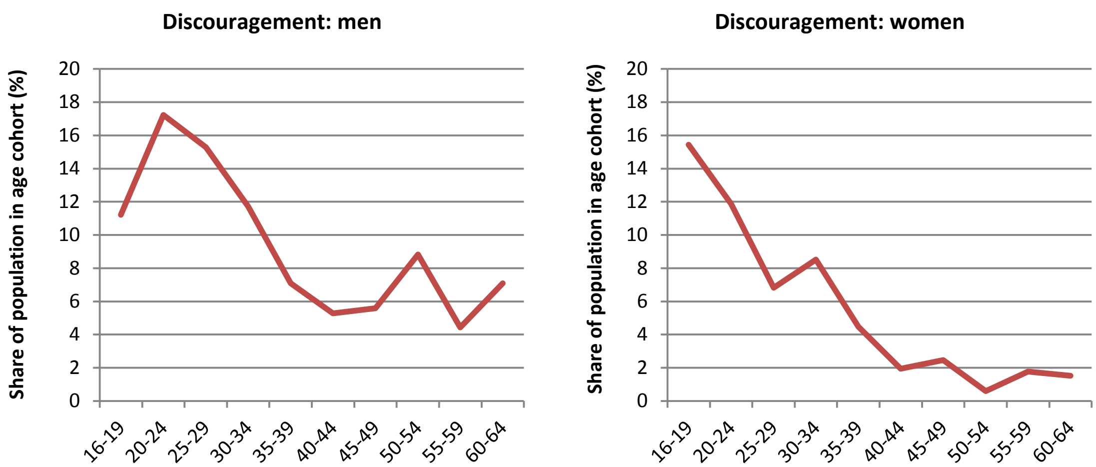
High youth labor market discouragement could have important implications for Tajikistan's future quantity and quality of labor supply; recent studies find that inadequate skills are at the root of the problem. A qualitative study finds that young males in particular face barriers to finding jobs because they do not meet skills and experience requirements by employers.[11] A recent labor market study also supports this finding, and points to a lack of work experience and vocational skills as a cause of youth labor market discouragement.[12] Given that a sizeable part of the young working-age population is out of the labor market as a result of high discouragement, addressing the issue is among the most pressing priorities.

[10] ILO, KILM (2013).

[11] World Bank (forthcoming).

[12] ETF (2010).

Figure 5: Labor market discouragement is a problem in Tajikistan, especially among the youth, 2013

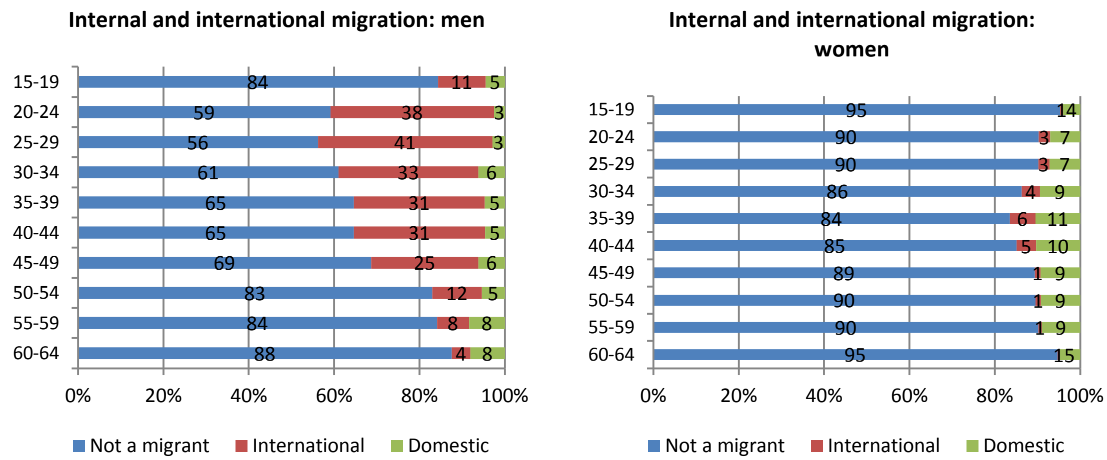


Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: The figures depict the number of discouraged as a share of the population in the age cohort.

International migration rates are exceptionally high in Tajikistan—one-third of all prime-aged men are migrants. International migration is often a coping mechanism for workers who are unable to find a (good) job domestically. It is particularly striking that more than one in three men aged 20–39 in Tajik households are currently abroad; however, this share is considerably lower among women (Figure 6). Due in part to regional cooperation agreements permitting visa-free entry, the Russian Federation is the primary destination for Tajik labor migrants. More than 90 percent of Tajik labor migrants are in the Russian Federation, working mostly in construction, trade, housing and cleaning services, agriculture, and maintenance.[13] In contrast to international migration, domestic migration rates are very low, which suggests that labor allocation within the country may be less than optimal. Domestic migration, or internal migration, plays a key role in fostering local agglomeration economies.

[13] Mughal (2007).

Figure 6: International migration rates are high among young men in Tajikistan, 2013

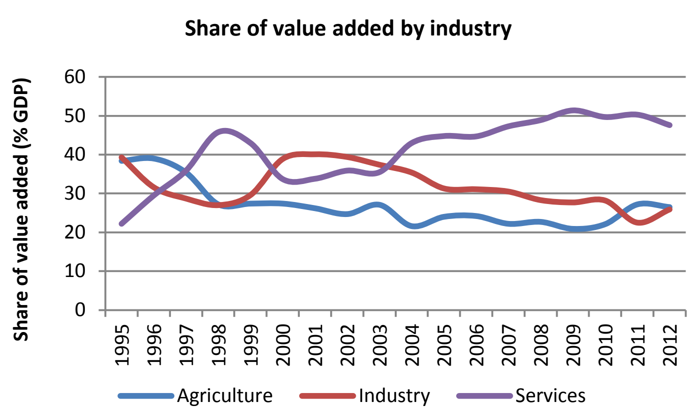


Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).

1.3 The labor market has undergone significant transformations

Tajikistan's economy has undergone fundamental structural changes over the last 15 years, with a shift in value added away from agriculture and industry toward services. Despite substantial fluctuations in value added by sector, this trend is especially evident in the last decade (Figure 7). The share of value added of the services sector has more than doubled since 1995, from 22 percent in 1995 to 48 percent in 2012. The share of agriculture and industry in value added has in turn decreased from approximately 40 percent each in 1995 to 26 percent each in 2012. However, compared to OECD members, agriculture continues to be a relatively important sector in Tajikistan (representing just 1.5 percent of value added in OECD countries), while services are significantly more important in OECD countries (representing approximately 75 percent of value added).

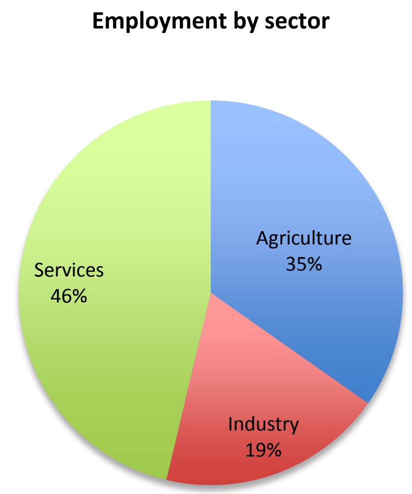
Figure 7: The share of services in GDP has increased while the share of agriculture and industry in GDP has decreased, 1995–2012



Source: Authors' calculations using the World Bank World Development Indicators, 2013.

Services and agricultural sectors account for the majority of employment in Tajikistan (Figure 8). Four out of five employed individuals are engaged in the services or agricultural sectors, but some of these workers are family workers or entrepreneurs. The share of employment in services is proportional to its share in GDP, but the value added in industry appears to be higher than the share of employment.

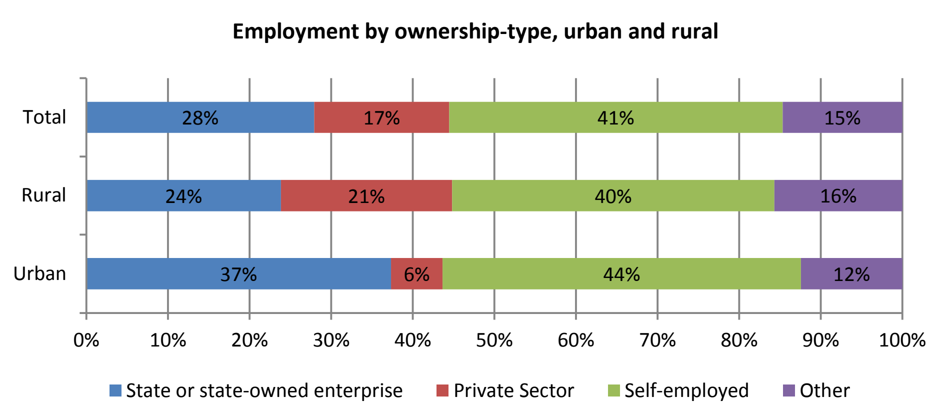
Figure 8: The services and agricultural sectors account for the majority of employment in Tajikistan, 2013



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

The majority of the employed population is self-employed or works in state-owned firms. In both urban and rural areas, self-employment is by far the most common type of employment; overall, 41 percent of the employed report to be self-employed (Figure 9). In addition, more than one in four people work in state-owned enterprises or for the government (28 percent). This is considerably higher than the number of people working for private firms (17 percent).

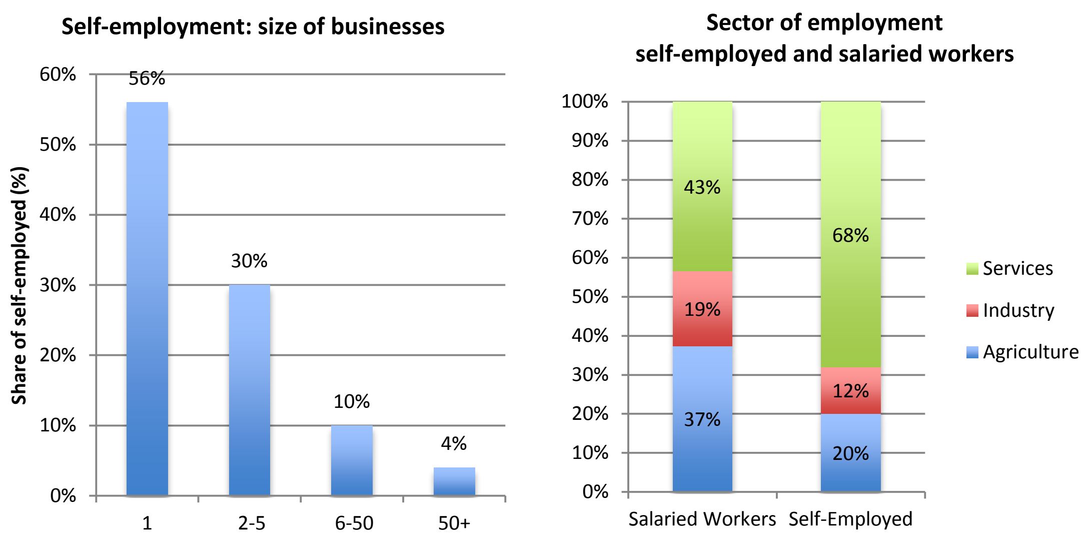
Figure 9: Self-employment dominates the labor market, followed by the state and state-owned enterprises, 2013



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

Entrepreneurship in Tajikistan is dominated by micro enterprises that operate in the services sector. Over half of all self-employed individuals do not employ any additional workers (56 percent) and another 30 percent employ fewer than five additional workers. Compared to salaried workers, the self-employed are more likely to engage in the services sector as opposed to industry and agriculture sectors. Note that the majority of individuals working in agriculture in Tajikistan are unpaid family workers (53 percent).

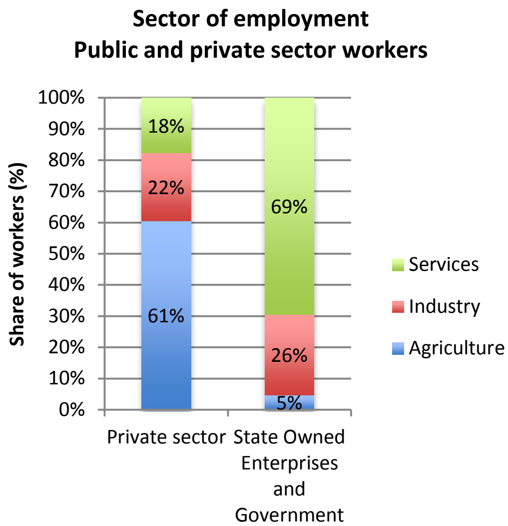
Figure 10: The vast majority of self-employed have micro-businesses in the services sector, 2013

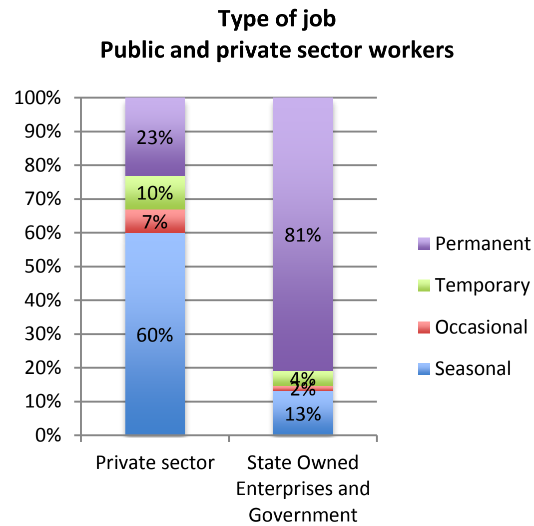


Source: Authors' estimates using World Bank/GIZ, *Tajikistan Jobs, Skills, and Migration Survey* (2013).

Private sector workers in Tajikistan typically perform seasonal labor in the agricultural sector. Nearly two-thirds (61 percent) of all workers engaged in the private sector work in agriculture (Figure 11), considerably above the country average of 35 percent (Figure 8). The vast majority of workers in agriculture have a seasonal job (80 percent), and overall four out of five workers in the private sector lack a permanent job. On the other hand, nearly all (81 percent) of the employees in the public sector consider their job to be permanent.

Figure 11: Private sector workers are typically employed in seasonal jobs in the agricultural sector, 2013





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

1.4 Job quality remains a concern in Tajikistan

Job quality is a multidimensional concept that includes earnings, but also other concepts such as workplace safety, job security, learning and advancement opportunities, and health and social protection benefits, mental and physical health, etc.[14] At the other extreme, not having a job undermines life satisfaction and especially in countries where wage employment is the norm and where the lack of opportunities translates into open unemployment rather than underemployment. In this section, the concept of informality, which is work without a labor contract; the type of work performed at typical workplaces; and the use of technology at work is explored in more detail.

Box 2: What are 'good jobs' in Tajikistan?

Qualitative study results suggest that the most important characteristics of a preferred job are a good income (30 percent), a permanent/long-term contract (11 percent), and access to benefits (11 percent). For women in particular, status/prestige (8 percent) and socially accepted jobs (6 percent) are other important considerations for a job. For younger men, a better work environment (6 percent) is among the preferred characteristics.

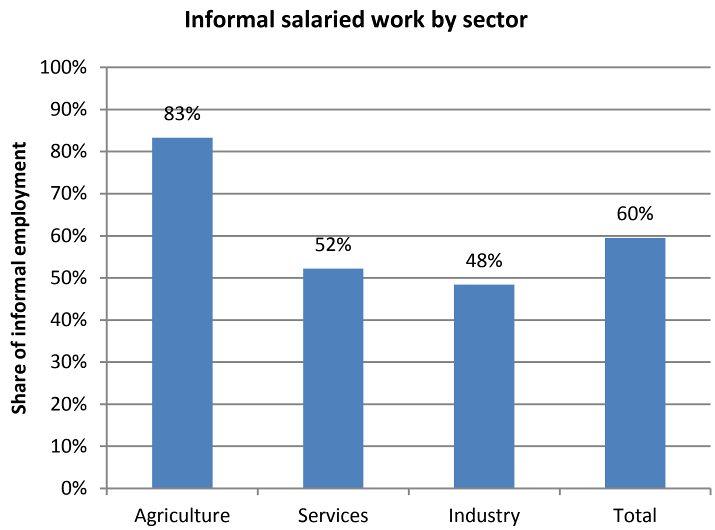
The majority of women prefer to be employed in the public sector, while men favor the private sector or self-employment. For women, the public sector ensures stability, a formal salary, and access to a pension upon retirement. While women (83.3 percent) tend to favor employment in large companies for its stability, men are less eager to work in large organizations (65 percent).

Source: World Bank (forthcoming).

[14] World Bank (2012).

