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Do Cognitive and Noncognitive Skills Explain the Gender Wage Gap in Middle-Income Countries?

An Analysis Using STEP Data

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Abstract

Gender-based wage discrimination is a highly researched area of labor economics. However, most studies on this topic have focused on schooling and paid limited attention to the mechanisms through which cognitive and noncognitive skills influence wages. This paper uses data from adults in seven low- and middle-income countries that participated in the STEP Skills Measurement Survey to conduct a comparative analysis of gender wage gaps. The paper uses schooling and skills measures, including reading proficiency and complexity of on-the-job computer tasks to proxy cognitive skills, and personality and behavioral measures to proxy for noncognitive skills in wage decompositions. The analysis finds that years of school explain most of the gender wage gap. The findings also suggest that cognitive and noncognitive skills affect men's and women's earnings in different ways, and that the effects of these skills vary across the wage distribution and between countries.

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An Analysis Using STEP Data

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Common Acronyms

ECA	Europe and Central Asia
IALS	International Adult Literacy Survey
ICT	information and communication technology
OECD	Organisation for Economic Co-operation and Development
PIAAC	Program for International Assessment of Adult Competencies
STEM	science, technology, engineering, and math

I. Introduction

Women's participation in the labor force has increased significantly throughout the world over the past 25 years (Duflo*,* 2012). Despite this, research shows that systematic gender gaps in wages and productivity persist across both developed and developing countries (Blau and Kahn, 2000; Jarrell and Stanley, 2003; Terrell, 1992). Ensuring parity in male-female labor outcomes is not only a matter of equity but also one of smart economics and efficiency (Doepke, Tertilt, and Voena, 2014; Duflo, 2012). The 2012 World Development Report, *Gender Equality and Development,* notes that eliminating gender discrimination against female workers could increase productivity by 25 to 40 percent (World Bank, 2012). Moreover, removing barriers faced by women in the labor market has implications for the next generation as well as for the inclusivity and representativeness of institutions and development policies (Hallward-Dreimeier and Gajigo, 2013).

Gender wage discrimination is a well-researched area and one that has been examined using a variety of estimation techniques. Previous studies on this topic have used various worker characteristics such as age, experience, education, occupation, and industry of employment in predicting male-female wages.[4] However, while recent research in labor economics has documented the critical role of skills, broadly defined, in predicting key life outcomes, including the associations between skills and earnings (Hanushek et al., 2013; Heckman and Kautz, 2011), the mechanisms through which cognitive and noncognitive skills are related to wages have received limited attention,[5] and most of the research has been conducted in countries belonging to the Organisation for Economic Co-operation and Development (OECD). Further, few studies have applied these skills measures to examine earnings differences between men and women.

This study aims to conduct a comparative analysis across seven low- and middle-income countries, examining the gender wage gap in these countries using data from the STEP Skills Measurement surveys. It is the first study to use measures of cognitive and noncognitive skills in wage decomposition analysis in this set of countries. The multi-dimensional conceptualization of skills in the STEP survey data offers a broader definition of human capital and thereby allows us to explore the potential role of other dimensions of human capital in understanding the gender wage gap.

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[4] Additionally, the structure of the labor market and women's legal (property) rights have also been examined in gender wage discrimination research (Blau and Kahn, 2003; Doepke, Tertilt, and Voena, 2011).

[5] Mueller and Plug (2006) hypothesize that personality can either directly (through productivity differences) or indirectly (through occupational segregation) affect gender differences in earnings. Further, personality differences can also affect occupational choices and thus lead to differences in wages.

It is known that occupational segregation can cause wage gaps, but the determinants of occupational segregation are not well established (Cobb-Clark and Tan, 2009). Using noncognitive and cognitive skills in gender decomposition analysis could potentially provide information on whether these skills measures are related to how women sort into different occupations. For example, it could be hypothesized that women with certain personality traits are more likely to opt to enter (and succeed in) male-dominated occupations than women with a different personality makeup. Overall, findings from this study can provide new insights for gender-focused development and economic policies.

Using schooling and skills measures in wage decompositions across seven countries, the study finds that years of completed education explain the bulk of the gender gap in wages. Cognitive and noncognitive skills differentially affect men's and women's earnings, and the effect of these skills varies along the wage distribution. These findings are not consistent across all of the countries examined, however, highlighting the need for context-specific studies to further explore correlates of wages among men and women in these environments.

The rest of the paper is structured as follows: Section II provides a brief review of the literature on gender wage gaps, highlighting work using skills measures beyond schooling. In Section III, we discuss the methods used, and follow with a description of the data in Section IV. Results are presented in Section V, and Section VI provides conclusions.

II. Literature Review

The human capital theory and the theory of competitive labor markets predict that workers with the same productive characteristics and skills (or endowments) will be paid the same wage (Becker, 1975; Schultz, 1991). However, often workers who have the same education, training, and experience but who belong to different groups may receive substantially different wages. These differences in wages (generally thought of as *discrimination*) are explained by the theory of labor market discrimination. The topic of gender wage discrimination is among the most researched in labor economics. In this section we discuss selected findings from this extensive literature on gender wage gaps, highlighting those studies carried out in low- and middle-income countries – with a focus on evidence from the countries included in this paper—and using measures of skills beyond educational attainment alone.

While most of the research on this topic comes from the OECD countries, several studies have focused on countries in Latin America, Africa, and Asia, as well as transitional economies in Eastern Europe. Among these studies, Liu (2004), Pham and Reilly (2007), and Pierre (2012) examined gender wage gaps in Vietnam between 1993 and 2009, Ganguli and Terrell (2005) used data from Ukraine to examine the earnings differentials between men and women during the 1986 to 2003 period, and Badel and Peña (2010) used survey data from 2006 to estimate gender wage differences in Colombia. All of these studies find that women's earnings are significantly lower than those of men, men earning up to 30 percent more than women in these countries. The authors note that education and experience account for a small proportion of the estimated wage gap, and that the bulk of the gap is attributed to differential returns to education and skills for men and women. Three of these studies use quantile regression-based decomposition methods, allowing researchers to examine wage differentials at different points of the wage distribution. In the case of Colombia, Badel and Peña (2010) found that women at the top and bottom of the wage distribution are those primarily affected by differences in returns to endowments or skills. For Ukraine, the gaps are widest at the top end of the wage distribution, while the opposite is true in Vietnam, where the wage gaps decrease as one moves along the distribution from bottom to top.

A limited set of studies on gender wage discrimination examines the contribution of cognitive and noncognitive skills in explaining the gender wage gap (Fortin, 2008; Mueller and Plug, 2006; Nordman, Sarr, and Sharma, 2014; Nyhus and Pons, 2012; Sakellariou, 2012; and Semykina and Linz, 2007). Most of these studies are based on data from OECD countries. To our knowledge, Nordman, Sarr, and Sharma (2014) present the only available evidence for developing countries. They used matched employer-employee data from Bangladesh to examine discrimination in male-female wages, and found that, when controlling for educational attainment, the mean wage gap is about 8 percent. The mean wage gap reduces marginally when cognitive and noncognitive skills are added to the model. Examining the wage gaps at different points of the wage distribution, they found that the gap in Bangladesh is wider at the bottom end of the distribution and that cognitive and noncognitive skills explain about 88 percent of the gap at the upper end of the wage distribution and about 69 percent at the bottom of the distribution.

Mueller and Plug (2006) and Fortin (2008) provide evidence for the United States. Mueller and Plug used data from the Wisconsin Longitudinal Study, and although they found significantly strong associations between their measure of cognitive skills (IQ) and earnings (especially for men), they found no gender differences in responses to cognitive skills. For noncognitive skills, they report that about 3 percent of the gender gap is explained by differences in, and returns to, personality traits. Fortin's study examined the effect of noncognitive skills—self-esteem, locus of control, the importance of money/work, and the importance of people/family—using data from two longitudinal surveys in the United States. Her results indicate that differences in these noncognitive traits explain about 8 percent of the wage gap. Similar results have been reported for the Netherlands, where adding the factor of personality was found to reduce the gender wage gap from 75 percent to 63 percent (Nyhus and Pons, 2012); and for Russia, where the authors found that the noncognitive skills used (locus of control and challenge-affiliation) explain about 8 percent of the gender wage gap (Semykina and Linz, 2007). Sakellariou (2012) used data from the International Adult Literacy Survey (IALS) for Norway, Denmark, Finland, Hungary, and the Czech Republic to examine whether cognitive skills matter in gender wage decomposition analysis. His results indicate that using the IALS score underestimates the effect of cognitive skills on earnings, but when cognitive skills are specified in terms of origin (i.e., acquired at school or outside of school), the size of the unexplained component changes substantially in Finland, Hungary, and the Czech Republic, with differing patterns in the different countries.

III. Methodological Approach

As a first step toward decomposing earnings differentials, we express earnings as a function of observed characteristics. In our first set of empirical examinations, we use the approach popularized by Mincer (1974); the standard wage function includes experience and schooling. We add a dummy variable for type of employment to this standard formulation in order to control for differences among workers:

$$w_i = \alpha_0 + \alpha_1 ObservedCharacteristics_i + \varepsilon_i \qquad (1)$$

In the equation above, w_i indicates (log) hourly earnings and *Observed Characteristics* represents a vector of variables that includes years of potential experience calculated as (*Age* – *Years of education* – 6), completed years of education, and a dummy variable for self-employed workers (wage workers serve as the reference group). The above equation can be estimated separately for men and women to get estimates of returns to schooling for men and women, respectively.

We add skills measures to the model above to estimate the association between skills and earnings, controlling for completed years of education. The resultant model is expressed as follows:

$$w_i = \alpha_0 + \alpha_1 ObservedCharacteristics_i + \beta_1 Skills_i + \varepsilon_i, \qquad (2)$$

where *Skills* represents scores on each of the selected personality traits that are used to estimate noncognitive skills' associations with earnings. The standardized score on the reading proficiency assessment is then added to estimate the association between cognitive skills and earnings, controlling for schooling and noncognitive skills. Finally, binary variables indicating complexity of computer use are added to the model to estimate the relationship between cognitive skills, as measured by computer skills, and earnings, controlling for schooling, noncognitive skills and cognitive skills measured by reading proficiency scores.

Based on the approach popularized by Blinder (1973) and Oaxaca (1973), the *mean* earnings differential between men and women is then decomposed as shown below. Here, men are treated as the reference group (i.e., we assume that in the absence of discrimination, the male earnings structure would be observed). The decomposition equation is thus written as:

$$\overline{w}_m - \overline{w}_f = (\overline{X}_m - \overline{X}_f)\alpha_m + (\overline{Skills}_m - \overline{Skills}_f)\beta_m + \overline{X}'_f(\alpha_m - \alpha_f) + \overline{Skills}'_f(\beta_m - \beta_f). \tag{3}$$

The mean earnings differential between men and women is expressed as a function of the average *observed characteristics* of men and women (*X*) and the average *skills* of men and women. The last two terms on the right-hand side provide a measure of the gender earnings gap due to differences in *returns* to observed characteristics and skills.

In order to get around problems incurred from the choice of reference group (or non-discriminatory wage structure), we follow a variant of the Blinder-Oaxaca method—the general decomposition method from Neumark (1988). In the equation below, α^* and β^* are estimated using the weighted average of the wage structures of men and women (from a pooled sample of men and women) and represent the returns to observed characteristics and skills under no discrimination. The unexplained component of the gender earnings differential is given by the terms in the box brackets.

$$\overline{w}_m - \overline{w}_f = (\overline{X}_m - \overline{X}_f)\alpha^* + (\overline{Skills}_m - \overline{Skills}_f)\beta^* + \left[\overline{X}'_m(\alpha_m - \alpha^*) - \overline{X}_f(\alpha_f - \alpha^*)\right] + \left[\overline{Skills}'_m(\beta_m - \beta^*) - \overline{Skills}_f(\beta_f - \beta^*)\right] \tag{4}$$

In our second set of empirical examinations, we focus on the role of occupation. Here, in addition to potential experience, type of employment and completed years of education, occupation dummies are included in the vector of *Observed Characteristics* in equations (1) and (2). Interaction terms between occupation and type of employment are also included. This formulation is then followed as noted above, where the role of skills is examined, controlling for characteristics, occupation, and schooling. Neumark's (1988) method is used to decompose earnings differentials between men and women.

