Are There Skills Payoffs in Low and Middle Income Countries? Empirical Evidence Using STEP Data

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I. Introduction

Most of the empirical work in labor economics has been motivated by human capital theory, which posits that human capital – or an individual's stock of skills – is a key determinant of individual and aggregate economic success (Becker, 1964; Schultz, 1996). Much attention has been paid to measuring human capital and how it is rewarded in the labor market. Human capital has traditionally been measured using data on education levels (or years of education) and the amount of training received by an individual (Card, 1999; Psacharopoulos, 1985). Recent evidence on the returns to schooling show a convex pattern indicating that the returns to primary levels of education are lower than those at the secondary and tertiary levels (Colclough, Kingdon, and Patrinos, 2010). It has also been noted that as educational attainment has increased, there has been an increase in wage inequality across both developed and developing countries (Berman, Bound & Machin, 1998; Katz & Autor, 1999; Murphy & Welch, 1992). Colclough, Kingdon, and Patrinos (2010) have suggested that the relationship between schooling, wages and inequality is more likely to be driven by supply-side pressures (rather than those on the demand side) i.e. changes in the relative supply of skilled labor. As a result, there has been a shift from using a general measure of human capital (e.g., schooling) to using a broader measure that goes beyond schooling by incorporating skill proficiency. Measures of cognitive and non-cognitive skills and skills that are relevant in today's technology-driven environment provide information on what individuals can do and their level of performance beyond educational attainment.

A notable body of research has examined the role of cognitive and non-cognitive skills[5] on various labor market outcomes. While most studies have focused on the effects of either cognitive skills or non-cognitive skills on wages, 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 & Anger, 2010; Ramos et al., 2013; Nikoloski & Ajwad, 2014). Researchers have also investigated the role of cognitive skills such as computer use in predicting wages, though never in conjunction with other skills

[5] According to the United States Department of Labor Secretary's Commission on Achieving Necessary Skills (1991), cognitive skills include reading, writing, numeracy, problem solving and critical thinking abilities. Non-cognitive skills (also called soft skills or socio-emotional skills) relate to traits covering multiple domains such as social, emotional, personality, behavioral, and attitudinal (Pierre et al., 2014).

measures (Handel, 2007; Sakellariou & Patrinos, 2003). Most of this 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 & Ajwad, 2014) This emphasis has been largely driven by the specific requirements for and availability of data needed to conduct such studies. There remains an unmet need for research to examine these issues in the context of developing countries.

In this paper, the role of various dimensions of human capital on labor market productivity is examined for the first time in the context of low- and middle-income countries, using comparable data sets. Specifically, the paper estimates the independent effect of cognitive skills (proxied by reading proficiency and use of computers on the job), and non-cognitive skills (specifically, personality traits and behaviors) on earnings, controlling for education and other relevant economic and demographic factors. The analysis also examines the net effect of various skills in the labor market; this is done by estimating the effect of each type of skill, controlling for other skills and education. Using novel data for Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam, we are able to provide, for the first time, comparative estimates of the payoffs of cognitive, non-cognitive, and computer skills in each of these countries.

The results of this study have important implications for policy and programs focused on improving the skills profile of workers to better suit the needs of the labor market. Our results show significant payoffs of skills in the labor market even after controlling for education, particularly cognitive skills and computer use. While non-cognitive skills show small but significant effects on earnings, the association between earnings and reading proficiency (our first measure of cognitive skills) is larger and more stable. Further, we find that computer use, our second measure of cognitive skills, has the largest association with earnings across the countries in our sample.

In addition to these overall findings, results suggest that there is significant heterogeneity across countries in how skills are valued. There is also some indication of possible subgroup differences by gender, employment status and occupational group.

This highlights the need for context-specific programming that takes into account the characteristics of the education system and labor market needs of each country.

The rest of the paper is structured as follows. The next section provides a brief description of 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 discusses the findings.

II. Literature Review

There is a vast econometric literature examining returns to schooling across developed and developing economies (Card, 2001; Psacharopoulos & Patrinos, 2004). The purposes of this strand of research are manifold; it can inform individual choices about education and occupations, it can help one assess the extent to which the labor market is meritocratic, it can inform the design of programs and policies through better knowledge of education-wage differentials, and so on. Most of the studies examining the returns to schooling are based on the standard Mincerian framework and estimate that each additional year of schooling is associated with an earnings increase of about 7 to 10 percentage points (Psacharopoulos, 1994; Psacharopoulos & Patrinos, 2004; Montenegro & Patrinos, 2014). Recent evidence from a study comparing 139 economies (Montenegro & Patrinos, 2014) finds 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 or because of the so-called skill biased technological change.

While findings on the returns to education have proven to be robust and for the reasons noted above useful (Heckman, Lochner & Todd, 2001), there are serious methodological challenges associated with estimating returns (Card, 1999). That schooling develops general skills and therefore is a good measure of human capital is a basis of Mincer's framework. However, Hanushek, et al. (2013) note that Mincer's formulation assumes that schooling is the only systematic source of skill differences[6]. But research shows that other factors (an individual's ability, family inputs, school and labor market characteristics, and so on) also determine skill acquisition (Card, 2001). Excluding them from the wage equation thus leads to endogeneity bias (due to omitted variables) (Heckman & Vyatcil, 2001).[7]

Further, it is widely accepted that regardless of how skills are acquired, different dimensions of human capital – cognitive and non-cognitive skills and job-related skills – are important determinants of labor market success (Bowles, Gintis, and Osborne, 2001; Borghans, Duckworth, Heckman, and ter Weel, 2008; Cawley, Heckman, and Vytlacil, 2001; Heckman, Stixrud, and Uruza, 2006). Thus, using only education (as a proxy for general skills) in the earnings function 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-education studies noted above, a substantial literature has examined how cognitive skills, and to a lesser extent how non-cognitive skills, are rewarded in the labor market (Cawley, et al., 1996; Hanushek & Zhang, 2006; Hanushek et al., 2013). This literature has used a variety of measures, from student achievement tests to international literacy surveys, to proxy cognitive skills. Studies examining the effect of non-cognitive skills have mostly used self-reported measures of behaviors, and personality. Findings from these studies indicate cognitive skills have a statistically significant effect on wages although the magnitude of the association varies by type of measure and specification used. The effect of non-cognitive skills is ambiguous, largely due to the multiplicity of measures used to proxy for these skills, and the inherent difficulty in measuring non-cognitive skills reliably, using large scale surveys. Depending upon the type of measure used, some studies claim effects comparable to those observed for cognitive skills, while others find small or no effects for measured non-cognitive skills (Bowles, Gintis, and Osborne, 2001; Heckman Stixrud, and Uruza, 2006; Mueller & Plug, 2006).

[6] "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).
[7] Besides endogeneity bias, the Mincerian earnings function can also suffer from sample selectivity bias. See Section IV for a brief discussion.

Early research examining cognitive skills in the context of labor market outcomes was based mostly in the United States and used 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, 2001). Findings from these studies showed modest effects of cognitive ability on wages. Findings also showed large residuals in the wage regression not explained by cognitive skills. The authors concluded that the residualized variation could be explained by non-cognitive abilities.

Subsequent research on the role of cognitive skills moved towards using literacy tests such as the International Adult Literacy Survey (IALS) and the Adult Literacy and Life Skills Survey (ALLS), which, it was argued, were better measures of demonstrated capacity and functional literacy than were tests of underlying ability, such as the ASVAB and the Armed Forces Qualification Test (Barrett, 2012; Barone & van de Werfhorst, 2011; Fasih, Patrinos, & Sakellariou, 2013; Green & Riddell, 2003; Hanushek & Zhang,). Using the Canadian IALS, Green & Riddell (2003) examined the effect of cognitive skills on average earnings and the stability of effects across the earnings distribution. They found statistically significant effects for cognitive skills, controlling for education. These results are supported by the literature review prepared by the Canadian Literacy and Learning Network (2012). They also found that these effects did not vary across the earnings quantiles. Barrett (2012) used the Australian ALLS and found similar results – cognitive skills significantly predicted earnings and this association was consistent across earnings quantiles.