Informal employment, which is prevalent in all three employment sectors—state-owned firms, private sector, and self-employed—plays a key role in the Tajik economy. About 60 percent of all Tajik salaried workers are engaged in the informal sector. Although the definition of informality varies across countries,[15] for the purposes of this analysis, the following definition is applied: informal sector salaried workers are those who lack an employment contract or are unpaid family workers. Informality is particularly common in the agricultural sector, a pattern observed in most countries around the world, and informality is also more common among less educated workers (Figure 12).[16]

Figure 12: A large share of salaried workers is employed in the informal sector, in particular in the agricultural sector, 2013



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

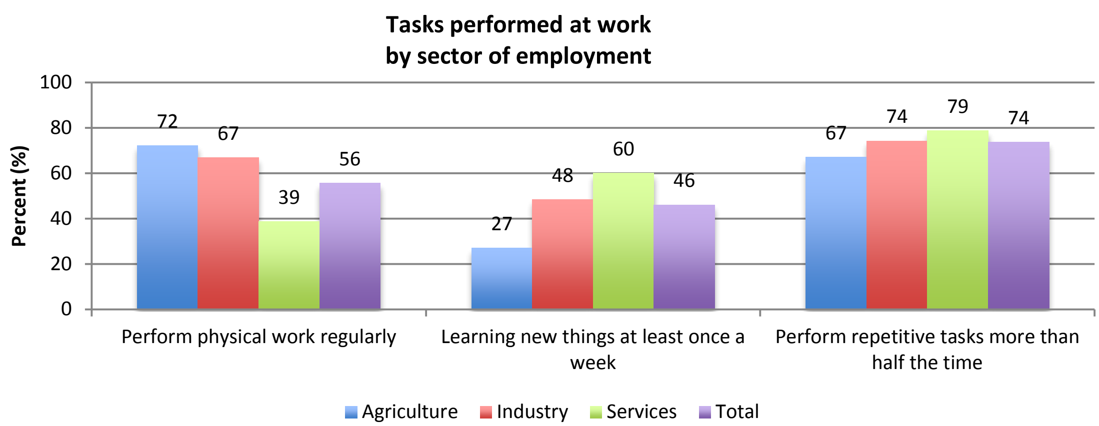
Informal employment offers remuneration and working conditions inferior to those in comparable formal sector jobs, and can impose costs to the economy at large. Consistent with evidence in other regions,[17] jobs in the informal sector in Tajikistan are associated with significantly lower earnings than comparable jobs[18] in the formal sector. Working conditions, as well, are inferior to those in formal sector jobs. Whereas approximately one in four workers in the formal sector are entitled to sick leave, less than one in ten workers have this entitlement in the informal sector. Moreover, people working informally typically face explicit and implicit barriers to public and privately provided insurance instruments to manage shocks. Indeed, the vast majority of respondents in the qualitative study report to prefer a job in the formal sector because of stability and access to

[15] See, for example, Perry et al. (2007).
[16] In some studies, the self-employed in businesses with fewer than six employees are also considered part of the informal sector. In Tajikistan, however, there is indication that a considerable share of these small businesses pay taxes, so while they are non-corporate, they should not be considered informal.
[17] Koettl et al. (2012).
[18] A comparable job is defined as a job in the same sector of employment (i.e. private/public/self-employed and agriculture/industry/services) held by an individual with the same level of completed education.

pensions and benefits.[19] More broadly, a large informal economy imposes heavy costs to the economy at large that tend to deteriorate the provision of services and public goods.[20]

Physical work and repetitive tasks are key components of most jobs in Tajikistan and less than half of all workers seem to learn new things on the job. Doing physical work is defined as regularly lifting or pulling anything weighing at least 50 pounds (25 kilograms). Such tasks are common in jobs in the agriculture and industry sectors, and less so in the services sector (Figure 13). The majority of tasks performed at work are repetitive in nature, and this holds for all three sectors of employment. Manual, repetitive tasks limit the scope for on the job learning, which is confirmed by respondents in all three sectors. Only one in four respondents working in agriculture (27 percent) and half of all workers in industry (48 percent) state that they learn new things at least once a week. This share is slightly higher in services (60 percent).

Figure 13: High shares of physical work and repetitive tasks, 2013



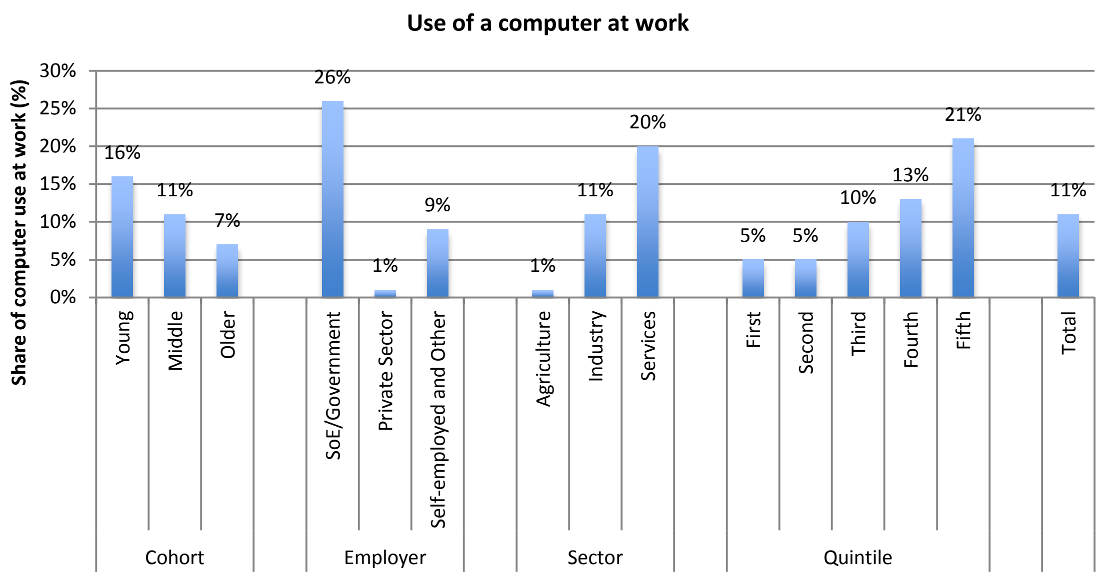
Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).

Few workers use computers on the job, and workers who do use computers are typically young employees in state-owned enterprises in the service sector. Overall, only one-in-ten workers in Tajikistan use computers at work. This is relatively low compared to other developing countries. In the Yunnan province in China 55 percent or workers use computers, and this share is 35 percent in Bolivia and Vietnam, and 30 percent in Sri Lanka (World Bank, 2013e). In Tajikistan, younger workers are more than twice as likely to use computers at work as older workers. The share of workers using computers is the highest in state-owned enterprises or the government (26 percent) and in the services sector (20 percent). Moreover, workers in richer households are considerably more likely to use computers at work than workers in poorer households, suggesting that higher paying jobs are more likely to require computer use.

[19] World Bank (forthcoming).

[20] Koettl et al. (2012).

Figure 14: Computer use is low, but is more common among young workers in the government or in state-owned enterprises in the services sector, 2013



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

1.5 Labor market systems are weak, hindering the job search and skills signaling process

Weak labor market information systems are hindering the job matching process. Difficulties in learning about job vacancies or demonstrating their skills make it harder for employees to find suitable jobs. Finding a job is usually a difficult and time-consuming process. Workers should know where an opening exists, how to search for work, and how to present their qualifications in a way that convinces the employer. There is evidence that information gaps and signaling problems form barriers to efficient and equitable job allocations in the Tajik labor market.

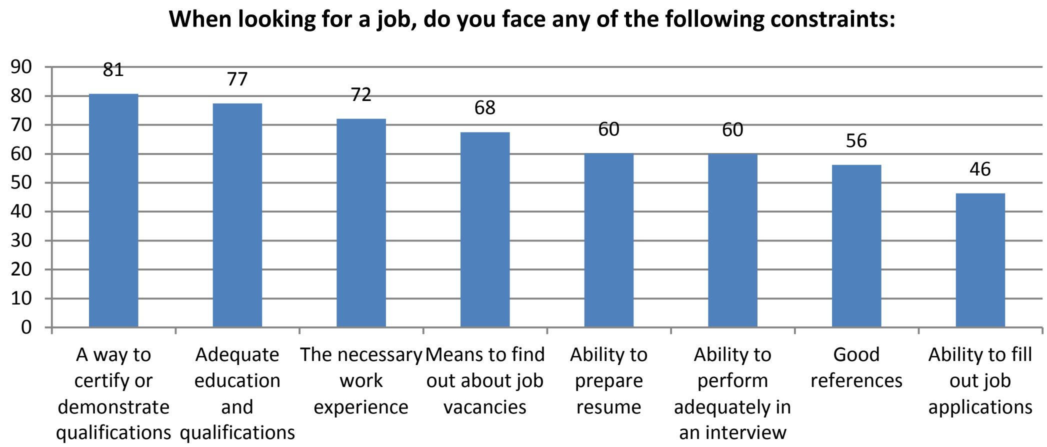
The majority of respondents in Tajikistan feel constrained by a lack of adequate qualifications and face difficulties demonstrating their qualifications when finding a job. Approximately 80 percent of the respondents in Tajikistan state that they are unable to certify or demonstrate their qualifications to an employer, or lack adequate qualifications to begin with. Qualitative study results show that, among other factors, having access to further training can help individuals get a job.[21]

In addition, two-thirds of individuals face significant barriers to learning about job vacancies. Information is a key element in the quest to successfully match labor supply and labor demand. Workers should have the ability to learn about vacancies and assess the nature of the jobs that are offered. In Tajikistan, however, two out of three respondents (68 percent) indicate that they do not have the means to find out about job vacancies, in the event that they would be looking for a

[21] World Bank (forthcoming).

job (Figure 15). In other words, there is scope for improvement in accessing labor market information in Tajikistan, for instance through public employment services.

Figure 15: A majority of respondents face significant barriers to finding a suitable job, 2013



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

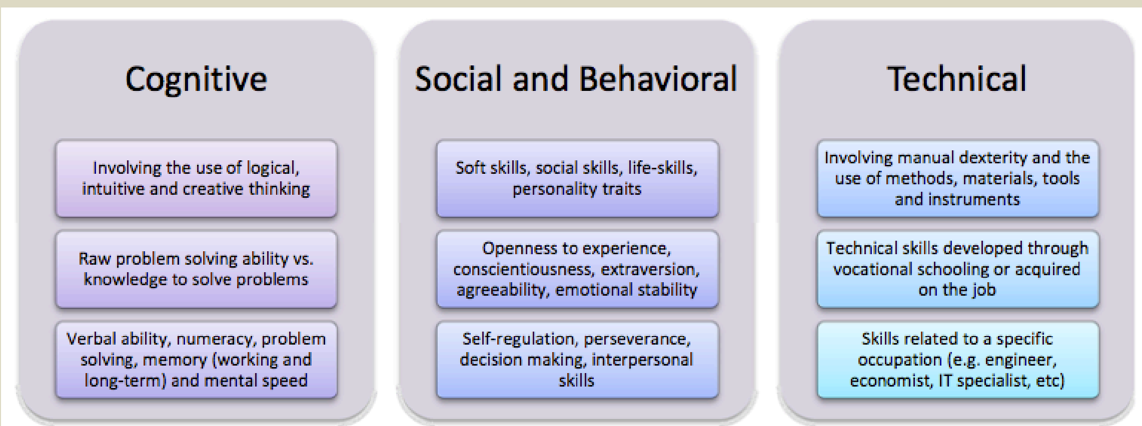
2 Skills and Employability

This section presents findings about the returns to skills in the Tajik labor market and the use of skills on the job, mostly drawing from the 2013 household survey data. In doing so, it addresses a fundamental question, namely what skills are valued and used in the Tajik labor market? Four key findings are explained in this section. First, the types of skills needed in both the domestic and international labor markets are changing. Second, educational attainment is valued in the labor market, but employers are not always able to find adequately educated individuals in the Tajik workforce. Third, skills are an important factor in employability. And fourth, workers with better skills tend to use them more frequently in the workplace. The section begins by defining skills. Box 3 defines skills for the purposes of this report. Because of data constraints, this study focuses on cognitive and non-cognitive skills. In addition to the results presented in the main body of the report below, Appendix F: Cognitive and Non-Cognitive Skill Mean Scores contains more detailed information on cognitive and non-cognitive skill outcomes.

Box 3: Defining skills

Workers' skills consist of cognitive, non-cognitive, and technical skills (Figure B3). Because of data constraints, 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. Social and behavioral skills represent personality traits that are relevant in the labor market, including extraversion, conscientiousness, openness to experience, agreeability, and emotional stability.

Figure B3: A worker's skillset can be divided into three types of skills: cognitive, social/behavioral, and technical



Source: Pierre et al. (forthcoming); "STEP Skills Measurement Surveys: Innovative Tools for Assessing Skills," cited in World Bank (2013b).

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

2.1 The skill needs in the domestic and international market are evolving

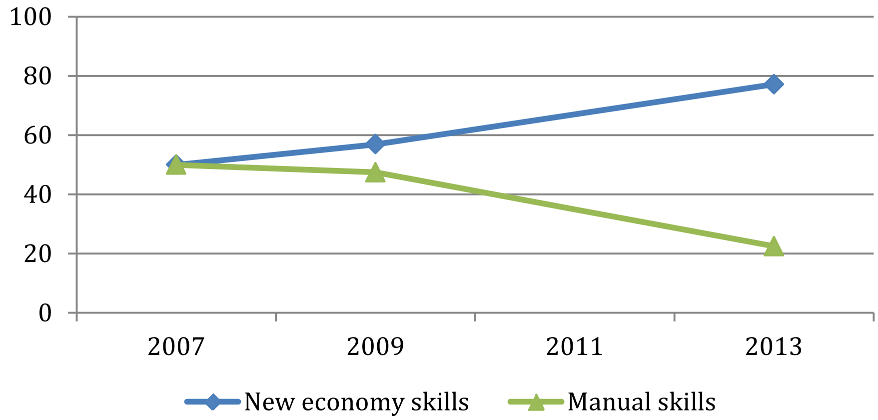
In an increasingly interconnected and globalizing world economy, newly created jobs require a high degree of analytical and interpersonal skills. The rapid developments in technology, business organization, and trade have led to changes in the key competencies needed in a dynamic labor market. The occupational structures in most economies worldwide and in ECA have undergone a significant change: a shift in value added and employment toward knowledge-intensive activities and services has reduced the demand for manual tasks that can be easily automated, and occupations requiring high analytical and interpersonal skills are becoming more prevalent.[22]

In Tajikistan, too, there is an increasing demand for "new economy" skills. Figure 16 shows the evolution of the skill intensity of jobs in Tajikistan between 2007 and 2013. It depicts the change in an index of the task-skills intensity of jobs relative to the skills intensity of jobs in 2007, measured in "centiles" (or less precisely, the percentile change in skills requirements in jobs in the Tajik economy). The demand for new economy and routine cognitive skills increased (often in manufacturing and services jobs) while the demand for routine manual skills declined (often in low productivity agriculture and retail services). This shift has occurred primarily in the four years

[22] Arias et al. (2014).

between 2009 and 2013, while the change was less apparent from 2007 to 2009. This shift in skills demand is consistent with those observed in other Eastern European and Central Asian countries as well as in many OECD countries.

Figure 16: Evolution of skill intensity of employment in Tajikistan reveals an increase in "new economy" skills, 2007–2013

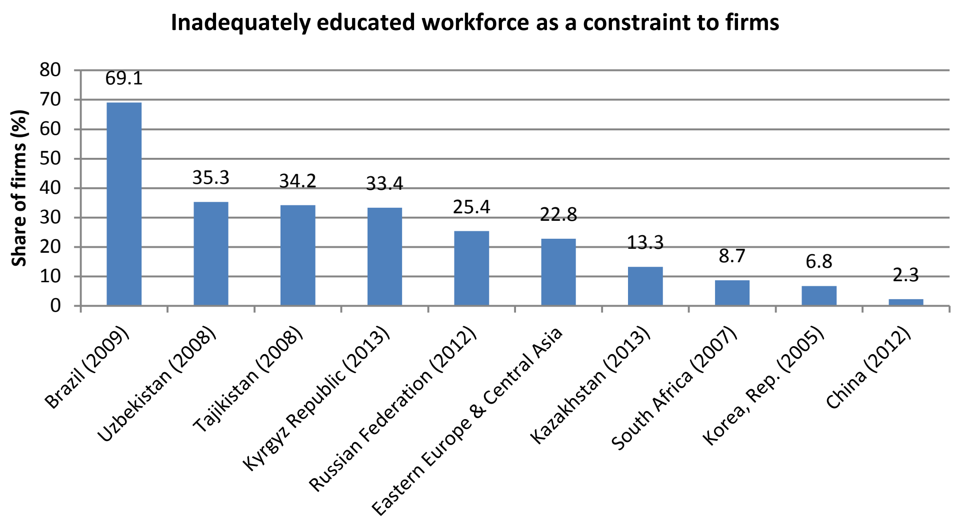


Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013); *Tajikistan Living Standards Survey* (2009), and *Tajikistan Living Standards Survey* (2007).

2.2 Education matters to employers

A considerable share of firms in Tajikistan complains about an inadequately educated workforce. The World Bank Enterprise Survey reveals that approximately one third of all firms in Tajikistan (34.2 percent) identifies an inadequately educated workforce as a major constraint (Figure 17). This share is higher than the average in Eastern Europe and Central Asia (22.8 percent) and also higher than in most comparator countries (with the exception of Brazil). Note that the question does not specify whether inadequately educated means that workers' skills are on average too low, or that workers on average have the wrong set of skills and/or specialization for their job. The former implies a problem related to skill formation, as discussed in section 4. The latter, on the other hand, is inherently also a problem in the labor market. Even if workers possessed the right level of skills, there may be inefficiencies in matching workers to jobs. In this case, the problem is in the allocation of jobs in the labor market.

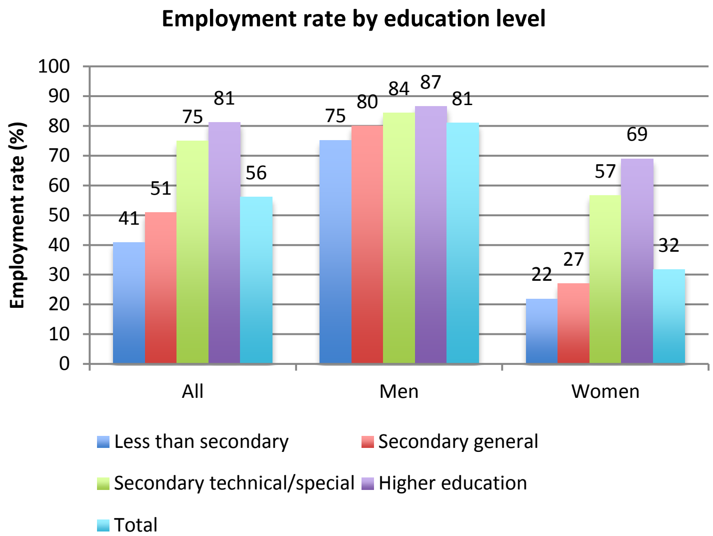
Figure 17: Employers in Tajikistan report that inadequate education of the workforce is a major constraint to firm growth



Source: Authors' calculations using the World Bank Enterprise Surveys.

