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Are There Skills Payoffs in Low- and Middle-Income Countries?

Empirical Evidence Using STEP Data

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Abstract

Most research on the economic payoffs of skills has used individuals' level of schooling attained—typically years or level of education or training received—as a key proxy for skills. Such research has consistently found that individual returns to schooling are positive and that returns tend to be higher in low- and middle-income countries than in higher-income countries. However, years in school is only one proxy for skills—are these returns still observed using other measures as proxies? This study uses data from the STEP Skills Measurement Survey to examine the extent to which there is an independent association between cognitive and noncognitive skills and earnings in low- and middle-income countries. The study uses measures of reading proficiency and complexity of on-the-job computer tasks to proxy cognitive skills, and personality and behavioral measures to proxy noncognitive skills. The results demonstrate that even when controlling for schooling and background factors, these skills pay off in the labor market. This is particularly the case for the measures of cognitive skills, while noncognitive skills show some significant, but small, effects on earnings. The findings also suggest that there is significant heterogeneity across countries in how skills are valued in the labor market.

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I. Introduction

As countries continue to invest in their education systems to develop skilled workforces, an inherent question arises: *does* it pay off economically to be more skilled? Are certain types of skills associated with higher wages? Most of the empirical work in labor economics has been motivated by human capital theory, which posits that human capital—that is, an individual's stock of skills—is a key determinant of individual and aggregate economic success (Becker, 1964; Schultz, 1999). Much attention has been paid to measuring this human capital and examining how it is rewarded in the labor market.

To do so, most literature on the payoffs of individual skills has used individuals' level of *schooling*—typically years or level of education or training received—as the main variable (Card, 1999; Psacharopoulos, 1985). Such research has consistently found that individual returns to schooling are positive and that returns tend to be higher in low- and middle-income countries than in higher-income countries (Montenegro and Patrinos, 2014).

However, schooling is not the only variable that can be used to in calculating the economic payoff of individual skills. More recent research on skills payoffs has broadened beyond schooling to incorporate *skills proficiency*. Measures of cognitive and noncognitive skills, including those relevant in today's technology-driven environment, provide information on what individuals can do and what their level of performance can be in a way that goes well beyond measures of schooling. Most of these recent studies have focused on the effects of either *cognitive skills* or *noncognitive skills* on wages, and a smaller set of studies has sought to understand the differential contribution of these skills to labor market outcomes (Heckman, Stixrud, and Urzua, 2006; Heineck and Anger, 2010; Ramos et al., 2013; Nikoloski and Ajwad, 2014). Research has also investigated the role of cognitive skills such as *computer use* in predicting wages (Handel, 2007; Sakellariou and Patrinos, 2003). Most of the research on the payoff of various skills in the labor market has been based in the United States and other OECD countries, with the exception of a handful of recent studies based in low- and middle-income economies (Acosta et al., forthcoming; Ajwad et al., 2014; Bassi et al., 2012; Ramos et al., 2013; Nikoloski and Ajwad, 2014). This overrepresentation of high-income countries has been largely driven by the specific requirements for and availability of data needed to conduct such studies.

This paper uses data from the *Skills towards Employability and Productivity (STEP)* surveys of urban adults in eight countries, namely Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam. The paper analyzes the extent to which there is an independent association between earnings and cognitive skills—proxied by measures of reading proficiency and complexity of computer use on the job—and noncognitive skills—using personality and behavioral measures. The STEP data sets are a rich globally comparable information base that include direct and indirect measures (or proxies) for different types of skills as well as information on individual education, training and labor market trajectories and family background characteristics.

The results of this study have important implications for policy and programs focused on improving the education, training and skills profiles of workers to better suit the needs of the labor market. Our results show that skills yield significant payoffs in the labor market, even after controlling for education and other relevant individual and family background factors. This is particularly the case for our two measures of cognitive skills, reading proficiency and complexity of computers use on the job, while noncognitive skills show some significant, albeit small effects on earnings. Even after controlling for schooling, we find the association between earnings and reading proficiency (our first measure of cognitive skills) to be large and stable while the complexity of computer use on the job (our second measure of cognitive skills), has the largest association with earnings across the countries in our sample.

Beyond these overall findings, our results suggest that there is significant heterogeneity across countries in how skills are valued in the labor market. There is also some indication of possible subgroup differences by gender, employment status, and occupational group. These differences across groups highlight the need for additional analysis for a more nuanced understanding of the role of skills in labor market success and context-specific programming that takes into account the characteristics of the education and training systems and labor market needs of each country.

The paper is structured as follows. The next section (Section II) briefly describes the literature on the effect of skills on wages. Section III provides a description of the data and the analytic sample used in the empirical analysis. Section IV provides a discussion of the methodology. The results are reported in Section V, and Section VI provides conclusions.

II. Literature Review

There is a vast econometric literature that examines returns to education and training as proxied by schooling (years of school or level of education completed) in high-, middle-, and low-income countries (Card, 2001; Psacharopoulos and Patrinos, 2004; Hanushek et al. 2013). Most studies on returns to schooling are based on the standard Mincerian framework, which posits that schooling develops general skills and is thus a good measure of human capital (Mincer 1974). They estimate that each year of additional schooling is associated with an earnings increase of about 7 to 10 percentage points (Psacharopoulos, 1994; Psacharopoulos and Patrinos, 2004;

Montenegro and Patrinos, 2014). Although historically most research found the highest payoffs came from primary education, recent evidence from a study comparing 139 economies (Montenegro and Patrinos, 2014) suggests that the returns to tertiary education surpass those at the primary and secondary education levels. These findings may be an indication of important shifts taking place, whether as a result of massive expansion in educational attainment, because of so-called skill-biased technological change (Katz and Murphy, 1992; Autor, Katz and Krueger, 1998) or because of rising inequality in the wage structure (DiNardo and Pishcke, 1997; DiNardo and Card, 2002).

However, while findings on the returns to schooling have proven to be robust and useful (Heckman, Lochner, and Todd, 2001), there are limitations (i.e., unobserved ability and effort, endogeneity, etc.) and methodological challenges associated with using schooling as a proxy for estimating schooling returns (Card, 1999). For example, Hanushek et al. (2013) have pointed out that Mincer's formulation assumes that schooling is the only systematic source of skill differences.[5] But research shows that other factors, such as an individual's ability, family inputs, and school and labor market characteristics also determine skill acquisition (Card, 2001 Heckman, and Vytlacil, 2001). Further, not all skills are acquired or demonstrated through years of formal schooling. Cognitive and noncogntive skills are important determinants of labor market success (Bowles, Gintis, and Osborne, 2001; Borghans et al., Duckworth, Heckman, and ter Weel, 2008; Cawley, et al., 1996; Heckman, Stixrud, and Urzua, 2006). Using schooling alone as a proxy for general skills severely underestimates the returns to human capital and obscures our understanding of how the labor market rewards various skills.

In response to the conceptual and methodological limitations of the returns-to-schooling studies noted above, a substantial literature has examined how cognitive skills, and to a lesser extent noncognitive skills, are rewarded in the labor market (Cawley, et al., 1996; Hanushek and Zhang, 2006; Hanushek et al., 2013). Although available metrics are fairly heterogeneous and seldom comparable across data sets, *cognitive skills* tend to be measured through student achievement tests and reading and numeracy assessments. *Noncognitive skills* are typically estimated through self-reported measures of behaviors and personality traits (such as the Big Five personality inventory dimensions).

Overall, findings indicate that, like years or level of schooling, cognitive skills tend to have a statistically significant effect on wages—the magnitude of which varies by the specific

[5] "Mincer's empirical innovation has perhaps been too successful as it has also led researchers to ignore many important and continuing measurement issues. Implicitly the Mincer formulation assumes that schooling is the sole systematic source of skills differences" (Hanushek et al., 2013, p. 4).

populations under review, metrics and model specifications used. Most early research examining cognitive skills in the context of labor market outcomes is based in the United States and uses data from the National Longitudinal Survey of Youth (NLSY), which includes a measure of cognitive and vocational ability—the Armed Services Vocational Aptitude Battery (ASVAB) (Cawley, et al., 1996; Cawley, Heckman, and Vytlacil, 2001). Findings from these studies show cognitive ability having modest effects on wages.

Subsequent research on the role of cognitive skills moved toward using comparable data from large-scale international reading literacy tests, such as the International Adult Literacy Survey (IALS) and the Adult Literacy and Life Skills Survey (ALLS). It is argued these reduce the heterogeneity of cognitive skills metrics and are also better measures of functional literacy and reading proficiency (Barrett, 2012; Barone and van de Werfhorst, 2011; Fasih, Patrinos, and Sakellariou, 2013; Green and Riddell, 2003; Hanushek and Zhang, 2006). Separate studies using the Canadian IALS (Green and Riddell, 2003) and the Australian ALLS (Barrett, 2012) find that cognitive skills significantly predicted higher earnings. Similarly, IALS data have been used in cross-country comparisons.

More recent research examining the effect of cognitive skills on earnings has used reading assessment data from the Program for the International Assessment of Adult Competencies (PIAAC) survey, which is sponsored by the OECD and is designed to measure key cognitive and workplace skills. The PIACC survey measures cognitive skills in three domains: literacy, numeracy, and problem solving in technology-rich environments. It addresses some of the measurement issues noted with the IALS and ALLS.[6] Hanushek et al. (2013) used the PIAAC data to estimate the returns to skills in 22 countries. Their findings indicate that higher cognitive skills (proxied using the numeracy and literacy skills components of the PIAAC assessment) lead to higher wages across all countries, with prime-age workers (ages 35 to 54) showing higher returns than recent entrants to the labor market. When they added years of schooling to the model, along with numeracy skills, their results showed that the estimated effect of cognitive skills went down by about 43 percent, but coefficients remained positive and significant.

In contrast to the literature on returns to cognitive skills, which demonstrates strong links between cognitive skills and labor market options, similar evidence on *noncognitive* skill payoffs is relatively sparse—and it is more difficult to consolidate findings. This is largely due to the variety of ways in which noncognitive skills are defined, measured, and interpreted. In general, however, available evidence shows that noncognitive skills have small positive effects on earnings, and the

[6] See Hanushek et al. (2013) for a brief discussion of these issues.

magnitude of these effects varies by the type and number of measures used. In some cases, studies show effects that are comparable with the estimates found for cognitive skills (Bowles, Gintis, and Osborne, 2001; Heckman, Stixrud, and Urzua, 2006; Heineck and Anger, 2010; Mueller and Plug, 2006; Nyhus, and Pons, 2005).