The IALS data has also been used for cross-country comparisons (Barone & van de Werfhorst, 2011; Blau & Kahn, 2001; Fasih, Patrinos, & Sakellariou, 2013; Leuven Oosterbeek, and Ophem, 2004; Hanushek & Zhang, 2006). A couple of these studies used IALS data to better estimate the education-earnings relationship (Fasih, Patrinos, & Sakellariou, 2013; Hanushek & Zhang, 2006)[8], the study by Leuven, Oosterbeek, and Ophem (2004) examined the demand and supply of skills, and the rest examined the

[8] Hanushek & Zhang (2006) use IALS data to adjust for quality of schooling across countries in their dataset while Fasih, Patrinos, & Sakellariou (2013) decompose the effect of cognitive skills into those acquired at school and outside of school.

effect of cognitive skills on wages (Barone & van de Werfhorst; 2011; Blau & Kahn, 2001).

Barone & van de Werfhorst (2011) used IALS data for four countries – the United States, Britain, Germany and the Netherlands. Their research study used two measures of cognitive skills (general cognitive skills and work-specific cognitive skills). Controlling for a variety of factors, they found that the association between cognitive skills and earnings was as high as 62 percent across the countries in their sample. Their study also showed that the effect varied systematically by country. Blau & Kahn (2001) examined IALS data for the Netherlands, Sweden, Switzerland, Canada and the United States. They too controlled for a variety of factors including education and reported significant effects for cognitive ability on wages – in the 10 to 24 percent range for men and between 7 to 25 percent for women.

More recent research examining the effect of cognitive skills on earnings has used literacy data from the Program for the International Assessment of Adult Competencies (PIAAC) survey sponsored by the OECD. This survey is designed to measure key cognitive and workplace skills. It 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.[9] Hanushek et al. (2013) used the PIAAC data to estimate the returns to skills in 22 countries. Their findings indicate that higher cognitive skills lead to higher wages across all countries, with prime-age workers showing higher returns than recent entrants to the labor market. Their study finds significant variation in estimated returns across countries and systematically lower returns to skills in countries with higher union density, larger public sectors and strict employment protection legislation.

While there is a large and relatively established body of research establishing strong links between cognitive skills and labor market outcomes, the research examining the effect of non-cognitive skills is still relatively sparse. As a result available findings are not as easily consolidated. One reason for this is that non-cognitive skills have been defined, measured and interpreted in a variety of ways to reflect individuals' multi-faceted personalities and behaviors. Not surprisingly studies have relied on a wide range

[9] See Hanushek et al. (2013) for a brief discussion.

of different measures to proxy for non-cognitive skills (Borghans et al., 2008; Duckworth & Yaeger, 2015). In general, available evidence shows that non-cognitive skills have small positive effects on earnings. The magnitude of these effects varies by the type and number of measures used. In some cases studies show effects that are comparable with estimates found for cognitive skills (Bowles, Gintis, and Osborne, 2001; Heckman Stixrud, and Uruza, 2006; Heineck & Anger, 2010; Mueller & Plug, 2006; Nyhus & Pons, 2005).

Bowles, Gintis, and Osborne (2001) were among the first to articulate that the unexplained variance in the earnings function could be attributed to non-cognitive traits, controlling for education, experience, and cognitive skills. They argued that these non-cognitive traits - an inclination to truth telling, identifying with the organization's goals and thinking about the future - meet the preferences of employers and are thus rewarded in the labor market. Their research suggested that less than 20 percent of the returns to education could be attributed to cognitive skills and that the remainder might be explained by these non-cognitive traits.

Heckman, Stixrud, and Uruza (2006) used the NLSY79 data, which includes measures of individual's self-worth and individual's perceived degree of control over their lives, to determine the effect of these measures (used as proxies for non-cognitive skills) on labor market outcomes. In their paper non-cognitive skills were specified as a latent construct predicting wages through their effect on education and occupational choice. They found small but significant effects for these measures of non-cognitive skills in predicting wages (less than one percent). Their findings suggest that the estimated effects of non-cognitive skills on wages are as strong as those estimated for cognitive skills when controlling for schooling and family characteristics.

Other studies have used the Big Five personality scale as a measure of non-cognitive skills (Heineck and Anger, 2010; Mueller and Plug, 2006). The Big Five – formally known as the Five Factor Model of Personality – describes individual differences using five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Goldberg, 1990). These five dimensions have been used in the literature as proxies for non-cognitive skills and as measures to estimate their individual and collective impact on labor market outcomes. Mueller and Plug (2006) used data from the Wisconsin Longitudinal Study and examined the effect of these personality traits on earnings separately for men and women. They find that controlling for IQ, occupation, and a range of covariates, openness, agreeableness and neuroticism have small albeit significant effects on earnings amongst men. In contrast, openness and conscientiousness significantly predict earnings among women. In a similar study using data from the Netherlands, Nyhus and Pons (2005) report significant effects for neuroticism (they use the inverse, emotional stability) among both men and women and find that agreeableness has a significant *negative* effect (about -0.04) on men's earnings.

Heineck and Anger (2010) used the Big Five personality measures to estimate the impact of non-cognitive skills on labor market outcomes in Germany. In addition to the Big Five, they added measures of locus of control and reciprocity to their analytical model. Their results indicate that controlling for cognitive abilities and several socio-demographic and job-related characteristics, personality is a significant predictor of earnings. In particular, they note that individuals with an external locus of control have substantially lower average earnings than reporting an internal locus of control.

Beyond adding measures of cognitive and non-cognitive skills in the earnings equation, there is a related research strand exploring the extent to which different types of job-relevant skills are rewarded in the labor market. For this paper we focus on the literature related to the payoff of computer use under the assumption that greater reliance on computers is partly responsible for the changes in the nature of work. The use of computers at work has received considerable attention over the past two decades (Handel, 2007), complementing the literature on labor market implications of technological change (Acemoglu & Autor, 2011) which has also received extensive attention. According to Handel (2007), the research related to computer use at work, and technological change more broadly, have changed the nature of work and such changes can be divided into four categories:

(i) *Computer use has increased the demand of computer-specific human capital*. The use of computers require an acquisition of certain type of skills that may be costly and scarce at the beginning. Thus, the introduction of more computers at work should be accompanied of a premium of the required skills.

(ii) *Computers require higher human capital levels among its users.* The use of computers has transformed jobs by requiring workers to perform tasks that require the use of non-routine skills, including problem solving, abstract reasoning all of which are associated with higher human capital (Autor, Levy and Murnane, 2013).

(iii) *The introduction of computers in the workplace has transformed the workplace and increased overall human capital demands from both computer users and non-users.* The organizational change of the workplace is the main driver of the effect of computer skills requirements across the board, even beyond the individual effect of actual computer use. This is because there is an increased skill requirement to the workers that will impact their human capital, regardless of whether they use or not computers at work; and

(iv) *Computer use may be behind the polarization of the labor market*. Computer use have increased the demand for "high-skilled" (i.e. statistician, data management) jobs, where they complement the worker and increase its productivity, and the demand for "less-skilled" (i.e. waiters and personal care workers) jobs, where the tasks are yet susceptible to be computerized. They have decrease the demand for the "middle-skilled" (i.e. clerical work, travel agents) jobs where computers can, as of today, substitute the worker (Autor, 2014).

The computer use payoff results across the literature have been heterogeneous. This is largely due to methodological challenges in estimating the relationship between computer skills and wages. For instance, 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. The results were estimated using a sample size of around 13,000 for both periods, and the model included computer use at work, years of education experience and experience squared, and occupations, alongside socio-demographic characteristics. His findings indicated that the computer use payoff over the same time period ranged from 10 to 15 percent, and that about 40 percent of the increase in earnings during the second half of the 1980s was attributed to computer use.

However, as Handel (2007) pointed out, the premium on computer use may have not be reflective of changes in the wage structure by themselves, but rather that reflected some unobserved heterogeneity within a job or occupation. This was evidenced by DiNardo and Pischke (1997) who replicated Krueger's study of computer use in West Germany. They reported similar results (between 11 and 18 percentage points) for computer use but also found high effect sizes for other on-the-job tools.