Employment prospects are stronger for higher educated and secondary special/technical educated individuals. While individuals who have completed a secondary special/technical or higher education enjoy high employment rates, individuals who have only completed secondary general or who have not completed secondary school are less likely to have a job. Overall, the employment rate among adults with a university degree (81 percent) is roughly twice as high as the employment rate among adults who have not completed a secondary general education (41 percent). This ratio is in fact three-to-one for women, with employment rates of 69 percent for women with a higher education compared to 22 percent for women with less than a secondary education.

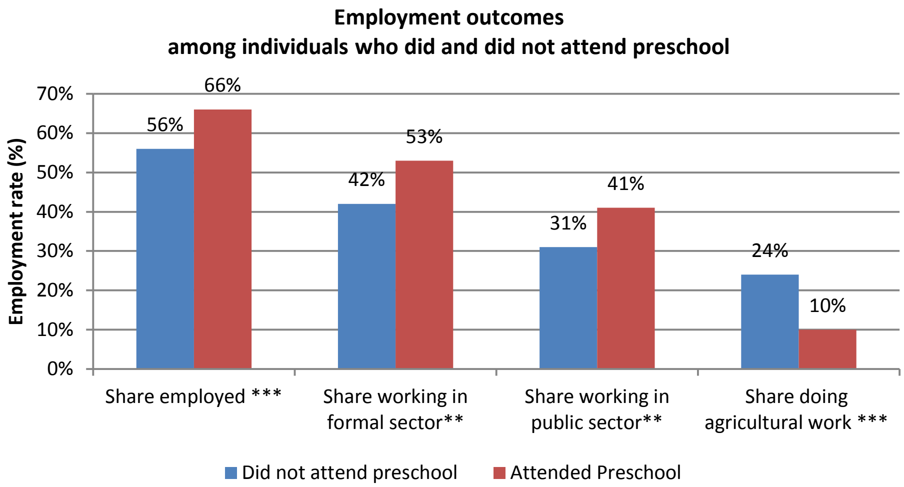
Figure 18: Employment prospects are stronger for university and secondary special/technical educated individuals, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 25–64.

Preschool attendance as a child is significantly correlated with employment outcomes, but mainly as a result of higher educational attainment. Adults who attended preschool as a child on average are more likely to be employed (66 percent) compared to adults who did not attend preschool (56 percent), and, among those employed, a larger share of adults who went to preschool as a child have formal sector jobs or public sector jobs (Figure 19). Doing 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, geographic location, and educational attainment, preschool is no longer a significant correlate of employment outcomes; rather, educational attainment is a more significant correlate of labor market outcomes. Preschool attendance may not be correlated with employment outcomes directly, but rather through higher educational attainment.

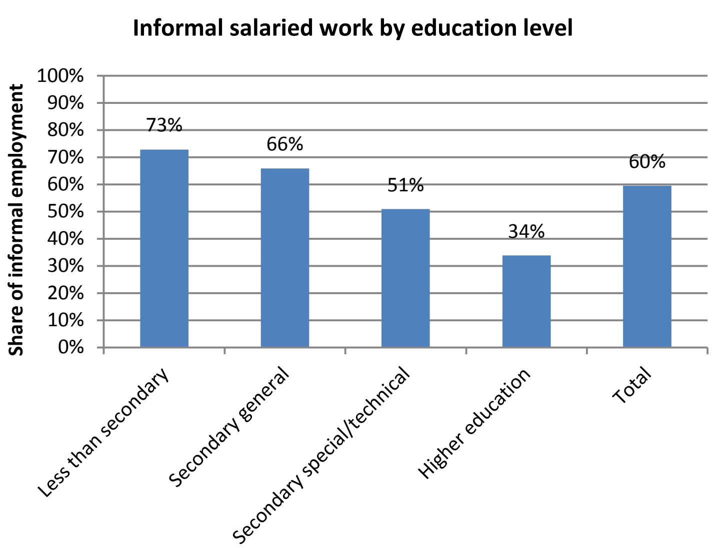
Figure 19: Employment outcomes are positively correlated with preschool attendance as a child, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan 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.

Informality rates fall sharply with educational attainment. As shown, approximately 60 percent of all salaried workers in Tajikistan are engaged in the informal sector. This share is even higher among lower educated individuals. In fact, workers with less than a secondary education are roughly twice as likely to be engaged in the informal sector as workers with higher education (Figure 20). As discussed earlier, informal sector jobs are usually associated with lower pay, job insecurity, and no access to benefits.

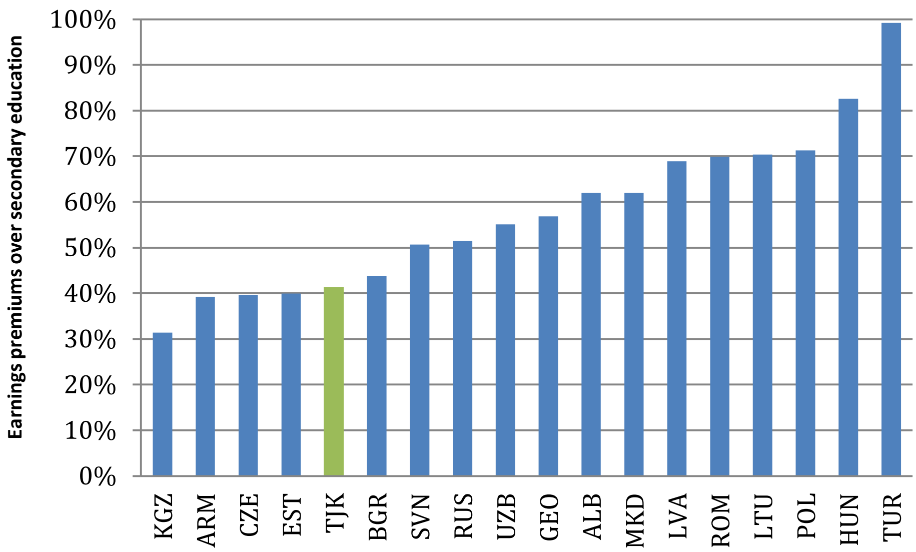
Figure 20: Job quality improves with educational attainment



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 25–64.

In addition, there is a considerable wage premium to higher education in the labor market in Tajikistan. Figure 21 shows the average percentage earnings premium for workers with higher education relative to workers with secondary education (both general and technical) with similar observed characteristics. In Tajikistan, workers with higher education on average have a 40 percent higher wage than similar workers with secondary education. Such a considerable return to higher education is a signal of strong demand for higher educated individuals in the labor market. As such, there is a positive correlation between the degree of modernization (reforms to transition to a market economy) and the returns to higher education.[23] Average college premiums are highest in most EU-10 countries and are comparable to other middle- and high-income countries. Hence, the value and importance of higher education is likely to increase as Tajikistan's economy continues to modernize.

Figure 21: The average returns to higher education are large among salaried workers aged 25–64 in Tajikistan, circa 2009



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

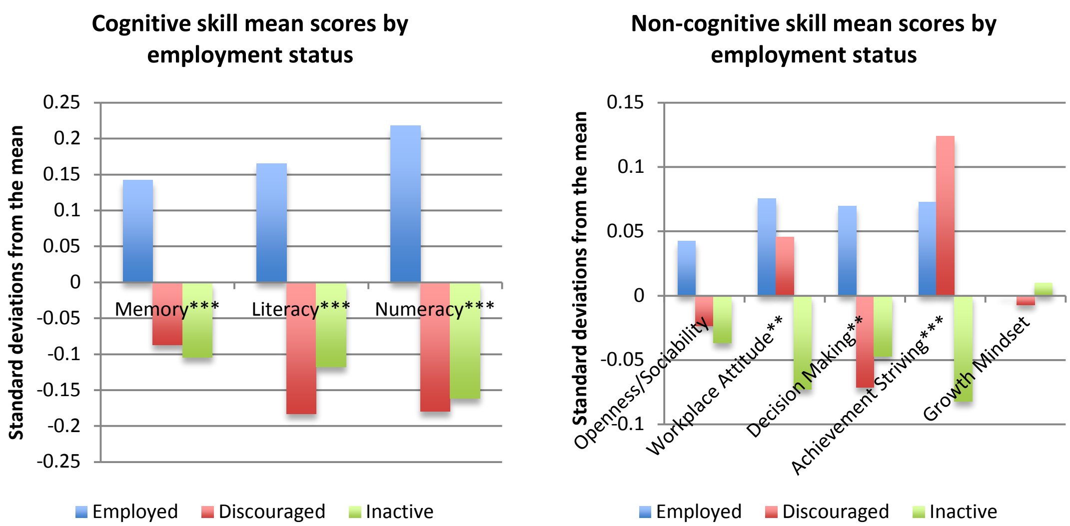
2.3 Skills and employability are closely linked

In Tajikistan, workers have significantly better cognitive and non-cognitive skills than individuals who are out of work (Figure 22). Employed adults scored significantly higher than the inactive population average on all measured cognitive skills, including memory, literacy, and numeracy. The gap is especially large for numeracy, where employed adults on average receive nearly half a standard deviation higher scores than adults without a job. Non-cognitive skills are also considerably better among the employed. In particular—as found in other studies (see Box 4)—workplace attitude, decision making, and achievement striving are significantly correlated with being employed in Tajikistan.

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

Moreover, individuals who are discouraged in the labor market have significantly lower cognitive skills than the employed. Discouraged individuals have similar cognitive skills as individuals who are out of the labor force. Non-cognitive skill outcomes are more mixed but decision making, in particular, seems to be falling short. These results may, in part, explain why discouraged individuals face difficulties finding a job in the labor market. Of course, others factors both on the demand side—including high reservation wages or a lack of mobility—and on the supply side—most notably constraints in the business environment—should not be discounted. Nonetheless, low skill levels among the discouraged are noteworthy in particular because youth are overrepresented in the discouraged population, and given the youth bulge in Tajikistan, the mismatch in skills raises the stakes for policy makers.

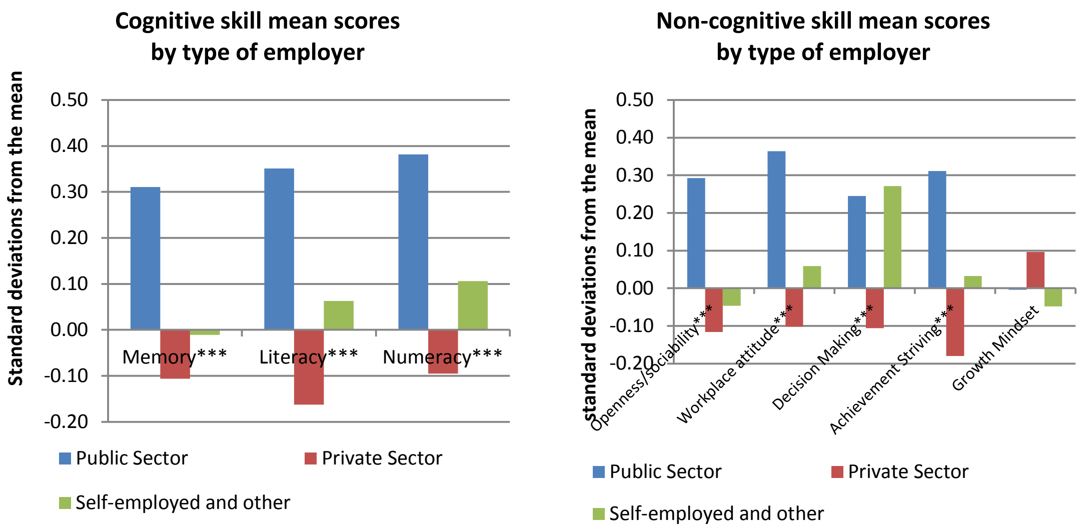
Figure 22: Both cognitive and non-cognitive skills are significantly better among employed adults compared to adults who are out of work or are discouraged, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan 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; and * significant at the 10% level.

Individuals with better skillsets typically work in the public sector. Figure 23 depicts the cognitive and non-cognitive skills for employed adults in the public and private sector, as well as for self-employed individuals. Higher-skilled individuals are clearly concentrated in the public sector. Cognitive skills are up to half a standard deviation higher among employees in the public sector compared to employees in the private sector (in the case of literacy). Similar gaps are found for non-cognitive skills such as openness/sociability, workplace attitude, decision making, and achievement striving. The lack of high-skilled individuals in the private sector suggests that this sector is currently a relatively unattractive sector to work in.

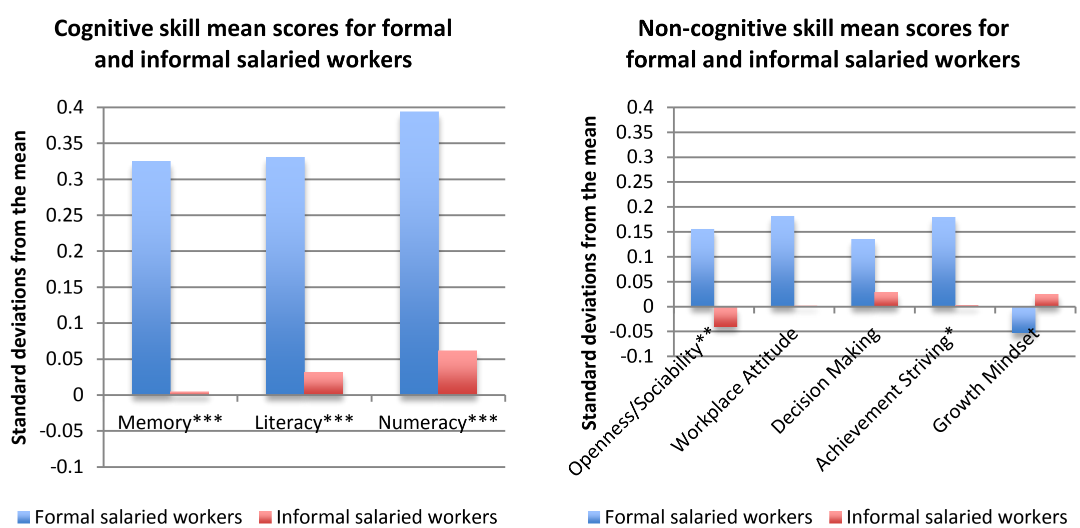
Figure 23: Higher cognitive and non-cognitive skills are observed in the public sector, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan 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; and * significant at the 10% level.

There is a stark difference between skills of formal and informal sector workers—with formal sector workers having better cognitive and non-cognitive skills (Figure 24). All measured cognitive skills among formal sector salaried workers are significantly higher than those among workers in the informal sector. Similarly, there are large differences in non-cognitive skills between workers in the formal and informal sector. Statistically significant differences are can be observed for openness or sociability and for achievement striving.

Figure 24: All measured cognitive skills, and certain non-cognitive skills, are considerably lower among informal compared to formal salaried workers in Tajikistan, 2013



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

Note: Respondents aged 25–64. *** significant at the 1% level; ** significant at the 5% level; and * significant at the 10% level.

Regression analysis confirms that both cognitive and non-cognitive skills matter for employment outcomes in Tajikistan.[24] Controlling for the usual socio-demographic variables,[25] several cognitive and non-cognitive skills remain significantly associated with being employed, as opposed to being out of work. Although no causality is implied, numeracy (cognitive) skills and decision making (non-cognitive) skills are found to be positively and significantly associated with the probability of being employed. An increase in the numeracy score by one standard deviation is associated with a 24 percent higher likelihood of being employed; similarly an increase in the decision-making score by one standard deviation is associated with a 9 percent higher likelihood of having a job. The other cognitive and non-cognitive scores are not correlated significantly with being employed.

In the more modern sectors (i.e. industry and services) in particular, the probability of employment is significantly higher for individuals with better cognitive and non-cognitive skillsets. As the economies develop and prosper, they also undergo a process of structural shift, whereby jobs are shifted from the traditional sectors (agriculture and mining) to the modern ones (industry and services). This shift also implies a rise in importance of the cognitive and non-cognitive skills in this so-called "modern" sector.[26] In order to gauge this relationship, the analysis above is restricted only to the industry and services sectors, as opposed to working in agriculture or being out of work. The results reveal that, in addition to numeracy and decision making, workplace attitude is also found to be positive and statistically significantly correlated with employment in the industry or services sector, although only within the female sub-sample.

Workers with better cognitive and non-cognitive skills are typically more likely to have a formal sector job. A higher skillset implies not only higher employability, but also a higher chance of obtaining a formal sector job, typically a job in the state administration or a state owned enterprise (SOE), as well as in a medium or big privately owned company. There are numerous benefits associated with employment in these sectors, thus including job security and various social protection benefits. In order to explore the relationship between a respondent's skillset and the probability of having a formal sector job, we repeat the analysis from above, restricting it to employment in the state administration, SOEs, as well as private enterprises employing more than 6 workers. The results confirm the findings that the numeracy score and workplace attitude (only when the analysis is restricted to the female sub-sample) are associated with a higher probability of being employed in a formal sector job.

[24] See Nikoloski and Ajwad (forthcoming) for details. A probit analysis was conducted in order to assess the probability of being employed, conditional on a respondent's set of cognitive and non-cognitive skills.
[25] Namely, age, gender, place of residence, and education attainment.
[26] OECD (2010).