Based on findings from the literature on substantial differences in gender wage gaps along the wage distribution, we also adopt a quantile decomposition framework. Quantile regression provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of hourly earnings, not merely its conditional mean, and thus provides a deeper understanding of existing wage differentials. For decompositions based on quantile regression methods, we use the method proposed by Machado and Mata (2005), whereby the conditional earnings distribution[6] is estimated using quantile regression separately for men and women at specific quantiles. For each gender group, the quantile function is expressed using the following linear specification:

$$Q_\theta\left(w_g \middle| X_g\right) = X_{i,g}\beta_{g,\theta} \mathit{for\ each}\ \theta \in (0,1),$$

where, *w* denotes log earnings and the group subscript *g* includes both genders (*m*, *f*). *X* is a vector of covariates (including observed characteristics and skills measures) for individual *i* and β is a vector of coefficients estimated at different quantiles θ. The quantile regression coefficients are interpreted as the returns to different observed characteristics and skills at specific quantiles of the earnings distribution. It is assumed that all quantiles of *w*, conditional on *X*, are linear in *X*.

Instead of using the simulation-based technique proposed by Machado and Mata (2005) to estimate the unconditional earnings distribution function, we use the procedure from Melly (2006), which is computationally less intense but is shown to be numerically identical when the number of simulations goes to infinity. Melly's procedure[7] integrates the conditional distribution function over a range of covariates, then inverts the unconditional distribution function to obtain unconditional quantiles. The counterfactual for women using observed characteristics and the skills profile of women and the male wage structure is expressed as:

$$CF_\theta^f = X_{f,i}{}'\beta_{m,\theta}\ .$$

The decomposition of earnings gaps of the unconditional quantile functions between men and women is then given by:

$$\Delta_\theta = \left[Q_{m,\theta} - CF_\theta^f\right] + [CF_\theta^f - Q_{f,\theta}],$$

where the first term on the right-hand side represents the quantile endowment effects or the effect of characteristics and skills, and the second term represents the effects of coefficients.

The issue of self-selection or general endogeneity leading to biased results is a concern in this and most decomposition analysis. Men and women could follow different decision-making

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[6] The conditional quantile distribution is the distribution of an outcome Y at specific quantiles conditional on a set of covariates X.

[7] Melly's (2006) procedure has been implemented using the "cdeco" program in Stata.

patterns that inform their decisions whether to enter the labor market or to self-select into specific occupations. Self-selection has been found to have a significant impact on wage estimates and estimates of the pay gap (Belbo et al., 2003). Thus, we adopt Heckman's (1979) method to correct for selection bias. However, the selection correction method is used only in the case of the mean decomposition analysis and not for the quantile decompositions discussed above. Selection correction within decomposition techniques, in general, can be problematic and is more complex in the context of quantile decompositions.[8]

As a first step in applying the selection correction method proposed by Heckman, a probit model predicting labor force participation is estimated:

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

In this equation, Z_i is a vector of instruments that includes number of children below age 6 in the household and number of shocks experienced in childhood. The predicted probabilities from this selection equation are then used to compute the selectivity term, which is added to the wage equation as an additional explanatory variable.

IV. Data

The data for this study come from the STEP Skill Measurement surveys. These data were collected in 2012 and 2013 in seven countries—Armenia, Bolivia, Colombia, Georgia, Kenya, Ukraine, and Vietnam.[9] The household survey gathers information from urban adults between the ages of 15 and 64. The survey provides various measures of cognitive and noncognitive skills that are the focus of this paper (see Pierre et al. (2014) for a detailed description of the skills measures included in the STEP surveys). The STEP surveys provide a direct, objective measure of *reading proficiency skills,*[10] using an assessment scored on the same scale as the OECD's PIAAC (Program for International Assessment of Adult Competencies). The scores on this assessment range from 0 to 500 and span six levels of proficiency.[11]

In addition to the reading proficiency assessment, we use a self-reported measure of *complexity of computer use on the job* as a second proxy for cognitive skills. Respondents report

[8] Sensitivity to the choice of estimator (Belbo et al., 2003) or use of a semi-parametric approach using power series approximation for the selection term (Buchinsky, 1998) are some of the complexities encountered in correcting for selection within decomposition analysis.
[9] Surveys were also conducted in Ghana, Lao PDR, Macedonia, Sri Lanka, and the Yunnan Province of China. Data for these countries do not meet the requirements for this paper, since the surveys did not include direct measurement of reading proficiency skills.
[10] STEP also provides indirect measures of reading, writing, and mathematics skills, which are not used in this paper.
[11] Interpretation of score levels can be found in Pierre et al., 2014, p.83.

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. These computer tasks are used to define binary variables indicating different levels of complexity of computer use on the job. Four levels of complexity have been defined: level 1 includes using *browser-based tasks* (for example, use of email and Internet); level 2 involves use of *basic Microsoft Office functions* like the word processor, presentations, and graphics; level 3 involves use of *basic programming tasks* (involving spreadsheets and databases); and level 4 captures *advanced programming tasks* (for instance, designing websites, using computer-aided software, programming software, and/or managing networks).

Noncognitive skills measures in the STEP surveys come from self-reported responses to various items measuring personality traits and behaviors. The personality traits include the Big Five traits—openness, conscientiousness, extraversion, agreeableness, and emotional stability (which is the obverse of neuroticism)—grit, and behaviors such as decision-making.[12] Items measuring these traits and behaviors are rated on a four-point Likert scale from "Almost never" to "Almost always."

The STEP household surveys include extensive modules on education and employment history that provide information on educational and labor market outcomes. Further, the household roster of the survey gathers information on several individual and household characteristics used in this study. These include information on the number of children in the household, the marital status of the respondent, and retrospective information on the economic status of the household when the respondent was 15 years of age. The Appendix includes descriptive statistics on some of these key variables.

Analytic Sample

To address the research questions posed in this study, the analytic sample for each country was limited to wage workers and self-employed adults between ages 25 and 64 who were in full-time employment. The self-employed group constitutes a large proportion of the sample in the countries examined in this paper (see Table 1) and is included in the analytic sample to enable policy-relevant inferences. The age range was selected to include adults mostly likely to have completed their education and who were below retirement age. Those currently enrolled in an educational or training program were excluded from the sample. Observations missing

[12] The STEP surveys also gather information on preferences through measures of risk preference and hostile attribution bias. These are not used in the current analysis.

information on the skills measures used in this study were also removed from the sample. In keeping with standard practice, individuals reporting zero earnings were assigned a small value of 0.0001 before this was transformed to the logarithmic scale.[13] Finally, both individuals in the top 1 percent of the earnings distribution and employers were excluded from the sample to avoid potential outliers and to minimize bias due to measurement error in earnings. The total proportion of missing data comprised less than 0.05 percent of the sample for each country. The resulting sample size for each country includes between 480 and 1,400 men and women.

Descriptive Statistics

We begin by comparing men and women, by country, on key variables of interest. As mentioned before, the sample includes a substantial number of self-employed workers in full-time employment. Table 1 shows that among men and women both, a larger proportion report being employed in wage work than in self-employment. More women than men belong to the self-employed group in Vietnam and Kenya. The opposite is true in Armenia and Ukraine, where a larger proportion of men than women are self-employed.

Table 1. Self-employed and Wage Workers as Proportions of All Workers, by Gender and Country

	Self-employed		Wage workers	
	Men	Women	Men	Women
Armenia	0.05	0.02	0.44	0.48
Bolivia	0.17	0.19	0.37	0.26
Colombia	0.16	0.15	0.37	0.32
Georgia	0.05	0.06	0.41	0.48
Kenya	0.16	0.21	0.40	0.23
Ukraine	0.06	0.01	0.47	0.46
Vietnam	0.11	0.23	0.31	0.35

Note. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, and part-time workers are excluded from the sample.
Source: STEP Surveys (2014).

Average hourly earnings for men and women are presented in Table 2. There is substantial variation in the earnings distributions across all countries, which is also evident in graphs of the earnings distributions (see Figure A1 in the Appendix). The distributions for most countries skew to the left, indicating that the average earnings in these countries are below the median. Women, on average, earn less than their male counterparts across the board. This

[13] The proportion of workers reporting zero earnings was within 1 percent of the sample.

difference in hourly earnings is statistically significant in six of the countries, with the exception of Kenya, where the mean hourly wage for men is US$2.58 and for women is US$2.50 (2011 PPP-adjusted US dollars). The small wage differences in Kenya have been documented by previous research (Schultz, 1991) and are explained by the greater involvement of women in market production. For countries other than Kenya, the raw (unadjusted) wage gap ranges from 22 percent in Vietnam to 39 percent in Armenia.[14] In Kenya, where the difference in the average wages of men and women is not significant, the wage gap is a modest 3 percent.

Table 2. Average Hourly Earnings among Men and Women, by Country
(in 2011 PPP-adjusted U.S. dollars)

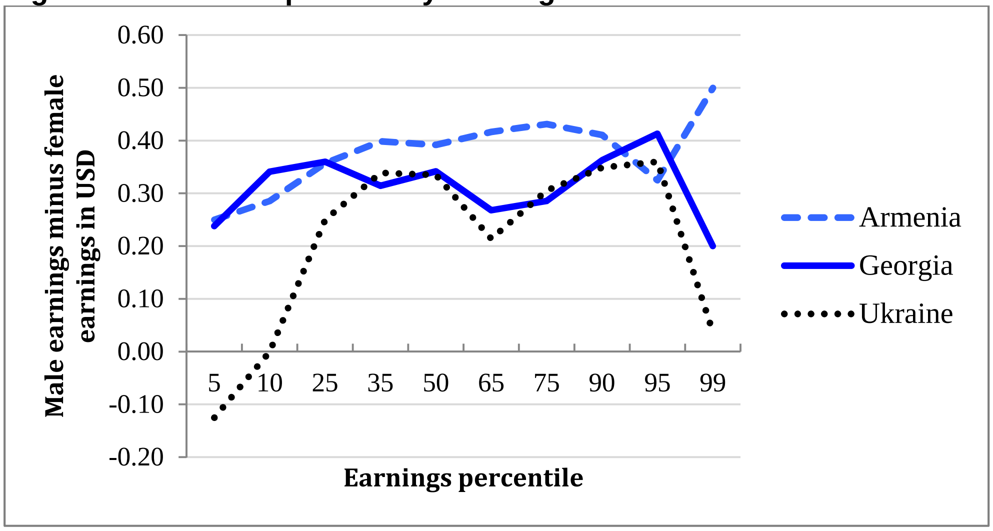
	Men		Women			
	Mean	SD	Mean	SD	N	*t* value
Armenia	3.33	2.00	2.02	1.18	530	8.83
Bolivia	4.11	4.12	2.92	3.25	653	4.52
Colombia	4.03	5.14	2.79	2.19	832	4.98
Georgia	4.12	3.27	2.76	2.67	481	4.56
Kenya	2.58	2.88	2.50	3.15	1160	0.87
Ukraine	4.14	1.72	2.88	1.71	730	7.62
Vietnam	3.66	3.57	2.87	3.43	1394	4.01

Note. Earnings have been converted to 2011 PPP-adjusted U.S. dollars. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, part-time workers, and the top 1 percent of earners are excluded from the sample.
Source: STEP Surveys (2014).

We examine the unconditional wage gap at different percentiles of the distribution. These are presented in Figures 1, 2, and 3. The distributions show substantial variation throughout the wage distribution. Further, the pattern is not systematic across countries. In Bolivia and Kenya we observe higher gaps at lower ends of the wage distribution, whereas in Armenia and Colombia we find the biggest gaps at the top of the wage distribution, implying that women do well in the labor market up to a point, beyond which their prospects and growth are limited (Albrecht, Bjorklund, and Vroman, 2003). In Ukraine, the second and fourth quartiles of the wage distribution show the biggest gaps. These patterns will be further explored in the decomposition analysis.