A third interpretation of the wage premium on computer use is a reflection of the ease in recovering the costs incurred in by high wage workers in gaining these skills. Sakellariou and Patrinos (2003) document this interpretation from a developed world perspective, as well as add the developing world scope by estimating the computer premium for higher education graduates in Vietnam. They use a tracer survey implemented in 1996 with a sample size of around 1,829. The model includes use of computer at work, age, age square, education performance and language proficiency, sector, and occupation. The effects are around 26 percentage points. However, they conclude that evidence of unobserved heterogeneity can be supported because "even workers with computer skills, which are not required at work, enjoy substantial wage premiums compared to those without computer skills" (p.16).

Finally, Borghans and ter Weel (2003) study aimed to disentangle the computer use from the computer skills. Their study used *Skills Survey of the Employed British Workforce* from 1997 to estimate the returns of computer, writing, and math skills on wages. The survey includes a 2,467 workers aged between 18 and 60 years old. The models included dummies for education level, experience, experience squared, and socio-demographic characteristics. Their findings indicate positive and significant returns to the use of writing (25 percentage points), math use (17 percentage points) and computer use (33 percentage points) at work as well as positive and significant effects for writing (short documents 4 percentage points, long documents 3 percentage points) and math skills (advanced math 2.5 percentage points) but no significant to using computer skills at work.

The evidence in computer payoff is limited to the developed world. Sakellariou and Patrinos (2003) documents findings for computer use in the United States, Australia, Canada, France, Germany, Netherlands, and United Kingdom. Also, they could only document the computer use in Vietnam, Mexico, Taiwan, and Colombia for the developing world.

Overall, available research indicates there is consensus on the contribution of cognitive and non-cognitive skills and their role in predicting labor market success, including increasing wages. The size and magnitude of effects varies and are in many ways a function of the range of metrics used to proxy for cognitive and non-cognitive skills. The literature on the effects of computer use shows mixed results and a wide variation in the interpretation of the true role and impacts of computer skills. That is, it is unclear whether the observed changes in computer use and associated earnings premia are a function of an increase in computer-specific human capital or changes in the organization of the workplace organization.

This paper aims to contribute to the skills literature by using internationally comparable metrics to estimate the role and pay-off of cognitive, non-cognitive and the use of computers across several developing countries.

III. Data

This paper uses the STEP Skill Measurement surveys from eight developing countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam. The STEP survey includes three unique modules that cover cognitive, and non-cognitive skills.

A reading proficiency assessment, scored on the same scale as the OECD's Programme for International Assessment of Adult Competencies (PIAAC) provides a measure of cognitive skills. This assessment includes three parts that together provide a measure of functional literacy among adults in each of the countries surveyed. Each part of the assessment spans different levels of difficulty and requires respondents to demonstrate their ability to access and identify information, integrate and interpret information, and evaluate the relevance of information for a particular task (Pierre et al., 2014). The scores on the reading literacy assessment range from 0 to 500 and represent six levels of proficiency. The different levels provide information on the kinds of tasks required to achieve proficiency in that level. (See Pierre et al., 2014, p.83 for a detailed description).

Several items on the STEP survey capture data on computer use at work, which was selected as a second measure of cognitive skills for this study. This variable provides the frequency and complexity of computer use on the job.

The STEP surveys also gather information on non-cognitive skills (referred to as socio-emotional skills in the STEP data), and behaviors. Information on the Big Five personality traits, 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".

In addition to the skills measures described above, the surveys gather extensive information on education and employment outcomes and on individual and household 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 limit the sample to adults between the ages of 25 and 64, excluding those currently attending an educational program. Further, the sample is restricted to wage and salaried workers and the self-employed. Among the self-employed, employers are excluded from the analytic sample to avoid biased estimates due to measurement error in earnings. Part-time workers (those working less than 40 hours a week) and unpaid workers are also excluded from the analytic sample. The proportion of salaried and wage workers and the self-employed group in each of the country samples are presented in Table 1.[10] As shown, the self-employed in Armenia, Georgia, and Ukraine constitute a much smaller group compared to the other countries in the sample.

In keeping with standard practice, the top 1 percent hourly earners are removed from the analytic sample to avoid potential outliers, and extremely low wages are imputed to those reporting zero hourly earnings.[11] Finally, cases missing information on education, gender, age, or any of the skills measures are dropped from the sample. The

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[10] Also, see Tables A.2 and A.3 in Appendix A for differences between the two workers types included in the analytic sample. These tables show that the groups are similar across measured characteristics.
[11] A value of 0.00001 was imputed to workers who reported no hourly earnings.

proportion missing constitutes less than 0.1 percent of the sample.[12] This is a small proportion of observations, and dropping them would not bias the estimates due to non-random loss of sample. The effective sample size for the empirical analysis ranges from 951 to 2,076 observations across the countries in our sample.

Description of the sample

The general panorama 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 rest of the countries.[13] The low employment rate observed in Armenia and Georgia impacts the effective sample size used to estimate the returns to education and the net effect of various skills on hourly earnings.

The average hourly earnings in 2011 International dollars[14] for all workers range from $2.62 in Armenia to $3.85 in Ukraine. There are also differences in the average hourly earnings of wage workers compared to the self-employed; the latter group earn between $0.68 and $1.90 dollars less in six of the eight countries. The relationship is different for Armenia and Ukraine, where the self-employed earn about $0.24 more than wage workers. This may be due to the different nature of self-employment in these countries [subsistence versus other type of entrepreneurs], or it may be due to small sample measurement error (since the proportion of self-employed in these countries is very small, less than one percent of the sample).

There are large differences in educational attainment across the countries (see Figure 1). 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

[12] In the case of Ghana, about 800 cases were missing data on the non-cognitive skills measures. These items were administered in English and respondents were found to have inadequate skills in English to respond to these items. As a result, data from Ghana is not included in estimating effects of non-cognitive skills.
[13] 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 for 2012 are 56 percent and 75 percent, respectively (http://unstats.un.org/).
[14] The International dollar (also known as the Geary-Khamis dollar) is a hypothetical unit of currency based on the twin concepts of purchasing power parity of currencies and international average prices of commodities. It has the same purchasing power parity as that of the United States Dollar.

pronounced when comparing the proportion of the sample completing various levels of education. More than half the workers in Georgia, Armenia and Ukraine have a tertiary education degree, while in Ghana and Kenya about 14 percent of the sample is at the tertiary level.

As mentioned before, the STEP surveys contain measures for different types of skills, which are the focus of this study. A description of how the countries in the sample compare on cognitive, and non-cognitive skills is provided in Tables A1-A3. Any within-country differences in these skills between wage workers and self-employed workers are also highlighted.

Cognitive skills, commonly understood to include reading, writing, math, and problem solving, are considered foundational[15] and directly affect various labor market outcomes. To measure cognitive skills among adults in low and middle-income countries (usually considered to be low-literacy settings) the STEP surveys administer a reading literacy assessment designed to mimic the diversity of tasks encountered by adults in daily life and assess the cognitive operations used to navigate these situations.[16] This reading literacy assessment is scored on the same scale as the PIAAC, allowing one to benchmark the reading literacy of the adult population in developing countries with that in OECD countries. The average score on reading literacy 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 a standard deviation of 50), the STEP countries are more than a standard deviation below their PIAAC counterparts.[17] (For a discussion of the implications of these differences see Section VI.)

Scores on the reading literacy assessment can be expressed in terms of five 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.[18] More than half of the workers across the countries in our sample score in the lower levels (0, 1 and 2) of reading literacy. The data also show heterogeneity across countries. For instance, as

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[15] See United States Department of Labor Secretary's Commission on Achieving Necessary Skills (1991).
[16] See Pierre et al. (2014) for a fuller discussion on the rationale for and description of the STEP reading literacy assessment. Also, the STEP surveys include self-reported measures of writing, math and problem solving. The most reliable of cognitive skills measures available in the STEP data i.e. reading literacy scores, have been used to proxy cognitive skills in this paper.
[17] See Educational Testing Service (2014).
[18] See Educational Testing Service (2014).

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 samples, respectively, are at these levels.