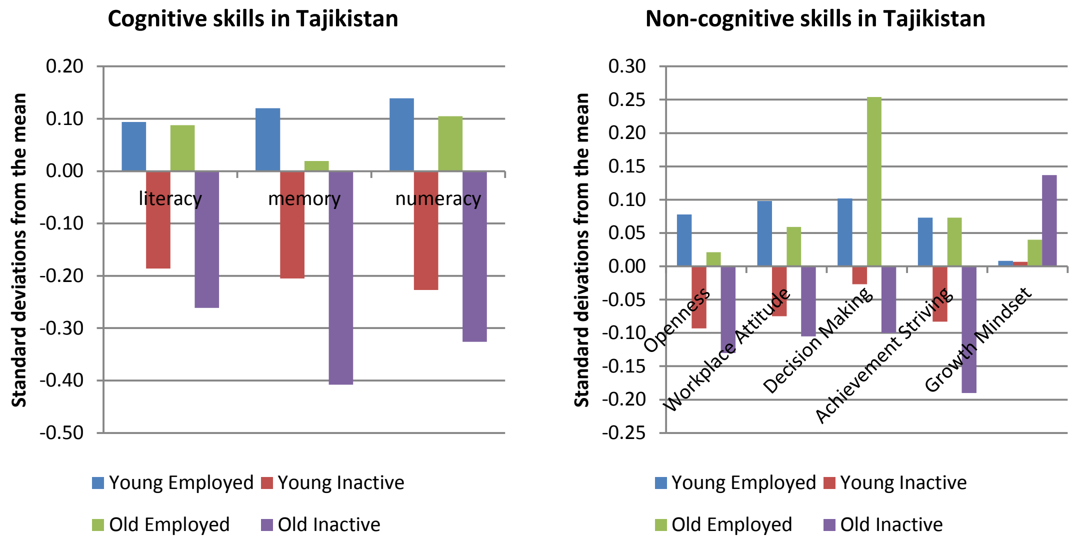
Box 4: Existing literature shows a strong relationship between both cognitive and non-cognitive skills and employment outcomes

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 (Sanchez 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).

Young adults possess better cognitive skills than older adults, but the pattern is not as clear for non-cognitive skills. Figure 25 shows two interesting patterns. First, young adults generally have better cognitive skills than older adults. Second, employed people have higher cognitive skills than inactive people. This holds both for the young and old age cohort. Similarly, employed people score higher than inactive people for most measures of non-cognitive skills as well, for both young and older cohorts. Among the employed, young people show more openness and better workplace attitude, a finding that is observed in other countries as well. However, older workers appear to be much better decision makers in Tajikistan relative to younger workers.

Figure 25: Cognitive and non-cognitive skills are generally better in young compared to older workers, especially among the inactive population, 2013



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

Box 5: Skills and migration in Tajikistan

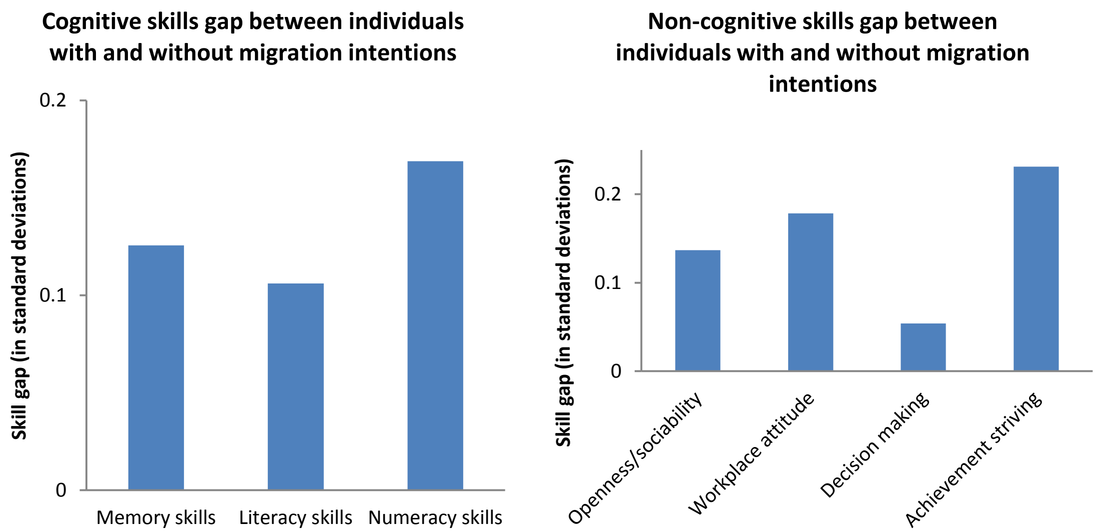
Existing studies find that migrants and non-migrants differ with respect to education and skills. Among the reasons are the selective migration of groups who can gain disproportionally from mobility (Borjas, 1987), investments in higher education for those who aspire to migrate (Mountford, 1997), or 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.

Individuals who intend to migrate from Tajikistan generally score above those who do not intend to migrate on cognitive and non-cognitive skills.[27] Given that migration is a common labor market outcome for Tajik youth, with one-third of all 20-39 year old males migrating for employment, it is important to analyze the skill profile of migrants. In Tajikistan, adults with migration intentions typically belong to the middle of the educational attainment distribution. However, individuals with intentions to migrate score significantly above average on all cognitive and non-cognitive skills compared to individuals who plan to stay in Tajikistan. The skills gap is sizeable for memory, literacy and numeracy skills (all greater than 10% of a standard deviation). 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 achievements and ambitions,

[27] The analysis of skill profiles among those who intend to migrate and those who return from working abroad is drawn from a background paper written by Alexander Danzer.

reflecting the fact that migrating abroad implies a strongly positive contribution to family income in Tajikistan. In support of selection theories, the results show that individuals planning to migrate have on average better cognitive and non-cognitive skills than others in the working-age population. The results also suggest that studies focusing exclusively on education may draw different conclusions.

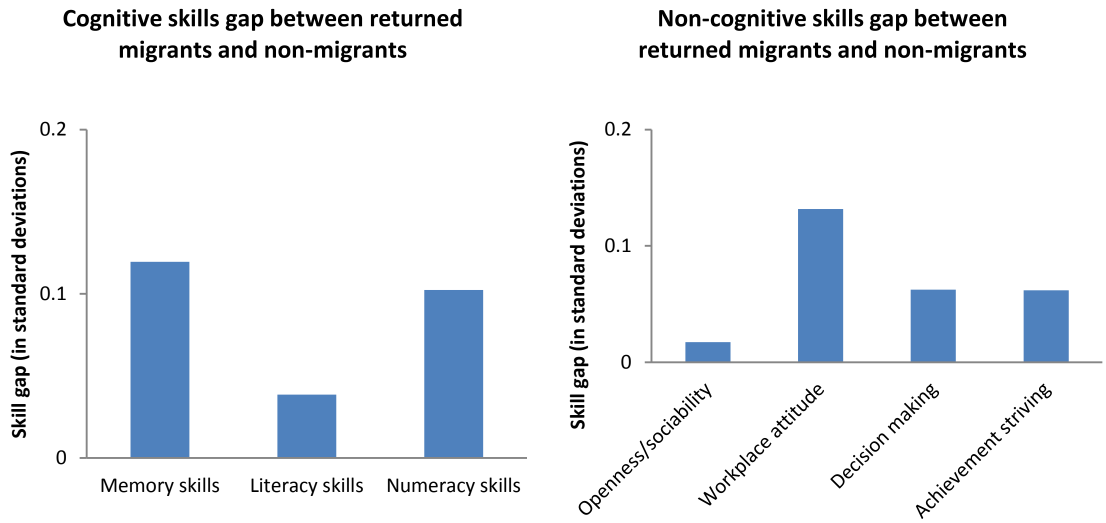
Figure 26: Adults with migration intentions on average have significantly higher cognitive and non-cognitive skills than adults without migration intentions, 2013



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

Migrants who return have significantly higher cognitive and non-cognitive skill outcomes than non-migrants (Figure 27). These return migrants typically have a secondary education diploma and have significantly higher cognitive and non-cognitive skill outcomes than non-migrants. The positive cognitive skills gaps migrants who have returned are of similar size to the positive cognitive skills gaps for individuals with migration intentions. Therefore, if many of those with intentions to migrate follow through and migrate (and if migrants had migration intentions before the move), this result suggests that migrants do not necessarily acquire cognitive skills during their stay abroad. Returned migrants also have better non-cognitive skills than non-migrants. For non-cognitive skills, the most interesting difference between returned migrants and individuals with migration intentions can be found for achievement striving skills. While individuals who plan to migrate are substantially more ambitious than non-migrants, actual migrants are only slightly more ambitious than non-migrants. This could result if the most ambitious adults tend to emigrate permanently and hence are not captured in the survey.

Figure 27: Returned migrants on average have significantly higher cognitive and non-cognitive skills than non-migrants, 2013



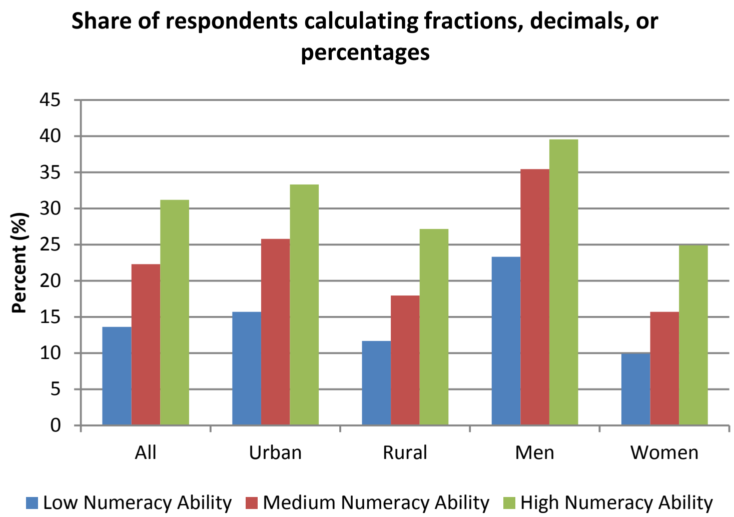
Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).

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

Comparing a worker's skillset and use of skills on the job can help to establish whether an individual's skillset is put to use in the labor market. If the labor market were to effectively make use of workers' skills, then there would be a positive correlation between ability and the use of skills on the job. For example, a person with better numeracy ability would use mathematics skills more frequently and intensely on the job. This section examines whether the labor market in Tajikistan indeed uses workers' skills in an effective way. It is important to note that the results presented are correlations—they do not imply causation. It may be that individuals who make more use of mathematics on the job score higher on a mathematics ability test precisely because they use such skills on a daily basis. Such bi-directional links between skill use and skill ability is an important caveat when interpreting the results.

In Tajikistan, workers with better cognitive skills typically make more frequent and intense use of mathematics and reading skills. Figure 28 shows that individuals with high numeracy ability are on average more than twice as likely to use mathematics on the job—calculating fractions, decimals, or percentages. These positive correlations hold in both urban and rural areas, as well as for both men and women. Similar results show that literacy ability is also positively correlated with the frequency and intensity of reading. Note that the use of math is generally considerably lower among women, compared to men.

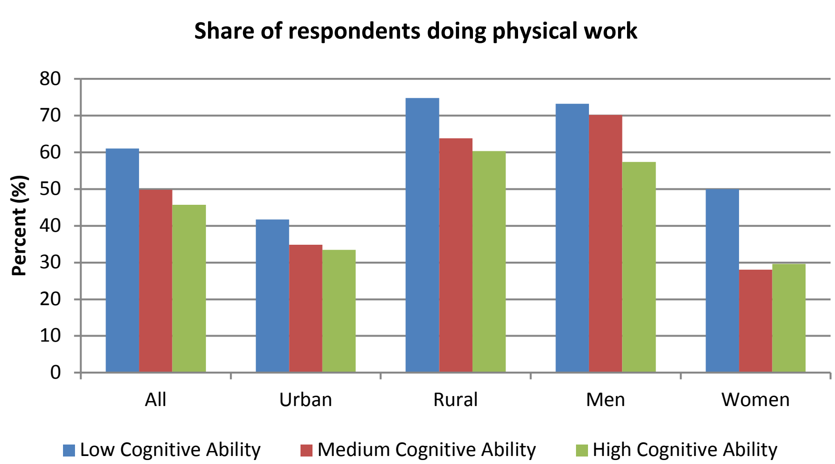
Figure 28: Workers with higher numeracy skills use more mathematics on the job, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Low, medium, and high numeracy ability are defined as the bottom, middle, and top third of the numeracy ability distribution.

Workers with higher cognitive ability are less likely to do physical work. The share of respondents who do physical work drops from 60 percent among those with low cognitive ability, to just over 40 percent among those with high cognitive ability (Figure 29). While this drop is significant, the share of physical work remains high even among individuals with a high cognitive ability. This underscores the earlier finding, in section 1.3, that the labor market in Tajikistan consists largely of jobs that require manual work.

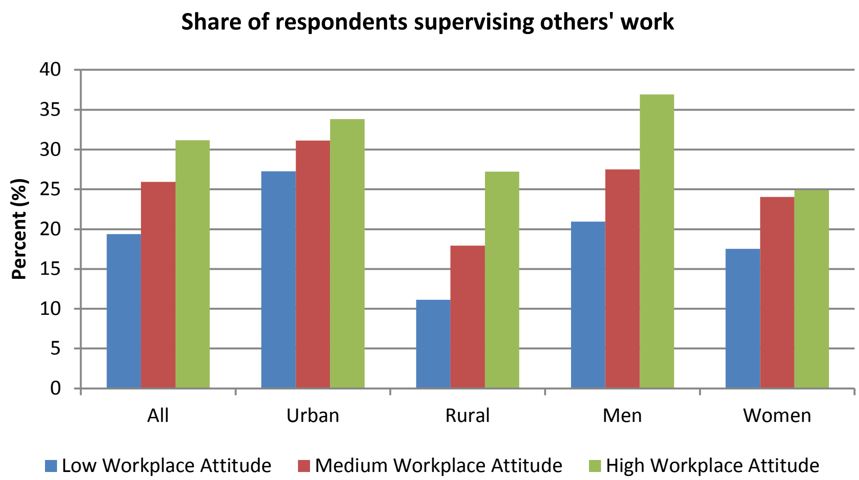
Figure 29: Physical tasks are a less common component of jobs occupied by workers with better cognitive skills, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 16–64. Physical work is defined as regularly lifting or pulling anything weighing at least 50 pounds (25 kilograms) as part of work.

Workers with strong non-cognitive skills tend to supervise other people. For example, individuals with a higher workplace attitude[28] are more likely to supervise other people's work (Figure 30). Similarly, being more open and sociable increases the likelihood of having contact with people other than colleagues, such as clients, customers, or students. Women at all levels of ability are considerably less likely to supervise others' work than men.

Figure 30: Workplace attitude non-cognitive skills are correlated with supervising other workers, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 16–64.

[28] Workplace attitude consists of traits such as coming up with ideas others haven't thought of before, working very hard, and enjoying working on things that take a long time to complete. See Appendix C for a full description of the socio-emotional skill measures.

3 Skill Formation over the Life Cycle

This section assesses skill formation coupled with educational attainment levels in Tajikistan. Specifically, it addresses the following question: does the education and training system impart the cognitive and non-cognitive skills needed to successfully participate in Tajikistan's labor market? The details ensue, but the four main findings on the role of the education system show a mixed record. To summarize, first, it is important to underscore that skills are formed throughout an individual's life cycle. Different skills are developed during different stages in the life cycle and a host of actors are involved—from families to formal schooling, to adult training, to employers. Second, although general educational completion rates are relatively high, preschool and vocational coverage rates fall short. Third, workers with higher educational attainment generally have higher cognitive and non-cognitive skills. Yet, there is considerable variation across workers in cognitive and non-cognitive skills despite identical educational attainment levels. Such significant variation in cognitive and non-cognitive skills within educational attainment levels raises questions about the quality of education in Tajikistan.

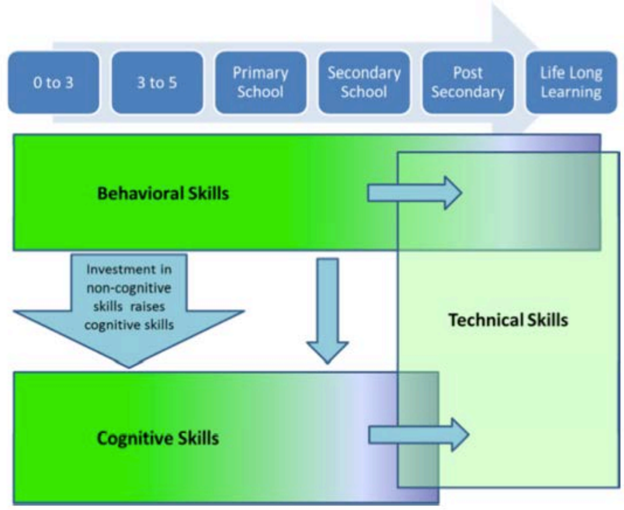
3.1 Skills are formed throughout the life cycle

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 31. Because cognitive and behavioral skills are formed earlier on in life, the early childhood period is critical in the development of these 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 foundations of an individual's cognitive abilities are well set. Technical skills are developed later—they are continuously developed throughout adolescence and into adulthood.[29]

The development of solid cognitive and non-cognitive skills early in life is central to building skills needed for productive employment. Strong cognitive and behavioral 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.[30] They also determine a person's readiness to learn over the life cycle by shaping the capacity and motivation to absorb new knowledge, adapt, and solve new problems. This is crucial in a dynamic economic environment 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 them is a powerful way to improve educational attainment, life-long learning, and thus employability.[31]

[29] Heckman and Cunha (2010); Heckman (1996, 2004).
[30] World Bank (2013b).
[31] Arias et al. (2014).

Figure 31: Skills are developed in all stages of life—very stylized



Source: World Bank (2013a).

Over the last two decades, the literature has shifted from focusing on enrollment levels and educational attainment to focusing on the skills obtained by students. An influential recent study shows that educational quality—that is, ensuring that students develop valuable skills—is what matters to achieve economic growth.[32] This section assesses cognitive and non-cognitive skill development and outcomes in the Tajik working-age population. We begin, however, by presenting the traditional educational attainment measures (section 3.2). The next sections discuss correlations between educational attainment and cognitive (section 3.3) and non-cognitive (section 3.4) skills.