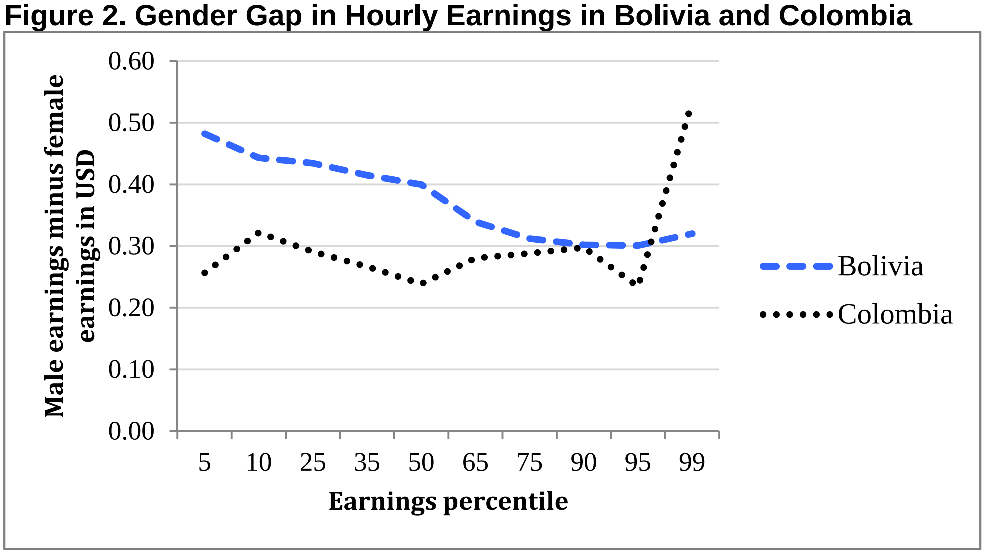
[14] It must be noted that the observed wage gap is for the urban population only and could be an over- or underestimate of the overall wage gap in the country.

Figure 1. Gender Gap in Hourly Earnings in Three ECA Countries



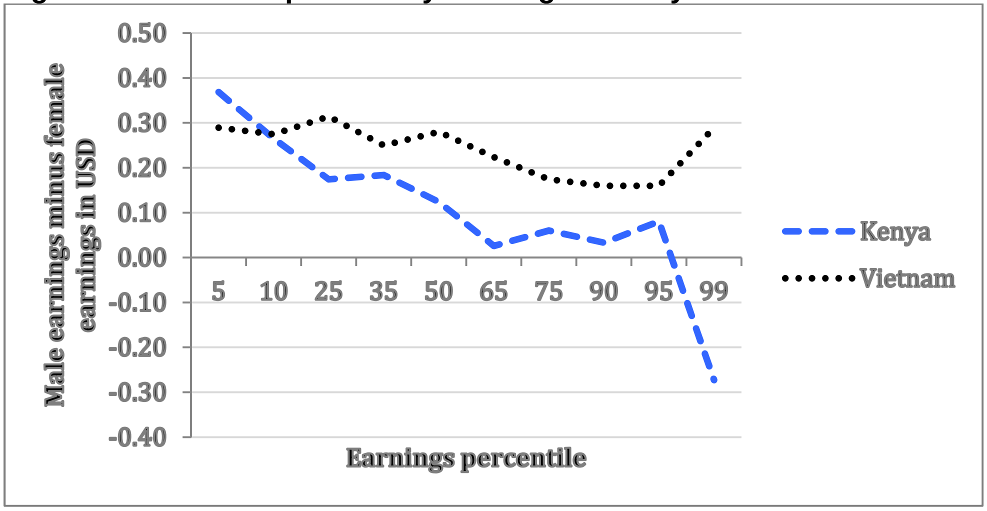
Note. Earnings have been converted to 2011 PPP-adjusted U.S. dollars. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, part-time workers, and the top 1 percent of earners are excluded from the sample. ECA = Europe and Central Asia.
Source: STEP Surveys (2014).

Figure 2. Gender Gap in Hourly Earnings in Bolivia and Colombia



Note. Earnings have been converted to 2011 PPP-adjusted U.S. dollars. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, part-time workers, and the top 1 percent of earners are excluded from the sample.
Source: STEP Surveys (2014).

Figure 3. Gender Gap in Hourly Earnings in Kenya and Vietnam



Note. Earnings have been converted to 2011 PPP-adjusted U.S. dollars. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, part-time workers, and the top 1 percent of earners are excluded from the sample.
Source: STEP Surveys (2014).

Gender differences in educational attainment and skills, our primary explanatory variables for the gender wage gap, are presented in Tables 3 through 6. With regard to educational attainment, we find that in countries other than those in the Europe and Central Asia (ECA) region (namely, Armenia, Georgia, and Ukraine), women show lower educational attainment than men. Although these differences are small in magnitude, they are statistically significant. These differences in endowments are likely to translate into higher average wages among men.

Table 3. Average Completed Years of Schooling for Men and Women, by Country

	Men		Women			
	Mean	SD	Mean	SD	N	*t* value
Armenia	13.77	3.30	13.78	3.10	530	1.76
Bolivia	11.56	4.58	10.68	5.05	653	4.93
Colombia	10.31	3.77	10.11	3.98	832	3.15
Georgia	15.30	2.66	15.56	2.74	481	-1.91
Kenya	10.10	4.73	8.91	4.90	1160	5.77
Ukraine	13.38	1.93	13.66	2.38	730	-1.45
Vietnam	11.35	4.28	10.81	4.40	1394	4.48

Note. The sample includes 25- to 64-year-olds in self-employment or wage work.
Source: STEP Surveys (2014).

Cognitive skills, as measured by scores on the reading proficiency assessment, also show that men, on average, have slightly higher scores than women (except in Georgia and Ukraine, where women's scores are higher; see Table 4). Differences in reading proficiency scores among men and women are statistically significant across some of the countries except Ukraine, Armenia, and Georgia. Research in psychology has also found that differences in cognitive abilities between gender groups might not be statistically significant but might show statistically significant differences in the case of groups defined by race or ethnicity (Hough and Oswald, 2000).

Table 4. Average Reading Proficiency Scores for Men and Women, by Country

	Men		Women	
	Mean	SD	Mean	SD
Armenia	254.37	2.41	253.96	1.89
Bolivia	191.14	6.89	172.57	6.01
Colombia	232.08	3.62	223.43	3.69
Georgia	237.47	2.63	243.63	1.89
Kenya	182.45	3.97	158.06	4.55
Ukraine	263.16	4.64	268.73	1.90
Vietnam	236.17	3.32	228.05	2.93

Note. Reading proficiency scores are measured on a 500-point scale. The sample includes 25- to 64-year-olds in self-employment or wage work.
Source: STEP Surveys (2014).

As mentioned previously, we also use a second measure of cognitive skills: complexity of computer use on the job. In Table 5, we present the proportion of men and women in the analytic sample who use computers on the job. In most countries, less than half of men and women use computers on the job. In Kenya, 22 percent of women and 28 percent of men reported using computers. In Ukraine, Georgia, and Armenia, 41 percent of men reported using computers. In Bolivia, the proportion of men using computers at work is slightly higher, at 43 percent, while in Colombia and Vietnam it is under 40 percent. The highest proportion of women reporting using computers on the job is in the ECA countries (55 percent in Georgia, 48 percent in Armenia, and 45 percent in Ukraine). The latter countries are also the ones where the proportion of women using computers on the job is higher than the proportion of men doing so. The difference in the proportions between men and women is not statistically significant in Armenia and Colombia.

Table 5. Proportion of Men and Women Using Computers on the Job, by Country

	Men	Women	Total	N
Armenia	0.41	0.48	0.43	530
Bolivia	0.43	0.35	0.39	653
Colombia	0.34	0.41	0.35	832
Georgia	0.41	0.55	0.44	481
Kenya	0.28	0.22	0.24	1160
Ukraine	0.41	0.45	0.42	730
Vietnam	0.37	0.35	0.38	1394

Note. The sample includes 25- to 64-year-olds in self-employment or wage work.
Source: STEP Surveys (2014).

Looking at the distribution of men and women by the complexity of computer-related tasks that they engage in on the job (see Table 6), we find that in Armenia, Colombia, Georgia, Ukraine, and Vietnam, the largest proportions belong to the group using MS Office applications. The associated tasks are word processing, making presentations, and using basic graphic applications. In Bolivia and Kenya, the largest proportion of men and women are found using advanced programming tasks on the job (22 percent of men and 16 percent of women in Bolivia, and 14 percent of men and 8 percent of women in Kenya).

Table 6. Proportion of Men and Women by Complexity of Computer Use, Both on the Job and by Country

	Browser-based tasks		Basic MS Office tasks		Basic programming		Advanced programming	
	M	W	M	W	M	W	M	W
Armenia	0.06	0.02	0.20	0.28	0.09	0.08	0.07	0.09
Bolivia	0.02	0.01	0.14	0.12	0.06	0.06	0.22	0.16
Colombia	0.01	0.01	0.15	0.18	0.08	0.11	0.10	0.11
Georgia	0.04	0.04	0.15	0.27	0.10	0.13	0.11	0.11
Kenya	0.01	0.01	0.05	0.06	0.08	0.06	0.14	0.08
Ukraine	0.04	0.03	0.16	0.20	0.15	0.17	0.07	0.05
Vietnam	0.04	0.01	0.15	0.18	0.06	0.05	0.13	0.10

Note. The sample includes 25- to 64-year-olds, in wage work or self-employment, using computers on the job. Highlighted cells indicate statistically significant differences between men and women.
Source: STEP Surveys (2014).

With regard to noncognitive skills, we find limited variation among men and women across average scores on the Big Five personality traits, grit, and decision-making. The average scores and standard deviations are presented in Table 7. While there are some differences in average scores across countries, the differences between men and women within countries is small. However, these seemingly small differences are statistically significant in several cases. For instance, in the ECA countries, we find that men and women show significant differences with regard to conscientiousness (women show higher average scores), extraversion (women score higher), and emotional stability (women's scores are higher in Armenia and Georgia but not in Ukraine). Gender differences in emotional stability (or neuroticism) are observed across all seven countries, with women showing higher emotional stability scores than men. Scores on decision-making are significantly different in five of the seven countries (here again, women have higher average scores), while gender differences in "openness to experience" are observed only in Colombia, Kenya, and Vietnam, where men score higher than their female counterparts.

Table 7. Average Scores on Noncognitive Skills among Men and Women Ages 25 to 64, by Country

Panel 1

		Armenia		Bolivia		Colombia	
		Men	Women	Men	Women	Men	Women
Openness	Mean	3.23	3.21	3.22	3.16	3.22	3.17
	SD	0.49	0.50	0.56	0.61	0.50	0.53
Conscientiousness	Mean	3.23	3.26	3.18	3.19	3.32	3.34
	SD	0.50	0.49	0.50	0.51	0.53	0.48
Extraversion	Mean	2.98	3.03	3.00	2.88	3.09	2.94
	SD	0.54	0.59	0.70	0.73	0.64	0.69
Agreeableness	Mean	3.20	3.27	3.08	3.18	3.26	3.26
	SD	0.51	0.54	0.61	0.66	0.53	0.57
Emotional	Mean	2.44	2.26	2.62	2.31	2.78	2.33
stability	SD	0.61	0.61	0.64	0.69	0.70	0.69
Grit	Mean	3.15	3.15	3.04	3.03	3.08	3.05
	SD	0.57	0.57	0.63	0.65	0.56	0.58
Decision-making	Mean	3.20	3.19	3.04	3.07	3.02	3.17
	SD	0.52	0.55	0.63	0.64	0.62	0.58

Panel 2

		Georgia		Kenya	
		Men	Women	Men	Women
Openness	Mean	2.92	2.98	3.02	2.93
	SD	0.57	0.50	0.58	0.56
Conscientiousness	Mean	3.09	3.19	3.26	3.21
	SD	0.57	0.51	0.50	0.50
Extraversion	Mean	2.47	2.54	2.85	2.83
	SD	0.51	0.52	0.61	0.58
Agreeableness	Mean	3.13	3.18	2.88	2.87
	SD	0.55	0.52	0.57	0.54
Emotional	Mean	2.63	2.51	2.71	2.68
stability	SD	0.65	0.70	0.49	0.47
Grit	Mean	2.78	2.79	2.74	2.67
	SD	0.62	0.59	0.61	0.58
Decision-making	Mean	3.27	3.39	3.16	3.14
	SD	0.50	0.45	0.52	0.51

Panel 3

		Ukraine		Vietnam	
		Men	Women	Men	Women
Openness	Mean	3.02	3.10	2.90	2.70
	SD	0.50	0.59	0.60	0.62
Conscientiousness	Mean	2.93	3.09	2.86	2.79
	SD	0.45	0.54	0.50	0.49
Extraversion	Mean	2.49	2.76	2.69	2.74
	SD	0.53	0.64	0.48	0.53
Agreeableness	Mean	2.81	2.98	3.02	3.01
	SD	0.54	0.64	0.52	0.52
Emotional	Mean	2.77	2.40	3.07	2.74
stability	SD	0.53	0.71	0.52	0.54
Grit	Mean	2.79	2.78	2.80	2.75
	SD	0.56	0.67	0.54	0.49
Decision-making	Mean	3.02	3.20	2.91	2.87
	SD	0.48	0.61	0.61	0.60

Note. Noncognitive skills are self-reported. Each scale consists of 3 to 5 items scored on a 4-point scale from “Almost never” to “Almost always.” Highlighted cells indicate statistically significant differences between scores for men and women. The sample includes 25- to 64-year-olds in self-employment or wage work.
Source: STEP Surveys (2014).

