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More Than Schooling

Understanding Gender Differences in the Labor Market When Measures of Skill Are Available

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Abstract

This paper uses measures of cognitive and noncognitive skills in an expanded definition of human capital to examine how schooling and skills differ between men and women and how those differences relate to gender gaps in earnings across nine middle-income countries. The analysis finds that post-secondary schooling and cognitive skills are more important for women's earnings at the lower end and middle of the earnings distribution, and that men and women have positive returns to openness to new experiences and risk-taking behavior and negative returns to hostile attribution bias. Especially at the lower end of the earnings distribution, women are disadvantaged not so much by having lower human capital than men, but by institutional factors such as wage structures that reward women's human capital systematically less than men's.

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More Than Schooling: Understanding Gender Differences in the Labor Market When Measures of Skill Are Available[1]

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I. Introduction

Increasingly globalized markets and economies and profound technological shifts are placing pressure on the skills that people are required to bring to the workplace. Over the coming decades, half of the jobs performed today are expected to disappear and become obsolete, to be replaced by new ones as yet unimagined (International Commission on Financing Global Education Opportunity, 2016). Where schooling and life experiences fail to build new skills and engender innovation, flexibility and adaptation in the workforce, the result will be higher unemployment, slower growth and more inequality. In the case of girls and women, these stresses are compounded by constraints that stem from social norms, potential labor market biases and gender-related policies that shape their labor force participation, occupational choices, and earnings.

The Education for All movement of the 1990s and the Millennium Development Goals of the 2000s enshrined enrollment and school completion rates as key indicators of educational progress. As enrollment rates have risen, however, it has become clear that schooling without learning is not sufficient progress. With increased evidence that millions of schoolchildren are not mastering basic skills of reading and math, the global conversation about education has shifted towards learning outcomes.[3] A recent addition to this dialogue is whether "noncognitive", "socio-emotional" or "soft" skills such as openness, conscientiousness, and grit are at least as important as cognitive skills.[4]

[3] See, for example, World Bank (2011), UN (2014), Robinson and Winthrop (2016), Global Education Commission (2016), ASER (2016), Pritchett (2013), and Almlund et al. (2011).

[4] Whatever label is applied to these skills, it is useful to unpack the omnibus variables "human capital" and "education" into the skills that best prepare young men and women for life and the workplace. Throughout this paper, we use the term "noncognitive skills" when we refer to these skills.

This paper provides empirical support for the shift in the global educational discourse to a learning focus and for a gender-differentiated approach in the analysis of skills. Our analysis includes a measure of cognitive skill, alongside number of years of schooling completed, as well as measures of noncognitive skills to predict an individual's labor market performance. We use individual-level data from the World Bank's Skills toward Employment and Productivity (STEP) project which surveyed middle-income countries during the period 2012-2015. Each survey collected comparable, direct measures of cognitive and noncognitive skills, and individual and household socioeconomic characteristics, for a random sample of adults.

The focus of our analysis is gender differences in schooling and skills and whether such differences are related to the earnings gap between men and women in each country and across the countries. The schooling levels of men and women have converged dramatically across world regions, as well as within most countries.[5] Results from years of regional and international assessments of student competencies in reading, math and science also indicate that the gender gap in cognitive performance has narrowed, although there remain gender disparities in which boys outperform girls in math while girls outperform boys in reading (OECD-PISA, 2009).[6] Much less is known, however, about gender patterns in noncognitive skills and how such patterns relate to gender gaps in employment and earnings. There has been a growing literature on this research

[5] Over the past 60 years, the ratio of women's schooling to men's schooling rose from 0.47 to 0.65 in South Asia, 0.58 to 0.78 in Sub-Saharan Africa, 0.48 to 0.89 in the Middle East, and 0.48 to 0.92 in East Asia (King and Winthrop, 2015). Gender patterns in competencies tend to translate into the fields of study that young men and women choose in post-secondary education and also their choice of occupation as adults. In the U.S., for instance, more young women than young men are proceeding to college, but they tend to concentrate in certain areas of study, with consequences for their future jobs (Jacob, 2002).

[6] This gender disparity among students continues into adulthood: Data on 22 OECD countries show that men do significantly better than women on numeracy; on average, 52 percent of men score in the top two performance brackets compared to 42 percent of women, and a one-standard deviation increase in numeracy skills is associated with an average 18 percent wage increase among prime-age workers (Hanushek et al., 2015).

question in high-income countries, especially in the U.S. and Europe, but it is a relatively nascent area of study in middle- and low-income countries.[7]