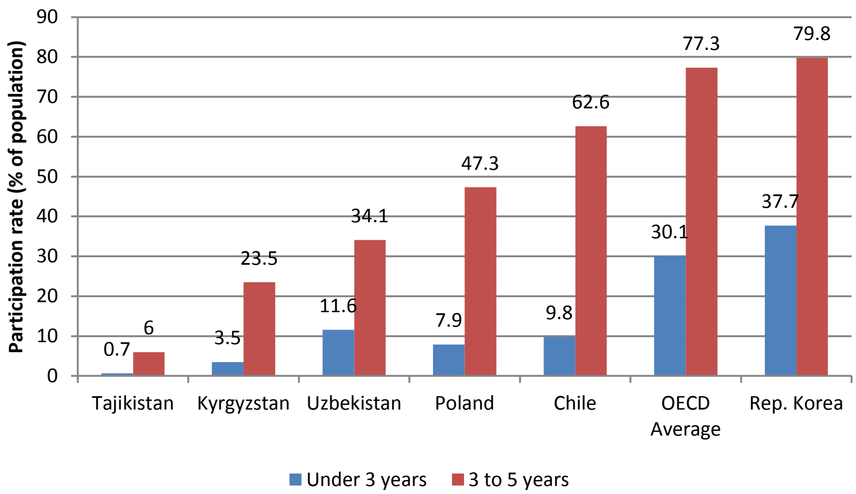
3.2 General educational completion rates are high, but preschool and vocational coverage rates fall short

Skill formation challenges start at the youngest ages; it is alarming that a significant percentage of Tajik children suffer from malnutrition and that preschool enrollment levels are exceptionally low. Proper nutrition, cognitive stimulation, and nurturing care during children's early years have lasting positive effects for their subsequent educational attainment, amongst other indicators.[33] Aside from early childhood skill formation, there are many other reasons to invest in early childhood development, as illustrated in Box 6.Starting at an early age, proper nutrition is key to building cognitive and non-cognitive fundamentals. However, in Tajikistan, 15 percent of all children under the age of five suffer from malnutrition.[34] In addition, moderate and severe stunting is prevalent, affecting 39 percent of all children under the age of five.[35] In terms of schooling, preschool enrollment is exceptionally low in Tajikistan (Figure 32). Less than one percent of all children under 3 years old are participating in preschool, compared to approximately 30 percent in the average OECD country. More striking is that even in the 3- to 5-year-old cohort, only 6 percent

[32] Hanushek and Woessmann (2009).
[33] Shonkoff and Phillips (2000); and Cunha et al. (2006).
[34] UNICEF (2013).
[35] WHO (2013).

of children are in preschool, which falls far below the average in comparator countries. In the Republic of Korea, for example, almost 80 percent of 3- to 5-year-olds are enrolled in preschool programs and in Poland almost half of all 3- to 5-year-olds are enrolled in preschool programs. Qualitative study results suggest that there are not enough preschool facilities in Tajikistan.[36] In particular, women suggested that most of the preschool facilities are located in urban areas and capacity is limited.

Figure 32: Enrollment in preschool programs is very low in Tajikistan, 2013



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

Box 6: Early childhood development (ECD) investments can promote social equity and have positive externalities

Aside from promoting skills development at the early childhood stage, investments in ECD can contribute to social equity by reducing the intergenerational transmission of poverty. The family environment is crucial to any child's development of skills and abilities, but poor children frequently do not have access to the resources enjoyed by their wealthier peers. This disparity leads to the emergence of performance gaps between children from different socioeconomic backgrounds and the widening of these gaps as the children grow older (Paxson and Schedy, 2007). By using public resources to create a supportive environment for the most disadvantaged children, ECD programs can make up for some early family differences. Research has convincingly shown that early childhood interventions can equalize opportunities for children and reduce the intergenerational transmission of poverty and inequality (Heckman, 2006).

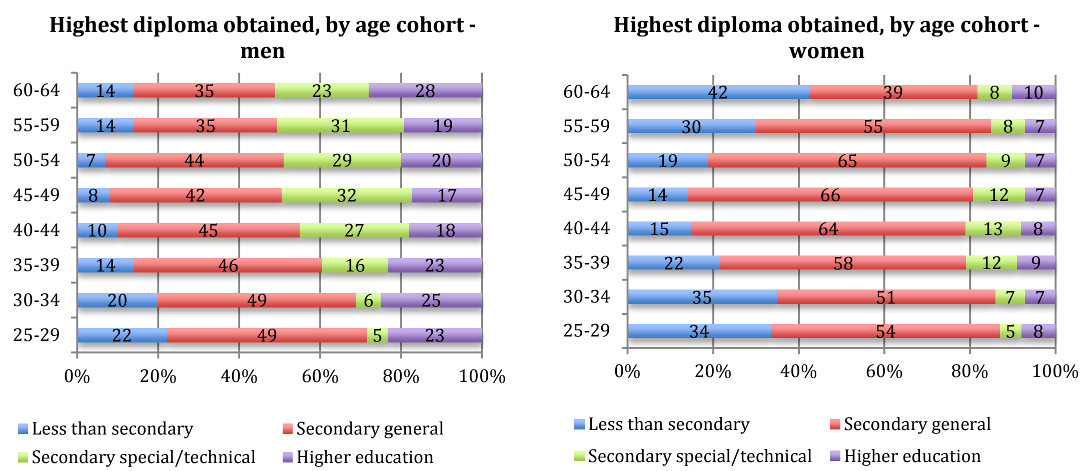
Provision of ECD services has positive externalities, including increased female labor supply. ECD interventions that also provide childcare can free household members to participate in other productive activities such as education or employment. For example, the expansion of Argentina's pre-school programs increased maternal employment by about 7 to 14 percent.[37] In this way, ECD can create win-win situations whereby there is an immediate payoff in the form of an increase in female labor force participation and a longer-term return in the form of a healthier, more educated workforce.

[36] World Bank (forthcoming).

[37] Berlinski et al. (2009)

While education completion rates are relatively high at the secondary level, an increasing share of people, women in particular, are not completing secondary general schooling. The education system in Europe and Central Asia was well-regarded prior to the transition, due to the Soviet system's emphasis on equalizing the population's access to education (an overview of the education system in Tajikistan can be found in Appendix D: The Education System in Tajikistan).[38] Tajikistan's achievement in terms of access to general education remains strong: educational enrollment is high at the secondary general level. The proportion of adults (25 years and older) who have attained at least a secondary level education is approximately 80 percent (Figure 33). Note that this is due to national compulsory education requirements. Worryingly, however, the share of individuals who have dropped out of school before completing secondary general has increased among younger cohorts. The share of men and women with less than a secondary level of educational attainment is more than twice as high among 25- to 34-year-olds compared to 40- to 54-year-olds. In addition to the results presented, Appendix E: Summary Tables contains more detailed results on educational attainment in Tajikistan among the working age population.

Figure 33: Education completion rates are favorable at the secondary level, but are low at the vocational level, 2013



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

Vocational degree completion is low and decreasing in Tajikistan. Vocational education in Tajikistan includes a secondary technical and secondary special degree. Prior to the transition, the share of individuals who obtained such a degree was approximately 30 percent among men and 12 percent among women. This share has dropped considerably in recent decades, and only approximately 6 percent of young men and women aged 25–34 have completed a secondary technical or secondary special degree (Figure 33). 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.[39] As a result, there are 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.

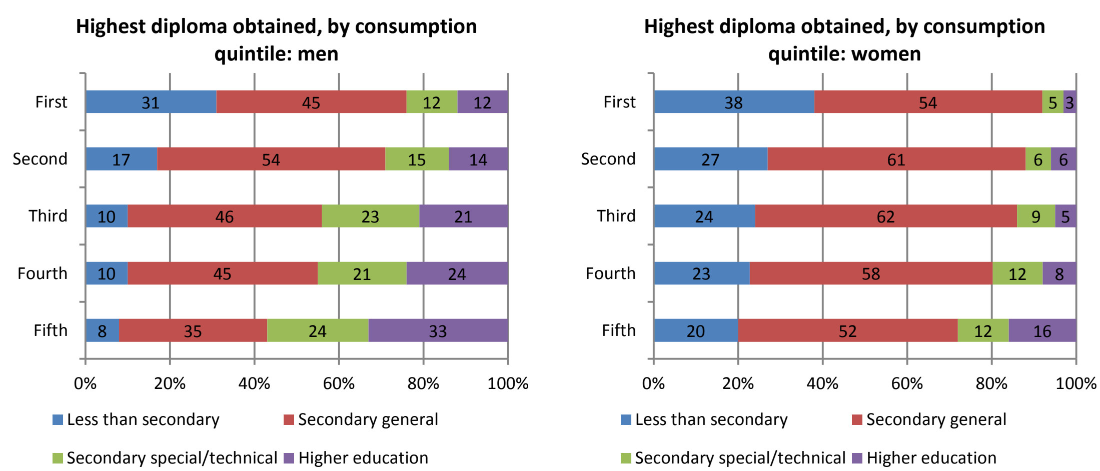
[38] World Bank (forthcoming).

[39] Arias et al. (2014).

Higher education attainment levels are on par with those in countries with similar levels of development, although the average enrollment rates among women are relatively low. As the economy in Tajikistan shifts away from agriculture and manufacturing and toward the services sector (see 1.3), labor demand is moving away from lower skilled jobs and toward higher skilled jobs (see section 2.1). Tajikistan's gross higher education attainment rate is comparable to other countries with similar levels of GDP per capita, at approximately 13 percent. The largest discrepancy is found among Tajik women—only 8 percent of Tajik women complete higher education. Moreover, while higher education completion has increased among men in the last decades, it has remained constant and low among women (Figure 33). Higher education completion rates are greater in urban areas (36 percent among men and 18 percent among women), compared to rural areas (15 percent among men and 3 percent among women).

Education completion is correlated with wealth. The higher education completion rate is nearly three times greater among men belonging to households in the richest per capita consumption quintile (33 percent), compared to men belonging to the poorest quintile (12 percent). Among women, this ratio is five to one. In households in the poorest quintile, approximately one-third of all men and women have not completed secondary education, compared to just 8 percent of men and 20 percent of women in households in the richest quintile (Figure 34). Education completion is higher among all levels of education for those individuals belonging to wealthier households. This finding implies that either education pays off or, alternatively, that those who are richer have better access to higher education than those who are poorer.

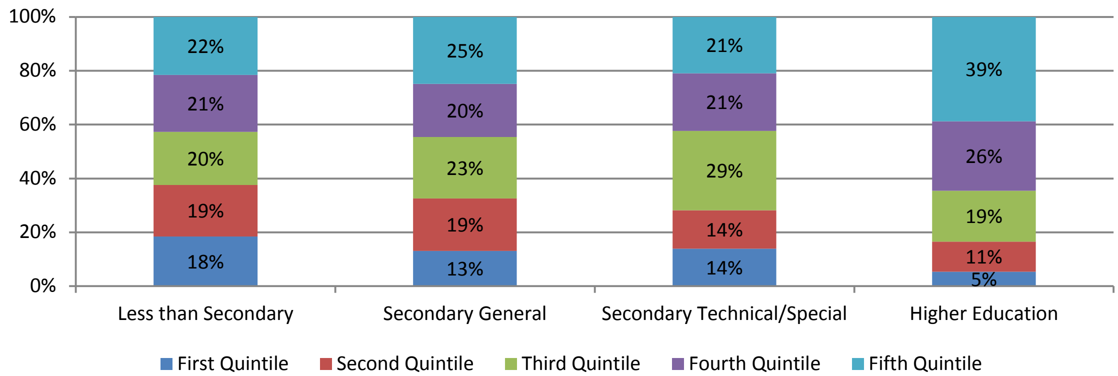
Figure 34: Women and men belonging to richer households typically completed a higher level of education, 2013



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

Students from better-off families are more likely to enroll in higher education than poorer students. In fact, two out of three students currently enrolled in higher education belong to households in the top two consumption quintiles (Figure 35). Conversely, only one in twenty students from the poorest consumption quintile are enrolled in higher education. This suggests that there may be individuals who, despite having high cognitive ability, are unable to pursue higher education because they belong to low-income households. There is evidence that financial barriers and weak governance play a key role in accessing education. A study on informal payments in general education reveals that among parents, 37 percent believe that informal payments are "necessary for higher educational attainment." Students reportedly can pay thousands of dollars to access more prestigious universities while less prestigious universities require hundreds of dollars.[40]

Figure 35: Higher education enrollment disproportionately benefits students from better-off families, 2013



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

Learning does not end upon graduation from formal education, however, and a significant portion of skill formation takes place on the job and in adult (post-formal) training. This includes skills acquired during learning by doing and on-the-job training. In the United States, it is estimated that on-the-job training contributes approximately from a quarter to half of all human capital.[41] Not surprisingly, there is an extensive body of literature documenting (albeit largely in OECD countries) that adult education and training increases worker productivity.[42]

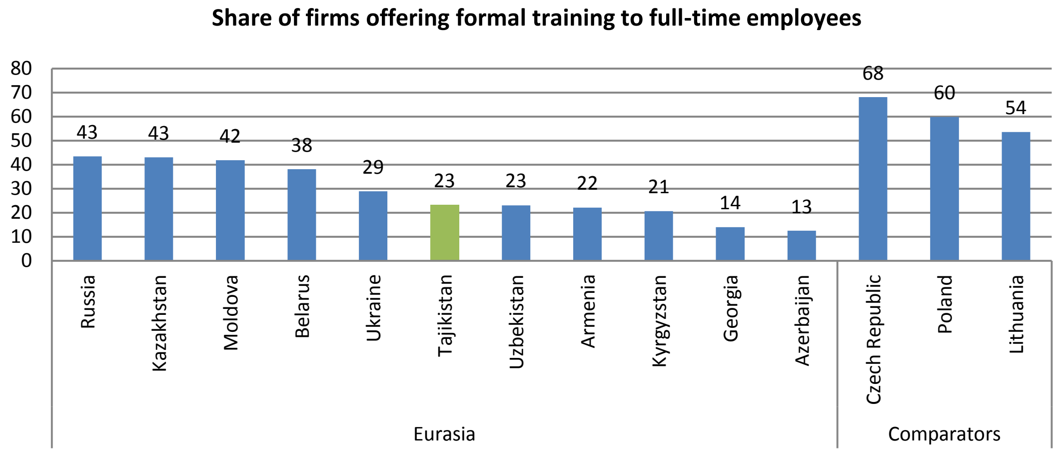
Yet, few firms in Tajikistan offer formal training programs to full-time employees. In Tajikistan, less than a quarter of all firms offer their full-time employees formal training programs. This is well below the proportion of firms offering training in comparator countries in Eastern Europe and other countries in Eurasia as well. For example, almost 70 percent of firms in the Czech Republic and 60 percent of Polish firms offer formal training to their full-time employees (Figure 36).

[40] US Department of State (2011).

[41] Heckman et al. (1998).

[42] A study by the OECD (2004) shows, among other things, that employee training impacts wage growth of young or highly educated employees, and employee training allows attaining and maintaining the competences required to bring productivity in line with market wages of older and low-educated workers.

Figure 36: Few Tajik firms offer formal training programs to full-time employees, 2009



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

3.3 While cognitive skills outcomes generally increase with educational attainment, there is significant variation within the different levels of education, raising questions about Tajikistan's quality of education

Past studies have shown that educational attainment and cognitive ability are generally positively correlated. This correlation exists for two reasons. First, to the extent that ability is an innate characteristic of an individual, it can influence school choice, since more abled people face lower costs to acquire education.[43] For this reason, people with higher cognitive ability are able to progress through the education levels and hence, achieve higher levels of attainment. In addition, cognitive skills can be built in particular in early stages of the life cycle (see section 3.1) through education and training.[44]

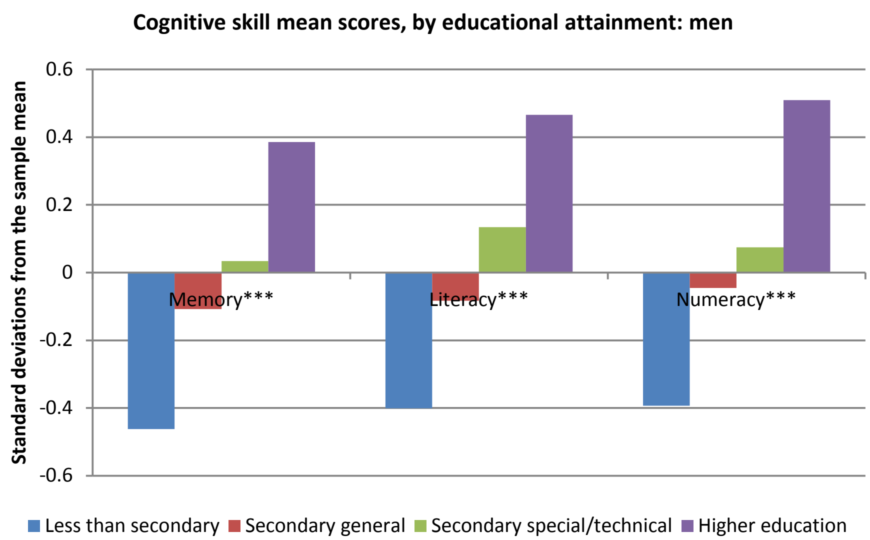
Educational attainment is also correlated with better cognitive skills. Cognitive skill outcomes include scores on memory, literacy, and numeracy test modules (Appendix B: Constructing Cognitive Skills Scores Methods for Scale Development and Scoring). Figure 37 shows that cognitive ability is positively correlated with educational attainment among both working-age men and women. Individuals with less than secondary education attainment typically score below average on all cognitive tests, including memory, literacy, and numeracy. Meanwhile, individuals who completed higher education typically scored above average on all cognitive skill assessments. Note that educational attainment remains a significant determinant of these cognitive scores even after controlling for background characteristics such as area, age, marital status, household consumption quintile, and employment status.

[43] Cunha et al. (2005).