Table A1 in the appendix presents descriptive statistics for the control variables used in the analysis. The men and women in our sample average around 40 years of age—the women are slightly younger, except in Armenia and Georgia. With regard to the distribution of men and women across three broad groups of occupations—*high-skilled* white-collar jobs, *low-skilled* white-collar jobs, and blue-collar jobs—we find that a larger proportion of men than women report working in blue-collar jobs. In Colombia and Ukraine, about 50 percent of the male sample is in blue-collar occupations. The distribution of men and women in white-collar jobs varies by country. In Armenia, Georgia, and Ukraine, a larger proportion of men and women are in *high-skilled* white-collar occupations than in *low-skilled* white-collar occupations. In Colombia, Kenya, and Vietnam, we find that a larger share of men and women are in *low-skilled* white-collar jobs than in *high-skilled* white-collar jobs.

V. Results

We begin by reporting findings from the mean decomposition analysis for two sets of equations: one set without controlling for occupation and the other with occupation controls added. Assuming that there is occupational segregation in our sample of countries, the first specification without occupational controls provides the "true" gender wage gap. When controlling for occupation, we expect that occupation partially mediates the relationship between skills and earnings. As mentioned above, we use the Heckman selection correction method for these mean decompositions. Results are reported by country. Then, we discuss results from the quantile-based decomposition analysis separately for each country in our sample.

Mean Decomposition Analysis with Selection Correction

In order to decompose the wage gap between men and women into the part explained by observed differences in characteristics and the returns to these characteristics, we begin with mean decompositions using the pooled method from Neumark (1988) and Heckman's selection correction method.[15] The contributions to the gender wage gap of observed characteristics (experience and type of employment) and schooling are estimated first. Building on this model, we subsequently add skills measures in four separate steps. The results are reported in Table 8. Panel A of Table 8 shows results when schooling is included in the model, controlling for potential experience and type of employment. In Panel B we add noncognitive skills. Cognitive skills as measured by reading proficiency scores and complexity of computer use on the job are added in

[15] The decomposition was carried out with and without selection correction. The latter results are not shown in the paper but are discussed in the Results section and are available upon request.

Panels C and D, respectively. Detailed results for schooling and skills in each panel are presented in Table A2 in the Appendix.

Table 8. Mean Decomposition Estimates with Selection Correction –- Excluding Occupation Controls

Panel A: Controls and schooling

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.688	0.094	0.594
	0.162	*0.047*	*0.153*
Colombia	-0.106	0.017	-0.123
	0.187	*0.033*	*0.184*
Armenia	0.181	0.002	0.179
	0.190	*0.020*	*0.190*
Georgia	0.996	-0.027	1.023
	0.354	*0.035*	*0.352*
Ukraine	0.444	-0.034	0.478
	0.052	*0.022*	*0.176*
Vietnam	0.077	0.054	0.023
	0.180	*0.024*	*0.109*
Kenya	-0.294	0.179	-0.474
	0.174	*0.043*	*0.168*

Panel B: Adding noncognitive skills

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.745	0.126	0.619
	0.208	*0.049*	*0.194*
Colombia	-0.092	0.032	-0.124
	0.173	*0.040*	*0.164*
Armenia	0.219	0.013	0.205
	0.276	*0.024*	*0.275*
Georgia	1.074	-0.028	1.102
	0.291	*0.038*	*0.286*
Ukraine	0.116	0.015	0.101
	0.126	*0.031*	*0.117*
Vietnam	0.066	0.115	-0.049
	0.097	*0.027*	*0.098*
Kenya	-0.217	0.178	-0.394
	0.308	*0.044*	*0.304*

Panel C: Adding cognitive skills (reading proficiency scores)

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.725	0.119	0.607
	0.205	*0.051*	*0.190*
Colombia	-0.087	0.032	-0.119
	0.180	*0.040*	*0.171*
Armenia	0.171	0.016	0.154
	0.290	*0.024*	*0.289*
Georgia	1.129	-0.035	1.164
	0.306	*0.039*	*0.302*
Ukraine	0.118	0.010	0.108
	0.126	*0.030*	*0.117*
Vietnam	0.064	0.116	-0.052
	0.100	*0.028*	*0.101*
Kenya	-0.063	0.179	-0.243
	0.438	*0.045*	*0.434*

Panel D: Adding cognitive skills (complexity of computer use at work)

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.648	0.129	0.520
	0.338	*0.053*	*0.329*
Colombia	-0.028	0.006	-0.034
	0.173	*0.043*	*0.165*
Armenia	0.224	0.016	0.208
	0.273	*0.027*	*0.271*
Georgia	0.950	-0.066	1.016
	0.274	*0.044*	*0.269*
Ukraine	0.144	-0.001	0.144
	0.137	*0.031*	*0.128*
Vietnam	0.066	0.107	-0.041
	0.097	*0.028*	*0.099*
Kenya	0.150	0.192	-0.042
	0.210	*0.049*	*0.201*

Note: The dependent variable is the log hourly earnings. Controls include potential experience, the quadratic of experience, and type of employment. The sample includes 25- to 64-year-old women in self-employment or wage work. Noncognitive skill scores and reading proficiency scores are standardized with mean 0 and SD = 1. Binary variables indicate complexity of computer use at work where the reference category is ‘No computer use on the job’. Highlighted cells indicate statistical significance at the 1% level or lower.
Source: STEP Surveys (2014).

We find that with schooling, controlling for experience and type of employment, the difference in male-female earnings tips in favor of males in Bolivia, Georgia, and Ukraine (the total earnings difference ranges from 0.44 in Colombia to 0.99 in Georgia). Without selection correction, however, we find wages favoring males across all countries with differences ranging from 0.15 to 0.45. Differences in educational attainment between men and women explain about 13 percent of the earnings gap in Bolivia and a staggering 70 percent of the earnings differential in Vietnam. In the ECA countries (Armenia, Georgia and Ukraine) we find that schooling does not explain differentials in the wages of men and women. This follows from the high average educational attainment among men and women in these countries (see Table 3).

In Panel B, the addition of noncognitive skills scores increases the total difference in the earnings of men and women in Bolivia and Georgia. Differences in men and women's noncognitive skills (emotional stability, specifically) accounts for an additional 3 percent of the wage gap in Bolivia, controlling for schooling and other observed characteristics. The role of noncognitive skills in Ukraine indicates that differences in personality traits (specifically, extraversion, emotional stability, and conscientiousness) are associated with gender differences in earnings. In Vietnam, noncognitive skills over-explain the wage gap, as seen in Panel A of Table 8.

The role of cognitive skills in explaining the gender wage gap, controlling for experience, education, and personality, is examined using reading proficiency scores (Panel C, Table 8) and computer use on the job (Panel D, Table 8). For reading proficiency scores we find that the wage gap, although still favoring males, is slightly smaller in Bolivia. The differences in cognitive skill endowments are significant in Bolivia, Vietnam, and Kenya but do not significantly explain the gender wage gaps in these countries over and above schooling and noncognitive skills. In contrast to these findings, Nordman et al. (2014) found that adding cognitive skills to the model reduces the unexplained portion of the wage gap by 2 percent in Bangladesh. The measure of cognitive skills used in their study is self-reported, and not a direct assessment of reading proficiency skills like the one available in the STEP data.

For our second measure of cognitive skills—complexity of computer use at work—we find that the estimated wage gap shrinks significantly in Bolivia and Georgia but increases in Armenia and Kenya when computer skills are added to the model. The addition of computer skills, along with schooling, noncognitive skills, and reading proficiency scores, explains an additional 3 percent of the unexplained wage gap in Bolivia but shows no effect in other countries.

At each stage of the estimation we find substantial differences in the gender wage gap when comparing estimates corrected for selection bias with uncorrected estimates across most countries. Correcting for selection increases the estimated wage gap across all specifications in Bolivia and Georgia, whereas in the other countries it reduces the gap.

Next, the results presented above are compared to estimates where dummy variables for occupation are included in the specification. Two binary variables defining broad occupational groups are added: for high-skill white-collar occupations and for low-skill white-collar occupations. The reference category is blue-collar occupations. This specification allows us to explore the role of skills in the sorting of men and women into different occupations. We present these results in Table 9. These results, like the ones reported above, correct for selection bias.[16] It must be noted that results for Armenia are not reported in Table 9 as the small sample size does not support reliable estimates. The panels in Table 9 are as specified—Panel A includes control variables (including occupation dummies) and schooling, followed by the addition of noncognitive skills in Panel B and cognitive skills in Panels C and D. Detailed estimates are presented in Table A3 in the Appendix.

Table 9. Mean Decomposition Estimates with Selection Correction -- Including Occupation Controls

Panel A: Controls and schooling

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.635	0.091	0.544
	0.394	*0.062*	*0.385*
Colombia	0.293	0.013	0.280
	0.129	*0.036*	*0.123*
Georgia	0.854	0.060	0.795
	0.448	*0.047*	*0.445*
Ukraine	0.270	0.016	0.254
	0.524	*0.030*	*0.526*
Vietnam	0.070	0.032	0.038
	0.107	*0.027*	*0.107*
Kenya	-0.254	0.137	-0.391
	0.257	*0.045*	*0.250*

[16] Uncorrected estimates are available upon request.

Panel B: Adding noncognitive skills

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.652	0.116	0.536
	0.207	*0.063*	*0.193*
Colombia	0.298	0.034	0.264
	0.132	*0.042*	*0.121*
Georgia	1.053	0.065	0.989
	0.404	0.048	0.397
Ukraine	0.107	0.057	0.050
	0.122	*0.033*	*0.115*
Vietnam	0.067	0.093	-0.026
	0.093	*0.030*	*0.097*
Kenya	0.097	0.139	-0.042
	0.300	*0.046*	*0.292*

Panel C: Adding cognitive skills (reading proficiency scores)

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.712	0.113	0.599
	0.208	*0.063*	*0.193*
Colombia	0.292	0.032	0.259
	0.146	*0.042*	*0.136*
Georgia	1.131	0.061	1.070
	0.357	*0.049*	*0.350*
Ukraine	0.098	0.053	0.045
	0.117	*0.033*	*0.109*
Vietnam	0.064	0.094	-0.029
	0.096	*0.030*	*0.100*
Kenya	0.091	0.140	-0.048
	0.271	*0.047*	*0.264*

Panel D: Adding cognitive skills (complexity of computer use at work)

	Total Difference	Difference in endowments	Difference in coefficients
Bolivia	0.709	0.136	0.573
	0.213	*0.063*	*0.200*
Colombia	0.298	0.020	0.278
	0.110	*0.044*	*0.097*
Georgia	0.906	0.049	0.857
	0.330	*0.051*	*0.323*
Ukraine	0.104	0.048	0.056

	0.114	*0.034*	*0.106*
Vietnam	0.066	0.095	-0.029
	0.095	*0.031*	*0.099*
Kenya	0.177	0.164	0.013
	0.186	*0.050*	*0.175*

Controlling for occupation in the wage models reveals interesting patterns in the decompositions as compared to those reported in Table 8. We find that accounting for experience, type of employment and occupational group, the gender wage gap in Colombia is now statistically significant and favors males (0.30). In Bolivia and Ukraine, however, the inclusion of occupation controls renders male-female differences in wages insignificant and smaller in magnitude.

Compared to the previous specification, with occupation and other controls in the model, differences in educational endowments are significant only in Kenya and favor women. We also find that when occupation is included in the model, the proportion of the gender wage gap explained by differences in schooling goes down (by about 2 percent) in Kenya, Colombia, Bolivia, and Vietnam. We also find significant effects for low-skill white-collar occupations, favoring men, in Ukraine and Georgia, controlling for schooling, potential experience, and type of employment.