The next section presents an empirical model of labor market outcomes when measures of a range of skills are available and added to years of schooling. The model starts with the familiar Mincer (1965) log-earnings function but expands the measure of human capital to include not only schooling and experience but also direct measures of cognitive and noncognitive skills. The section also reviews the related literature with a focus on developing countries. Section III describes the data we analyze and discusses the gender patterns in the distributions of skills that emerge from the data. Sections IV, V and VI present our results in three parts—section IV on estimates for the pooled sample of countries, section V on estimates for individual countries, and section VI focusing on the decomposition of the gender gaps in earnings. The selection bias-adjusted estimates of the returns to schooling and skills in individual earnings are estimated separately for men and women. To examine further how returns to schooling and skills differ for men and women and potentially contribute to the gender earnings gap, we estimate quantile regressions which allow us to determine whether the returns to schooling or skills vary along the earnings distribution. We then draw from the regression results to decompose the gender earnings gap into the contribution of gender difference in covariates (the observed human capital of men and women) and gender-specific coefficients (the gender structure of returns to schooling and skills). Finally, Section VII synthesizes the findings and draws policy implications.

[7] See Bertrand (2011) and Blau and Kahn (2017) for reviews of this research.

II. Literature Review and Empirical Strategy

An earnings model with an expanded measure of human capital

The basic Mincer (1965) model is

$$\ln y_i = \beta_0 + \Upsilon H_i + \varepsilon_i \, , \qquad [1]$$

in which the earnings (y_i) of individual *i* are a function of that person's human capital (H_i) and a stochastic term (ε_i) that represents idiosyncratic earnings differences, presumed to be orthogonal to H_i. Due to the lack of direct measures of human capital, *H* has been typically measured by years of schooling attained. This human capital earnings function has been the basis of a large empirical literature, including on developing countries.[8] We expand this basic earnings function to include other measures of human capital—in particular, cognitive skills and noncognitive skills—besides years of schooling and experience.[9] Glewwe (1996) and Hanushek et al. (2015), among others, find that including cognitive skills as a measure of human capital lowers the return to schooling estimated using just the basic earnings function.[10] A growing literature shows statistically significant earnings returns to noncognitive skills.[11]

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[8] A summary of the estimates for developing countries is provided by Psacharopoulos (1984) and Psacharopoulos and Patrinos (2004).

[9] Even when measures of skills are included, we expect schooling years to affect earnings because of measurement error (that is, our skills measures are not likely to be a comprehensive set) and because years of schooling itself may be valued in the labor market where it is perceived to signal useful information about the individual (Spence, 1973; Belman and Heywood, 1991; Riley, 2001).

[10] These two studies illustrate the types of data sources used for this growing literature. Glewwe (1996) uses a household survey in Ghana which administered tests to household members of abstract reasoning (Raven's Coloured Progressive Matrices), mathematics, and (English) reading comprehension. Using the multi-country PIAAC data, Hanushek et al. (2015) find that in 22 countries a one-standard deviation increase in numeracy skills is associated with an average 18 percent wage increase among prime-age workers. They note that due to measurement errors in skills, these estimates may be lower bounds on the return to cognitive skill.

[11] Among relatively recent studies are Kuhn and Weinberger (2005), Nyhus and Pons (2005), Wanberg et al. (2005), Heckman, Stixrud, and Urzua (2006), Mueller and Plug (2006), Losoncz (2007); Schmitt et al. (2007), Fortin (2008), Borghans, ter Weel, and Weinberg (2008), Heineck and Anger (2010), Lindqvist and Vestman (2011), and Segal (2013). Table 1 summarizes the studies on low- and middle-income countries.

The literature offers many definitions of noncognitive skills. In general, however, the term pertains to the competencies, behaviors, attitudes, and personal qualities that enable people to navigate their environment, work well with others, perform well in different settings, and achieve their goals; they are different from academic or technical/vocational skills. Although termed noncognitive skills, these skills require cognition, as psychologists have emphasized (Borghans, et al., 2008).[12] Both cognitive and noncognitive skills have roots in early childhood but are also learned and shaped throughout a person's life experiences and in various situations—at home, in the playground, in schools, at work and in the streets.

We therefore expand the basic log-earnings model given by [1] as follows,

$$\ln y_i = \beta_0 + \beta_1 S_i + \beta_2 E_i + \beta_3 E_i^2 + \Upsilon_1 C_i + \Upsilon_2 NC_i + \beta_4 R_i + \varepsilon_i, \qquad [2]$$

where human capital is measured by years of schooling (*S*)[13], years of work experience (E) proxied by age, a set of measured cognitive and noncognitive skills (*C* and *NC,* respectively), and *R* is metropolitan area of residence.[14,15]

[12] The terms used for this cluster of skills have varied by discipline. Psychologists distinguish between traits and skills, where traits underlie and influence multiple behaviors and attitudes, and are considered relatively stable, though not immutable. These have been consistently found, especially conscientiousness, to relate to workforce outcomes (Lippman, et al., 2015). On the other hand, skills are specific, teachable and malleable. The psychology literature on intelligence points to different types of intelligences—that it is about how well a person deals with environmental changes throughout life, processes that involve knowledge acquisition, problem-solving, decision-making and creation—and that there is more than one ability associated with intelligence. For example, Dweck's "growth mindset" and Duckworth's "grit" scales have been used to predict educational achievement and attainment as well as workforce outcomes (Duckworth et al., 2007; Dweck et al., 2011).