Many studies have used the *Big Five personality traits*—openness, conscientiousness, extraversion, agreeableness, and neuroticism (Goldberg, 1990) as proxies for noncognitive skills (Heineck and Anger, 2010; Mueller and Plug, 2006). Mueller and Plug (2006) used data from the Wisconsin Longitudinal Study and examined the effect of these five personality traits on earnings separately for men and women. They found that controlling for IQ, occupation, and a range of covariates, openness, agreeableness, and neuroticism had small albeit significant effects on earnings among men. In contrast, openness and conscientiousness significantly predicted earnings among women. Heineck and Anger (2010) used the Big Five personality measures to estimate the impact of noncognitive skills on labor market outcomes in Germany. In addition to the Big Five, they added measures of *locus of control* and *reciprocity*[7] to their analytical model. Their results indicated that after controlling for cognitive abilities and several socio-demographic and job-related characteristics, personality was a significant predictor of earnings. Other research has also explored noncognitve skills outside of the Big Five. Heckman, Stixrud, and Urzua (2006) used the NLSY 1979 data, which included measures of individuals' self-worth and individuals' perceived degree of control over their lives, to determine the effect of these measures on labor market outcomes. They found small but significant effects (less than 1 percent) for these measures of noncognitive skills in predicting wages. Their findings suggest that the estimated effects of noncognitive skills on wages are as strong as those estimated for cognitive skills when one controls for schooling and family characteristics.

As technology changes, and its use continues to increase in labor markets throughout the world, some research has expanded the definition of cognitive skills to include those skills necessary for success in technology-rich environments. In this study, in addition to reading proficiency, we proxy cognitive skills with a variable that measures the complexity of computer use on the job. The literature on this technological transition shows that the changes introduced by the use of technology (mostly computers) has shifted the premiums for those skilled workers who are able to complement what technology can do, introducing a skill bias. These changes have likewise replaced workers whose skills can be substituted by technology in a labor-saving

[7] *Locus of control* refers to an individual's perception of the relation between her/his own behavior and its consequences. *Reciprocity* entails showing much more cooperation than predicted in response to friendly actions from others and, conversely, being "much more brutal" in response to hostile actions (Heineck and Anger, 2010).

pattern (Acemoglu and Autor, 2011; Autor, 2014; Autor, Levy, and Murnane, 2003; MacCrory et al., 2014). These findings have generated further interest in examining the role of technology (or computer use) at an individual level to explain changes in hourly earnings.

Most of the evidence on this matter has been documented for high-income countries. Krueger (1993) was among the first to attempt to establish a link between computer use at work and a wage premium. He used the supplemental questions containing information about computer use from the Current Population Survey (CPS) in 1984 and 1989. His findings indicated that the computer use payoff over the same time period ranged from 10 to 15 percent. He also found that about 40 percent of the increase in earnings during the second half of the 1980s was attributable to computer use. DiNardo and Pischke's (1997) study and, later, Handel's (2007) study noted that the premium on computer use might not be reflective of changes in the wage structure but instead reflect unobserved heterogeneity within a job or occupation.

Sakellariou and Patrinos (2003) put forth another interpretation for the wage premium on computer use. They suggested that the observed premium is a reflection of the ease in recovering the costs that high-wage workers incur when they gain these skills. Their correlational research with higher education graduates in Vietnam showed wage premiums close to 26 percentage points. In addition, Borghans and ter Weel (2003) aimed to disentangle computer *use* from computer *skills*. Their study used the Skills Survey of the Employed British Workforce from 1997 to estimate the returns to computer, writing, and math skills. The study, which sampled workers ages 18 to 60, found positive and significant returns for writing (25 percentage points), math (17 percentage points) and computers (33 percentage points), but found no significant relationship between wages and computer *skills* at work. They inferred that higher wage premiums are associated with computers *if* computers are used in an advanced manner.

More recently, Falck et al. (2016) used PIAAC data from 19 countries to estimate labor market returns of information and communication technology (ICT) skills. Starting with the premise that developing such skills is facilitated by internet access, the authors employed an instrumental-variable strategy based on variation in broadband internet access—and found that a one stand deviation increase in ICT skills increased earnings by 24 percent.

Overall, the existing research on wage premiums related to cognitive and noncognitive skills, as measured by reading proficiency levels, frequency and complexity of computer use on the job, and personality traits and selected behaviors, shows some consensus on the role of these skills in predicting labor market success. The size and magnitude of these relationships vary and are in many ways a function of the range of metrics used to proxy for cognitive and noncognitive skills.

With regard to the relationship between computer-related skills and earnings premiums, the results are more heterogeneous; there is as yet no consensus on whether this relationship is driven by an increase in computer-specific human capital or changes in the organization of the workplace.

III. Data

This paper uses the STEP Skill Measurement surveys from eight low- and middle-income countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam. It gathers information from urban adults between the ages of 15 and 64 and includes three unique modules that cover various measures cognitive and noncognitive skills.

The STEP surveys provide a direct, objective assessment of *reading proficiency skills*, which is scored on the same scale as the OECD's PIAAC assessment. The assessment includes three parts that together provide a measure of reading proficiency among adults in each of the countries surveyed. The items used in STEP were developed based on the literacy frameworks developed for PIAAC, which defines literacy as: *"understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential"* (OECD, 2012). This definition provides a broad understanding of the processes and goals of literacy as measured in STEP. The main aspects of the construct—contexts for reading and underlying cognitive processes required to complete the presented tasks—have been taken into consideration when selecting the texts and developing items included in the STEP literacy assessment (Pierre et al., 2014; Educational Testing Service, 2014). The scores of the assessment range from 0 to 500 and represent six levels of proficiency.[8]

In addition to reading proficiency, several items on the STEP survey capture data on *computer use at work*, which we use as a second measure of cognitive skills for this study. This variable provides the frequency and complexity of computer use on the job and was selected to help determine the extent to which these skills are being rewarded in the labor market. Respondents report the frequency with which they use computers at work—never, a couple of times a week, or more than three times per week—followed by a description of the computer-related tasks required in their job. Four levels of computer use are defined: level 1 includes browser-based tasks (such as use of email and the internet), level 2 includes basic Microsoft Office functions (such as word processing and graphics), level 3 includes basic programming (such as spreadsheets or databases), and level 4 includes advanced programming tasks (such

[8] See Pierre et al. (2014), p. 83, for a detailed description of the assessment and levels of proficiency.

as web design, software programming, or network management). The surveys also include items to determine the use of computer skills in daily life, which could be a broader measure of the availability of such skills in the workforce—although it is also plausible that such skills may not be required in their jobs.

The STEP surveys also gather information on noncognitive skills. Information on the Big Five personality traits (openness, conscientiousness, extroversion, agreeableness and neuroticism), grit, and behaviors such as decision-making and hostility bias is gathered through a series of Likert-type items with four possible responses ranging from "almost never" to "almost always." Items measuring these traits and behaviors are rated on a four-point Likert scale from "Almost never" to "Almost always."

Along with the skills measures described above, the STEP surveys gather extensive information on individual education and employment outcomes, labor market trajectories and on family background characteristics.

Analytic sample

The STEP surveys are targeted to the urban working-age population (those between the ages of 15 and 64). For this study, we limited the sample to adults between the ages of 25 and 64, excluding those currently attending an educational program. The sample was further restricted to include only wage and salaried workers and those who are self-employed. Employers were excluded from the self-employed group to avoid biased estimates due to measurement error in earnings. Part-time workers (those working less than 40 hours a week) and unpaid workers were also excluded from the analytic sample, conforming to standard practice in these types of analyses. The proportion of salaried and wage workers and the self-employed group in each of the country samples is presented in Table 1.[9] As shown, the self-employed in Armenia, Georgia, and Ukraine constitute a much smaller group compared to those in the other countries in the sample.

[9] Also, see Tables A.2 and A.3 in Appendix A for differences between the two worker types. These tables show that the groups are similar across measured characteristics.

Table 1. Percentage of wage and self-employed workers, sample countries

	Wage/ salaried workers	Self-employed workers	Number employed
Armenia	87.87	8.98	1,047
Bolivia	51.85	32.89	1,788
Colombia	53.20	35.62	1,735
Georgia	84.13	10.23	958
Ghana	35.67	50.80	2,181
Kenya	56.59	33.03	2,419
Ukraine	88.83	6.96	1,307
Vietnam	56.34	28.32	2,366

Note: “Employed” includes employers and unpaid workers.
Source: STEP Surveys (2014).

In keeping with standard practice, the top 1 percent hourly earners were removed from the analytic sample to avoid potential outliers, and extremely low wages were imputed to those reporting zero hourly earnings.[10] Finally, cases missing information on any of the key variables were dropped from the sample. The proportion missing constitutes less than 0.1 percent of the sample.[11] This is a small proportion of observations; we believe that excluding them would not bias the estimates due to nonrandom loss of sample. The effective sample size for the empirical analysis ranges from 849 to 1,953 observations across the countries in our sample.

Description of the sample

The general landscape of the labor market in each country is presented in Tables 2 and 3. Overall, labor force participation across the sample of countries is high and ranges from 49.5 percent in Armenia to 84.3 percent in Ghana. However, the employment rate is fairly low in Armenia (27.8 percent) and Georgia (25 percent), while it is above 50 percent in the other countries.[12] The low employment rate observed in Armenia and Georgia impacts the effective sample size used to estimate the returns to education and the relationship between various skills and hourly earnings.

The average hourly earnings in 2011 purchasing-power-parity-(PPP)-adjusted U.S. dollars range from approximately US$2.15 in Ghana to US$3.60 in Bolivia and Ukraine. There are also

[10] A value of 0.00001 was imputed to workers who reported no hourly earnings.
[11] In the case of Ghana, about 800 cases are missing data on the noncognitive skills measures. These items were administered in English and respondents reported inadequate English language skills to complete this battery. As a result, data from Ghana are not included in estimating the effects of noncognitive skills.
[12] According to UN data, labor force participation among males and females in Armenia in 2012 was about 51 percent and 73 percent, respectively. Corresponding figures for Georgia in 2012 were 56 percent and 75 percent, respectively (http://unstats.un.org/).

differences in the average hourly earnings of wage workers compared to the self-employed; the latter group earn approximately US$0.50 to US$2.00 less than wage workers in six of the eight countries. The relationship is different for Armenia and Ukraine, where the self-employed earn about US$0.20 more than wage workers; this may be due to the different nature of self-employment in these two countries or to small-sample measurement error (the proportion of self-employed in these countries constitutes less than 1 percent of the sample).

Table 2. Labor market indicators, population ages 25 to 64, sample countries

Country	Labor force participation	Employment rate	Unemployment rate	Observations
Armenia	49.5%	27.8%	43.7%	2,076
Bolivia	79.5	72.6	8.6	951
Colombia	73.7	61.9	15.9	1,391
Georgia	51.6	25.0	51.6	2,080
Ghana	84.3	76.3	9.5	1,346
Kenya	83.2	66.4	20.2	1,877
Ukraine	58.4	50.1	14.2	1,741
Vietnam	72.6	71.1	2.0	2,075

Source: STEP Surveys (2014).