When noncognitive skills are added to the model, we find that the differences between the earnings of men and women increase slightly in Bolivia, Ukraine, Vietnam, Georgia and Kenya. The difference in noncognitive skills endowments between men and women, controlling for occupation, are statistically significant in Bolivia and Vietnam. In Bolivia, emotional stability explains about 4 percent of the gender wage gap, and in Vietnam openness to experience and emotional stability matter. We also find significant effects for low-skill white-collar occupations in Ukraine, Georgia, and Vietnam, even after noncognitive skills are included in the model. Schooling continues to explain the bulk of the gender wage gaps in Vietnam but is no longer significant in other countries.

With regard to cognitive skills, although we note differences in the role of reading proficiency scores depending on whether occupation is accounted for, the addition of cognitive skills beyond schooling and noncognitive skills does not substantially explain the wage gap. The effect of personality continues to be significant in Vietnam, and the role of low-skill white-collar occupations continues to matter in Ukraine, Georgia, and Vietnam. Differences in educational attainment significantly explain the gender wage gap in Vietnam and Kenya.

The inclusion of complexity of computer use increases differences in earnings between men and women (favoring men) in Ukraine, Georgia, and Kenya. We find a small significant effect of computer skills favoring women in Georgia and men in Kenya. In this fully specified model we find that belonging to low-skill white-collar occupations continues to favor men in Bolivia, Ukraine, Georgia, and Vietnam. Further, schooling plays a substantial and significant role in explaining the gender wage gap in Vietnam and Kenya. With regard to noncognitive skills, we see that in Vietnam, when all other observed characteristics and skills are accounted for, openness to experience and emotional stability matter for earnings.

Overall, we find evidence for the role of noncognitive skills in Ukraine and Vietnam and for the role of cognitive skills in Georgia and Kenya in explaining earnings differences between men and women.

Quantile Decomposition Analysis

Given our findings from the descriptive analysis, we also estimate quantile regression-based decompositions using the male coefficients, implying the effect of earnings for women if they had been paid like men. We estimate log earnings at the 10th, 30th, 50th, 70th, and 90th percentiles separately for each country. Selected results are reported in Table 10, and detailed results are included in Tables A.4 through A.10 in the Appendix.[17]

Looking at Table 10, our findings for the differences in earnings in each country in turn support some of the findings from the descriptive analysis, namely the "sticky floor" pattern in Bolivia, Colombia, Kenya, and Vietnam, where the wage gaps are higher at the bottom of the wage distribution, and the "glass ceiling" effect in Armenia, Georgia, and Ukraine, where the wage gaps are higher at higher percentiles of the wage distribution. These patterns are also evident in the coefficient estimates in Appendix Tables A.4 through A.10. The share of the coefficients in countries depicting the sticky floor phenomenon decreases from the bottom to the top of the distribution, while in countries with the glass ceiling pattern the coefficients go up as one moves along the wage distribution.

The three columns in Table 10 show an estimate of the conditional wage gap and the proportion explained by differences in observed endowments at the 10th, 50th, and 90th percentiles under three conditions: when educational attainment, potential experience, and occupational controls are used; when reading proficiency scores are added to the model with controls and

[17] In the Appendix, the first column in Tables A.4 – A.10 ("Difference") shows the wage gap, the second column ("Characteristics") indicates the contribution of male and female differences in endowments such as schooling and skills, and the third column ("Coefficients") shows the proportion unexplained by differences in the characteristics of men and women. Panel A includes the usual control variables. In Panel B we add educational attainment, followed by reading proficiency scores in Panel C, computer skills in Panel D, and noncognitive skills scores in Panel E.

schooling; and when noncognitive skills are added to the model, including all controls, schooling, and cognitive skills.

In the case of Armenia, we find that under the three conditions presented, the unexplained portion of the wage gap declines from 0.81 to 0.69 for those at the 10th percentile when education and skills measures are added to the model. Schooling explains about 9 percent of the wage gap, over and above what is explained by potential experience and occupational status (about 20 percent). There is no change when cognitive and noncognitive skills are added to the model.

We find a greater reduction in the unexplained portion of the gap in Bolivia—over 30 percent—when all of the relevant variables are included in the model. Schooling and our control variables account for about 12 percent of the gap at the 10th percentile, 18 percent of it at the 50th percentile, and 25 percent of it at the 90th percentile. Cognitive skills explain an additional 10 percent of the wage gap at the 10th percentile and about 5 percent of it at the 50th percentile. When noncognitive skills are added to the model, the unexplained gap further decreases by 12 percent at the bottom of the wage distribution and by about 10 percent at the median and 90th percentile.

The wage gap in Kenya is about 0.34 at the 10th percentile and is not significant at either the 50th or 90th percentile. As in Armenia, schooling explains most of the gender wage gap in our model (nearly 20 percent). The addition of noncognitive and cognitive skills does not further reduce the unexplained portion of the wage gap.

Similar results for schooling are observed in Vietnam, where the wage gap is highest at the bottom of the distribution. Differences in educational attainment explain about 14 percent of the wage gap at the 10th percentile, 18 percent of it at the median wage, and about 17 percent at the top end of the wage distribution. We find that cognitive skills matter for women at the 50th percentile and reduce the unexplained portion of the wage gap by 5 percent. We also find evidence for the role of noncognitive skills in explaining gender wage gaps in Vietnam. The reduction in the wage gap when noncognitive skills are added to the model is substantial. It ranges from 3 percent at the 10th percentile to 6 percent and 11 percent at the 50th and 90th percentiles, respectively.

Our results for Colombia, Georgia, and Ukraine are not in line with the findings for the countries noted above. We find some effect of schooling in reducing the unexplained portion of the gender earnings gap at the bottom of the wage distribution in Colombia (by 4 percent).

However, the addition of skills measures does not further explain male-female differences in wages.

Table 10. Quantile Decompositions of Log Wage Gaps

	Controls + Schooling		Adding Reading Scores		Adding Noncognitive skills	
Wage percentile	Wage Gap	Proportion explained by characteristics	Wage Gap	Proportion explained by characteristics	Wage Gap	Proportion explained by characteristics
ARMENIA						
10th	**0.363**	0.30	**0.359**	0.27	**0.358**	0.31
50th	**0.523**	0.12	**0.526**	0.13	**0.535**	0.17
90th	**0.522**	-0.10	**0.520**	-0.11	**0.525**	-0.05
BOLIVIA						
10th	**0.680**	0.12	**0.646**	0.23	**0.659**	0.35
50th	**0.459**	0.18	**0.449**	0.23	**0.469**	0.33
90th	**0.328**	0.25	**0.329**	0.26	**0.352**	0.36
COLOMBIA						
10th	**0.349**	0.10	**0.348**	0.10	**0.329**	-0.05
50th	**0.291**	0.00	**0.290**	-0.01	**0.300**	0.00
90th	**0.296**	-0.10	**0.297**	-0.09	**0.332**	-0.02
GEORGIA						
10th	0.312	0.22	0.327	0.17	**0.372**	0.20
50th	**0.392**	0.04	**0.385**	0.01	**0.384**	-0.04
90th	**0.434**	-0.11	**0.426**	-0.15	**0.388**	-0.21
KENYA						
10th	**0.341**	0.33	**0.357**	0.31	**0.360**	0.32
50th	0.154	0.88	0.165	0.87	0.144	1.12
90th	-0.011	-10.40	0.000	302.48	0.064	3.06
UKRAINE						
10th	0.051	2.25	0.027	2.48	0.045	1.45
50th	**0.355**	-0.01	**0.348**	-0.02	**0.363**	-0.09
90th	**0.441**	-0.06	**0.440**	-0.07	**0.414**	-0.09
VIETNAM						
10th	**0.373**	0.22	**0.369**	0.22	**0.392**	0.25
50th	**0.288**	0.23	**0.287**	0.28	**0.282**	0.34
90th	**0.203**	0.19	**0.197**	0.18	**0.203**	0.29

Note. Coefficients in bold face are significant at the 5% level or lower. The dependent variable is the log hourly earnings. Controls include potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

VI. Conclusions

In this paper we have used a unique set of surveys measuring cognitive and noncognitive skills in low- and middle-income countries to examine differences in earnings between men and women. Focusing on seven low- and middle-income countries (Armenia, Bolivia, Colombia, Georgia, Kenya, Ukraine, and Vietnam), our objective was to determine if these newly available skills measures could explain the gender wage gap beyond what is explained by traditional measures of schooling and experience. While gender wage discrimination has been extensively studied in various contexts, our use of measures capturing different dimensions of human capital extends what we know about the gender wage gap in developing contexts and contributes to our understanding of the role of cognitive and noncognitive skills in research related to labor market outcomes. The findings from this paper are summarized next.

Mean decompositions with and without occupation controls can be indicative of the role of sorting in earnings differences between men and women. Controlling for occupation, we find that in Vietnam, openness to experience and emotional stability are important factors in explaining gender wage gaps. Our decomposition results indicate that men receive a reward for scoring higher, on average, on openness and emotional stability traits. The sorting argument would suggest that men sort into occupations that require the appearance of more openness and emotional stability. Controlling for occupation, however, we can infer that sorting perhaps does not explain the entire difference between men's and women's returns to noncognitive skills in Vietnam. Mueller and Plug (2006) found similar results for men with lower agreeableness scores than women in the United States, and Nyhus and Pons (2005) found that emotional stability scores positively affect wage setting for women. Our mean decompositions also show some evidence for the influence of cognitive skills in Georgia and Kenya.

Findings from the quantile decompositions indicate that the wage gap follows a "sticky floor" pattern in the Latin American countries as well as Kenya and Vietnam but follows a "glass ceiling" effect in the ECA countries. Previous research has also found evidence for the glass ceiling effect in transitional economies, and this pattern has been observed in Vietnam (Pham and Reilly, 2007). Further, our results indicate that schooling matters, across countries, in explaining differences in earnings between men and women. In some countries, schooling explains a larger share of the wage gap at the top end of the wage distribution (Bolivia and Vietnam) while in others education and skills are found to matter more at the lower end of the wage distribution (Kenya and Armenia).

The results discussed here have some important implications. First, education remains a crucial building block for success in the labor market. While measures of cognitive and noncognitive skill add incremental predictive power, the bulk of the gender wage gap is explained by differences in educational attainment. Policy makers therefore need to focus on ensuring school completion and on improving the quality of learning outcomes in school.

Second, the role of noncognitive skills, although modest in explaining gender-based wage differences, is notable. In the absence of discrete measures of occupational characteristics and sample-size limitations, the results highlighted in this paper can be considered an upper-bound on the role of noncognitive skills in explaining gender differences in earnings. Using other measures of occupational characteristics will not only enable a better understanding of the role of sorting in male-female wage differences but also enable examination of the extent to which skills determine occupational segregation.

Third, based on the results we observe for cognitive skills associated with the use of computers and technology-driven shifts in the demand for skills, students must develop information and communication technology (ICT) skills to be successful in today's economy. Research shows that women are less likely to work in ICT occupations than men (World Bank, 2016). This is in part due to lower participation of girls in science, technology, engineering, and math (STEM) fields (Dasgupta and Stout, 2014; Smith, 2010). Policies and programs focusing on creating appropriate learning environments for girls' participation in STEM should be encouraged.

Fourth, our results show that a substantial portion of the wage gap (over 60 percent in most countries) remains unexplained after controlling for schooling and additional measures of cognitive and noncognitive skills. The literature discusses several other factors (sex segregation in occupations, women's nonrandom selection in fields of work, wage setting institutions, and so on) that are beyond the scope of this paper but must be explored in further research (Olivetti and Petrongolo, 2008; Terrell, 1992).

Finally, future research on this topic must replicate these analyses in the same and other contexts with larger sample sizes and more reliable measures of noncognitive skills in order to validate and extend the findings reported here.