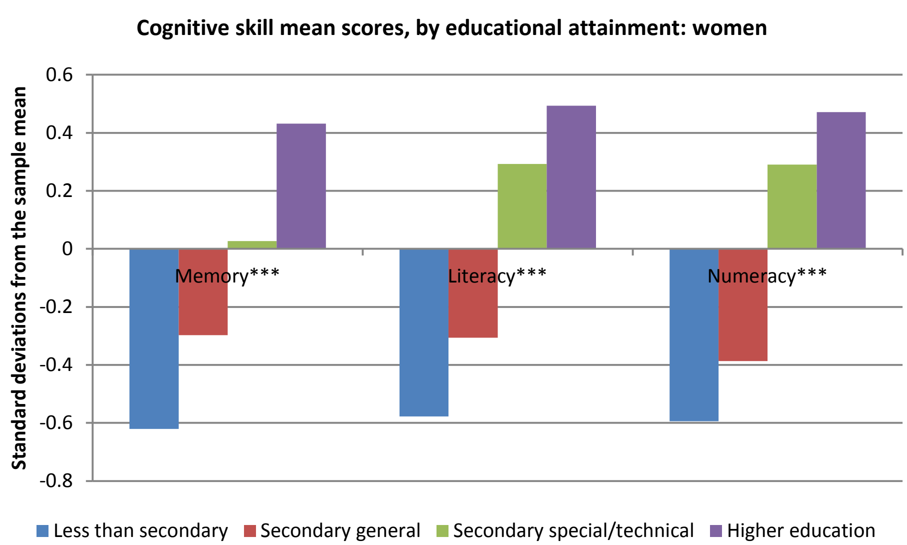
[44] Mincer (1958); Cunha et al. (2005); Cunha and Heckman (2006).

Figure 37: Cognitive skills are significantly better in individuals with a high level of education, 2013

A. Men



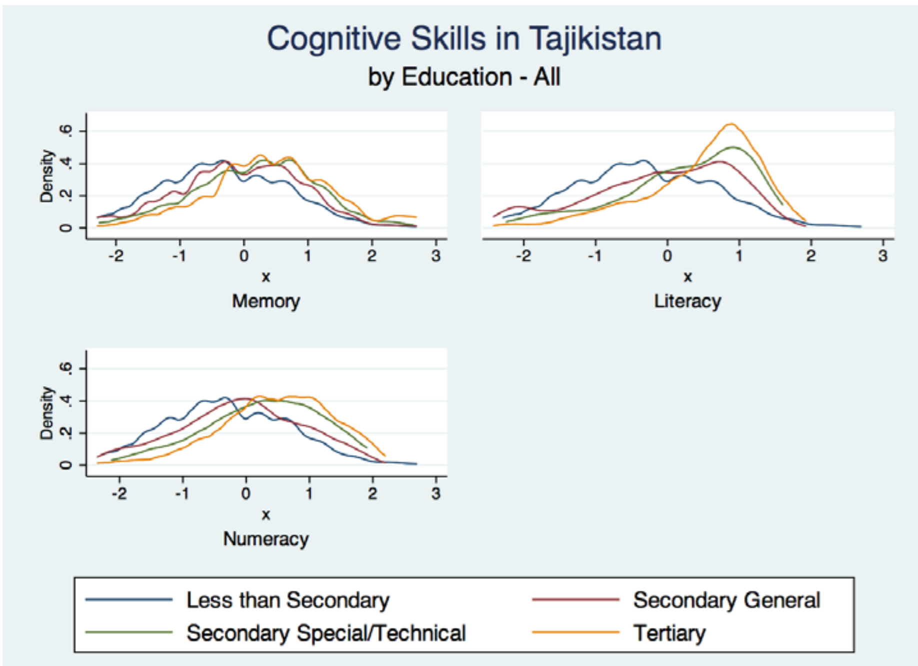
B. Women



Source: Authors' estimates using the World Bank/GIZ *Tajikistan 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; and * significant at the 10% level.

There is, however, a significant variation in cognitive ability among individuals with identical education levels, raising concerns about the education system's quality. While, on average, cognitive ability is positively correlated with educational attainment, it is important to note that there is considerable heterogeneity in cognitive ability even within education levels (Figure 38). An important caveat to mention is that part of this result is likely due to measurement error in the cognitive skill outcomes. In particular, the cognitive skill questions are not able to precisely distinguish high ability individuals from very high ability individuals. Given these limitations, however—as Figure 38 illustrates—there are individuals in the sample who have completed higher education but have a lower cognitive ability than individuals with less than secondary education, and vice versa. While some heterogeneity is to be expected, the degree of overlap found in these cognitive skill distributions may suggest issues with quality and selection of the education system.

Figure 38: There is significant variation in cognitive skill ability among individuals with identical educational attainment, 2013

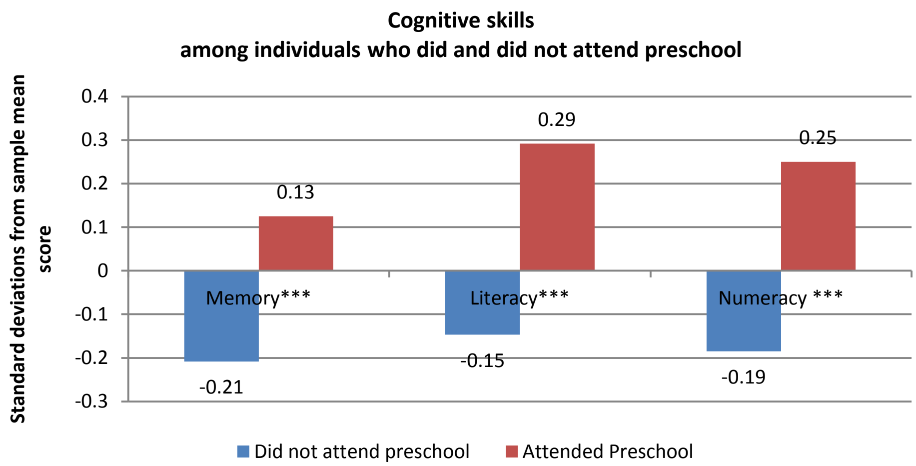


Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 25–64.

There is little data available about the quality of education in Tajikistan, but the most recent OECD Program for International Student Assessment (PISA) results in the neighboring country of Kazakhstan indicate that there is cause for concern. PISA participation has led a number of countries to realize that their education systems are in great need of reform and has, in fact, prompted policy responses. While there are several examples, Germany and Poland are good case studies where educational reform came about following weak PISA results, thereby improving their subsequent PISA performance. The OECD PISA captures the cognitive abilities—reading, math, and science—of 15-year-olds and thus reflects the new generation of labor market entrants. Both Kazakhstan and the Kyrgyz Republic participated in 2009, and both scored well below other participating countries, such as Mexico and Turkey, both of which have comparable GNI per capita levels.

Preschool attendance is 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 cognitive skills tests—which measure memory, literacy, and numeracy skills—than adults who did not attend preschool (Figure 39). When demographic characteristics such as age, gender, marital status, geographic location, and (most importantly) educational attainment are taken into account, having attended preschool as a child remains a significant correlate of cognitive ability, particularly numeracy skills and, to a lesser extent, literacy skills.

Figure 39: **Cognitive skills outcomes are significantly better in adults who attended preschool as children, 2013**



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

3.4 There is significant variation in non-cognitive skills within educational attainment levels

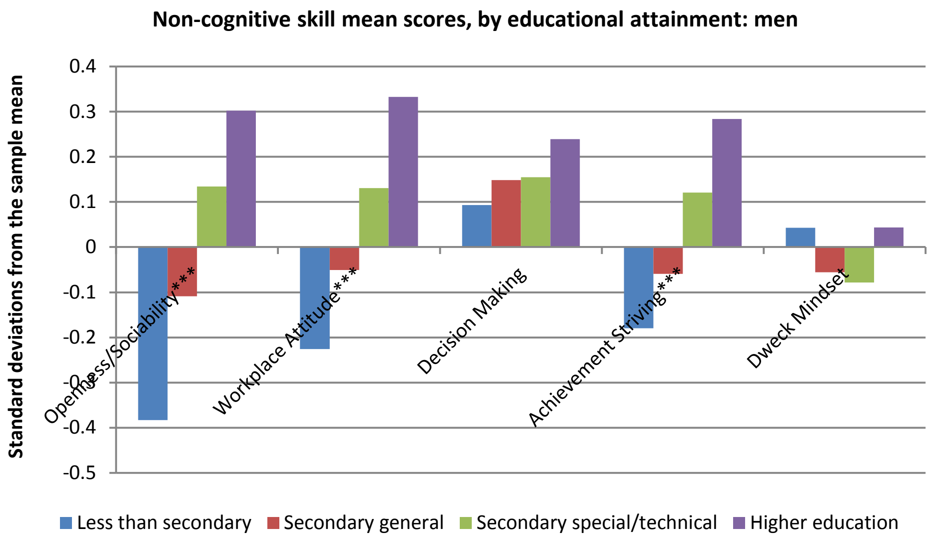
There is increasing evidence of a positive correlation between schooling and non-cognitive skills; if done well, schooling can enhance non-cognitive skills of students. Several studies in the psychology literature have shown the important role of non-cognitive skills on schooling performance,[45] comparable to that of cognitive skills. At the same time, schooling itself is also a determinant of non-cognitive skills in individuals.[46]

Non-cognitive skills are positively correlated with schooling in Tajikistan. Non-cognitive skill outcomes include openness/sociability, workplace attitude, decision-making, and achievement striving (see Appendix C: Constructing Non-Cognitive Skills Scores Methods for Scale Development and Scoring for more details). Figure 40 demonstrates that non-cognitive skill outcomes for openness/sociability, workplace attitude, and achievement striving are, on average, significantly higher among higher educated individuals.

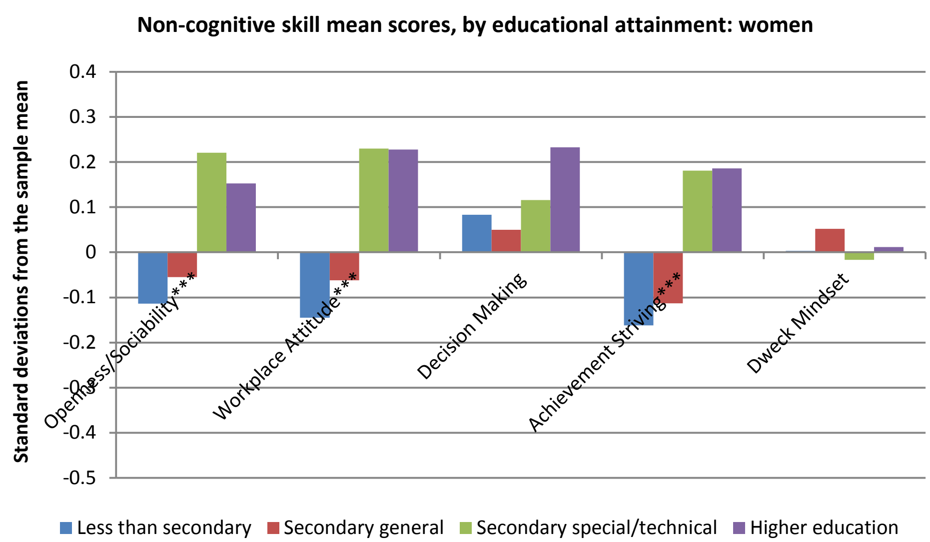
[45] Wolfe and Johnson (1995); Duckworth and Seligman (2005).
[46] Heckman, Stixrud, and Urzua (2006).

Figure 40: Non-cognitive skills are significantly better in individuals with a higher level of education, 2013

A. Men



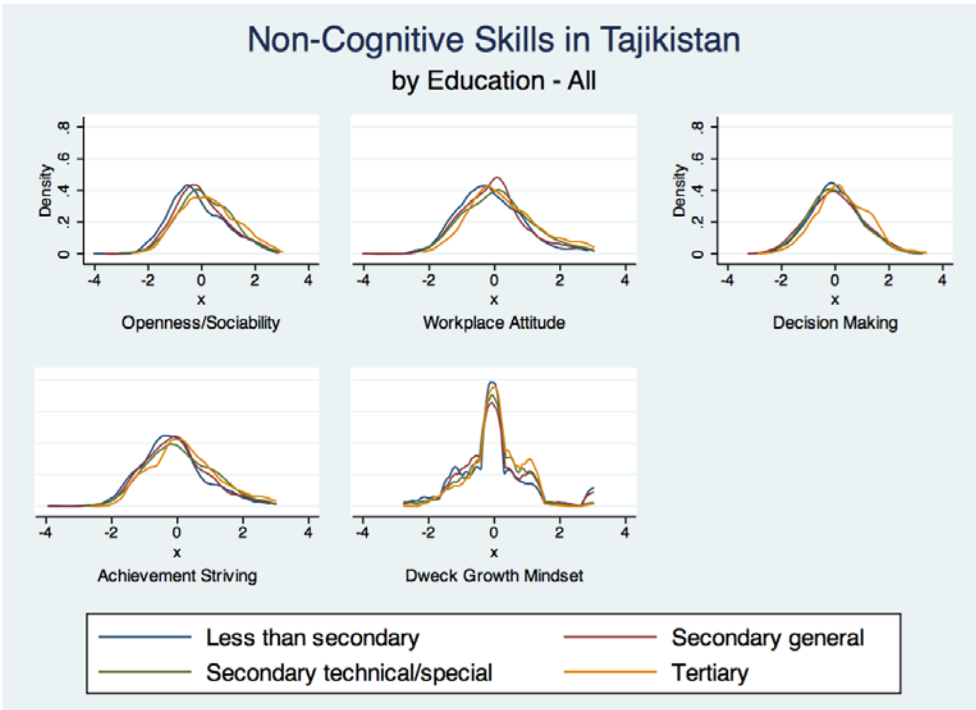
B. Women



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 25–64. Z-scores are calculated for the population aged 16–64. F-test results are depicted by: *** significant at the 1% level; ** significant at the 5% level; and * significant at the 10% level.

However, there is also a large degree of variation in non-cognitive skills among individuals with the same level of educational attainment. Non-cognitive skills are not always better among higher educated individuals across the entire distribution. In fact, there are respondents with less than a secondary education who scored higher on the non-cognitive skills measured than respondents with a higher education. Hence, while non-cognitive skills and educational attainment are correlated on average, the development of non-cognitive skills in school seems to vary substantially (Figure 41). These findings suggest that there may be variation in the extent to which non-cognitive skills are taught in schools and the quality of such teaching, although, admittedly, families and communities have a central role in the early development of non-cognitive skills in children, and such factors should not be discounted.

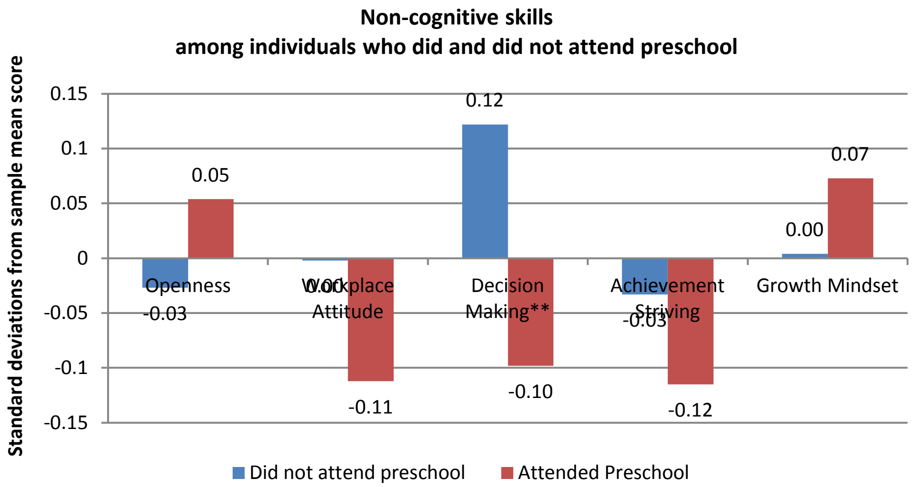
Figure 41: While on average different, non-cognitive skill distributions show a large degree of variation within education levels, 2013



Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Note: Respondents aged 25–64.

Most adult non-cognitive skills are largely unaffected by whether or not the person attended preschool as a child. As Figure 42 shows, non-cognitive skills outcomes do not differ significantly between adults who did and did not attend preschool as a child. The notable exception is decision making, which is weakly negatively correlated with preschool attendance. Hence, adults who attended preschool as a child rated themselves lower on questions such as "do you finish whatever you begin?" and "do you think carefully before you make an important decision?" than adults who did not attend preschool as a child. The lack of a significant positive correlation between non-cognitive skills and preschool attendance is somewhat surprising given past findings in other countries. Hence, one area that warrants policy reform in Tajikistan is placing more emphasis on non-cognitive skills development in preschools.

Figure 42: Adult non-cognitive skills outcomes are largely unaffected by preschool attendance as a child, 2013



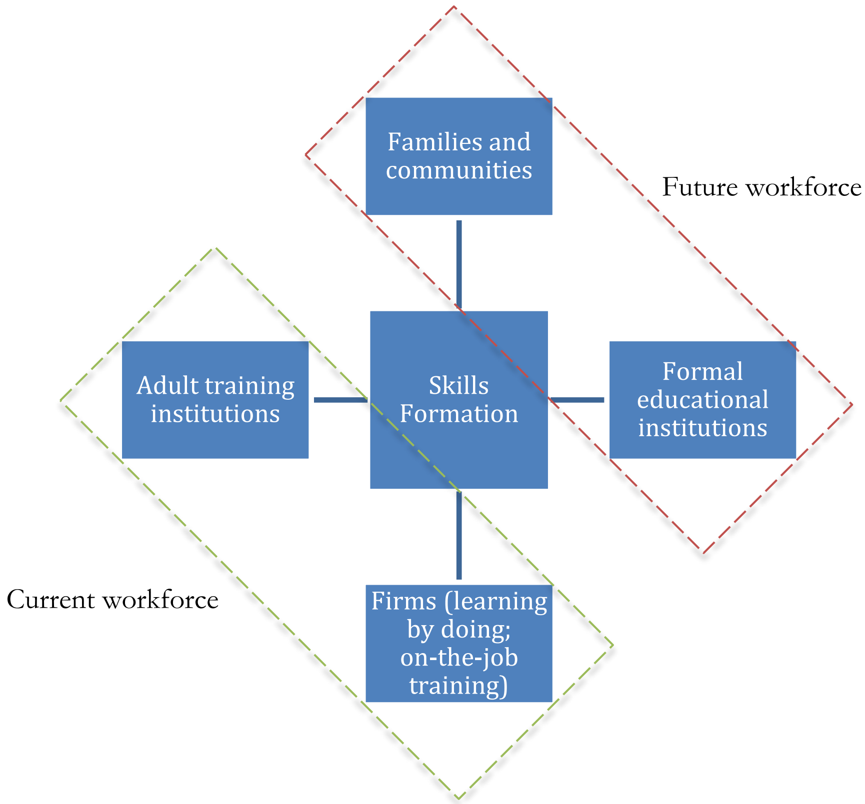
Source: Authors' estimates using the World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey* (2013).
Notes: Respondents aged 25–64. ***/**/* represent significant differences in outcome between individuals with and without preschool at the 1%/5%/10% significance level, respectively.