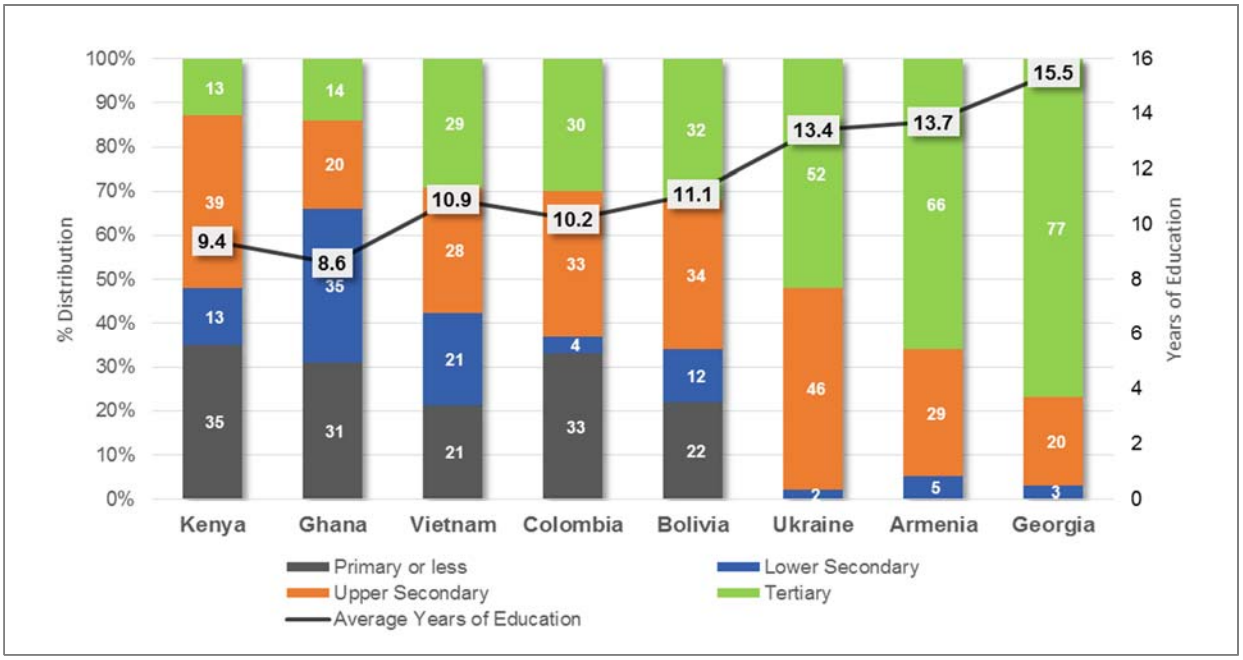
Table 3. Average hourly earnings, workers ages 25 to 64, sample countries
(in 2011 PPP-adjusted U.S. dollars)

	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Ukraine	Vietnam
All workers	2.66	3.57	3.45	3.39	2.15	2.55	3.52	3.21
	(1.79)	(3.82)	(4.07)	(3.05)	(3.81)	(3.00)	(1.92)	(3.51)
N	*530*	*653*	*830*	*481*	*560*	*1159*	*731*	*1384*
Wage workers	2.65	3.99	3.69	3.59	2.60	3.06	3.51	3.42
	(1.71)	(3.98)	(4.52)	(3.14)	(4.34)	(3.35)	(1.87)	(3.18)
Self-employed	2.89	2.82	2.90	1.66	1.81	1.64	3.67	2.80
	(2.62)	(3.37)	(2.69)	(1.19)	(3.33)	(1.96)	(2.44)	(4.03)

Note: Standard deviations in parentheses.
Source: STEP Surveys (2014).

There are large differences in educational attainment across the countries, as Figure 1 illustrates. The average completed years of education for those currently employed ranges from 8.63 years in Ghana to 15.47 years in Georgia. These differences are more pronounced when one compares the proportion of the sample completing various *levels* of education. More than half the sampled workers in Georgia, Armenia, and Ukraine have a tertiary education degree, while in Ghana and Kenya only about 14 percent of the sample do.

Figure 1. Average completed years of education and educational attainment: workers ages 25 to 64 (percent distribution)



Source: STEP Surveys (2014)
Note: Dark line indicates average number of years for entire analytic sample.

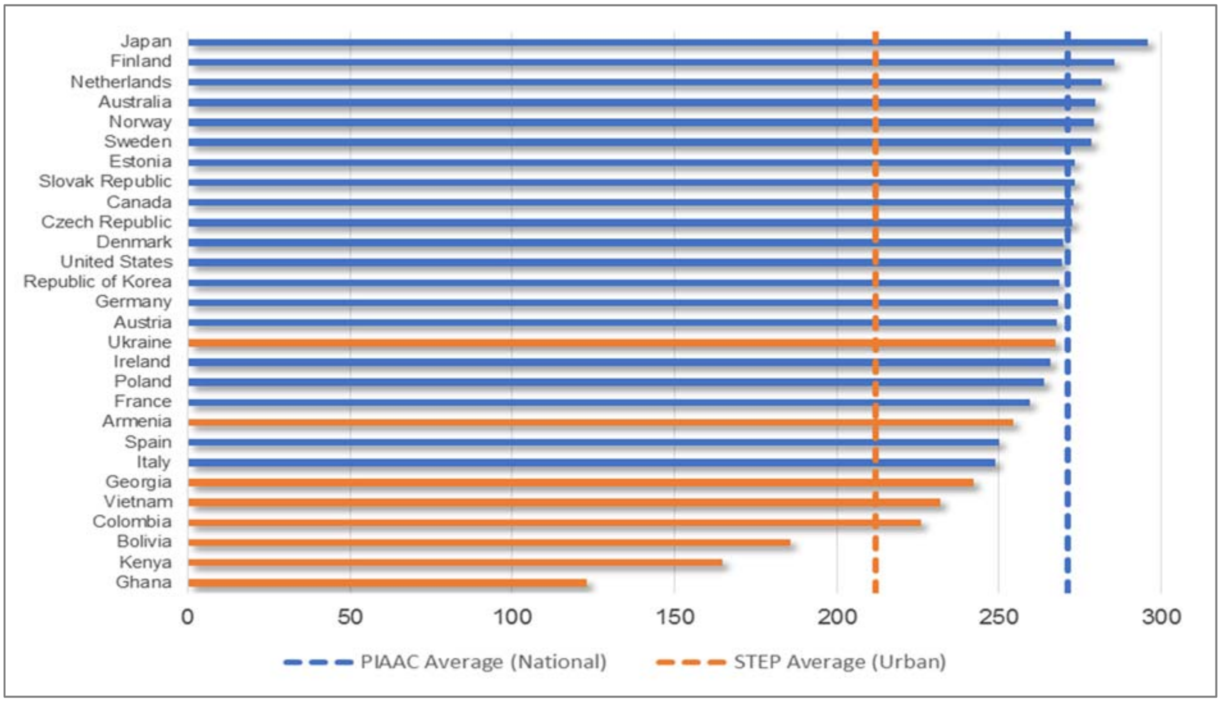
As mentioned before, the STEP surveys contain measures for different types of skills, which are the focus of this study. Results showing how the countries in the sample compare on cognitive and noncognitive skills are provided in Appendix Tables A.1 through A.3., including within-country differences in these skills between wage workers and self-employed workers. The findings are described below.

To measure cognitive skills among adults in low- and middle-income countries, the STEP surveys administer a reading proficiency assessment designed to mimic the diversity and gradual degree of complexity of tasks encountered by adults in daily life and assess the cognitive operations used to navigate these tasks.[13] The reading proficiency assessment is scored on the same scale as the PIAAC assessment, allowing one to benchmark the reading proficiency of the adult population in low- and middle-income countries with that in OECD countries. The average score on reading proficiency for STEP countries is around 212 points, while the average score for PIAAC countries is about 271 (see Figure 2). Given the score construction (a 500-point scale with

[13] See Pierre et al. (2014) for a fuller discussion on the rationale for and description of the STEP reading proficiency assessment. Also, the STEP surveys include self-reported measures of writing, math and problem solving. The most reliable of the cognitive skills measures available in the STEP data, the reading proficiency scores, have been used to proxy cognitive skills in this paper.

a standard deviation of 50), the STEP countries are more than a standard deviation below their PIAAC counterparts.[14] (For a discussion of the implications of these differences, see Section VI.)

Figure 2. Average reading proficiency scores for PIAAC and STEP assessments, ages 25 to 64, sample and selected OECD countries

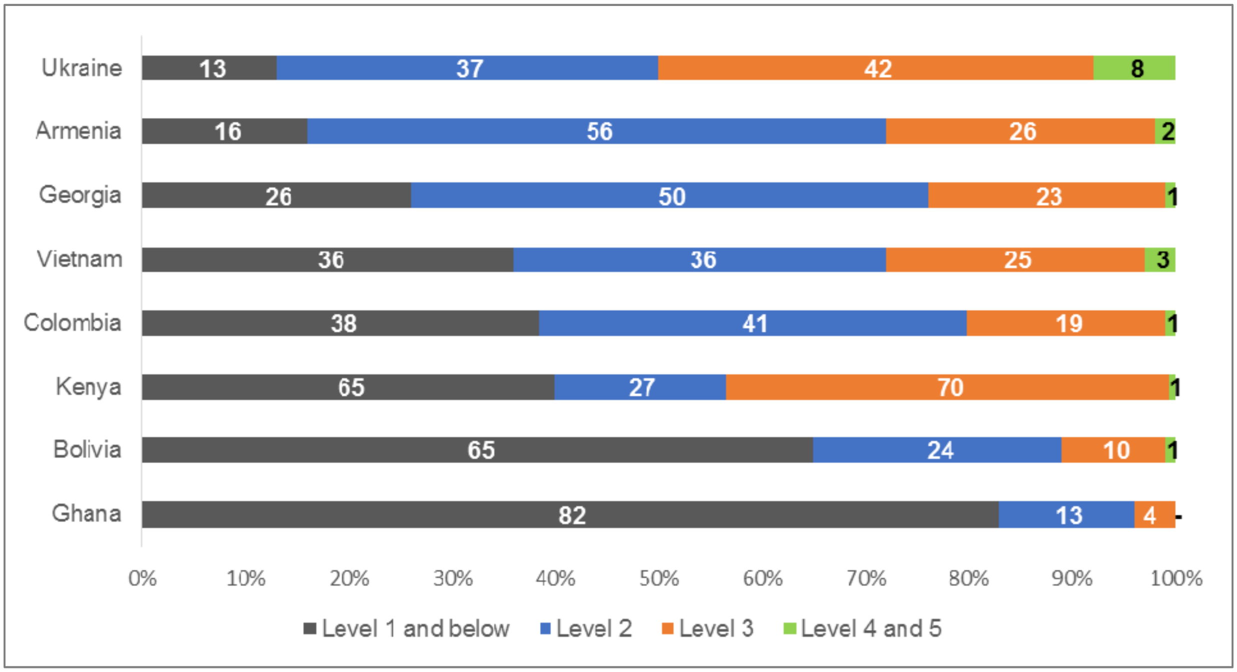


Note: The PIAAC estimates correspond to the national resident population 25 years and older in each country. The STEP estimates correspond to the urban population 25 years and older, excluding unpaid workers.
Source: STEP Surveys (2014), OECD (2013).

Scores on the reading proficiency assessment can be expressed in terms of six levels, where each level corresponds to a cumulative set of tasks that an individual can undertake with his or her reading capabilities. Task difficulty increases by level.[15] More than half of the workers across the countries in our sample score in the lower levels of reading proficiency (levels 0, 1, and 2). The data also show heterogeneity across countries. For instance, as shown in Figure 3, in Ghana, Bolivia, and Kenya more than 65 percent of the workers (between ages 25 and 64) are clustered in level 1 or below, while in Armenia and Ukraine about 13 percent and 16 percent of the sample, respectively, is at level 1 or below.