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Appendix – Additional Tables and Figures

Table A.1. Means and Standard Deviations for Key Variables, by Country and Gender

Panel 1

	Armenia		Bolivia		Colombia		Georgia	
	Men	Women	Men	Women	Men	Women	Men	Women
Potential experience	23.69	23.14	22.48	22.90	22.66	23.01	20.00	20.61
	11.86	12.67	12.85	12.51	12.10	11.51	11.25	10.85
High-skill occupations	0.39	0.50	0.29	0.25	0.18	0.20	0.41	0.49
	0.47	0.52	0.45	0.44	0.39	0.40	0.48	0.51
Low-skill white-collar occupations	0.17	0.35	0.22	0.49	0.30	0.42	0.18	0.38
	0.37	0.49	0.41	0.51	0.46	0.49	0.37	0.50
Blue-collar occupations	0.44	0.15	0.49	0.269	0.51	0.37	0.42	0.13
	0.48	0.37	0.49	0.45	0.50	0.48	0.48	0.34
Number of children under 6 years	0.50	0.38	0.49	0.60	0.47	0.28	0.55	0.34
	0.78	0.71	0.76	0.94	0.73	0.52	0.82	0.62
Shocks								
	0.27	0.28	1.55	1.43	0.89	0.87	0.26	0.23
	0.58	0.68	1.67	1.66	1.21	1.14	0.60	0.59

Panel 2

	Kenya		Ukraine		Vietnam	
	Men	Women	Men	Women	Men	Women
Potential Experience	20.04	20.27	20.89	22.86	24.44	23.27
	11.32	11.41	9.44	11.86	11.59	11.32
High-skill occupations	0.22	0.18	0.41	0.53	0.26	0.27
	0.42	0.37	0.41	0.57	0.44	0.44
Low-skill white-collar occupations	0.49	0.64	0.12	0.25	0.34	0.48
	0.51	0.47	0.27	0.49	0.47	0.50
Blue-collar occupations	0.29	0.18	0.47	0.23	0.40	0.25
	0.46	0.38	0.41	0.48	0.49	0.44
Number of children	0.52	0.58	0.33	0.21	0.43	0.49
under 6 years	0.73	0.72	0.51	0.53	0.65	0.71
Shocks	1.08	0.96	0.29	0.26	0.53	0.49
	1.38	1.28	0.54	0.71	0.97	0.92

Note. The sample includes 25- to 64-year-olds in self-employment or wage work.
Source. STEP Household Surveys

Table A.2. Mean Decomposition (Neumark Method) of Log Wage Gaps with Selection Correction (excluding occupation controls)

Panel A: Schooling

	Bolivia	Colombia	Armenia	Georgia	Ukraine	Vietnam	Kenya
				Explained			
Controls	0.023	0.002	0.003	-0.006	-0.022	0.010	0.068
	0.019	*0.011*	*0.010*	*0.026*	*0.019*	*0.009*	*0.020*
Schooling	0.071	0.015	0.000	-0.021	-0.011	0.045	0.111
	0.043	*0.032*	*0.016*	*0.022*	*0.011*	*0.022*	*0.038*
				Unexplained			
Controls	-0.385	0.546	-0.073	0.119	-0.152	0.257	0.275
	0.320	*0.315*	*0.182*	*0.250*	*0.245*	*0.217*	*0.282*
Schooling	-0.413	0.064	-0.319	-0.183	-0.568	0.066	0.238
	0.260	*0.220*	*0.293*	*0.424*	*0.429*	*0.189*	*0.201*

Panel B: Adding Noncognitive Skills

	Bolivia	Colombia	Armenia	Georgia	Ukraine	Vietnam	Kenya
				Explained			
Controls	0.023	0.002	0.002	-0.007	-0.029	0.005	0.072
	0.020	*0.011*	*0.010*	*0.027*	*0.020*	*0.009*	*0.020*
Schooling	0.068	0.014	0.000	-0.020	-0.011	0.039	0.103
	0.042	*0.031*	*0.016*	*0.022*	*0.011*	*0.019*	*0.035*
Noncognitive skills	0.034	0.016	0.011	-0.001	0.055	0.071	0.003
	0.020	*0.021*	*0.012*	*0.017*	*0.024*	*0.018*	*0.011*
				Unexplained			
Controls	-0.336	0.586	-0.084	0.181	0.150	0.235	0.247
	0.337	*0.279*	*0.175*	*0.232*	*0.183*	*0.214*	*0.349*
Schooling	-0.357	0.045	-0.525	-0.340	-0.211	0.088	0.165
	0.274	*0.197*	*0.322*	*0.412*	*0.410*	*0.205*	*0.244*
Noncognitive skills	-0.031	-0.020	0.028	-0.042	-0.050	-0.027	-0.015
	0.027	*0.019*	*0.020*	*0.036*	*0.020*	*0.015*	*0.016*

Panel C: Adding Cognitive Skills (Reading proficiency scores)

	Bolivia	Colombia	Armenia	Georgia	Ukraine	Vietnam	Kenya
				Explained			
Controls	0.022	0.002	0.003	-0.007	-0.027	0.006	0.071
	0.020	*0.011*	*0.010*	*0.027*	*0.019*	*0.009*	*0.020*
Schooling	0.063	0.014	0.000	-0.018	-0.010	0.036	0.090
	0.039	*0.031*	*0.016*	*0.020*	*0.009*	*0.018*	*0.033*
Noncognitive skills	0.032	0.016	0.011	0.002	0.050	0.070	0.004
	0.019	*0.021*	*0.012*	*0.016*	*0.024*	*0.018*	*0.012*

	Bolivia	Colombia	Armenia	Georgia	Ukraine	Vietnam	Kenya
Cognitive skills	0.001	0.000	0.003	-0.012	-0.003	0.004	0.015
	0.007	*0.005*	*0.006*	*0.012*	*0.008*	*0.005*	*0.012*
			Unexplained				
Controls	-0.203	0.602	-0.074	0.208	0.107	0.223	0.133
	0.339	*0.279*	*0.175*	*0.234*	*0.181*	*0.214*	*0.423*
Schooling	-0.559	-0.058	-0.494	-0.234	-0.491	0.271	0.217
	0.292	*0.227*	*0.361*	*0.415*	*0.385*	*0.227*	*0.286*
Noncognitive skills	-0.034	-0.022	0.029	-0.051	-0.052	-0.026	-0.018
	0.027	*0.019*	*0.021*	*0.040*	*0.020*	*0.015*	*0.018*
Cognitive skills	-0.036	0.004	-0.002	-0.011	0.019	0.003	-0.005
	0.026	*0.008*	*0.005*	*0.011*	*0.011*	*0.008*	*0.006*

Panel D: Adding Cognitive Skills (Computer use)

	Bolivia	Colombia	Armenia	Georgia	Ukraine	Vietnam	Kenya
			Explained				
Controls	0.014	0.001	0.004	-0.012	-0.028	0.001	0.042
	0.017	*0.010*	*0.010*	*0.022*	*0.019*	*0.009*	*0.017*
Schooling	0.050	0.010	0.001	-0.011	-0.008	0.026	0.046
	0.032	*0.022*	*0.012*	*0.013*	*0.008*	*0.013*	*0.020*
Noncognitive skills	0.026	0.012	0.011	0.016	0.050	0.068	0.005
	0.019	*0.021*	*0.012*	*0.015*	*0.024*	*0.018*	*0.011*
Cognitive Skills	0.039	-0.018	-0.001	-0.059	-0.015	0.012	0.100
	0.024	*0.021*	*0.013*	*0.030*	*0.013*	*0.012*	*0.033*
			Unexplained				
Controls	-0.205	0.524	-0.152	0.303	0.123	0.100	-0.041
	0.342	*0.256*	*0.167*	*0.204*	*0.189*	*0.221*	*0.268*
Schooling	-0.514	0.057	-0.386	-0.345	-0.235	0.330	-0.001
	0.358	*0.246*	*0.369*	*0.401*	*0.371*	*0.249*	*0.203*
Noncognitive skills	-0.034	-0.023	0.031	-0.040	-0.058	-0.025	-0.025
	0.029	*0.019*	*0.020*	*0.035*	*0.021*	*0.015*	*0.016*
Cognitive skills	-0.090	-0.077	-0.074	0.069	-0.041	-0.066	-0.009
	0.098	*0.053*	*0.048*	*0.059*	*0.047*	*0.046*	*0.036*

Note. The dependent variable is the log of hourly earnings. Controls include potential experience, squared term for experience, and type of employment. Reading proficiency scores and noncognitive skills scores are standardized with mean=0 and SD=1. The reference category for binary variables indicating complexity of computer use at work is ‘No computer use on the job’. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work. Highlighted cells indicate statistical significance at the 1% level or lower.
Source: STEP Surveys (2014).

Table A.3. Mean Decomposition (Neumark Method) of Log Wage Gaps with Selection Correction (including occupation controls)

Panel A: Schooling

	Bolivia	Colombia	Georgia	Ukraine	Vietnam	Kenya
			Explained			
Controls	0.037	0.001	0.078	0.023	-0.006	0.055
	0.043	*0.019*	*0.042*	*0.028*	*0.015*	*0.028*
Schooling	0.055	0.012	-0.018	-0.007	0.038	0.082
	0.035	*0.026*	*0.019*	*0.009*	*0.019*	*0.029*
			Unexplained			
Controls	-0.196	0.642	0.081	0.015	0.037	0.079
	0.479	*0.277*	*0.281*	*0.536*	*0.222*	*0.336*
Schooling	-0.354	0.381	-0.530	-0.739	0.167	0.287
	0.395	*0.226*	*0.458*	*0.691*	*0.224*	*0.236*

Panel B: Adding noncognitive skills

	Bolivia	Colombia	Georgia	Ukraine	Vietnam	Kenya
			Explained			
Controls	0.034	0.001	0.079	0.016	-0.012	0.060
	0.042	*0.019*	0.043	*0.027*	*0.015*	*0.028*
Schooling	0.052	0.011	-0.018	-0.007	0.033	0.076
	0.033	*0.024*	0.020	*0.009*	*0.016*	*0.027*
Noncognitive skills	0.031	0.021	0.004	0.048	0.073	0.003
	0.018	*0.022*	0.016	*0.024*	*0.018*	*0.010*
			Unexplained			
Controls	-0.129	0.697	0.193	0.166	0.077	-0.184
	0.359	*0.275*	0.280	*0.193*	*0.217*	*0.372*
Schooling	-0.329	0.292	-0.577	-0.645	0.143	0.079
	0.289	*0.204*	0.441	*0.398*	*0.238*	*0.223*
Noncognitive skills	-0.017	-0.036	-0.050	-0.042	-0.033	-0.021
	0.028	*0.019*	0.042	*0.021*	*0.015*	*0.017*

Panel C: Adding cognitive skills (Reading proficiency scores)

	Bolivia	Colombia	Georgia	Ukraine	Vietnam	Kenya
			Explained			
Controls	0.034	0.001	0.082	0.020	-0.012	0.059
	0.042	*0.019*	*0.042*	*0.027*	*0.015*	*0.027*
Schooling	0.049	0.012	-0.017	-0.007	0.029	0.067
	0.032	*0.025*	*0.018*	*0.008*	*0.015*	*0.026*
Noncognitive skills	0.029	0.021	0.006	0.043	0.071	0.003
	0.018	*0.022*	*0.015*	*0.024*	*0.017*	*0.010*

Cognitive skills	0.001	-0.002	-0.010	-0.004	0.005	0.011
	0.005	*0.005*	*0.011*	*0.007*	*0.005*	*0.011*
			Unexplained			
Controls	-0.110	0.687	0.200	0.108	0.064	-0.141
	0.372	*0.277*	*0.285*	*0.188*	*0.217*	*0.356*
Schooling	-0.371	0.228	-0.494	-0.810	0.333	0.231
	0.293	*0.222*	*0.433*	*0.390*	*0.260*	*0.238*
Noncognitive skills	-0.024	-0.036	-0.060	-0.043	-0.032	-0.019
	0.029	*0.019*	*0.040*	*0.020*	*0.015*	*0.016*
Cognitive skills	-0.025	0.003	-0.010	0.014	0.004	-0.005
	0.025	*0.006*	*0.011*	*0.010*	*0.008*	*0.006*

Panel D: Adding cognitive skills (Computer use)