4 The Skills Roadmap in Tajikistan

As employers in Tajikistan demand more workers with strong cognitive and non-cognitive skills, policy makers will have to make a concerted effort to improve skills as part of their development strategy. This report argues that skills gaps hinder labor market performance in Tajikistan. There is a strong demand for skills in the Tajik economy, as evidenced by significant positive labor market returns to both cognitive and non-cognitive skills. Yet considerable skills gaps persist. A large share of employers report shortages of adequately skilled individuals in the workforce, and workers themselves also complain about the inadequacy of their training for productive employment. Other studies have shown that an educated workforce alone does not in itself guarantee economic growth or job growth, but that the availability of skilled workers is key to the growth of high skill jobs. As a result, policies and programs to up-skill current workers and better prepare children and youth to become more productive workers in the future are an important development strategy for Tajikistan.

A number of actors play a role in building skills throughout the life cycle of an individual, targeting the current and future workforce to different degrees. 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 firms. Families and communities play an important role in skill development of the future workforce, especially during the early years by ensuring good nutrition and stimulation, but they continue to play a role throughout the life cycle. Formal educational institutions, beginning with pre-schools and extending through to tertiary education, are also important for skill formation of future workers. Adult training institutions, which include non-traditional training institutions and second-chance educational institutions, can help to strengthen the skillsets of the current workforce. Similarly, adults derive skills at work, either during on-the-job training programs or by learning by doing.

Figure 43: Actors that play a role to build skills throughout the life cycle of an individual



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

To meet the expected growing demand for higher-order skills in the workplace, policy makers should therefore address skill formation across the life cycle: from conception to preschools (or ECD more generally), in general education, in higher education, and while part of the workforce. At all levels of education and training, a broader focus on cognitive and non-cognitive skill formation is crucial to ensure that skills are valued today's, as well as tomorrow's, labor market. A comprehensive skills development strategy is required that improves the quality and relevance of education and training systems to ensure that they build market-valued skills.

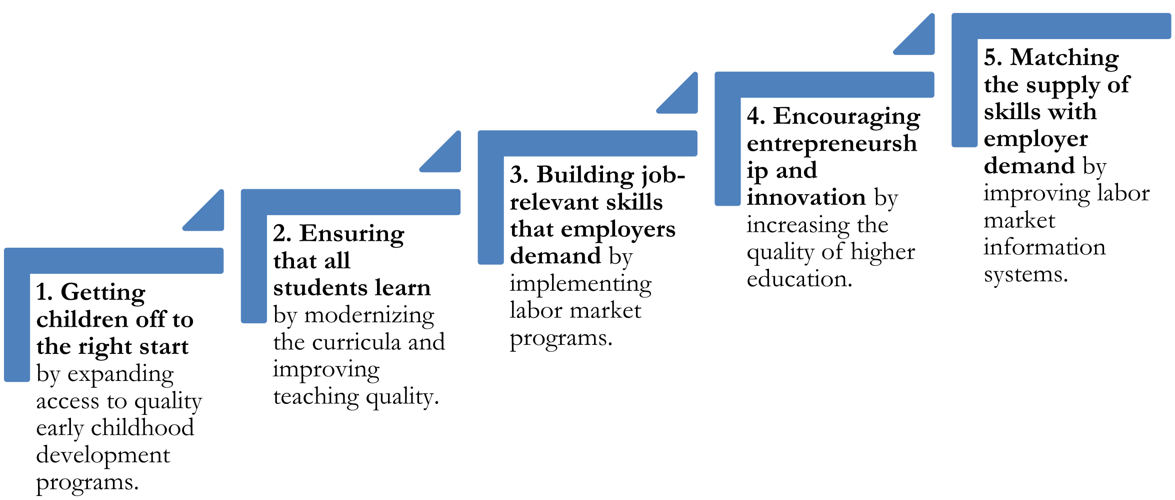
The Skills Toward Employability and Productivity (STEP) Framework can inform the government's strategic vision to enhance skills in Tajikistan. The STEP framework brings together research-based evidence and practical experience from diverse areas—from research on the determinants of early childhood development and learning outcomes to policy experience in the reforming of vocational and technical education systems and labor markets[47].

[47] Valerio et al. (2014).

In Tajikistan, policy makers can boost employment outcomes through a more skilled workforce by focusing on the following five policy goals:

1. Getting children off to the right start by expanding access to quality early childhood development (ECD) programs—including nutrition, preschool—which are critical to ensuring that all children acquire the cognitive and non-cognitive skills that are conducive to high productivity and flexibility in the labor market.
2. Ensuring that all students learn by modernizing the curricula and improving teaching quality, in order to strengthen the link between educational attainment and cognitive and non-cognitive skills.
3. Building job-relevant skills that employers demand by implementing selective active labor market programs, focused particularly on expanding employment opportunities for labor market discouraged and the female population, and incentivizing firms to provide training.
4. Encouraging entrepreneurship and innovation by managing the expansion of higher education, focusing on quality assurance, selection, and information provision, to ensure that higher education graduates possess market-valued skills and that investments in higher education pay off.
5. Matching the supply of skills with employer demand by improving labor market information systems, in order to make labor markets more efficient by alleviating current constraints in the job search and skill signaling process.

Figure 44: The skills roadmap to boost employability and productivity through a more skilled workforce consists of five areas of policy reform in Tajikistan



Source: Authors' illustration for Tajikistan, based on Valerio et al. (2014).

4.1 Get children off to the right start by expanding access to quality early childhood development programs

Getting children off to the right start requires adequate early childhood development programs (ECD) with an emphasis on nutrition, stimulation, and basic cognitive skills. The formation of cognitive and non-cognitive foundations critically occurs during early childhood. This stage marks the first step in skills building, and high-quality ECD programs have been shown to be critical in developing the technical, cognitive, and behavioral skills conducive to high productivity and flexibility in the work environment. Handicaps developed early in life are difficult if not impossible to remedy later. Furthermore, the benefits of ECD generally by far outweigh the program costs. Nobel laureate James Heckman estimates that every dollar invested in high-quality ECD programs yields a 7–10 percent return per annum, and, in fact, policies that provide ECD to disadvantaged children have even higher returns.[48] These high rates of return are fairly consistent in the literature because ECD, it is argued, raises the returns to investment later in life as children learn how to learn.

In Tajikistan, malnutrition rates are high and enrollment in early childhood development (ECD) programs is exceptionally low. As demonstrated, approximately 15 percent of all children under the age of five suffer from malnutrition and moderate and severe stunting is prevalent, affecting 39 percent of all children under the age of five.[49] Less than one percent of all children under the age of 3 and approximately 6 percent of all children aged 3–5 years in Tajikistan are currently enrolled in preschool primarily due to a lack of preschool facilities in Tajikistan, especially in rural areas.[50] This is far below the enrollment levels in comparator countries in Central Asia and globally.

Hence, to ensure that future cohorts of labor market entrants have strong cognitive and non-cognitive skills foundations, policy makers should continue prioritizing the expansion of the coverage and improve the quality of ECD programs in Tajikistan. More resources could be directed toward investments and interventions in skill formation during critical development periods in a person's life, when cognitive and non-cognitive skills are most malleable. Since skills development is a cumulative process, and given low current levels of ECD enrollment in Tajikistan, increased access to quality ECD programs could have a considerable impact on cognitive and non-cognitive, as well as technical, skill development of the future workforce. Increasing access to ECD within Tajikistan could also assist in ensuring that young children's nutrition needs are met and that developmental skills are nurtured. The government has already started investing in an expansion of preschool education with support from Global Partnership for Education (GPE) and other donor-funded projects, and should continue investing in this cost-effective activity.

[48] Heckman (2000).

[49] UNICEF (2013); WHO (2013).

[50] World Bank (forthcoming).

4.2 Ensure that all students learn by modernizing the curricula and improving teaching quality

To ensure that all students learn, policy makers can focus on building stronger general education systems with clear learning standards, good teachers, adequate resources, and a proper regulatory environment. The continued development of foundational cognitive skills—reading, numeracy, and writing—and non-cognitive skills throughout childhood is key for a person's capacity to learn, discover, and innovate throughout life. Schooling plays an important role in ensuring that students acquire the skills and abilities that are valued by employers and that are useful for self-employment.

While enrollment in general education and higher education is strong, the education system in Tajikistan is not developing market-valued skills to full potential. Access to primary and basic education is universal in Tajikistan, and higher education coverage also compares favorably with countries at similar levels of development. However, significant improvements can be made in the education system in both cognitive and non-cognitive skills development. Although, on average, cognitive and non-cognitive skills are better in higher educated individuals, there is a large degree of variation in skills outcomes even among individuals with the same level of education. These findings likely reflect issues of quality and selection in the education system.

Tajikistan can strengthen the link between educational attainment and cognitive and non-cognitive skills by developing the school curricula and improving teaching quality. There is a large body of research and emerging consensus that interventions can be implemented to support skills development during distinct life stages. In a number of countries, non-cognitive skill interventions have been integrated into the academic curriculum. The empirical evidence for Tajikistan clearly shows that stronger cognitive and non-cognitive skills enable workers to obtain better jobs. Therefore, to improve labor market outcomes for future generations in Tajikistan, workers need to acquire better cognitive and non-cognitive skills, including problem-solving, critical thinking, communication, and team player skills.

Mainstreaming non-cognitive learning in the education system can strengthen the formation of such skills in the future workforce. An increasing number of countries worldwide have integrated 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. There is a wide range of international experience from which to draw lessons related to mainstreaming non-cognitive learning in the education system. For example, some countries have implemented national legislation to promote non-cognitive skill building in schools, including Australia, Colombia, Romania, Spain, and the United Kingdom.[51]

[51] Arias et al. (2014).

4.3 Build job-relevant skills that employers demand by implementing labor market programs

To build job-relevant skills that employers demand in the current workforce, policy makers can develop the right incentive framework for labor market programs (LMPs) and on-the-job training (OTJ) programs. Although strong cognitive and non-cognitive skill foundations are critical for workers to develop and use skills on the job, specific job-relevant skills are typically acquired while in the workforce. Shortages of such skills can pose considerable constraints to workers' employability. Similarly, a shortage of crucial skills can prevent firms from performing to their full potential.

There are considerable skills gaps between the employed and inactive populations in Tajikistan. While job creation has kept pace with the country's rapid population growth in the last decade, a large share of the working-age population remains out of the workforce. This is especially the case for women and youth. Adults who are out of work scored significantly lower on both cognitive and non-cognitive skills assessments than the employed population.

Labor market programs (LMPs) that address labor market information asymmetry, job searching skills, and technical or job-specific skills gaps can boost the employment rates in Tajikistan. LMPs can include job placement assistance services, counseling with employment advisors, job application and interview preparation, CV composition, informational interviews, and in-depth assessment of skills and abilities. One element in common is that all LMPs are designed to encourage the unemployed, discouraged, and inactive populations to more actively seek jobs, thereby improving their prospects for employment. Countries offer a menu of LMPs including training programs, public works projects, employment subsidies, and matching workers and jobs through intermediation services. As with any program, its efficacy should be evaluated.

Cognitive and non-cognitive skills are particularly low among workers in the private sector, Tajikistan can also benefit from addressing market failures that prevent firms from providing on-the-job training (OJT) and incentivizing them to do so. OJT is an important channel through which workers upgrade skills during their time at work. It is also a vehicle that can help firms adopt new technologies and improved business practices. In Tajikistan, less than a quarter of all firms offer their full-time employees formal training programs. This is a lower proportion than most countries in Europe and Central Asia. In Europe, OJT is far more common. For example, almost 70 percent of firms in the Czech Republic offer formal training to their full-time employees; 60 percent of Polish firms do so; and 54 percent of Lithuanian firms do the same. Identifying the reasons for the varying levels of OJT in each country context is a prerequisite for designing effective policy responses. Tajikistan must design policies that strive to support firms that, despite positive expected returns, do not train their workers. To encourage the implementation of LMPs, policy makers have several instruments at their disposal, such as credit and subsidy programs or tax grants that can be used to deal with liquidity constraints and incentivize training. These types of programs have been used successfully in a number of countries in Western Europe and Eastern Asia.

Similarly, improving migrant skills increases their earning capacity, and therefore their ability to support their families in Tajikistan. 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. Furthermore, in order to help migrants secure better jobs abroad, it is important that existing skills are appropriately recognized and valued. Enhancements to the existing migrant job placement system, including better registration and pre-selection assessment, could help avoid the "brain waste" that often impacts mid-skilled workers, devaluing not only their skills while abroad, but also the benefits of the international migration experience for both the individual workers and Tajikistan.

Education and labor market reforms—such as public-private partnerships on business-friendly curriculum development, support for on-the-job training and apprenticeship programs, and improved labor market diagnostics—can also benefit international migrants. Such programs could increase Tajik migrants' ability to apply their skills abroad by making skills more visible to employers. This would in turn enable them to expand their skills abroad, which could then be absorbed into the domestic market upon their return, resulting in productivity and wage improvements at home. This is particularly important given the large number of migrant workers in sectors such as construction and those with secondary or technical education, and the fact that mid-skilled workers are often at the highest risk of brain waste.[52]

To improve the link between migrants' skills and labor market needs abroad, the quality of workers' skills, and the visibility of those skills, the government of Tajikistan could pursue a three-pronged strategy. First, develop partnerships with Ministries of Labor and business leaders in key destination countries and sectors to identify skills needs and raise the profile of Tajik laborers. Second, conduct labor market diagnostics to identify sectors with demand for laborers, both domestically and abroad. And third, invest in improved vocational and technical training programs.

4.4 Encourage entrepreneurship and innovation by increasing the quality of higher education

To encourage entrepreneurship and innovation, policy makers could increase the quality of higher education. As the Tajik economy further develops, high-skilled graduates from universities are likely to become a more important group of labor market entrants. Within the context of Tajikistan's modernization strategy, the demand for non-routine skills is likely to increase, as observed in other middle- and high-income countries. While enrollment rates in higher education are currently favorable, quality concerns persist. More specifically, skill outcomes reveal that there is a large share of individuals in Tajikistan who gained a higher education degree but had lower cognitive and non-cognitive scores relative to individuals who have not finished their secondary general education.

To ensure quality at the college and university level, measuring the skills produced is important. The development of an independent quality assurance agency is critical for a modern higher education system. In addition, individual institutions of higher education should perform

[52] World Bank (2013a).

"internal" quality assurance through so-called Quality Enhancement Cells based partly on self-assessments and peer reviews by other higher education institutions.

There is also a need to better equip college and university graduates with market-relevant skills. Several steps are required to achieve this goal. First, regular and independent market surveys should monitor the skills requirements in the labor market. Second, partnerships with both domestic and foreign academic institutions (research partnerships, faculty exchanges, and training) as well as with domestic and foreign industry (modernizing curricula, laboratories, innovation platforms, research, and joint business development) can help strengthen the links between higher education institutions and the labor market. Third, more generally, ensuring high-quality equipment in relevant and priority technical fields, together with modern curricula, trained faculty and staff, and related university-industry linkages is crucial.

Merit-based admission to higher education programs is another key priority for the government of Tajikistan. As shown, approximately 40 percent of students currently enrolled in higher education belong to households in the top consumption quintile. This may occur for various reasons, including the importance of parental background for educational achievement and/or financial barriers. For the first year in 2014, high school students took a unified university entrance exam, which is a reform by the government aimed at improving fairness and transparency in access to universities. In addition, the reform is expected to help ensure that state funding is allocated in a more transparent and fair manner to students using a merit-based system. [53] If implemented successfully, the reform will be an important accomplishment in Tajikistan.

4.5 Match the supply of skills with employer demand by improving labor market information systems

To match the supply of skills with employer demand, labor market information systems are needed that will ease the transition from school to work. In Tajikistan, more than two-thirds of all survey respondents (68 percent) indicated that they face significant constraints in learning about job vacancies. The problems caused by asymmetric information between job seekers and employers are far-reaching because they affect students' educational choices, firms' selection of workers, and the time it takes to fill vacancies.[54] In other words, poor labor market information flows hinder the efficient allocation of resources in a country. Improving the flow of labor market information in Tajikistan will be particularly helpful for youth and first-time job-seekers.

A number of modernizing countries have successfully implemented labor market information systems designed to dismantle planned manpower education structures. In Poland, for example, employment observatories were introduced to provide information on job availability, wages, career prospects, and hiring expectations.[55] Employment observatories have also been established in Chile and Colombia. The rationale behind employment observatories is that information about major industries, recent growth areas, occupations experiencing shortages,

[53] The World Bank has supported the government in putting this reform into place.

[54] Jensen (2010); Kaas and Manger (2010); World Bank (2012).

[55] Arias et al. (2014).

qualifications needed for jobs, and so on, can help people make better-informed choices about their education and careers. Access to this type of information is routine in the United States, the EU countries, and Australia. A number of emerging countries are also beginning to expand their labor market information systems.

Employment observatories use a rich array of data to monitor and disseminate information about the labor market. The data managed by employment observatories include: (1) administrative data from public employment offices on unemployment, vacancies, and active labor market programs; (2) data from the national statistics office including labor force survey and household survey information, usually disaggregated by region; and (3) data from special-topic surveys (usually "sociological"). Employment observatories use multi-media to disseminate information, ranging from traditional paper-based information to YouTube videos and text/SMS messaging. The information is disseminated at irregular intervals, dictated by the speed with which the information is processed.

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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)[56]. 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;[57] (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

[56] 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.

[57] 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.

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).

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.[58] 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).

[58] 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.