We also use computer use at work as a proxy for cognitive skills. This measure is based on the frequency with which computers are used in the workplace. The frequency of computer use ranges from no use and moderate use (less than three times per week) to intensive use (three times or more per week, or every day). In the countries in our sample, around 66 percent of workers reported not using a computer at work, while 29 percent reported using a computer intensively at work (see Figure 4). This suggests low use of computers at work among these countries. However, when a computer is used at work, it is used intensively. 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.

In Figure 5 we present the distribution of average scale scores on the non-cognitive skills across the countries in our sample. Respondents select one of four responses ("Almost never", "Some of the time", "Most of the time" or "Almost always") to a series of items designed to assess personality and behavior traits.[19] Figure 4 shows that the average scores on each of the Big Five personality traits as well as grit and decision-making are similar across the countries in our sample. While scores on emotional stability (which contrasts 'neuroticism') and extraversion seem to show some across-country differences, these differences are not significant.

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

[19] See Pierre et al (2014) for a description of the Non-cognitive skills module in the STEP Surveys.

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 follows. Dummy variables for gender and type of employment have been added to the basic Mincer formulation to capture subgroup differences.

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \delta_1 Self\ Employed + \alpha_4 Schooling_i + \varepsilon_i$$

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

In order to estimate the net effect of skills on earnings, schooling attainment in the wage function above is substituted by measures of cognitive skills, non-cognitive skills, and job-relevant computer skills. Thus, to examine the effect of cognitive skills on earnings, the model is expressed with the reading proficiency measure as shown here:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \delta_1 Self\ Employed + \alpha_4 Schooling_i + \beta_1 Reading_i + \varepsilon_i$$

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

To estimate the net effect of frequency of computer use at work, the model is given by:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \delta_1 Self\ Employed + \alpha_4 Schooling_i + \gamma' Computer + \varepsilon_i$$

where, *Computer* is given by a dummy variable for each level of the frequency of computer use at work.

The model when using non-cognitive skills is expressed this way:

$$w_i = \alpha_0 + \alpha_1 Experience_i + \alpha_2 Experience_i^2 + \alpha_3 Gender_i + \delta_1 Self\ Employed + \alpha_4 Schooling_i + \lambda' Noncognitive + \varepsilon_i$$

Where, *Non-Cognitive* is a vector of skills composed of standardized scores for the Big Five (Extraversion, Conscientiousness, Openness, Agreeableness, and Emotional Stability) as well as 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 produces 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 non-random sample of the population – and this sample selection can lead to bias in OLS estimates (Wooldridge, 2010).

The extant literature provides various techniques to address these inconsistencies in estimating wage equations. Card's (2001) review finds that 80 percent of these studies 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 net effect of skills on earnings. 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 as shown:

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

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 labor dependency (number employed/total household size), number of financial shocks at age 15, current household asset index, and socio-economic status at age 15. The predicted probabilities from the selection equation are used to compute the selectivity term *lambda*, which is added to the wage equation as an additional explanatory variable.

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).[20]

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 countries. Our results show a positive and significant return to education (see Table 4). For instance, an additional completed year of education is associated with a 4-percentage point to 9-percentage point increase in hourly earnings, controlling for experience, gender, and type of employment.[21] These results are just below the 10-percentage point worldwide average return reported by Montenegro and Patrinos (2014).[22] The heterogeneity in country estimates indicates differences in how the labor market rewards educational attainment across the countries in our sample.

[20] The full-information maximum likelihood method relies heavily on normality assumptions and could have difficulties converging in the absence of exclusion restrictions.
[21] 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.
[22] 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, & 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 while this study corrects for selection bias.

Our estimates for the returns to education also show a strong and consistent discrimination against women in terms of their hourly earnings. The evidence suggests that women earn between 20 and 38 percentage points less than men in these countries.[23]

It is also important to note that in five of the eight countries there is a high cost in hourly earnings for the self-employed. The average cost of being self-employed is around 31 percentage points, ranging from 18 percentage points in Colombia to 51 percentage points in Georgia.

To gain a better understanding of the dimensions of human capital potential beyond education, we examined the role of skills in explaining hourly earnings. As such, the results presented here should not be interpreted as the *returns* to skills but rather 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 effect of skills on hourly earnings 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 such skills, even when the model controls for completed years of education. Thus, it is not possible to estimate the time dimension of forgone earnings.

The first skill we examined was reading literacy, which we use as a proxy for cognitive skills. Our empirical results show that the effect of reading literacy is large, positive, and significant for all countries except Armenia.[24] One standard deviation increase in reading literacy scores is associated with an hourly earnings increase ranging from 9 percentage points in Ukraine to 30 percentage points in Ghana and Kenya. These results are comparable to those found in Hanushek et al. (2013) and Acosta, Muller, and Sarzosa (forthcoming). The results are presented in Panel A of Table 5.

We also find evidence that cognitive skills matter beyond education in the countries in our sample. The net effect of reading literacy is significant over and above completed years of education in Georgia, Ghana, Kenya, and Ukraine. The net effect ranges from 7 percentage points in Ukraine to 20 percentage points in Ghana. (See Panel B of Table 5.) It is important to note that the returns to completed years of education remain similar in

[23] Further analysis and discussion of gender differences is presented in Tognatta et al. (forthcoming).
[24] The reading literacy score was standardized to have mean 0 and standard deviation of 1, to ease up the interpretation. This was done on a country-by-country basis.

magnitude and significance to those presented in Table 4. This suggests that reading literacy is capturing other dimensions of human capital not explained by schooling.

The role of computers in the workplace has steadily increased across jobs worldwide. Much of the literature on technological change shows that the changes introduced by the use of technology (mostly through computers) has shifted the premiums on those skilled workers who are able to complement what computers can do (skill-biased) and replaced workers whose skills can be substituted by computers (labor-saving).[25] Thus, there is an interest in examining the role of technology at an individual level in explaining changes in hourly earnings, especially in the developing world.[26] The big advantage of the STEP surveys is that they include a comparable battery of questions related to computer use at work across countries.

The use of computers at work is associated with earnings premium across all eight countries. Furthermore, more frequent use is associated with a larger net effect on hourly earnings when compared to those who do not use computers. Among computer users, those using computers at work most frequently show on average 108-percentage-point increase in earnings compared to those not using computers at work. There is also large heterogeneity across countries, with the net effect ranging from 36 percentage points (Ukraine) to 252 percentage points (in Kenya). These results are presented in column 1 of Table 6.

The large magnitude of these effects could be a function of selection into high-paying occupations that require frequent computer use. They could also be capturing the education effect since education and computer use is significantly correlated. However, we find that even after controlling for occupations and schooling, the magnitude of these effects, although slightly smaller, is still large (see Table 6).

Another explanation for the large magnitude of these effects could be due to the relatively smaller share of jobs requiring frequent use of computers across these countries

[25] For instance Autor, Levy, & Murnane (2003), Acemoglu and Autor (2011), Autor (2014), MacCrory, Westerman, Alhammadi, and Brynjolfsson (2014) to cite a few in developed countries. Monroy, Moreno and Santos (forthcoming) discuss this for a set of developing countries. Also, the World Development Report (2015) analyzes the effect of digital technologies on development.

[26] Most of the evidence on this matter has been documented for the developed world. For instance, Krueger (1993) has documented this in the United States, while DiNardo and Pischke (1997) and Borghans and ter Weel (2003) have done the same for Germany and the United Kingdom respectively.

making these jobs highly remunerated. We do not have sufficient information to test this hypothesis in our analysis.

Models similar to the ones above were estimated using measures of the Big Five, grit, and decision-making. Each of the Big Five personality traits, grit, and decision making were measured using three to five items. We believe the limited number of items for each scale might limit the reliability of our measures and obscure the true relationship between these non-cognitive skills and earnings. Our results show that openness is significantly related to hourly earnings in four countries (Georgia, Kenya, Ukraine, and Vietnam). (See Panel A of Table 7). In these countries, a one-standard-deviation increase in openness increases hourly earnings anywhere from 9 percentage points (Georgia) to 17 percentage points (Vietnam).

The results reported in Table 7 hold for three out of four countries when schooling is added to the model (Panel B). The net effect on hourly earnings remains positive (around 8 to 9 percentage points) and significant, while the returns to completed years of education are fairly consistent with those presented in Table 4. The noticeable difference is in Ghana, where the returns to completed years of education increase from 6 percentage points to 9 percentage points after accounting for non-cognitive skills.