	Bolivia	Colombia	Georgia	Ukraine	Vietnam	Kenya
			Explained			
Controls	0.040	0.013	0.106	0.036	-0.012	0.033
	0.040	*0.018*	*0.039*	*0.027*	*0.014*	*0.021*
Schooling	0.043	0.009	-0.012	-0.006	0.024	0.041
	0.028	*0.018*	*0.013*	*0.007*	*0.012*	*0.018*
Noncognitive skills	0.025	0.018	0.015	0.040	0.070	0.004
	0.018	*0.021*	*0.014*	*0.024*	*0.017*	*0.010*
Cognitive skills	0.029	-0.020	-0.060	-0.023	0.012	0.086
	0.020	*0.021*	*0.031*	*0.015*	*0.012*	*0.030*
			Unexplained			
Controls	-0.061	0.679	0.223	0.169	0.038	-0.213
	0.380	*0.253*	*0.267*	*0.195*	*0.224*	*0.300*
Schooling	-0.406	0.296	-0.378	-0.576	0.371	0.071
	0.322	*0.235*	*0.401*	*0.357*	*0.261*	*0.201*
Noncognitive skills	-0.021	-0.034	-0.039	-0.045	-0.031	-0.024
	0.032	*0.018*	*0.038*	*0.020*	*0.015*	*0.015*
Cognitive skills	-0.067	-0.066	0.031	-0.075	-0.072	-0.004
	0.089	*0.059*	*0.068*	*0.053*	*0.046*	*0.040*

Table A.4. Quantile Decompositions of Log Wage Gaps – Armenia

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	**0.356**	0.065	**0.291**
	(0.063)	(0.055)	(0.063)
0.3	**0.474**	0.071	**0.403**
	(0.072)	(0.061)	(0.076)
0.5	**0.510**	0.045	**0.465**
	(0.055)	(0.040)	(0.059)
0.7	**0.545**	0.001	**0.545**
	(0.055)	(0.035)	(0.060)
0.9	**0.491**	-0.106	**0.597**
	(0.072)	(0.052)	(0.100)
Panel B: Adding schooling			
0.1	**0.363**	0.109	**0.254**
	(0.073)	(0.053)	(0.082)
0.3	**0.475**	0.089	**0.386**
	(0.068)	(0.048)	(0.068)
0.5	**0.523**	0.062	**0.461**
	(0.059)	(0.040)	(0.060)
0.7	**0.534**	0.018	**0.516**
	(0.055)	(0.039)	(0.064)
0.9	**0.522**	-0.049	**0.571**
	(0.087)	(0.051)	(0.098)
Panel C: Adding reading proficiency scores			
0.1	**0.359**	0.096	**0.264**
	(0.072)	(0.055)	(0.080)
0.3	**0.476**	0.091	**0.385**
	(0.065)	(0.051)	(0.069)
0.5	**0.526**	0.066	**0.460**
	(0.062)	(0.042)	(0.064)
0.7	**0.533**	0.019	**0.514**
	(0.059)	(0.039)	(0.068)
0.9	**0.520**	-0.039	**0.559**
	(0.085)	(0.045)	(0.098)
Panel D: Adding computer skills on the job			
0.1	**0.361**	0.092	**0.269**
	(0.069)	(0.058)	(0.082)
0.3	**0.475**	0.097	**0.377**
	(0.069)	(0.052)	(0.072)
0.5	**0.544**	0.081	**0.463**
	(0.058)	(0.045)	(0.062)

0.7	**0.547**	0.037	**0.510**
	(0.057)	(0.044	(0.066)
0.9	**0.511**	-0.026	**0.537**
	(0.080)	(0.050)	(0.096)
Panel D: Adding noncognitive traits scores			
0.1	**0.358**	0.110	**0.248**
	(0.071)	(0.067)	(0.092)
0.3	**0.465**	**0.113**	**0.351**
	(0.069)	(0.056)	(0.074)
0.5	**0.535**	0.092	**0.443**
	(0.062)	(0.050)	(0.071)
0.7	**0.536**	0.030	**0.505**
	(0.058)	(0.048)	(0.072)
0.9	**0.525**	-0.028	**0.553**
	(0.081)	(0.054)	(0.094)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

Table A.5. Quantile Decompositions of Log Wage Gaps – Bolivia

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	**0.684**	0.091	**0.593**
	(0.129)	(0.070)	(0.145)
0.3	**0.510**	0.017	**0.493**
	(0.092)	(0.042)	(0.099)
0.5	**0.507**	0.009	**0.498**
	(0.079)	(0.045)	(0.089)
0.7	**0.395**	0.030	**0.365**
	(0.097)	(0.039)	(0.093)
0.9	0.265	0.059	0.207
	(0.131)	(0.074)	(0.129)
Panel B: Adding schooling			
0.1	**0.680**	0.083	**0.597**
	(0.135)	(0.064)	(0.146)
0.3	**0.532**	0.097	**0.435**
	(0.084)	(0.058)	(0.096)
0.5	**0.459**	0.085	**0.375**
	(0.087)	(0.062)	(0.085)
0.7	**0.403**	0.107	**0.296**

	(0.104)	(0.061)	(0.084)
0.9	**0.328**	0.083	0.244
	(0.136)	(0.072)	(0.124)
Panel C: Adding reading proficiency scores			
0.1	**0.646**	**0.148**	**0.499**
	(0.135)	(0.071)	(0.153)
0.3	**0.541**	**0.114**	**0.427**
	(0.083)	(0.055)	(0.093)
0.5	**0.449**	0.102	**0.347**
	(0.086)	(0.055)	(0.087)
0.7	**0.418**	**0.105**	**0.313**
	(0.090)	(0.052)	(0.079)
0.9	**0.329**	0.087	**0.242**
	(0.118)	(0.065)	(0.112)
Panel D: Adding computer skills on the job			
0.1	**0.626**	**0.191**	**0.434**
	(0.134)	(0.076)	(0.159)
0.3	**0.556**	**0.152**	**0.404**
	(0.083)	(0.060)	(0.099)
0.5	**0.478**	0.**153**	**0.325**
	(0.087)	(0.060)	(0.093)
0.7	**0.390**	**0.128**	**0.261**
	(0.091)	(0.058)	(0.087)
0.9	**0.343**	0.092	**0.251**
	(0.120)	(0.067)	(0.114)
Panel E: Adding noncognitive traits scores			
0.1	**0.659**	**0.230**	**0.429**
	(0.132)	(0.084)	(0.156)
0.3	**0.546**	**0.141**	**0.405**
	(0.080)	0.062)	(0.095)
0.5	**0.469**	**0.154**	**0.316**
	(0.083)	(0.064)	(0.089)
0.7	**0.392**	**0.143**	**0.249**
	(0.093)	(0.062)	(0.087)
0.9	**0.352**	0.128	**0.223**
	(0.121)	(0.067)	(0.108)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

Table A.6. Quantile Decompositions of Log Wage Gaps – Colombia

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	**0.384**	0.002	**0.382**
	(0.113)	(0.032)	(0.114)
0.3	**0.323**	-0.017	**0.340**
	(0.052)	(0.017)	(0.049)
0.5	**0.257**	-0.013	**0.270**
	(0.042)	(0.018)	(0.042)
0.7	**0.343**	-0.022	**0.366**
	(0.061)	(0.024)	(0.054)
0.9	0.299	-0.033	**0.332**
	(0.117)	(0.043)	(0.109)
Panel B: Adding schooling			
0.1	**0.349**	0.035	**0.313**
	(0.107)	(0.038)	(0.116)
0.3	**0.359**	0.010	**0.350**
	(0.050)	(0.021)	(0.050)
0.5	**0.291**	-0.001	**0.292**
	(0.046)	(0.020)	(0.042)
0.7	**0.287**	-0.003	**0.290**
	(0.066)	(0.024)	(0.055)
0.9	**0.296**	-0.030	**0.327**
	(0.113)	(0.037)	(0.102)
panel c: adding reading proficiency scores			
0.1	**0.348**	0.036	**0.312**
	(0.104)	(0.043)	(0.108)
0.3	**0.356**	0.010	**0.346**
	(0.050)	(0.027)	(0.050)
0.5	**0.290**	-0.002	**0.292**
	(0.044)	(0.023)	(0.041)
0.7	**0.289**	-0.004	**0.293**
	(0.060)	(0.027)	(0.053)
0.9	**0.297**	-0.026	**0.323**
	(0.101)	(0.043)	(0.094)
Panel D: Adding computer skills on the job			
0.1	**0.358**	0.031	**0.326**
	(0.112)	(0.041)	(0.115)
0.3	**0.367**	0.008	**0.359**
	(0.050)	(0.024)	(0.050)
0.5	**0.288**	0.001	**0.288**
	(0.045)	(0.024)	(0.040)

0.7	**0.280**	0.004	**0.276**
	(0.065)	(0.031)	(0.054)
0.9	**0.327**	-0.013	**0.340**
	(0.097)	(0.047)	(0.088)
Panel E: Adding noncognitive traits scores			
0.1	**0.329**	-0.018	**0.347**
	(0.101)	(0.052)	(0.104)
0.3	**0.356**	0.000	**0.356**
	(0.047)	(0.034)	(0.051)
0.5	**0.300**	0.000	**0.300**
	(0.043)	(0.030)	(0.042)
0.7	**0.276**	0.003	**0.273**
	(0.063)	(0.035)	(0.055)
0.9	**0.332**	-0.007	**0.339**
	(0.097)	(0.053)	(0.091)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

Table A.7. Quantile Decompositions of Log Wage Gaps – Georgia

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	0.352	0.079	0.273
	(0.156)	(0.087)	(0.166)
0.3	**0.438**	0.057	**0.380**
	(0.083)	(0.058)	(0.100)
0.5	**0.387**	0.018	**0.369**
	(0.082)	(0.061)	(0.090)
0.7	**0.316**	-0.041	**0.357**
	(0.083)	(0.076)	(0.099)
0.9	**0.417**	-0.072	**0.489**
	(0.110)	(0.067)	(0.110)
Panel B: Adding schooling			
0.1	0.312	0.069	0.243
	(0.143)	(0.084)	(0.154)
0.3	**0.440**	0.064	**0.376**
	(0.093)	(0.053)	(0.099)
0.5	**0.392**	0.018	**0.375**
	(0.083)	(0.057)	(0.080)
0.7	**0.323**	-0.038	**0.362**

	(0.078)	(0.067	(0.093)
0.9	**0.434**	-0.047	**0.481**
	(0.105)	(0.052)	(0.119)
Panel C: Adding reading proficiency scores			
0.1	**0.327**	0.057	0.271
	(0.142)	(0.090)	(0.154)
0.3	**0.437**	0.054	**0.383**
	(0.083)	(0.056)	(0.092)
0.5	**0.385**	0.004	**0.381**
	(0.072)	(0.050)	(0.075)
0.7	**0.332**	-0.042	**0.374**
	(0.080)	(0.056)	(0.087)
0.9	**0.426**	-0.062	**0.488**
	(0.108)	(0.054)	(0.113)
Panel D: Adding computer skills on the job			
0.1	**0.316**	0.007	**0.309**
	(0.136)	(0.092)	(0.146)
0.3	**0.434**	0.006	**0.429**
	(0.086)	(0.066)	(0.093)
0.5	**0.393**	-0.029	**0.422**
	(0.077)	(0.061)	(0.076)
0.7	**0.346**	-0.083	**0.429**
	(0.086)	(0.067)	(0.085)
0.9	**0.415**	-0.094	**0.509**
	(0.110)	(0.071)	(0.113)
Panel E: Adding noncognitive traits scores			
0.1	**0.372**	0.073	**0.299**
	(0.137)	(0.088)	(0.149)
0.3	**0.413**	0.046	**0.367**
	(0.090)	(0.069)	(0.097)
0.5	**0.384**	-0.015	**0.400**
	(0.079)	(0.069)	(0.084)
0.7	**0.357**	-0.082	**0.439**
	(0.082)	(0.069)	(0.087)
0.9	**0.388**	-0.082	**0.470**
	(0.106)	(0.076)	(0.110)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