[14] See Educational Testing Service (2014).
[15] See Educational Testing Service (2014).

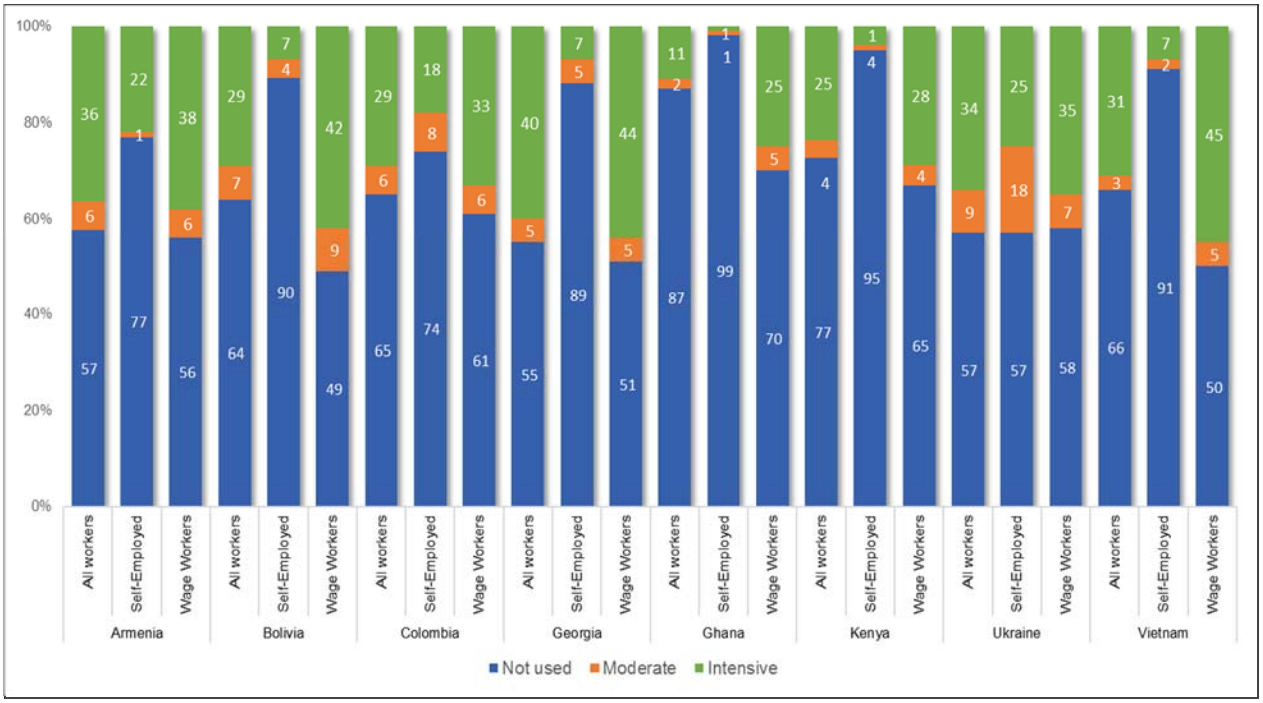
Figure 3. Reading proficiency levels, workers ages 25 to 64, sample countries
(Percent distribution)



Source: STEP Surveys (2014).
Note: See text for explanation of reading levels.

We also treat computer use at work as a proxy for cognitive skills. This measure is based on the complexity of computer-based tasks undertaken by the respondent in his or her job. For respondents using computers on the job, the measures of complexity range from using email and browser-based tasks (the lowest level), followed by using Microsoft Office applications including presentations and graphics (the next level of complexity), followed by tasks involving basic programming functions (for example, working with spreadsheets, databases, and/or book-keeping applications), and finally to tasks involving advanced programming at the highest level (these include designing websites, using computer-aided design software, programming software and/or managing networks). In the countries in our sample, around 66 percent of workers reported not using a computer at work, while 29 percent reported using computers at their jobs with high frequency (see Figure 4). This suggests that, in general, across the countries in our sample, computer use at work is low, but when used on the job it is used with high frequency. Furthermore, this use varies across types of workers. About 43 percent of wage workers tend to use computers (with any frequency) as compared to 16 percent of self-employed workers.

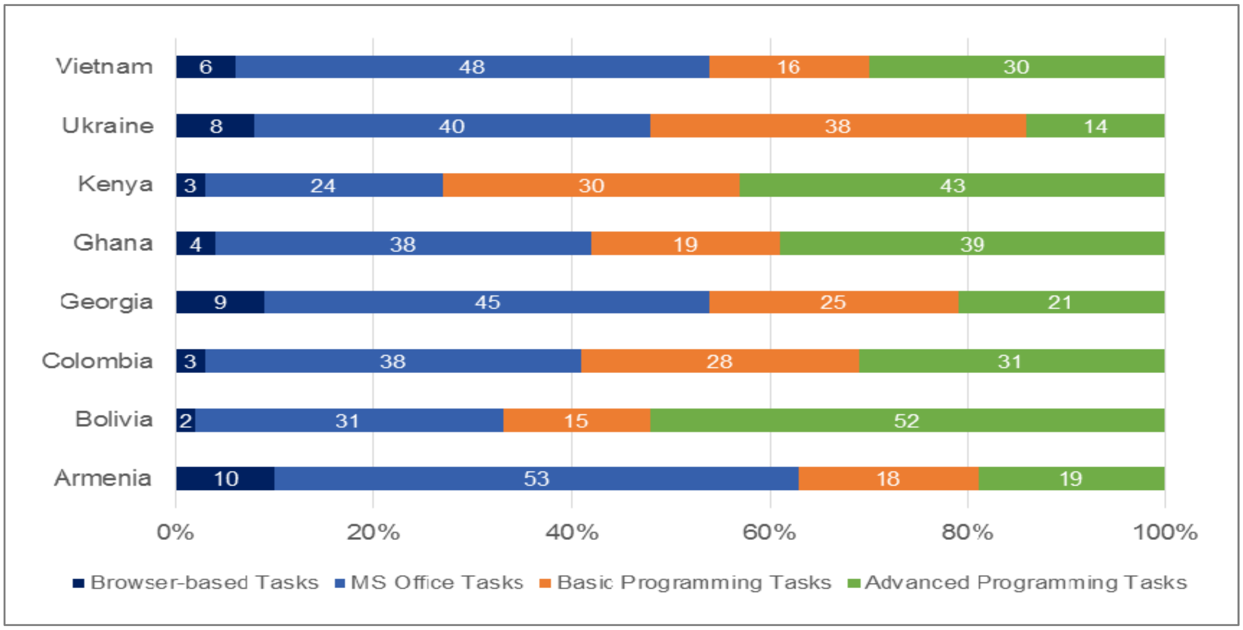
Figure 4. Intensity of computer use at work, workers ages 25 to 64, by employment type (percent distribution)



Source: STEP Surveys (2014).

With regard to the distribution of workers by the complexity of their computer use, we find that the largest proportion of computer users at work are using basic applications involving a word processor, spreadsheets, making presentations, or doing data entry. This group accounts for 40 to 50 percent of computer users in most of the countries with the exception of Kenya and Bolivia (see Figure 5). In Kenya and Bolivia we find that the largest proportion of respondents who use computers on their job are using advanced programming skills. The proportion of workers handling tasks involving basic programming skills like advanced functions in spreadsheets or bookkeeping applications is also substantial across all the countries (from about 15 percent in Bolivia and Vietnam to more than 30 percent in Kenya and Ukraine). Finally, we find that less than 10 percent of respondents who use computers at work limit their computer usage to browser-based tasks.

Figure 5. Level of complexity of computer use at work, workers ages 25 to 64 (percent distribution)

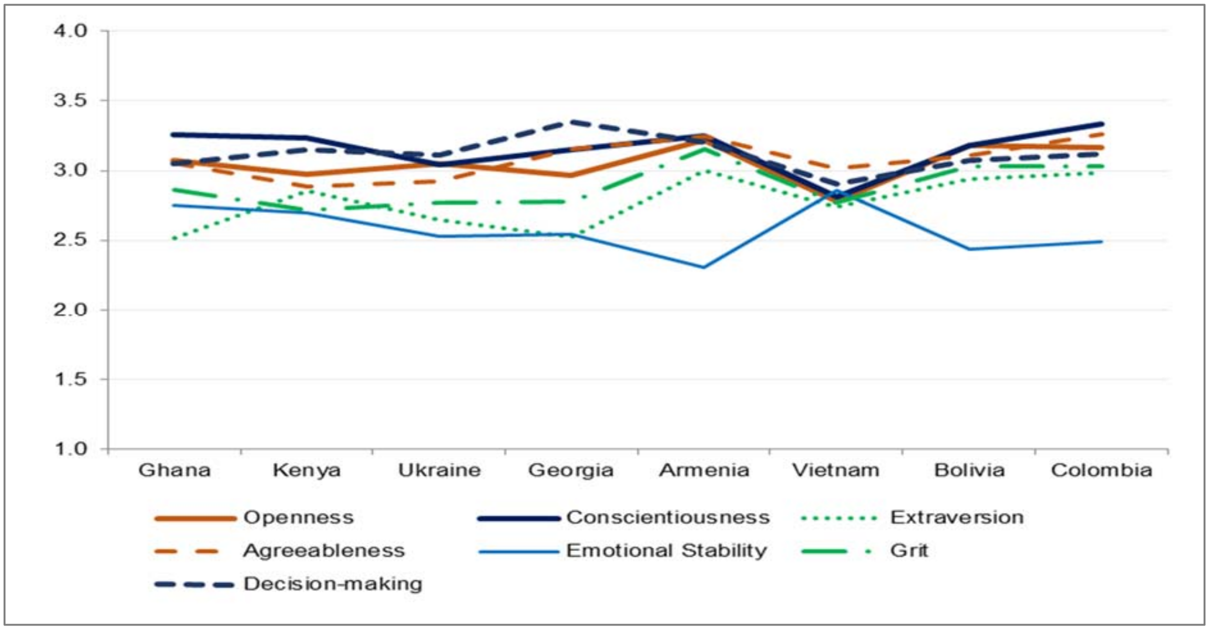


Source: STEP Surveys (2014).

In Figure 6 we present the distribution of average scale scores on the noncognitive skills across the countries in our sample. For items measuring personality and behavior traits, respondents select one of four responses ("Almost never," "Some of the time," "Most of the time," or "Almost always").[16] Figure 6 shows that the average scores on each of the Big Five personality traits, grit, and decision-making are similar across the countries in our sample. While scores on emotional stability and extraversion seem to show some cross-country differences, these differences are not substantial.

[16] See Pierre et al (2014) for a description of the noncognitive skills module in the STEP Surveys.

Figure 6. Average scores on the 'Big Five' personality traits, workers ages 25 to 64



Source: STEP Surveys (2014).

We also investigate within-country differences between subgroups (wage workers and the self-employed, for instance) in their average scores on any of the personality and behavior traits. While we do not find substantial within-country differences in the distribution of these skills for most countries, in Vietnam the average scores for openness—and to a lesser extent for conscientiousness—differ across wage workers and self-employed workers.