In order to examine the net effect of computer skills, controlling for other types of skills and education, we estimate a model with all skills included on the RHS. The results, presented in Table 8, show that computer skills continue to matter most for labor market success, with significant variation across countries. Further, the magnitude of the effect of cognitive skills is larger than that of schooling, though again, this is not consistent across countries. In Georgia, Kenya, and Ukraine, a one-standard-deviation increase in reading literacy scores is associated with an increase in earnings of between 7 and 10 percentage points, while across all countries the returns to education are in the 3 to 5 percentage-point range. Controlling for schooling, cognitive skills, and job-relevant skills, the effect of non-cognitive skills on earnings is smaller and variable across contexts.

VI. Conclusions

This paper makes use of unique data to examine the payoffs of various dimensions of human capital in the labor market; namely, cognitive skills, and non-cognitive skills. Cognitive skills in this study have been measured using an objective measure of reading proficiency and a self-reported measure of computer use at work. Non-cognitive skills have been measured using scores on personality and behavior scales. This is the first time the association between skills and earnings has been empirically estimated in the context of developing countries, using comparative data. Using rigorous methods and correcting for the selection bias inherent in wage equations, the preliminary results reported here show that there are significant payoffs of skills in the labor market, even after controlling for schooling. While cognitive skills – especially those related to computer use – see large rewards in most countries, reading proficiency scores also have a significant net effect on earnings (after accounting for the schooling effect) in some countries. Further, the results suggest that there is significant heterogeneity across countries in how skills are valued in the labor market. These results have implications for education, training and labor market policies. Specifically, the results can inform the development of programs and policies designed to improve the skills readiness of the working-age population as they relate to the technological changes in the labor market. The results reported here indicate significant differences by gender, type of employment, and across occupational groups. Extensions to this research can focus on examining differences in the association between skills and wages at different levels of the wage distribution, and better understanding differential effects of skills among subgroups to address issues of wage inequality.

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VIII. Tables & Figures

Table 1. Percentage of wage and self-employed workers, by country

	Wage 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 include employers and unpaid workers
Source: STEP Surveys (2014)

Table 2. General Labor Market Indicators, 25 to 64 years.

Country	Labor Force Participation	Employment Rate	Unemployment Rate	Observations
Armenia	49.5%	27.8%	43.7%	2076
Bolivia	79.5%	72.6%	8.6%	951
Colombia	73.7%	61.9%	15.9%	1391
Georgia	51.6%	25.0%	51.6%	2080
Ghana	84.3%	76.3%	9.5%	1346
Kenya	83.2%	66.4%	20.2%	1877
Ukraine	58.4%	50.1%	14.2%	1741
Vietnam	72.6%	71.1%	2.0%	2075

Source: STEP Surveys (2014)

Table 3. Average hourly earnings in 2011 International Dollars, 25 to 64 years.

	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Ukraine	Vietnam
All Workers	2.62	3.73	3.50	3.28	2.78	2.89	3.85	3.49
	(0.10)	(0.21)	(0.18)	(0.16)	(0.26)	(0.18)	(0.14)	(0.13)
	578	687	859	519	1024	1244	871	1475
Wage Workers	2.60	4.16	3.74	3.48	3.37	3.43	3.74	3.73
	(0.10)	(0.29)	(0.24)	(0.17)	(0.50)	(0.24)	(0.12)	(0.14)
	530	427	595	456	432	776	791	947
Self-Employed	2.83	2.95	2.94	1.59	2.34	1.93	3.99	3.05
	(0.48)	(0.27)	(0.24)	(0.18)	(0.27)	(0.16)	(0.76)	(0.23)
	44	253	262	57	571	453	44	455

Note: Standard errors in parentheses
Source: STEP Surveys (2014)

Table 4. Returns to years of education, 25 to 64 years.

	Schooling	Self-employed	Gender	N
Armenia	0.042***	-0.016	-0.436***	1,558
	(-0.01)	(-0.13)	(-0.06)	
Bolivia	0.077***	-0.261***	-0.476***	849
	(-0.01)	(-0.10)	(-0.11)	
Colombia	0.077***	-0.201**	-0.223***	1,190
	(-0.01)	(-0.08)	(-0.08)	
Georgia	0.086***	-0.724***	-0.466***	1,491
	(-0.01)	(-0.10)	(-0.08)	
Ghana	0.061***	0.032	-0.396***	1,173
	(-0.01)	(-0.12)	(-0.11)	
Kenya	0.087***	-0.379***	0.038	1,465
	(-0.01)	(-0.08)	(-0.06)	
Ukraine	0.056***	-0.403*	-0.399***	1,398
	(-0.01)	(-0.21)	(-0.05)	
Vietnam	0.076***	-0.052	-0.228***	1,953
	(-0.01)	(-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. Schooling is measured as completed years of education. Reference category for self-employed and gender variables is those not self-employed and males, respectively.
The wage model controls for experience and experience squared. The Heckman method is used to correct for selection bias.

Table 5. The net effect of reading literacy on hourly earnings, 25 to 64 years.

	Panel A			Panel B			
	Literacy	Self-employed	Gender	Literacy	Self-employed	Gender	N
Armenia	0.023	-0.082	-0.415***	-0.004	-0.016	-0.436***	1,558
	-0.03	-0.13	-0.06	(0.03)	(0.13)	(0.06)	
Bolivia	0.185***	-0.353***	-0.534***	0.085	-0.266***	-0.479***	849
	-0.05	-0.10	-0.13	(0.05)	(0.10)	(0.11)	
Colombia	0.142***	-0.220***	-0.248***	-0.012	-0.200**	-0.224***	1,190
	-0.05	-0.08	-0.09	(0.05)	(0.08)	(0.08)	
Georgia	0.172***	-0.750***	-0.464***	0.125***	-0.729***	-0.49***	1,491
	-0.04	-0.11	-0.08	(0.04)	(0.11)	(0.07)	
Ghana	0.252***	-0.011	-0.423***	0.174**	0.10	-0.37***	1,173
	-0.07	-0.13	-0.11	(0.08)	(0.13)	(0.11)	
Kenya	0.255***	-0.449***	-0.011	0.100*	-0.376***	0.04	1,465
	-0.05	-0.08	-0.06	(0.05)	(0.08)	(0.06)	
Ukraine	0.090***	-0.372*	-0.374***	0.067**	-0.376*	-0.40***	1,398
	-0.0289	-0.2152	-0.0498	(0.03)	(0.21)	(0.05)	
Vietnam	0.201***	-0.142**	-0.256***	0.06	-0.052	-0.226***	1,953
	-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. Literacy scores are standardized. Schooling is measured as completed years of education. Reference category for self-employed and gender variables is those not self-employed and males, respectively.
The wage model controls for experience and experience squared in Panels A and B and schooling in Panel B only. The Heckman method is used to correct for selection bias.

Table 6. The net effect of computer use at work on hourly earnings, 25 to 64 years.

	Without Schooling		With Schooling		
	Medium computer use	High computer use	Medium computer use	High computer use	N
Armenia	0.014	0.311***	-0.022	0.238***	1,558
	(0.07)	(0.05)	(0.07)	(0.06)	
Bolivia	0.238*	0.671***	0.124	0.422***	849
	(0.12)	(0.10)	(0.144)	(0.13)	
Colombia	0.459***	0.591***	0.373***	0.391***	1,190
	(0.11)	(0.07)	(0.12)	(0.08)	
Georgia	0.364***	0.715***	0.296**	0.607***	1,491
	(0.11)	(0.07)	(0.12)	(0.07)	
Ghana	0.859***	0.981***	0.652***	0.787***	1,173
	(0.185)	(0.17)	(0.20)	(0.19)	
Kenya	0.801***	1.259***	0.700***	1.070***	1,465
	(0.12)	(0.09)	(0.11)	(0.09)	
Ukraine	0.045	0.306***	-0.01	0.240***	1,398
	(0.10)	(0.05)	(0.11)	(0.06)	
Vietnam	0.411***	0.642***	0.181	0.372***	1,953
	(0.11)	(0.06)	(0.11)	(0.07)	

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 use is those not self-employed, males and no computer use, respectively.