Table A.8. Quantile Decompositions of Log Wage Gaps – Kenya

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	**0.338**	0.048	**0.290**
	(0.104)	(0.026)	(0.098)
0.3	**0.250**	0.068	0.182
	(0.082)	(0.028)	(0.083)
0.5	**0.140**	0.075	0.065
	(0.073)	(0.032)	(0.073)
0.7	0.044	0.084	-0.041
	(0.079)	(0.043)	(0.085)
0.9	0.039	0.084	-0.045
	(0.081)	(0.041)	(0.074)
Panel B: Adding schooling			
0.1	**0.341**	0.112	0.229
	(0.108)	(0.047)	(0.110)
0.3	**0.245**	**0.152**	0.093
	(0.073)	(0.037)	(0.068)
0.5	0.154	**0.136**	0.018
	(0.070)	(0.038)	(0.063)
0.7	0.067	**0.136**	-0.069
	(0.079)	(0.044)	(0.073)
0.9	-0.011	0.114	-0.124
	(0.085)	(0.048)	(0.071)
Panel C: Adding reading proficiency scores			
0.1	**0.357**	**0.111**	**0.246**
	(0.100)	(0.046)	(0.110)
0.3	**0.228**	**0.154**	0.074
	(0.072)	(0.038)	(0.071)
0.5	**0.165**	**0.143**	0.022
	(0.073)	(0.039	(0.068)
0.7	0.070	**0.135**	-0.064
	(0.080)	(0.045)	(0.070)
0.9	0.000	**0.123**	-0.122
	(0.082)	(0.051)	(0.069)
Panel D: Adding computer skills on the job			
0.1	**0.367**	**0.099**	**0.268**
	(0.096)	(0.034)	(0.098)
0.3	**0.214**	**0.148**	0.066
	(0.067)	(0.036)	(0.064)
0.5	0.145	**0.151**	-0.006
	(0.075)	(0.040)	(0.067)

0.7	0.075	**0.198**	-0.123
	(0.082)	(0.055)	(0.064)
0.9	0.056	**0.198**	-0.141
	(0.087)	(0.067)	(0.065)
Panel E: Adding noncognitive traits scores			
0.1	**0.360**	**0.115**	**0.245**
	(0.097)	(0.039)	(0.100)
0.3	**0.230**	**0.158**	0.073
	(0.068)	(0.037)	(0.067)
0.5	0.144	**0.162**	-0.018
	(0.074)	(0.043)	(0.066)
0.7	0.073	**0.216**	-0.143
	(0.081)	(0.057)	(0.063)
0.9	0.064	**0.197**	-0.132
	(0.084)	(0.064)	(0.066)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

Table A.9. Quantile Decompositions of Log Wage Gaps – Ukraine

Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	0.049	0.117	-0.068
	(0.090)	(0.071)	(0.127)
0.3	**0.347**	0.023	**0.324**
	(0.054)	(0.033)	(0.067)
0.5	**0.389**	0.006	**0.383**
	(0.055)	(0.027)	(0.062)
0.7	**0.362**	-0.032	**0.394**
	(0.045)	(0.032)	(0.061)
0.9	**0.433**	-0.059	**0.492**
	(0.060)	(0.039)	(0.070)
Panel B: Adding schooling			
0.1	0.051	0.115	-0.064
	(0.077)	(0.078)	(0.114)
0.3	**0.335**	0.026	**0.309**
	(0.052)	(0.035)	(0.062)
0.5	**0.355**	-0.003	**0.357**
	(0.047)	(0.031)	(0.053)
0.7	**0.361**	-0.038	**0.399**

	(0.043)	(0.030)	(0.052)
0.9	**0.441**	-0.024	**0.466**
	(0.063)	(0.040)	(0.069)
Panel C: Adding reading proficiency scores			
0.1	0.027	0.067	-0.040
	(0.080)	(0.071)	(0.105)
0.3	**0.335**	0.015	**0.320**
	(0.051)	(0.037)	(0.059)
0.5	**0.348**	-0.008	**0.356**
	(0.045)	(0.030)	(0.052)
0.7	**0.359**	-0.040	**0.399**
	(0.044)	(0.029)	(0.056)
0.9	**0.440**	-0.030	**0.469**
	(0.067)	(0.040)	(0.076)
Panel D: Adding computer skills on the job			
0.1	0.047	0.069	-0.022
	(0.077)	(0.072)	(0.109)
0.3	**0.329**	0.020	**0.309**
	(0.054)	(0.040)	(0.063)
0.5	**0.352**	-0.008	**0.360**
	(0.046)	(0.032)	(0.054)
0.7	**0.361**	-0.039	**0.399**
	(0.044)	(0.034)	(0.054)
0.9	**0.426**	-0.030	**0.456**
	(0.064)	(0.043)	(0.069)
Panel E: Adding noncognitive traits scores			
0.1	0.045	0.065	-0.020
	(0.099)	(0.070)	(0.123)
0.3	**0.293**	0.003	**0.290**
	(0.053)	(0.050)	(0.068)
0.5	**0.363**	-0.032	**0.395**
	(0.045)	(0.042)	(0.060)
0.7	**0.372**	-0.061	**0.433**
	(0.046)	(0.040)	(0.058)
0.9	**0.414**	-0.036	**0.450**
	(0.059)	(0.056)	(0.074)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

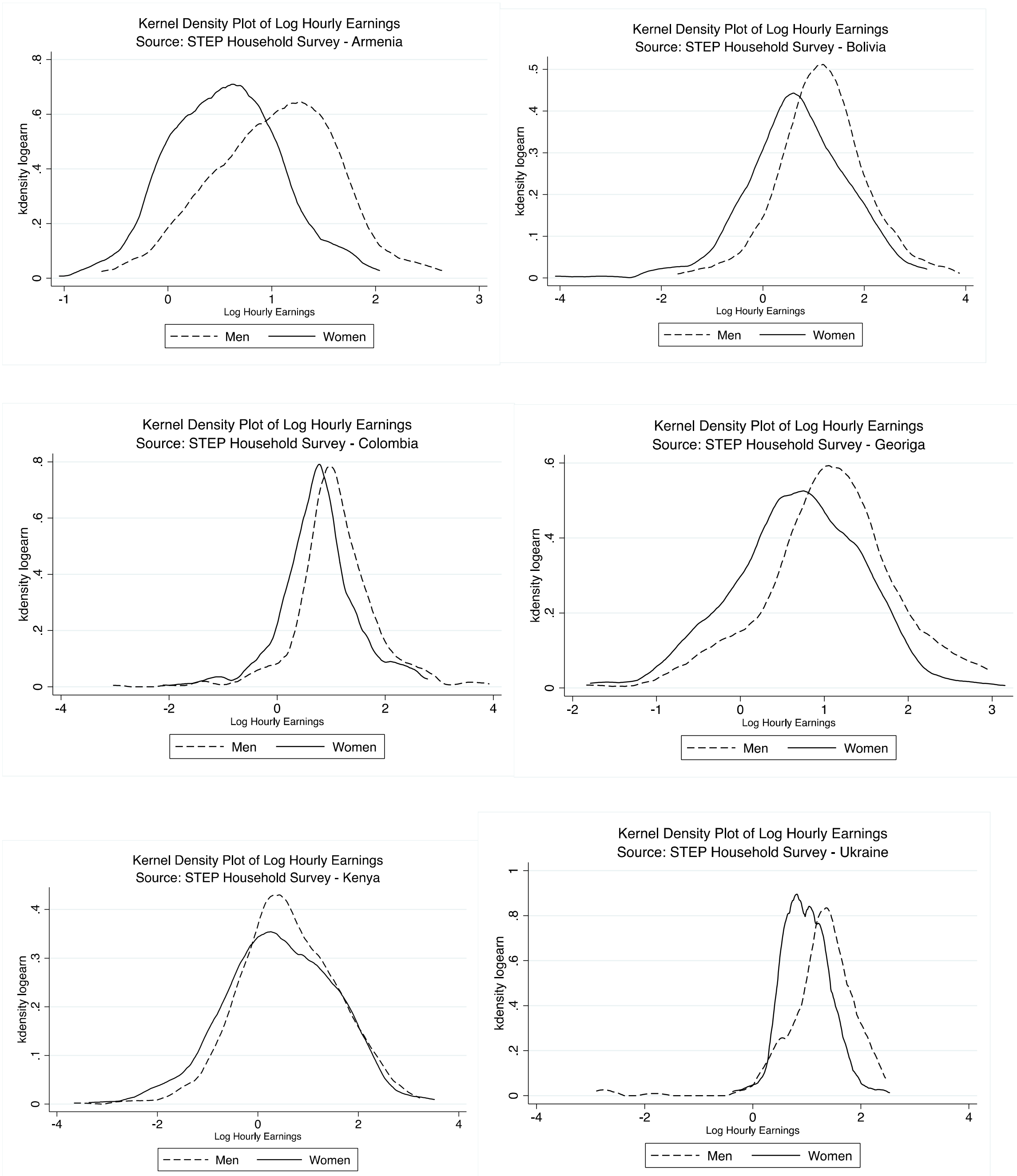
Table A.10. Quantile Decompositions of Log Wage Gaps – Vietnam

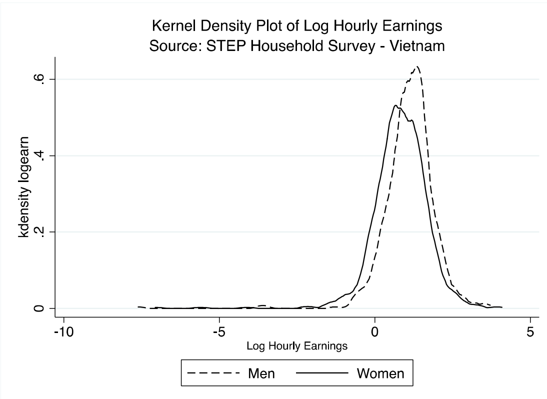
Percentile	Difference	Characteristics	Coefficients
Panel A: Controls			
0.1	**0.374**	0.030	**0.344**
	(0.066)	(0.030)	(0.064)
0.3	**0.327**	0.016	**0.311**
	(0.045)	(0.023)	(0.042)
0.5	**0.308**	0.013	**0.295**
	(0.051)	(0.021)	(0.049)
0.7	**0.228**	-0.002	**0.230**
	(0.043)	(0.015)	(0.040)
0.9	0.172	0.002	0.170
	(0.068)	(0.020)	(0.073)
Panel B: Adding schooling			
0.1	**0.373**	0.082	**0.291**
	(0.067)	(0.038)	(0.077)
0.3	**0.341**	0.071	**0.270**
	(0.048)	(0.030)	(0.047)
0.5	**0.288**	0.066	**0.222**
	(0.047)	(0.024)	(0.040)
0.7	**0.216**	0.044	**0.172**
	(0.040)	(0.022)	(0.037)
0.9	**0.203**	0.038	0.165
	(0.067)	(0.029)	(0.069)
Panel C: Adding reading proficiency scores			
0.1	**0.369**	0.082	**0.287**
	(0.071)	(0.035)	(0.071)
0.3	**0.347**	**0.073**	**0.274**
	(0.050)	(0.026)	(0.048)
0.5	**0.287**	**0.065**	**0.222**
	(0.045)	(0.023)	(0.041)
0.7	**0.213**	0.045	**0.168**
	(0.039)	(0.020)	(0.037)
0.9	**0.197**	0.035	**0.162**
	(0.065)	(0.027)	(0.066)
Panel D: Adding computer skills on the job			
0.1	**0.367**	0.078	**0.290**
	(0.071)	(0.035)	(0.071)
0.3	**0.355**	**0.082**	**0.273**
	(0.047)	(0.026)	0.045)
0.5	**0.296**	**0.083**	**0.212**
	(0.045)	(0.025)	(0.040)

0.7	**0.228**	**0.066**	**0.162**
	(0.040)	0.025)	(0.038)
0.9	**0.208**	0.059	0.150
	(0.061)	(0.030)	(0.061)
Panel E: Adding noncognitive traits scores			
0.1	**0.392**	0.098	**0.294**
	(0.068)	(0.042)	(0.071)
0.3	**0.350**	**0.113**	**0.237**
	(0.045)	(0.031)	(0.046)
0.5	**0.282**	**0.095**	**0.187**
	(0.043)	(0.030)	(0.043)
0.7	**0.234**	**0.080**	**0.154**
	(0.042)	(0.030)	(0.046)
0.9	**0.203**	0.059	0.144
	(0.063)	(0.035)	(0.065)

Note. Estimates in bold face are significant at the 5% level or lower. Bootstrap standard errors are in parentheses. The dependent variable is the log of hourly earnings. Panel A includes potential experience, squared term for experience, and occupation dummies. The sample includes 25- to 64-year-olds (both men and women) in self-employment or wage work.
Source: STEP Surveys (2014).

***Figure A.1*. Log Hourly Earnings Distribution for Men and Women, by Country**





Note. Earnings have been converted to 2011 PPP-adjusted U.S. Dollars. The sample includes 25- to 64-year-olds in self-employment or wage work. Employers, unpaid workers, part-time workers, and the top 1 percent of earners are excluded from the sample.
Source: STEP Surveys (2014).