IV. Empirical Strategy

In order to estimate returns to education and the net effect of skills on hourly earnings, we use the standard Mincer approach (Mincer, 1974). The Mincerian framework assumes that schooling, considered the main measure of human capital, develops general skills and can explain variations in individual earnings. The empirical formulation of this relationship is expressed as shown below. Dummy variables for gender, type of employment, and occupation have been added to the basic Mincer formulation to capture subgroup differences.

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \alpha_4 Self\ Employed_i + \alpha_5 Occupation_i + \alpha_6 Schooling_i + \varepsilon_i\ ,$$

where w_i indicates (log) hourly earnings; *Experience* is potential experience calculated as (*Age – Years of education* – 6); *Gender, Self Employed,* and *Occupation* are indicator variables; and ε_i is the unexplained residual.

In order to estimate the relationship between skills and earnings, schooling attainment in the wage function above is substituted by measures of cognitive skills (namely, reading proficiency scores and dummy variables indicating complexity of computer use on the job) and noncognitive skills. The coefficient on the skills measure provides the net effect of that skill on earnings, that is, the direct effect of skills on earnings and the effect through schooling (Heckman, Stixrud, and Urzua, 2006). Thus, to examine the effect of cognitive skills on wages, the model is expressed with the reading proficiency measure as shown here:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \alpha_4 Self\ Employed_i + \alpha_5 Occupation_i + \alpha_6 Schooling_i + \beta_1 Reading_i + \varepsilon_i\ ,$$

where *Reading* is the standardized score on the reading proficiency assessment. For each country, *Reading* has been standardized with mean 0 and standard deviation of 1.

To estimate the relationship between complexity of computer use at work and wages, the model is given thus:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \alpha_4 Self\ Employed_i + \alpha_5 Occupation_i + \alpha_6 Schooling_i + \gamma' Computer + \varepsilon_i\ ,$$

where *Computer* is a vector of dummy variables for each level of complexity described earlier.

The model when using noncognitive skills is expressed this way:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \alpha_4 Self\ Employed_i + \alpha_5 Occupation_i + \alpha_6 Schooling_i + \lambda' Noncognitive + \varepsilon_i\ ,$$

where *Noncognitive* is a vector of skills composed of standardized scores on the Big Five (extraversion, conscientiousness, openness, agreeableness, and emotional stability), grit, and decision-making.

The standard Mincer model is typically estimated using Ordinary Least Squares (OLS) regressions. However, in the case of wage functions, OLS regressions produce biased estimates of the effect of schooling (Card, 2001). The endogeneity of the schooling variable can lead to its being overestimated, while measurement error in the years of schooling can lead to an underestimated coefficient. Further, earnings are only observed for individuals employed in the labor force—a nonrandom sample of the population—and this sample selection can lead to bias in OLS estimates (Wooldridge, 2010).

The existing literature provides various techniques to address these inconsistencies in estimating wage equations. Card's (2001) investigation found that 80 percent of the studies reviewed used instrumental variables and about 15 percent used Heckman's correction method.

This paper uses Heckman's correction method (Heckman, 1979) to estimate the returns to education and the relationship between skills and wages.[17] The intuition behind Heckman's correction for sample selectivity is to construct a model that jointly represents both the regression equation to be estimated and the process that determines if the dependent variable (in this case, earnings) is observed.

As a first step, we estimate the probability of labor force participation. The model is expressed thus:

$$LFP_i = Z_i\gamma + u_i;\ LFP_i = 1[LFP_i^* > 0]\ ,$$

where labor force participation (LFP_i) is predicted by Z_i, a vector that contains instruments not included in the wage equation, in addition to the full specification of variables described in each model (except those that correspond directly to job characteristics such as self-employed and computer use at work). The vector of instruments includes number of shocks at age 15, socio-economic status at age 15, and an index based on current household assets. Shocks during childhood can affect children's educational attainment positively or negatively, depending upon the household's ability to withstand the same. The evidence from low- and middle-income countries, in particular, indicates that families adjust the educational and labor market activities of children in response to shocks (Jacoby & Skoufias, 1997; Duryea, 1998; Skoufias & Parker, 2002). Similarly, there is some evidence showing that household income is a significant predictor of labor force participation—especially among women (Klasen & Pieters, 2013). Household assets indicate potential income and the leisure likely to be afforded by the household. Households that can afford greater leisure are likely to show lower labor force participation.

[17] We also estimate unweighted and weighted OLS models for schooling and all the skills measures. We find some differences between weighted OLS and Heckman estimates for all countries besides Armenia and Georgia. Comparing results from the weighted and unweighted OLS, we find similar coefficients and small differences in estimated standard errors.

All the models are estimated using the Heckman correction method in Stata. The full-information maximum-likelihood approach, which is more efficient than the Heckman two-step procedure, is used for estimation (Leung and Yu, 1996; Puhani, 2000).[18]

V. Results

This section presents the results of the empirical models discussed in Section IV. As a first step, we estimate the returns to education for the urban adult population in the selected low- and middle-income countries.

Effects of schooling

Our results show a positive and significant return to schooling (see Table 4). For instance, an additional completed year of schooling is associated with a 5- to 7-percentage-point increase in hourly earnings, controlling for experience, gender, type of employment, and occupational group.[19] Montenegro and Patrinos (2014) report, on average, a 10-percentage-point return to each additional year of education worldwide, controlling for potential experience.[20] The heterogeneity in country estimates indicates differences in how the labor market rewards educational attainment across the countries in our sample.

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[18] The full-information maximum likelihood method relies heavily on normality assumptions and could have difficulties converging in the absence of exclusion restrictions.

[19] The coefficient in Table 4 represents an increase in log points. We use the following formula to convert to percentage points: $percentage\ points = e^{\beta} - 1$. For example, in Kenya the coefficient is 0.087, which suggests an 8.7 log point increase in earnings, which, using the suggested formula, indicates that there is a 9.1 percentage point increase ($e^{0.087} - 1$) in hourly earnings.

[20] A major difference between the estimates reported here and those reported in other studies (e.g., Hanushek et al. (2013); Montenegro and Patrinos (2014); and Fasih, Patrinos, and Sakellariou (2013) is that this study uses an urban sample that includes both wage and self-employed workers. Further, previous studies have estimated returns using OLS and a smaller set of control variables, while this study corrects for selection bias and uses a larger set of controls.

Table 4. Returns to years of education by selected characteristics, workers ages 25 to 64

	Schooling	Self-employed	Women	N
Armenia	0.019	0.015	-0.181**	1557
	(0.01)	(0.13)	(0.09)	
Bolivia	0.054***	-0.208**	-0.494***	847
	(0.01)	(0.10)	(0.11)	
Colombia	0.064***	-0.218***	-0.070	1190
	(0.01)	(0.08)	(0.09)	
Georgia	0.049***	-0.581***	-0.066	1464
	(0.01)	(0.10)	(0.09)	
Ghana	0.047***	0.133	-0.383***	1174
	(0.02)	(0.11)	(0.12)	
Kenya	0.072***	-0.310***	0.065	1454
	(0.01)	(0.08)	(0.08)	
Ukraine	0.051***	-0.395*	-0.383***	1370
	(0.02)	(0.22)	(0.06)	
Vietnam	0.060***	-0.006	-0.254***	1948
	(0.01)	(0.06)	(0.05)	

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample includes wage and self-employed workers. *Schooling* is measured as completed years of education. The reference categories for *Self-employed* and *Gender* variables are those not self-employed and males, respectively. Control variables include potential experience, the quadratic of potential experience, and two occupation dummy variables indicating highly skilled and low skilled white-collar jobs (with blue-collar jobs as the reference group). The Heckman method is used to correct for selection bias.

Our estimates for the returns to education also show a strong and consistent discrimination against women in their hourly earnings. The evidence suggests that in five of the eight countries, women earn between 18 and 49 percentage points less than men in these countries.[21]

We also find that after controlling for schooling and potential experience, in five of the eight countries self-employed workers show lower average earnings than those in wage work. For the self-employed group, the earnings are between 21 percentage points (Bolivia and Colombia) and 58 percentage points (Georgia) lower than the average earnings of wage workers. We also find that those in *high-skilled* white-collar occupations earn more than blue-collar workers, a difference that is not observed in the case of *low-skilled* white-collar workers. In fact, in three of the eight countries low-skilled white-collar workers have lower earnings than blue-collar workers.

[21] Further analysis and discussion of gender differences is presented in Tognatta, Valerio, and Sánchez Puerta, forthcoming.

To gain a better understanding of the dimensions of human capital potential beyond education, we next examine the role of skills in predicting hourly wages. As such, the results presented here should not be interpreted as the *returns* to skills but as the *net effect* of skills on earnings, holding other factors constant. There are two reasons for this: First, when schooling is not included in the model, the coefficient on the skills measures captures the direct effect of skills plus the effect of skills acquired through schooling (see Heckman, Stixrud, and Urzua [2006] for a detailed explanation). Second, there is as yet no information on the time required to learn or acquire the cognitive and noncognitive skills examined in this study, even when the model controls for completed years of education. Thus, in the absence of an estimate for the time dimension of foregone earnings, we are not estimating the “returns” to cognitive and noncognitive skills.

Effects of cognitive skills

Our empirical results for cognitive skills, as measured using reading proficiency scores, show that the net association between reading proficiency and earnings is large, positive, and significant for all countries except Armenia.[22] An increase of one standard deviation in reading proficiency scores is associated with an hourly earnings increase ranging from 9 percentage points (in Colombia, Georgia, and Ukraine) to 19 percentage points (in Ghana). These results, presented in panel A of Table 5, are comparable to those found in Hanushek et al. (2013) and in Acosta, Muller, and Sarzosa (2015).

We also find evidence that cognitive skills predict earnings beyond educational attainment in some countries in our sample. The relationship between wages and reading proficiency is significant over and above completed years of education in Ghana, Ukraine, and Vietnam. The magnitude of this association ranges from 6 percentage points (in Vietnam) to 14 percentage points (in Ghana). These results are presented in panel B of Table 5. When reading proficiency scores are added to the model with schooling, we find that the returns to completed years of education remain similar in magnitude and significance to those presented in Table 4. This suggests that our measure of cognitive skills is capturing other dimensions of human capital not explained by schooling.

[22] The reading proficiency score was standardized to have mean 0 and standard deviation of 1 for ease of interpretation and comparison across countries. Scores were standardized by country.