The wage model controls for gender, self-employed workers, experience and experience squared. The Heckman method is used to correct for selection bias.

Table 7. Net effect of non-cognitive skills in hourly earnings, 25 to 64 years.

Panel A – Without education

	Openness	Conscientiousness	Extraversion	Agreeableness	Emotional Stability	Grit	Decision-making
Armenia	0.048	-0.012	0.035	-0.075***	0.0213	0.042	-0.026
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Bolivia	0.057	0.047	0.006	0.025	0.089*	0.003	-0.023
	(0.055)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Colombia	-0.00	0.002	-0.039	0.059	0.055	-0.027	0.102***
	(0.036)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Georgia	0.086**	0.010	-0.010	-0.010	0.035	0.058	0.025
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.041)	(0.04)
Kenya	0.108***	0.047	0.067**	-0.017	0.028	0.005	0.065
	(0.04)	(0.04)	(0.03)	(0.042)	(0.04)	(0.04)	(0.04)
Ukraine	0.095**	-0.010	-0.024	-0.013	-0.003	0.035	-0.017
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Vietnam	0.156***	0.027	0.016	-0.013	0.073**	-0.036	0.043
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)

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

The sample includes wage and self-employed workers. Reference category for self-employed and gender variables is 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, experience and experience squared. The Heckman method is used to correct for selection bias.

Panel B – With education

	Openness	Conscientiousness	Extraversion	Agreeableness	Emotional Stability	Grit	Decision-making
Armenia	0.029	0.002	0.042*	-0.068***	0.029	0.049*	-0.031
	(0.03)	(0.03)	(0.0234)	(0.03)	(0.03)	(0.03)	(0.03)
Bolivia	0.050	0.042	-0.028	0.000	0.048	-0.011	-0.014
	(0.05)	(0.04)	(0.0469)	(0.05)	(0.04)	(0.05)	(0.05)
Colombia	-0.022	0.015	-0.045	0.007	0.033	-0.010	0.048
	(0.04)	(0.03)	(0.0317)	(0.04)	(0.03)	(0.04)	(0.03)
Georgia	0.044	-0.002	-0.015	-0.011	0.050	0.069*	0.020
	(0.04)	(0.04)	(0.0387)	(0.04)	(0.04)	(0.04)	(0.04)
Kenya	0.077**	0.028	0.056*	-0.021	0.023	0.004	0.047
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Ukraine	0.084**	-0.027	-0.025	-0.016	-0.005	0.032	-0.013
	(0.0355)	(0.0272)	(0.0282)	(0.0287)	(0.0296)	(0.03)	(0.04)
Vietnam	0.086***	0.015	0.014	-0.016	0.064**	-0.021	0.019
	(0.0263)	(0.0220)	(0.0263)	(0.0312)	(0.0277)	(0.03)	(0.03)

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 and gender variables is 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, experience and experience squared. The Heckman method is used to correct for selection bias.

Table 8. The net effect of skills on hourly earnings, 25 to 64 years.

VARIABLES	Armenia	Bolivia	Colombia	Georgia	Kenya	Ukraine	Vietnam
Gender	-0.479***	-0.4471***	-0.256***	-0.564***	0.035	-0.402***	-0.198***
	(0.06)	(0.10)	(0.07)	(0.07)	(0.05)	(0.06)	(0.05)
Experience	0.020*	0.013	0.007	0.034***	0.027***	0.027***	0.009
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Experience Squared	-0.001**	-0.00	-0.00	-0.00***	-0.001**	-0.001***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Years of education	0.031***	0.050***	0.049***	0.033***	0.035***	0.025	0.044***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Standardized Literacy	-0.008	0.06	-0.021	0.093**	0.096**	0.064**	0.035
	(0.03)	(0.06)	(0.050)	(0.04)	(0.04)	(0.03)	(0.04)
Computer use (Med)	-0.0410	0.122	0.392***	0.294**	0.681***	-0.044	0.174*
	(0.07)	(0.15)	(0.12)	(0.12)	(0.11)	(0.10)	(0.10)
Computer use (Intense)	0.2297***	0.41***	0.399***	0.562***	1.046***	0.211***	0.353***
	(0.06)	(0.13)	(0.08)	(0.07)	(0.10)	(0.06)	(0.07)
Extraversion	0.0378*	-0.032	-0.052*	-0.034	0.045	-0.025	0.018
	(0.02)	(0.05)	(0.03)	(0.03)	(0.027)	(0.03)	(0.027)
Conscientiousness	0.0045	0.029	-0.003	0.023	0.05	-0.020	0.02
	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)	(0.03)	(0.022)
Openness	0.0260	0.029	-0.025	0.009	0.060*	0.075**	0.075***
	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Stability	0.0185	0.043	0.016	0.023	0.014	-0.020	0.062**
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Agreeableness	-0.0684***	0.008	0.020	-0.00	-0.046	-0.017	-0.018
	(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Grit	0.0483*	-0.00	-0.025	0.043	0.029	0.030	-0.022
	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)

Self-Employed	-0.0100	-0.176*	-0.177**	-0.578***	-0.223***	-0.365*	0.0213
	(0.12)	(0.10)	(0.07)	(0.11)	(0.069)	(0.21)	(0.06)
Constant	0.4284*	0.275	0.411**	0.212	-0.228	0.729***	0.340**
	(0.22)	(0.31)	(0.19)	(0.20)	(0.18)	(0.21)	(0.14)
Observations	1,557	846	1,190	1,464	1,445	1,374	1,948

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 use is those not self-employed, males and no computer use, respectively. Scores on the literacy 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 experience squared. The Heckman method is used to correct for selection bias.