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 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). [59] 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.[60] Responses were treated as ordered categorical data to account for the skewed nature of the data.

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).[61] 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).[62] 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

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[59] An oblimax rotation was chosen to account for the hypothesized correlation between factors.
[60] 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.
[61] 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).
[62] 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).

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).[63] 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).[64] 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
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

[63] 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.

[64] 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.

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 B1, below; Duckworth and Guerra, 2012). These non-cognitive skills can be conceptualized as falling into two domains:

Personality traits, defined as enduring patterns of thinking, feeling, and behaving which are relatively stable across time and situations (Borghans, Duckworth, Heckman, and 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 and Srivastava, 1999) and cultures (Soto, John, Gosling, and 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).

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, and 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 and Dweck, 2012). These skills include: hostile bias (2 items; Dodge, 2003), decision making (4 items; Mann, Burnett, Radford, and 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 and 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, and 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[65]

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?
Socio-emotional Skills	*Hostile Bias*	
		Do people take advantage of you?
		Are people mean/not nice to you?
	Decision Making	
		Do you think about how the things you do will affect your future?
		Do you think carefully before you make an important decision?
		Do you ask for help when you don't understand something?

[65] 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.

	Do you think about how the things you do will affect others?
	Achievement Striving
	Do you do more than is expected of you?
	Do you strive to do everything in the best way?
	Do you try to outdo others, to be best?
	Self Control
	Do you spend more than you can afford?
	Do you do crazy things and act wildly?
	Fixed Versus Growth Mindset
	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.
	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 to .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.

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 B1, 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.

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).[66] 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 and Muthén, 1998–2012; Version 6.12) and adjusted for any clustering of the data due to sampling design.[67] 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.[68]

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

[66] An oblimax rotation was chosen to account for the hypothesized correlation between factors.

[67] 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.

[68] 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.

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, and 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 and 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).[69] 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.[70] 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).[71]

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[69] 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).

[70] 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).

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

Table 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
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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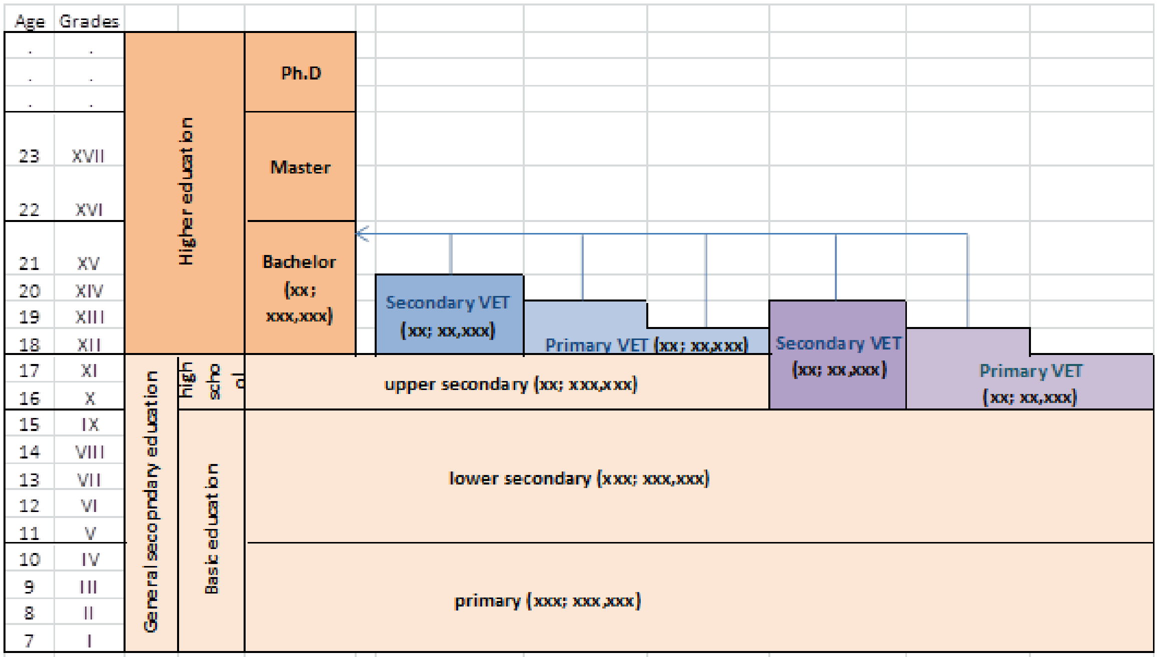
Appendix D: The Education System in Tajikistan

- Basic education (1-9) is compulsory
- Secondary general means 1-11
- Primary or initial vocational = vocational schools enroll regular and special education students.
- Secondary vocational = college = part of higher/tertiary education
- Higher education = university education



Sources: ETF, 2010, *Torino Process 2010: Republic of Tajikistan, and modified based on the government resolution #388 on National*
Notes: Colleges are also called "specialised secondary education institutions".
The numbers in parenthesis refer to (number of schools; number of students) in the academic year 2012/13.

Appendix E: Summary Tables

Employment Rate

Table E1. Employment Rate by Age Cohort

Age Cohort	All (%)	Male (%)	Female (%)
16-19	16.9	19.2	15.0
20-24	31.4	50.5	19.5
25-29	40.5	70.0	23.7
30-34	48.7	77.6	26.3
35-39	55.0	82.4	37.0
40-44	59.0	84.1	42.0
45-49	54.1	79.5	35.7
50-54	53.2	78.6	33.6
55-59	50.8	77.1	28.8
60-64	36.2	58.7	15.6
Total	39.6	59.6	25.1

Excluding current migrants.

Table E2. Employment Rate by Consumption Quintile

Consumption quintile	All (%)	Male (%)	Female (%)
1	32.5	54.3	18.7
2	38.6	57.6	25.3
3	39.6	60.4	23.8
4	41.8	61.2	27.9
5	43.9	62.9	29.1
Total	39.6	59.6	25.1

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

Table E3. Employment Rate by Rural/Urban Location

	All (%)	Male (%)	Female (%)
Urban	39.7	59.9	25.4
Rural	39.5	59.5	25.0
Total	39.6	59.6	25.1

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

Table E4. Employment Rate by Education Level

Education level	All (%)	Male (%)	Female (%)
Less than secondary	40.9	75.2	22.0
Secondary general	51.0	79.8	27.2
Secondary technical/special	75.2	84.4	57.3
Tertiary	81.0	86.3	69.1
Total	56.2	81.2	32.0

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

Labor Force Participation Rate

Table E5. Labor Force Participation Rate by Age Cohort

Age cohort	All (%)	Male (%)	Female (%)
16-19	18.4	20.3	16.9
20-24	34.2	54.1	21.7
25-29	43.6	73.4	26.7
30-34	51.3	79.0	29.9
35-39	57.1	84.9	38.9
40-44	61.3	86.4	44.3
45-49	57.7	83.9	38.9
50-54	55.2	80.4	35.7
55-59	52.2	78.6	30.3
60-64	37.4	59.6	17.1
Total	41.1	60.4	25.1

Excluding current migrants.

Table E6. Labor Force Participation Rate by Consumption Quintile

Consumption quintile	All (%)	Male (%)	Female (%)
1	33.8	54.9	20.4
2	39.5	57.9	26.7
3	41.3	61.8	25.7
4	44.2	62.2	31.3
5	45.0	63.5	30.6
Total	41.1	60.4	27.1

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

Table E7. Labor Force Participation Rate by Rural/Urban Location

	All (%)	Male (%)	Female (%)
Urban	41.7	60.9	28.1
Rural	40.8	60.2	26.7
Total	41.1	60.4	27.1

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

Table E8. Labor Force Participation Rate by Education Level

Education level	All (%)	Male (%)	Female (%)
Less than secondary	43.1	76.2	24.7
Secondary general	53.3	81.8	29.8
Secondary technical/special	77.2	86.9	58.5
Tertiary	83.1	88.2	71.9
Total	58.4	83.1	34.5

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

Employment Status

Table E9. Employment Status by Age Cohort: All

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	16.9	1.5	13.6	68.0
20-24	31.4	2.8	14.0	51.8
25-29	40.5	3.1	10.0	46.4
30-34	48.7	2.6	10.0	38.7
35-39	55.0	2.1	5.7	37.2
40-44	59.0	2.3	3.3	35.4
45-49	54.1	3.7	3.8	38.5
50-54	53.2	1.9	4.2	40.7
55-59	50.8	1.5	2.9	44.8
60-64	36.2	1.2	4.2	58.4
Total	39.6	2.3	8.1	50.1

Excluding current migrants.

Table E10. Employment Status by Age Cohort: Male

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	19.2	1.1	11.4	68.4
20-24	50.5	3.7	17.2	28.6
25-29	70.0	3.4	15.3	11.3
30-34	77.6	1.4	11.7	9.3
35-39	82.4	2.5	7.1	8.0
40-44	84.1	2.3	5.3	8.3
45-49	79.5	4.4	5.5	10.6
50-54	78.6	1.7	8.8	10.9
55-59	77.1	1.5	4.4	17.0
60-64	58.7	0.9	7.1	33.4
Total	59.6	2.1	9.8	28.4

Excluding current migrants.

Table E11. Employment Status by Age Cohort: Female

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	15.0	1.8	15.4	67.7
20-24	19.5	2.2	12.0	66.4
25-29	23.7	3.0	6.9	66.4
30-34	26.3	3.6	8.7	61.4
35-39	37.0	1.9	4.7	56.4
40-44	42.0	2.3	1.9	53.8
45-49	35.7	3.1	2.5	58.7
50-54	33.6	2.1	0.6	63.7
55-59	28.8	1.4	1.8	68.0
60-64	15.6	1.5	1.5	81.4
Total	25.1	2.4	6.8	65.7

Excluding current migrants.

Table E12. Employment Status by Consumption Quintile: All

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	34.7	2.1	11.4	51.8
2	40.9	1.7	10.0	47.4
3	41.0	2.4	8.8	47.7
4	43.8	3.1	7.6	45.4
5	46.0	2.3	6.0	45.7
Total	41.6	2.4	8.6	47.5

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

Table E13. Employment Status by Consumption Quintile: Male

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	58.8	2.0	13.7	25.5
2	62.0	1.9	14.2	21.8
3	62.8	2.8	9.5	24.8
4	63.8	2.1	10.9	23.2
5	66.0	2.6	6.1	25.3
Total	63.0	2.3	10.5	24.2

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

Table E14. Employment Status by Consumption Quintile: Female

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	19.8	2.2	9.9	68.1
2	26.8	1.6	7.2	64.5
3	24.8	2.1	8.3	64.9
4	29.4	3.9	5.2	61.5
5	30.6	2.1	5.9	61.4
Total	26.5	2.4	7.2	63.9

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

Table E15. Employment Status by Education Level: All

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	34.6	2.4	7.7	55.2
Secondary general	42.9	2.5	6.9	47.8
Secondary technical/special	70.4	2.5	4.0	23.0
Tertiary	78.9	2.3	3.5	15.3
Total	49.6	2.5	6.2	41.7

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

Table E16. Employment Status by Education Level: Male

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	68.8	1.4	10.2	19.6
Secondary general	73.5	2.4	12.7	11.5
Secondary technical/special	80.5	3.3	4.8	11.4
Tertiary	84.4	2.1	4.1	9.4
Total	76.5	2.3	8.9	12.2

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

Table E17. Employment Status by Education Level: Female

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	21.2	2.8	6.8	69.1
Secondary general	26.0	2.6	3.7	67.7
Secondary technical/special	55.0	1.2	2.8	40.9
Tertiary	67.9	2.9	2.3	26.9
Total	30.6	2.6	4.3	62.6

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

Table E18. Employment Status by Rural/Urban: All

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	41.6	2.9	6.8	48.7
Rural	41.6	2.1	9.3	46.9
Total	41.6	2.4	8.6	47.5

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

Table E19. Employment Status by Rural/Urban: Male

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	63.0	2.5	8.5	26.0
Rural	63.0	2.2	11.4	23.4
Total	63.0	2.3	10.5	24.2

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

Table E20. Employment Status by Rural/Urban: Female

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	26.6	3.1	5.6	64.6
Rural	26.4	2.1	7.9	63.7
Total	26.5	2.4	7.2	63.9

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

Educational Attainment

Table E21. Educational Attainment by Age Cohort: All

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	29.7	52.1	4.9	13.3
30-34	28.2	50.3	6.9	14.6
35-39	19.0	53.1	13.5	14.5
40-44	13.0	56.4	18.5	12.1
45-49	11.6	56.2	20.8	11.4
50-54	13.8	55.8	17.7	12.6
55-59	23.1	45.8	18.3	12.9
60-64	28.7	37.2	15.3	18.7
Total	21.4	51.9	13.2	13.5

Excluding current migrants.

Table E22. Educational Attainment by Age Cohort: Male

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	22.5	49.1	5.4	23.0
30-34	19.6	49.5	6.3	24.7
35-39	14.3	46.1	16.3	23.4
40-44	9.9	45.0	26.9	18.2
45-49	8.4	42.4	32.3	16.8
50-54	7.3	44.0	28.8	19.9
55-59	14.3	35.2	31.0	19.5
60-64	14.1	35.1	22.9	27.9
Total	14.5	44.5	19.3	21.6

Excluding current migrants.

Table E23. Educational Attainment by Age Cohort: Female

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	33.8	53.8	4.6	7.8
30-34	34.9	50.9	7.4	6.8
35-39	22.1	57.7	11.7	8.6
40-44	15.1	64.2	12.8	7.9
45-49	13.9	66.2	12.4	7.4
50-54	18.8	64.9	9.2	7.1
55-59	30.3	54.6	7.7	7.3
60-64	42.1	39.1	8.4	10.4
Total	26.3	57.1	8.8	7.8

Excluding current migrants.

Table E24. Educational Attainment by Consumption Quintile: All

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	35.5	50.2	7.8	6.5
2	22.6	58.4	9.7	9.3
3	18.2	55.3	14.6	11.9
4	17.6	52.3	15.4	14.7
5	15.0	44.3	17.3	23.4
Total	21.4	51.9	13.2	13.5

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

Table E25. Educational Attainment by Consumption Quintile: Male

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	30.9	45.0	12.2	11.9
2	16.9	54.5	14.6	14.0
3	10.2	45.7	22.9	21.1
4	10.0	45.1	20.5	24.3
5	8.3	34.6	24.0	33.1
Total	14.5	44.5	19.3	21.6

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

Table E26. Educational Attainment by Consumption Quintile: Female

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	38.4	53.5	5.0	3.1
2	26.5	61.0	6.3	6.2
3	24.0	62.3	8.5	5.2
4	23.1	57.5	11.8	7.7
5	20.2	51.8	12.1	15.9
Total	26.3	57.1	8.8	7.8

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

Table E27. Educational Attainment by Urban/Rural: All

	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
Urban	16.8	41.6	15.8	25.7
Rural	23.3	56.2	12.0	8.4
Total	21.4	51.9	13.2	13.5

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

Table E28. Educational Attainment by Urban/Rural: Male

	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
Urban	10.5	35.7	17.5	36.2
Rural	16.2	48.3	20.0	15.4
Total	14.5	44.5	19.3	21.6

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

Table E29. Educational Attainment by Urban/Rural: Female

	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
Urban	21.3	45.9	14.6	18.2
Rural	28.3	61.8	6.4	3.4
Total	26.3	57.1	8.8	7.8

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

Appendix F: 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	-0.091	-0.051	-0.083	0.019	0.035	0.113	-0.003	0.009
Region	**Urban**	0.037	0.132	0.188	0.043	0.091	0.054	0.042	-0.016
Region	**Rural**	-0.151	-0.136	-0.21	0.008	0.009	0.141	-0.024	0.02
Gender	**Male**	0.042	0.102	0.116	0.05	0.085	0.169	0.066	-0.038
Gender	**Female**	-0.184	-0.157	-0.222	-0.003	0.001	0.074	-0.051	0.042
Consumption quintile	**Quintile 1**	-0.133	-0.182	-0.18	-0.061	0.042	0.084	-0.032	-0.087
Consumption quintile	**Quintile 2**	-0.257	-0.116	-0.16	-0.001	-0.051	0.161	-0.018	0.003
Consumption quintile	**Quintile 3**	-0.094	-0.077	-0.116	0.053	0.049	0.002	-0.063	-0.049
Consumption quintile	**Quintile 4**	-0.041	-0.031	0.007	0.004	0.054	0.139	0.015	0.009
Consumption quintile	**Quintile 5**	0.051	0.121	0.008	0.088	0.078	0.17	0.073	0.147
Age cohort: 16-35 years old	**Young**	-0.057	-0.055	-0.097	0.062	0.058	0.175	0.024	-0.029
Age cohort: 50-65 years old	**Old**	-0.201	-0.121	-0.145	-0.039	0.001	0.014	-0.066	0.043
Employment status	**Employed**	0.059	0.101	0.141	0.054	0.105	0.196	0.059	-0.016
Employment status	**Out of work**	-0.271	-0.2	-0.327	-0.029	-0.052	0.033	-0.094	0.058
Sector of employment	**Agriculture**	-0.245	-0.209	-0.127	-0.093	-0.148	0.054	-0.177	0.014
Sector of employment	**Industry**	0.076	0.148	0.112	0.008	0.113	0.335	0.029	0.071
Sector of employment	**Services**	0.242	0.28	0.324	0.155	0.265	0.253	0.229	-0.064
Type of employer	**SoE/Gov't**	0.311	0.351	0.382	0.293	0.364	0.245	0.311	-0.004
Type of employer	**Private Sector**	-0.106	-0.163	-0.095	-0.116	-0.102	-0.106	-0.18	0.096
Type of employer	**Self-employed + other**	-0.011	0.063	0.106	-0.046	0.059	0.271	0.033	-0.048
Educational attainment level	**Secondary general**	-0.241	-0.24	-0.283	-0.072	-0.059	0.079	-0.098	0.02
Educational attainment level	**Secondary technical/special**	0.043	0.202	0.164	0.166	0.167	0.142	0.141	-0.051
Educational attainment level	**Tertiary**	0.4	0.473	0.491	0.238	0.289	0.23	0.242	0.031