Table 5. Estimated effect of reading proficiency on hourly earnings, workers ages 25 to 64

	Panel A			Panel B – Controlling for schooling			
	Reading	Self-employed	Women	Reading	Self-employed	Women	N
Armenia	-0.003	-0.030	-0.154*	-0.011	0.015	-0.178**	1557
	(0.04)	(0.13)	(0.09)	(0.03)	(0.13)	(0.09)	
Bolivia	0.120**	-0.353***	-0.542***	0.067	-0.213**	-0.490***	847
	(0.05)	(0.10)	(0.12)	(0.05)	(0.10)	(0.11)	
Colombia	0.085*	-0.220***	-0.435***	-0.022	-0.217***	-0.074	1190
	(0.05)	(0.08)	(0.09)	(0.05)	(0.08)	(0.10)	
Georgia	0.086*	-0.750***	-0.111	0.065	-0.590***	-0.097	1464
	(0.04)	(0.10)	(0.09)	(0.05)	(0.10)	(0.09)	
Ghana	0.188***	-0.011	-0.408***	0.140**	0.179	-0.351***	1174
	(0.07)	(0.13)	(0.12)	(0.07)	(0.12)	(0.11)	
Kenya	0.158***	-0.449***	0.024	0.059	-0.311***	-0.061	1454
	(0.06)	(0.08)	(0.27)	(0.05)	(0.08)	(0.08)	
Ukraine	0.086***	-0.372*	-0.382***	0.072**	-0.368*	-0.382***	1370
	(0.03)	(0.25)	(0.06)	(0.03)	(0.21)	(0.05)	
Vietnam	0.148***	-0.142**	-0.301***	0.061*	-0.005	-0.254***	1948
	(0.03)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample includes wage and self-employed workers. Reading proficiency scores are standardized. *Schooling* is measured as completed years of education. The reference categories for *Self-employed* and *Gender* variables are those not self-employed and males, respectively. The wage model controls for potential experience, experience squared, and occupation. The Heckman method is used to correct for selection bias.

Results for our second measure of cognitive skills, complexity of computer use at work, show big earnings premiums across all eight countries, even after controlling for type of employment and occupation. In general, we find that the magnitude of the association between computer use at work and earnings increases with the complexity of computer use. Advanced programming skills show large magnitudes of association with hourly earnings (ranging from 24 percentage points in Ukraine to 107 percentage points in Kenya), while the coefficients for tasks related to word processing, spreadsheets, and data entry range from 24 percentage points in Armenia to 88 percentage points in Kenya. However, in the cases of Armenia, Ghana, Ukraine, and Vietnam, we notice a slightly different pattern. Computer use involving basic programming skills shows larger associations with earnings than computer use involving advanced programming skills. The magnitude of this association ranges from 34 percentage points in Ukraine to more than 100 percentage points in Ghana.

The magnitude of the observed associations could be a function of selection into high-paying occupations that require advanced computer use. It could also be capturing some of the education effect, since education and computer use are highly correlated. However, we find that even after controlling for schooling, the magnitude of these associations, although slightly smaller, is still substantial (see Table 6).

Another explanation for the large magnitude of these effects could be the relatively smaller share of jobs requiring complex computer use across these countries, making these jobs highly remunerated--even after controlling for type of employment and occupation. Unfortunately, the data used in this study do not allow for examining whether this hypothesis is supported. Additional research is needed to disentangle the effects of the use of computer skills as well as the complexity of computer skills.

Table 6. Estimated effect of computer complexity at work on hourly earnings, workers ages 25 to 64

Panel A					
	Browser-based tasks	MS Office tasks	Basic program tasks	Advanced program tasks	N
Armenia	0.116	0.242***	0.400***	0.388***	1,557
	(0.12)	(0.06)	(0.10)	(0.10)	
Bolivia	0.030	0.240	0.121	0.403***	847
	(0.14)	(0.15)	(0.14)	(0.15)	
Colombia	0.053	0.357***	0.5693***	0.603***	1,190
	(0.07)	(0.10)	(0.10)	(0.11)	
Georgia	0.307*	0.562***	0.5781***	0.653***	1,464
	(0.16)	(0.10)	(0.11)	(0.14)	
Ghana	0.878**	0.361	1.0244***	0.831***	1,174
	(0.37)	(0.27)	(0.21)	(0.26)	
Kenya	0.853***	0.881***	0.9474***	1.072***	1,454
	(0.15)	(0.12)	(0.12)	(0.13)	
Ukraine	0.160	0.255***	0.3344***	0.243*	1,370
	(0.10)	(0.09)	(0.08)	(0.14)	
Vietnam	0.451***	0.404***	0.555***	0.472***	1,948
	(0.16)	(0.08)	(0.09)	(0.09)	

Panel B - Controlling for Schooling					
	Browser-based Tasks	MS Office Tasks	Basic program tasks	Advanced program tasks	N
Armenia	0.070	0.196***	0.338***	0.322***	1557
	(0.12)	(0.06)	(0.10)	(0.10)	
Bolivia	0.019	0.103	0.019	0.251*	847
	(0.17)	(0.14)	(0.15)	(0.14)	
Colombia	-0.038	0.262**	0.468***	0.489***	1190
	(0.09)	(0.11)	(0.10)	(0.11)	
Georgia	0.199	0.472***	0.4836***	0.568***	1464
	(0.17)	(0.10)	(0.11)	(0.14)	
Ghana	0.823**	0.287	0.931***	0.745***	1174
	(0.37)	(0.26)	(0.21)	(0.25)	
Kenya	0.781***	0.787***	0.845***	0.946***	1454
	(0.11)	(0.11)	(0.12)	(0.12)	
Ukraine	0.143	0.211**	0.295***	0.182	1370
	(0.10)	(0.09)	(0.08)	(0.14)	
Vietnam	0.308*	0.256***	0.384***	0.310***	1948
	(0.17)	(0.08)	(0.09)	(0.09)	

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample includes wage and self-employed workers. *Schooling* is measured as completed years of education. The reference categories for *Self-employed* and *Gender* variables are those not self-employed and males, respectively. The wage model controls for gender, self-employed workers, potential experience and occupation. The Heckman method is used to correct for selection bias.

Effects of noncognitive skills

Models similar to the ones above were estimated using measures of the Big Five personality traits, grit, and decision-making. Our results show significant relationships between hourly earnings and openness, agreeableness, or grit in five countries: Kenya and Ukraine for openness; Armenia, Colombia, and Kenya for agreeableness; and Armenia and Vietnam for grit. We also find a positive significant relationship between decision-making and earnings in Colombia. The entire set of results is presented in panel A of Table 7. For openness, a one-standard-deviation increase in scores is associated with an hourly wage increase of 9 to 11 percentage points, which is comparable to the estimates for cognitive skills when measured using reading proficiency scores. Agreeableness shows mixed results; while it has a positive association with wages in Colombia, in Armenia and Ukraine we find a significant *negative* association between higher agreeableness scores and wages. We do not find significant results for conscientiousness, contrary to evidence from previous research on personality measures and job performance.[23]

We do not find statistically significant results for the other noncognitive skills included in the model. It must be noted that the noncognitive skills measures are a function of scores on three to five items each. We believe the limited number of items for each (noncognitive skill) scale could be limiting the reliability of these measures and obscuring the true relationship between noncognitive skills and earnings.

Table 7. Estimated effect of noncognitive skills on hourly earnings, workers ages 25 to 64

Part A – Without Education

	Openness	Conscientiousness	Extra-version	Agreeableness	Emotional stability	Grit	Decision-making
Armenia	0.015	-0.046	0.032	-0.066**	0.012	0.052*	-0.031
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Bolivia	0.049	0.045	0.016	0.021	0.064	-0.008	-0.039
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Colombia	-0.009	-0.028	-0.027	0.078*	0.028	-0.046	0.085**
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Georgia	0.041	-0.029	-0.036	0.009	-0.020	-0.072	0.009
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Kenya	0.117*	0.118	0.047	0.104	-0.027	-0.041	0.033
	(0.07)	(0.09)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
Ukraine	0.085**	0.039	0.030	-0.073**	0.011	-0.007	0.049
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Vietnam	0.030	-0.051	-0.006	0.008	-0.05	0.062**	-0.002
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)

[23] Research has found that personality traits other than conscientiousness are predictive of job performance for certain combinations of job title and outcome measures (Landy and Shankster, 1994). Further, more recent research in psychology indicates that contextual factors (on the job) could play a role in mediating the relationship between personality traits and job performance (Sanchez and Levine, 2012).

Panel B – With education							
	Openness	Conscien-tiousness	Extraversion	Agreeable-ness	Emotional stability	Grit	Decision-making
Armenia	0.013	-0.033	0.040	-0.064**	0.016	0.056**	-0.033
	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Bolivia	0.039	0.044	-0.003	0.007	0.048	-0.014	-0.032
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Colombia	-0.021	-0.016	-0.034	0.033	0.016	-0.032	0.053*
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Georgia	0.015	-0.040	-0.038	0.012	-0.010	-0.059	0.013
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Kenya	0.084	0.099	0.025	0.074	-0.047	-0.012	0.038
	(0.07)	(0.10)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
Ukraine	0.060*	0.053	0.034	-0.052	0.030	0.017	0.059*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Vietnam	0.030	-0.060*	-0.004	-0.000	-0.044	0.067**	0.003
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)

Note: Standard errors in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The sample includes wage and self-employed workers. Schooling is measured as completed years of education. Reference categories for *Self-employed* and *Gender* variables are those not self-employed and males, respectively. Personality and behavior traits are averaged across scales and standardized. The wage model controls for gender, self-employed workers, potential experience and occupation. The Heckman method is used to correct for selection bias.

The noncognitive skills results discussed above are also examined with schooling included in the model (Table 7, panel B). For agreeableness, the association with hourly earnings remains negative in Armenia (around 6 percentage points), controlling for education. The returns to completed years of education are consistent with those presented in Table 4, except in the case of Armenia and Ukraine. We find that after accounting for noncognitive skills, each additional year of education is associated with a wage increase of 2 percentage points in Armenia and nearly 4 percentage points in Ukraine. The results reported in Table 4 showed that without any skills measures in the model, the association between schooling and wages was 5 percentage points in Ukraine and not significant in the case of Armenia.

Relative impact of cognitive vs. noncognitive skills

In order to examine the association between cognitive and noncognitive skills and earnings, controlling for schooling, employment status, occupation, and gender, we estimate a model with all skills included on the right hand side. The results, presented in Table 8, show that cognitive skills indicated by computer use on the job continue to matter most for labor market success, with significant variation across countries. We find that the association between reading proficiency scores and earnings remains positive and significant only in the case of Ukraine, where cognitive skills show higher labor market payoffs than completed years of education. The returns to education range between 3 and 5 percentage points, and in Ukraine a one-standard-deviation increase in reading proficiency scores is associated with a 7-percentage-point increase in wages, controlling for completed years of education. Controlling for schooling and cognitive skills, the association between noncognitive skills and earnings is slightly smaller than that observed in Table 7, though it is stable.

We compare these results to those from a weighted OLS regression, using the same controls but without any correction for selection bias. The OLS results (see Table A.4 in the Appendix) are slightly larger in magnitude than those reported in Table 8. Further, reading proficiency and hourly earnings are significantly positively related to earnings in six of the eight countries after controlling for noncognitive skills, schooling, and the usual controls.