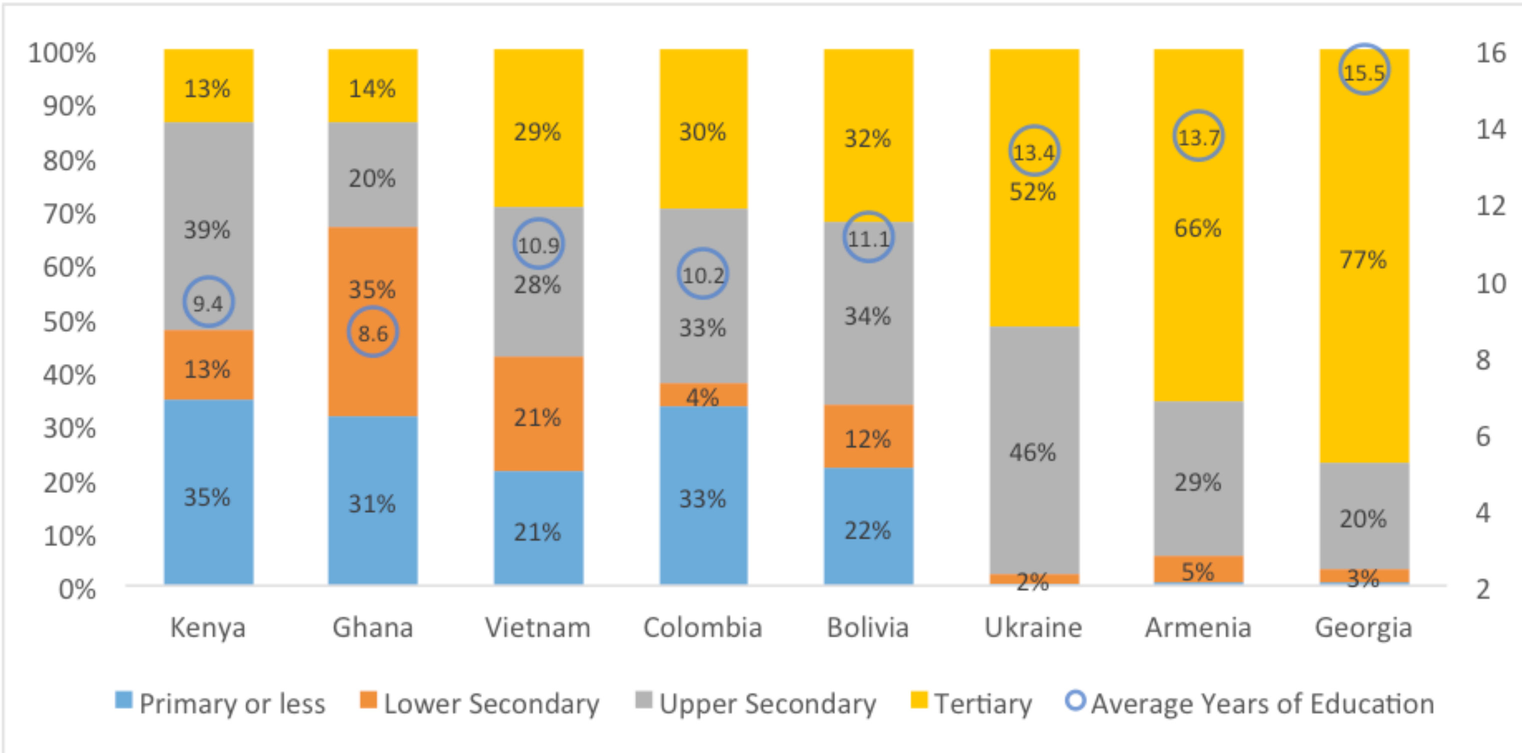

Figure 1. Average completed years of education and educational attainment composition of workers, 25 to 64 years.
Source: STEP Surveys (2014)

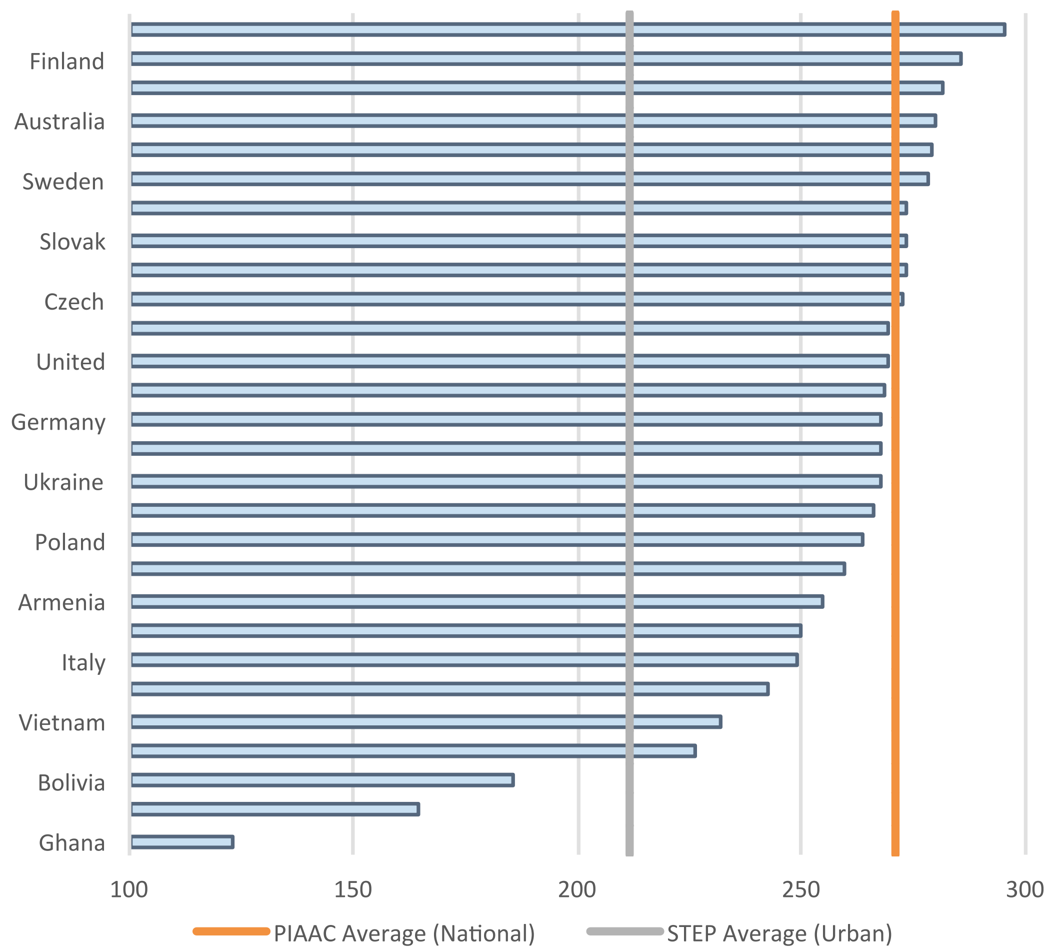

Figure 2. Average reading literacy score for PIAAC and STEP, 25 to 64 years.
Note: The PIAAC estimates correspond to the national resident population 25 years and older in the country. The STEP estimates correspond to the urban population 25 years and older, excluding unpaid workers.
Source: STEP Surveys (2014), OECD (2012).

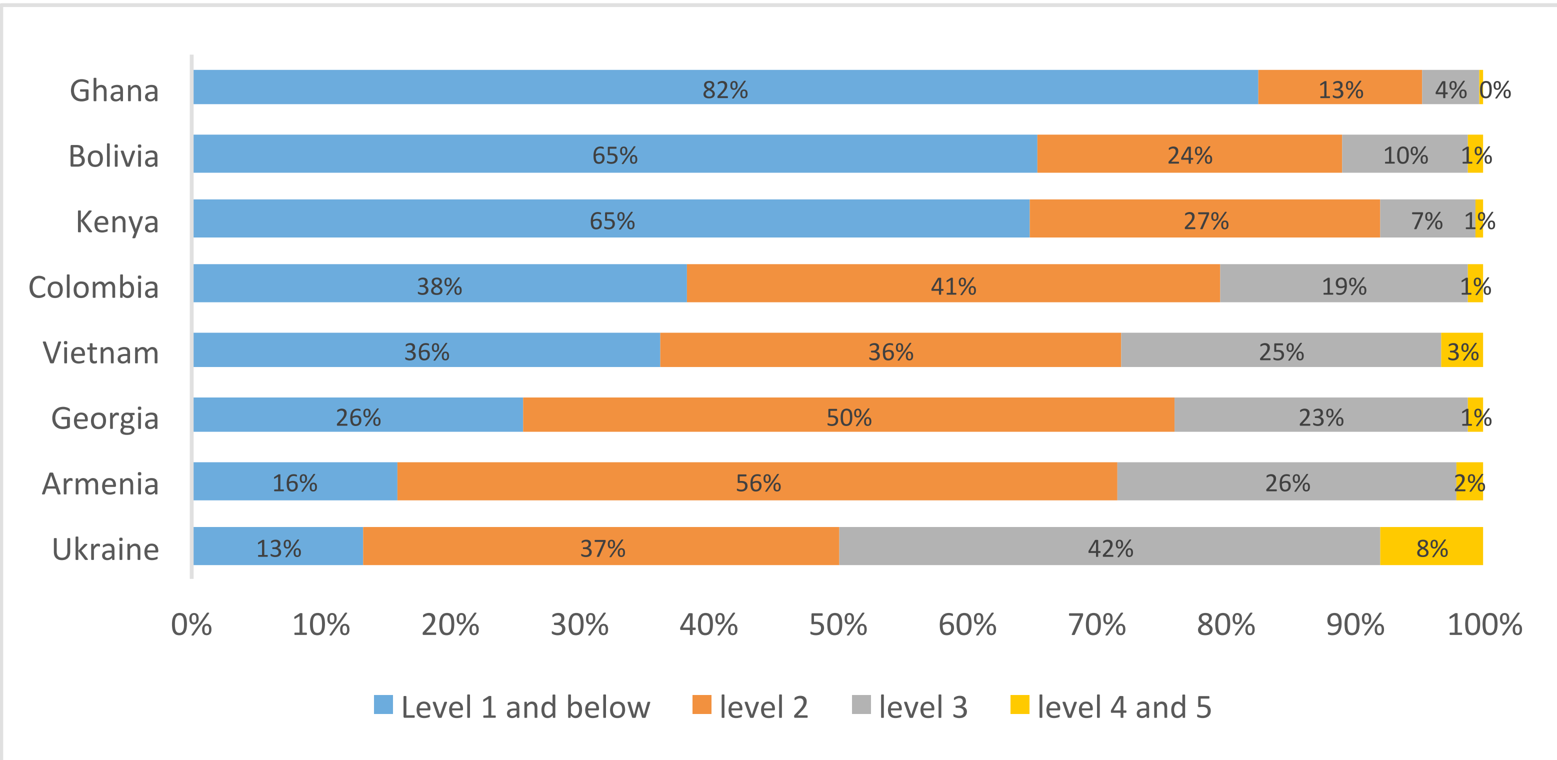

Figure 3. Share of workers by reading literacy levels, 25 to 64 years.
Source: STEP Surveys (2014)