Table 8. Net effect of skills on hourly earnings, workers ages 25 to 64

Variables	Armenia	Bolivia	Colombia	Georgia	Kenya	Ukraine	Vietnam
Gender	-0.203**	-0.438***	-0.120	-0.100	0.041	-0.382***	-0.092
	(0.1)	(0.11)	(0.08)	(0.10)	(0.10)	(0.06)	(0.09)
Self-employed	0.035	-0.199*	-0.193***	-0.492***	-0.195***	-0.351	0.087
	(0.13)	(0.10)	(0.07)	(0.10)	(0.07)	(0.22)	(0.07)
High-skilled white collar	-0.052	0.435***	0.262**	0.001	0.391***	-0.099	0.167**
	(0.08)	(0.15)	(0.11)	(0.10)	(0.11)	(0.07)	(0.07)
Low-skilled white collar	-0.216***	-0.020	-0.125*	-0.276***	0.078	-0.164**	-0.002
	(0.08)	(0.13)	(0.07)	(0.08)	(0.08)	(0.08)	(0.06)
Years of education	0.010	0.043***	0.044***	0.031**	0.035***	0.030*	0.051***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Standardized literacy	-0.012	0.049	-0.037	0.063	0.065	0.070**	0.022
	(0.03)	(0.06)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)
Browser-based tasks	0.065	0.023	-0.040	0.185	0.740***	0.073	0.326**
	(0.2)	(0.18)	(0.10)	(0.16)	(0.10)	(0.11)	(0.16)
MS Office tasks	0.190***	0.104	0.273**	0.462***	0.784***	0.208***	0.279***
	(0.06)	(0.14)	(0.11)	(0.10)	(0.12)	(0.08)	(0.08)
Basic program tasks	0.326***	-0.008	0.485***	0.480***	0.820***	0.256***	0.397***
	(0.10)	(0.16)	(0.09)	(0.11)	(0.16)	(0.08)	(0.09)
Advanced program tasks	0.302***	0.228	0.494***	0.531***	0.974***	0.128	0.298***
	(0.10)	(0.14)	(0.11)	(0.14)	(0.13)	(0.13)	(0.09)
Openness	0.009	0.029	-0.022	-0.016	0.060*	0.082**	0.061**
	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Conscientiousness	-0.038	0.040	-0.033	-0.032	0.066*	-0.017	0.001
	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Extraversion	0.037	-0.014	-0.039	-0.057	0.026	-0.018	0.015
	(0.02)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Agreeableness	-0.070**	0.011	0.030	0.016	-0.065**	-0.012	-0.002
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)

Emotional Stability	0.002	0.038	0.005	-0.034	0.017	-0.008	0.053*
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Grit	0.049*	-0.012	-0.036	-0.067	0.028	0.033	-0.037
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)
Decision-making	-0.031	-0.028	0.063**	0.004	0.040	-0.019	0.004
	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Observations	1,557	847	1190	1464	1454	1370	1948

Note: Standard errors in parentheses (* p < 0.1, ** p < 0.05, *** p < 0.01). The sample includes wage and self-employed workers. *Schooling* is measured as completed years of education. Reference categories for *Self-employed* and *Gender* variables and for computer complexity are those not self-employed, males, and no computer use, respectively. Scores on the reading proficiency assessment and personality and behavior traits have been standardized to a mean of 0 and standard deviation of 1. The wage model controls for gender, self-employed workers, experience and occupation. The Heckman method is used to correct for selection bias.

Capitalizing on the harmonized data used in this study, we also estimate pooled regressions to examine the overall association between cognitive skills (as measured by reading proficiency scores and complexity of computer use on the job) and earnings across all of the eight countries together.[24] We estimate a country-level fixed-effects model (allowing for differences in average relationships between skills and earnings across countries) with robust standard errors.[25] Our results are presented in Table 9. Column 1 of the table presents results for reading proficiency scores with the usual controls; in column 2 we add schooling to the model with reading proficiency scores; and in columns 3 and 4 we estimate the relationship between the computer complexity dummy variables and earnings before and after controlling for completed years of education. Finally, in column 5 we include all cognitive skills in the model with schooling. As reported above, we find that the estimated effect of cognitive skills is lower in magnitude but continues to be positive and significant after controlling for education. In the full model, the returns to education are 4 percentage points, and hourly earnings increase by a similar magnitude for every standard deviation increase in reading proficiency scores. For computer skills, we find that as complexity of computer use on the job increases, and after controlling for schooling and reading proficiency, hourly earnings increase by 28 to 51 percentage points.

Table 9. Pooled regression estimates for cognitive skills with country fixed effects, workers age 25 to 64

	(1)	(2)	(3)	(4)	(5)
Gender	-0.302***	-0.268***	-0.294***	-0.262***	-0.260***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Potential experience	-0.000	0.007	0.008	0.013**	0.013***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Experience squared	-0.000	-0.000	-0.000**	-0.000**	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Self-employed	-0.209***	-0.157**	-0.140*	-0.103	-0.100
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
High-skilled white collar	0.461***	0.283***	0.234***	0.103	0.096
	(0.09)	(0.08)	(0.06)	(0.06)	(0.06)
Low-skilled white collar	-0.034	-0.087	-0.115*	-0.152**	-0.155**
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Schooling		0.054***		0.047***	0.043***

[24] Noncognitive skills measures were not included in the pooled regression.
[25] An additional advantage of fixed effects models is that they can provide some control against bias due to omitted variables, provided that these variables and their effects are time-invariant. Our models do not include relevant labor market indicators that could potentially influence hourly earnings, and the fixed effects framework could serve as a potential safeguard from bias due to this omission.

		(0.00)		(0.00)	(0.00)
Standardized literacy	0.126***	0.056***			0.044***
	(0.02)	(0.02)			(0.02)
Browser-based tasks			0.357***	0.282**	0.275***
			(0.10)	(0.10)	(0.09)
MS Office-based tasks			0.443***	0.340***	0.332***
			(0.08)	(0.08)	(0.08)
Basic program tasks			0.566***	0.463***	0.456***
			(0.11)	(0.11)	(0.11)
Advanced program tasks			0.650***	0.521***	0.512***
			(0.11)	(0.11)	(0.11)
Constant	0.887***	0.169**	0.684***	0.085	0.131
	(0.06)	(0.07)	(0.06)	(0.10)	(0.09)
Observations	6,699	6,699	6,699	6,699	6,699
R-squared	0.19	0.23	0.23	0.25	0.25

Note: Robust standard errors in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The sample includes wage and self-employed workers. *Schooling* is measured as completed years of education. Reference categories for *Self-employed* and *Gender* variables and for computer complexity dummies are those not self-employed, males, and no computer use, respectively. Scores on the reading proficiency assessment and personality and behavior traits have been standardized to a mean of 0 and standard deviation of 1. The model includes country fixed-effects.

VI. Conclusions

Worldwide, low- and middle-income countries are investing in strategies to expand workforce skills. In the past, much of the research on skills payoffs focused high-income countries, and using years of schooling as a proxy for individual skills. The STEP Skills Measurement program provides a unique opportunity to explore the relationships between education, skills, and labor market outcomes in adult populations in low- and middle-income countries—and via measures that go beyond schooling. Our findings contribute to the growing literature on measuring cognitive and noncognitive skills and estimating the relationship between skills and key labor market outcomes in low- and middle-income countries. Key findings from our analysis include the following.

Reading proficiency—one of our proxies for cognitive skills—is associated with higher earnings, even when controlling for schooling. This association is large, positive, and significant in seven of the eight participating countries. In fact, a one-standard deviation increase in reading proficiency scores (equivalent to 50 points) is associated with an hourly earnings increase ranging from 9 percentage points in Colombia, Georgia, and Ukraine to 19 percentage points in Ghana. Reading proficiency predicts earnings beyond educational attainment in several countries. Interestingly, we find that returns to years of education remain similar in magnitude and significance even after adding reading proficiency to the traditional schooling model—which suggests that using reading proficiency as a proxy for cognitive skills does indeed capture additional dimensions of human capital not explained by schooling alone.

Similarly, *complexity of computer use at work*—the other element of cognitive skills in this study—is associated with substantial earnings premiums in all countries. This relationship exists even after controlling for type of employment and occupation and after controlling for years of schooling. The association increases with the complexity of computer use. That is, advanced programming skills show a larger magnitude of association with hourly earnings than tasks like world processing, using spreadsheets, and data entry—which is what we would expect. These findings suggest two potential explanations. First, only a relatively small share of jobs in the sample countries required advanced computer skills, which could explain the higher earnings associated with those skills. In addition, the results suggest education and computer use may be highly complementary—future research could explore interaction terms between schooling and computer use.

Findings on *noncognitive skills*, in contrast, are more mixed. Our study shows some statistical support for the value of openness and agreeableness, although not across all eight countries. The results show significant relationships between hourly earnings and openness, agreeableness, and grit in three countries and decision-making in one country. However, when we add controls for years of schooling, associations between earnings and grit and decision-marking are no longer significant. Of course, the small number of noncognitive skills items in our survey might not be sufficient to reliably measure personality or behavioral traits thus obscuring the true relationship between noncognitive skills and earnings.

Overall, our findings show that the returns to schooling remain a strong predictor of hourly earnings in most countries. We also find that cognitive skills matter above and beyond education and that they capture additional dimensions of human capital not usually captured by traditional measures of schooling. In particular, reading proficiency and the complexity of computer skills at work are both associated with higher hourly earnings, even after controlling for schooling, experience, and occupation variables.

Two broad policy implications emerge from these findings. First, it is important for educational systems to generate graduates who are proficient in comprehending, interpreting, analyzing, and using written texts, as such skills are valued in the labor market and are a key foundation for further lifelong learning. Second, the wide spread of digital technologies requires that workers develop digital skills to thrive in the workplace.

Finally, future country-specific research should account for labor market characteristics and institutional factors that could significantly affect the skills-earnings relationship and provide insight into some of the heterogeneity in the payoffs to skills observed across the countries in our sample.

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Appendix: Additional Information

Table A.1. Means and SD for key variables in empirical models, by country, ages 25 to 64

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Age	42.94	11.50	41.31	10.74	38.00	10.78	35.89	9.49	41.27	10.65	41.09	10.15	39.94	10.46	39.16	10.31
Experience	23.24	12.27	20.08	11.00	20.05	11.67	20.50	11.94	21.87	11.07	24.07	11.59	22.80	12.59	23.15	12.08
Schooling	13.69	3.12	15.23	2.77	11.95	3.60	9.39	4.99	13.40	2.21	11.02	4.33	11.14	4.80	10.01	3.96
Openness	0.11	1.02	0.04	0.97	0.01	0.99	0.04	1.00	0.09	1.01	-0.01	1.01	0.06	1.01	0.01	0.95
Conscientiousness	0.17	0.95	0.23	0.88	0.12	0.94	-0.09	0.95	0.05	1.03	0.14	0.98	0.15	0.94	0.10	0.99
Extraversion	0.01	1.02	0.01	0.97	0.07	0.99	0.01	0.98	-0.06	1.02	-0.05	0.99	0.00	0.98	0.05	0.96
Agreeableness	0.04	0.98	-0.01	0.96	0.07	0.98	-0.04	0.96	-0.02	1.07	-0.01	1.00	0.13	0.99	0.06	0.97
Emotional Stability	0.07	0.95	0.14	0.99	0.10	1.05	-0.05	0.97	0.10	1.02	0.08	0.98	0.07	0.96	0.06	0.98
Grit	0.09	0.97	0.27	0.92	0.13	1.01	-0.04	0.99	0.08	1.01	0.14	0.96	0.18	0.97	0.16	0.91
Decision-making	0.06	1.02	0.05	0.96	0.03	1.00	-0.11	0.94	0.05	0.97	0.00	1.01	0.02	1.01	-0.07	1.02
Browser-based tasks	0.03	0.18	0.04	0.20	0.00	0.06	0.01	0.09	0.03	0.16	0.02	0.15	0.02	0.12	0.00	0.07
Basic MS Office Tasks	0.22	0.42	0.18	0.39	0.04	0.21	0.05	0.22	0.17	0.38	0.17	0.37	0.12	0.33	0.16	0.36
Basic programming tasks	0.09	0.29	0.11	0.32	0.02	0.15	0.07	0.25	0.16	0.37	0.05	0.22	0.06	0.23	0.09	0.29
Advanced programming tasks	0.08	0.27	0.11	0.31	0.05	0.22	0.11	0.31	0.06	0.24	0.11	0.31	0.18	0.38	0.10	0.30
Active (Dummy)	0.96	0.19	0.93	0.26	0.96	0.18	0.97	0.18	0.96	0.20	0.96	0.19	0.95	0.22	0.94	0.23
Asset Index	0.05	0.98	0.07	0.97	0.39	0.85	0.02	1.02	0.05	0.97	-0.05	1.00	-0.06	0.98	0.00	0.92
Shocks	0.27	0.62	0.26	0.61	0.73	1.03	1.08	1.41	0.29	0.66	0.52	0.95	1.50	1.75	0.89	1.19
SES Status	6.07	2.07	5.95	1.83	5.15	1.93	4.62	1.72	4.98	1.61	4.09	1.58	3.94	1.68	4.23	1.80

Table A.2. Means and SD for key variables in empirical models, by country – Wage workers, ages 25 to 64

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Age	42.95	11.46	40.98	10.91	38.24	11.29	35.05	9.06	41.15	10.70	39.13	9.82	38.11	10.12	37.51	9.61
Experience	23.06	12.31	19.42	11.17	19.04	12.21	18.39	11.12	21.71	11.18	20.97	11.05	19.77	11.73	20.96	11.06
Schooling	13.89	3.08	15.56	2.67	13.21	3.57	10.66	4.71	13.44	2.21	12.16	4.28	12.34	4.44	10.55	3.79
Openness	0.16	1.00	0.08	0.94	0.10	0.97	0.02	0.97	0.10	0.99	0.10	0.96	0.07	0.98	0.01	0.95
Conscientiousness	0.18	0.94	0.20	0.89	0.25	0.92	-0.09	0.93	0.07	1.03	0.24	0.99	0.16	0.96	0.09	1.02
Extraversion	-0.01	1.02	0.04	0.91	0.11	0.96	0.00	0.99	-0.06	0.99	-0.04	0.99	0.08	0.97	0.02	0.94
Agreeableness	0.05	0.99	0.02	0.94	0.10	0.95	-0.05	0.97	0.00	1.06	0.03	1.03	0.09	0.99	-0.05	0.93
Emotional Stability	0.08	0.94	0.14	0.96	0.23	0.94	-0.10	0.98	0.12	0.99	0.19	0.94	0.15	0.97	0.13	0.97
Grit	0.10	0.96	0.26	0.90	0.14	1.00	0.00	0.97	0.07	1.01	0.16	0.96	0.15	0.93	0.11	0.92
Decision-making	0.05	1.03	0.08	0.93	0.15	0.99	-0.10	0.98	0.08	0.97	0.08	0.97	0.13	0.99	-0.05	1.01
Browser-based tasks	0.03	0.18	0.04	0.19	0.01	0.10	0.01	0.09	0.03	0.16	0.02	0.15	0.02	0.13	0.00	0.07
Basic MS Office Tasks	0.23	0.42	0.20	0.40	0.10	0.31	0.08	0.27	0.17	0.38	0.23	0.42	0.16	0.37	0.16	0.37
Basic programming tasks	0.10	0.29	0.13	0.33	0.05	0.23	0.10	0.30	0.16	0.37	0.08	0.27	0.09	0.29	0.11	0.31
Advanced programming tasks	0.08	0.27	0.12	0.33	0.11	0.32	0.16	0.37	0.06	0.25	0.16	0.37	0.26	0.44	0.11	0.32
Active (Dummy)	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.07	1.00	0.00	1.00	0.00	1.00	0.00
Asset Index	0.06	0.98	0.14	0.95	0.51	0.91	0.19	1.08	0.06	0.97	0.03	1.04	0.11	1.00	0.04	0.90
Shocks	0.27	0.63	0.25	0.59	0.74	0.99	0.90	1.25	0.29	0.67	0.46	0.97	1.40	1.64	0.82	1.16
SES Status	6.00	2.07	5.95	1.88	5.06	1.92	4.73	1.65	5.01	1.63	4.20	1.57	4.07	1.55	4.40	1.69

Table A.3. Means and SD for key variables in empirical models, by country – Self-employed workers, ages 25 to 64

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Age	46.29	10.36	46.30	8.49	38.88	9.91	37.02	9.35	41.47	9.44	44.14	9.30	43.23	10.16	42.84	10.66
Experience	28.15	10.11	25.42	9.03	22.68	10.41	23.36	11.22	22.51	9.31	29.21	10.22	28.28	12.41	27.60	12.38
Schooling	12.15	3.20	14.88	3.08	10.20	2.88	7.66	4.60	12.96	2.28	8.93	3.61	8.95	4.80	9.24	4.10
Openness	-0.36	0.97	-0.11	1.00	-0.10	1.02	0.12	1.02	0.08	1.07	-0.21	1.03	-0.05	1.08	0.01	0.97
Conscientious-ness	0.32	0.93	0.13	1.00	-0.05	0.94	-0.05	0.98	-0.25	1.06	-0.06	0.94	0.08	0.91	0.18	0.93
Extraversion	-0.20	0.88	-0.08	1.09	0.04	1.03	0.05	0.97	-0.05	1.33	-0.05	0.99	-0.16	1.01	0.12	0.94
Agreeableness	-0.26	1.05	-0.11	1.05	0.06	0.99	-0.02	0.94	-0.36	1.10	-0.07	0.93	0.14	1.02	0.21	0.97
Emotional stability	0.26	0.97	0.25	1.00	-0.01	1.16	0.02	0.93	0.37	0.96	-0.10	0.97	0.01	0.95	0.03	0.93
Grit	0.03	1.04	0.29	0.93	0.15	1.02	-0.05	1.03	0.18	1.06	0.07	0.95	0.16	1.06	0.28	0.87
Decision-making	0.11	0.89	-0.15	1.19	-0.15	0.98	-0.07	0.88	-0.42	0.93	-0.15	1.07	-0.17	1.04	-0.09	1.01
Browser-based tasks	0.04	0.20	0.04	0.20	0.00	0.00	0.01	0.08	0.02	0.13	0.02	0.14	0.01	0.11	0.00	0.06
Basic MS Office tasks	0.10	0.30	0.02	0.14	0.00	0.03	0.01	0.11	0.23	0.43	0.05	0.22	0.05	0.22	0.14	0.35
Basic programming tasks	0.05	0.23	0.02	0.14	0.00	0.04	0.02	0.13	0.17	0.38	0.00	0.04	0.01	0.08	0.05	0.22
Advanced programming tasks	0.04	0.20	0.03	0.17	0.01	0.10	0.02	0.13	0.01	0.07	0.01	0.12	0.05	0.21	0.07	0.26
Active (Dummy)	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Asset Index	-0.04	0.95	-0.03	0.80	0.29	0.74	-0.25	0.83	-0.04	0.94	-0.18	0.92	-0.34	0.83	-0.06	0.99
Shocks	0.26	0.61	0.24	0.62	0.71	1.10	1.28	1.45	0.36	0.53	0.58	0.88	1.73	1.84	1.05	1.22
SES Status	6.59	2.02	5.93	1.46	5.22	2.02	4.41	1.79	4.73	1.55	3.92	1.55	3.42	1.72	3.72	1.78

Table A.4. Weighted OLS estimates, urban adults 25 to 64 years

	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Ukraine	Vietnam
Schooling	0.039***	0.053***	0.060***	0.070***	0.047***	0.068***	0.047***	0.060***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Reading	0.020	0.122**	0.088*	0.124***	0.200***	0.163***	0.075**	0.149***
	(0.03)	(0.05)	(0.05)	(0.04)	(0.06)	(0.05)	(0.03)	(0.03)
Browser-based	0.115	0.023	0.054	0.3911**	0.880**	0.878***	0.124	0.453***
	(0.12)	(0.14)	(0.07)	(0.16)	(0.37)	(0.14)	(0.10)	(0.16)
MS Office	0.238***	0.241	0.370***	0.576***	0.363	0.904***	0.238***	0.406***
	(0.07)	(0.15)	(0.10)	(0.10)	(0.27)	(0.12)	(0.09)	(0.09)
Basic Prog.	0.393***	0.124	0.583***	0.596***	1.010***	0.962***	0.300***	0.557***
	(0.10)	(0.14)	(0.10)	(0.12)	(0.22)	(0.1175)	(0.0812)	(0.09)
Adv Prog.	0.383***	0.408***	0.609***	0.679***	0.857***	1.087***	0.182	0.475***
	(0.10)	(0.15)	(0.11)	(0.13)	(0.26)	(0.1296)	(0.1467)	(0.09)
Openness	0.040	0.056	-0.014	0.055	0.106	0.079**	0.097**	0.111***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.07)	(0.0380)	(0.0383)	(0.03)
Conscientiousness	-0.010	0.041	-0.005	0.024	0.090	0.063	-0.001	0.022
	(0.03)	(0.05)	(0.03)	(0.04)	(0.09)	(0.0426)	(0.0271)	(0.02)
Extraversion	0.028	0.002	-0.024	-0.011	0.037	0.037	-0.028	0.013
	(0.02)	(0.04)	(0.03)	(0.04)	(0.07)	(0.0307)	(0.0274)	(0.03)
Agreeableness	-0.065**	0.023	0.062	-0.012	0.100	-0.063*	-0.005	-0.011
	(0.03)	(0.04)	(0.04)	(0.04)	(0.07)	(0.0355)	(0.0303)	(0.03)
Emotional Stability	0.026	0.060	0.035	0.041	-0.027	0.031	-0.013	0.070**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.07)	(0.03)	(0.03)	(0.03)
Grit	0.048*	-0.013	-0.030	0.031	-0.028	0.017	0.039	-0.031
	(0.03)	(0.05)	(0.04)	(0.04)	(0.06)	(0.03)	(0.03)	(0.03)
Decision-making	-0.026	-0.032	0.070*	0.016	0.052	0.074**	-0.039	0.039
	(0.03)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)	(0.03)

Observations	530	653	830	481	560	1159	731	1384
R-squared	0.24-0.32	0.24-0.29	0.20-0.31	0.30-0.42	0.16-0.19	0.24-0.39	0.15-0.22	0.16-0.23

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The sample includes wage and self-employed workers. Schooling is measured as completed years of education. Reference category for self-employed, gender variables and computer complexity is those not self-employed, males and no computer use, respectively. Scores on the reading proficiency assessment and personality and behavior traits have been standardized to a mean of 0 and standard deviation of 1. The wage model controls for gender, self-employed workers, experience and occupation