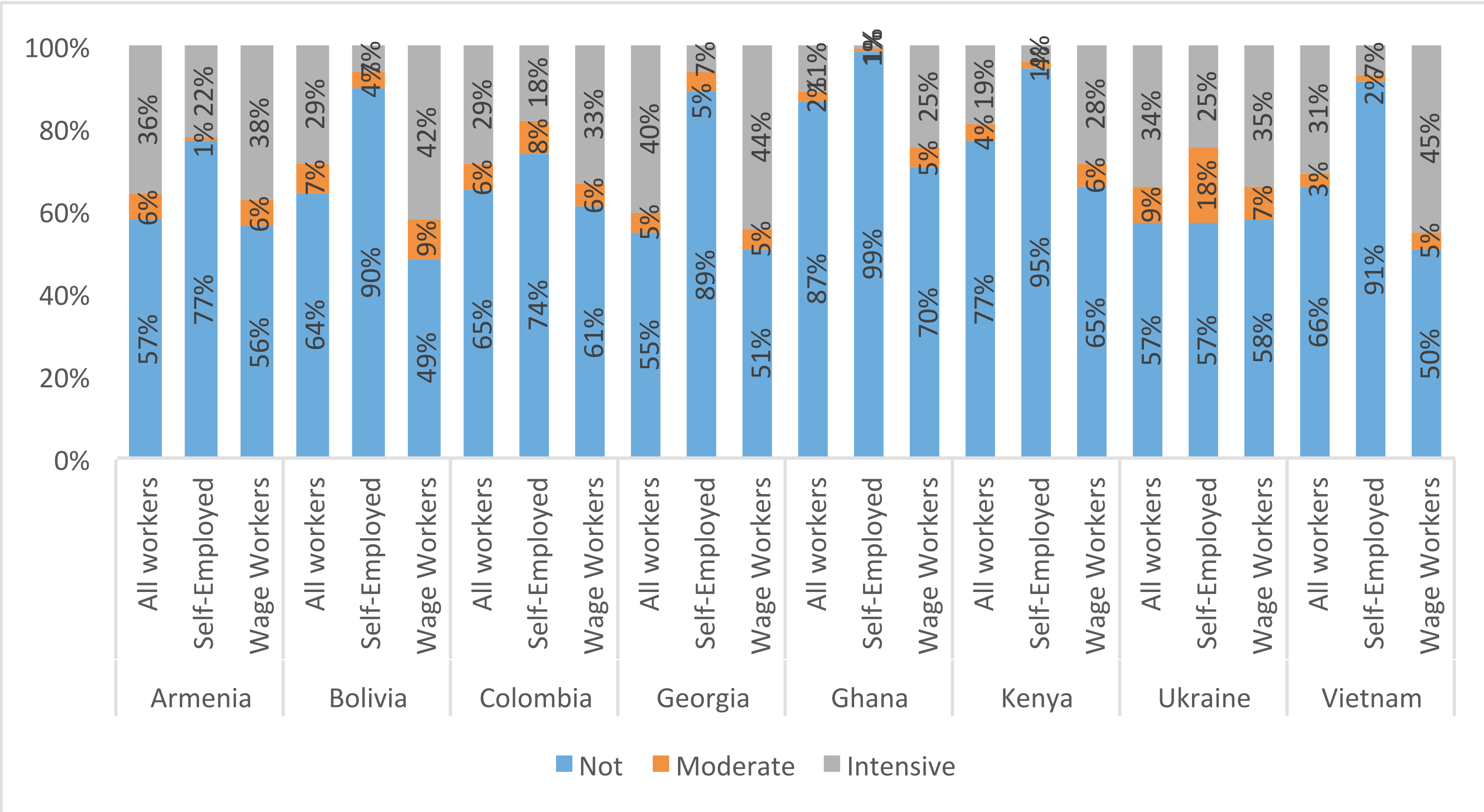

Figure 4. Computer use at work, 25 to 64 years old
Source: STEP Surveys (2014)

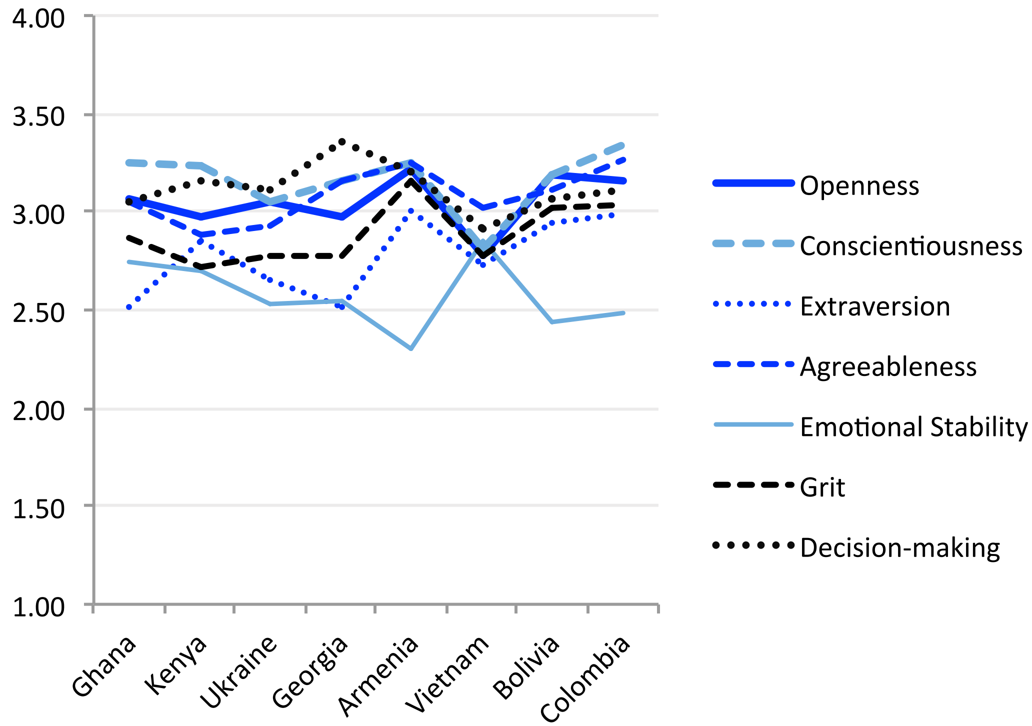

Figure 5. Average scores on the 'Big Five' Personality Traits, 25 to 64 year olds
Source: STEP Surveys (2014)

IX. Appendix A: Descriptive Statistics for country samples

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

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	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
Years of education	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
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
Labor Dependency	0.52	0.26	0.47	0.28	0.54	0.29	0.54	0.27	0.62	0.26	0.59	0.21	0.54	0.23	0.54	0.24
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
Socioeconomic 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, 25 to 64 years.

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	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
Years of education	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
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
Labor Dependency	0.55	0.24	0.54	0.25	0.61	0.29	0.60	0.27	0.64	0.24	0.60	0.22	0.54	0.21	0.58	0.23
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
Socioeconomic 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, 25 to 64 years.

	Armenia		Georgia		Ghana		Kenya		Ukraine		Vietnam		Bolivia		Colombia	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	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
Years of education	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
Conscientiousness	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
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
Labor Dependency	0.51	0.23	0.51	0.26	0.51	0.25	0.53	0.24	0.65	0.24	0.61	0.19	0.57	0.24	0.56	0.23
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
Socioeconomic 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