[13] We specify years of schooling as a spline variable with knots at 9 and 13 years of education, although we also estimated our model using total years of schooling.

[14] The survey data for the countries included in our study are restricted to urban households. We construct a variable to distinguish locations for each country that we considered to be a metropolis, or significantly different in terms of population density and economic activity.

[15] Throughout the analysis we refer to Υ as "returns" to skills inasmuch as the β_1, β_2 and β_3 coefficients have been typically referred to as estimates of returns to schooling and experience. However, we acknowledge that the term "returns" is used in a loose sense because the costs of producing schooling and skills are ignored, as is a potentially causal relationship between skills and schooling.

In estimating equation [2], we remain agnostic about which cognitive and noncognitive skills affect earnings and include all the measures that are available to us.[16] Table 1 organizes the results of studies that have followed a similar approach, highlighting their findings about cognitive and noncognitive skills when controlling for schooling and other covariates.

[16] This simple approach does not favor one psychological model of noncognitive skills over another (e.g., the five-factor model of skills over the locus-of-control model) and does not impose any arbitrary aggregation of individual skills. The "Big Five" is a taxonomy with five factors—openness, conscientiousness, extraversion, agreeableness, and neuroticism/emotional stability—used by industrial and organizational psychologists that have been identified using factor analysis. Other skills that have appeared in the research are academic self-concept, educational engagement, motivation, expectations, and goal-setting that propel students to success in school and work (Farrington et al., 2012; Moore et al., 2015) and grit (Duckworth et al., 2007; Duckworth and Quinn, 2009). The related literature also includes risk preferences and time preference.

Table 1. Summary of results of previous studies in low- and middle-income countries

Author(s)	Country (ies)	Data used and sampling	Estimation method	Dependent variable	Main results: Schooling	Main results: Cognitive skills	Main results: Noncognitive skills	Main results: Gender	Control variables
Acosta, Muller & Sarsoza (2015)	Colombia	STEP (Skills Measurement Survey) for Colombia, 2012; 1,363 men and women	Structural model with cognitive and noncognitive skills as latent variables	Log hourly earnings of men and women	Not included	0.161*** for reading proficiency in OLS model; 0.483** in IV model; 0.134*** in structural model	-0.026 (factors: extroversion, openness; emotional stability; conscientiousness and grit)	-0.198*** for female dummy variable	Age, age-squared; mother's education (splines); parental involvement; city dummies
Aslam, Bari & Kingdon (2012)	Pakistan	Research Consortium on Educational Outcomes and Poverty household survey, 2006–2007, in Punjab and NWFP, 700 men and women aged 15-60	OLS	Log earnings	0.054*** when including also cognitive & noncognitive skills; otherwise, 0.048*** when not including literacy score	−0.048 when conditioning for schooling and noncognitive skills; otherwise, 0.436*** without schooling but with noncognitive skills	0.061** for positive personality, .006 for negative personality, when no control for schooling or cognitive skills; 0.002 and -0.007, respectively, with controls for schooling and cognitive skills	0.581*** for male dummy variable when conditioning for schooling and cognitive and noncognitive skills	Constant, experience and experience-squared; whether sympathetic to religious parties or causes
Cunningham, Parra Torrado & Sarzosa (2016)	Peru	National Skills and Labor Market Survey (Encuesta Nacional de Habilidades, ENHAB), 2010, 770 men and women	OLS	Log hourly earnings of men and women; gender as a dummy variable	0.062*** - 0.067*** for years of schooling	(6.80)*** (0.50)	-0.086** - -0.093*** for kindness, -0.056* - -0.058* for cooperation, 0.067** - 0.074** for emotional stability	-0.168*** - -.132*** for female dummy	Age, age-squared; language; regional dummies; whether firstborn; economic sector
Cunningham, Parra Torrado & Sarzosa (2016)	Peru	National Skills and Labor Market	Structural model with cognitive and	Log hourly earnings of men and women;		Constant 7.183	0.3986* for stability, -0.0752 for plasticity, and 0.0532 for grit	-0.1908*** for female dummy.	Age, age-squared; language; regional

		Survey (Encuesta Nacional de Habilidades, ENHAB), 2010; 748 men and women	noncognitive skills as latent variables	gender as a dummy variable					dummies; whether firstborn; economic sector
Diaz, Arias & Tudela (2013)	Peru	Encuesta Nacional de Habilidades (ENHAB) (2010), final sample of 1,140 men and women aged 14-50	Two-step IV to address endogeneity of schooling	Log hourly earnings	0.055***	0.088*** for aggregate cognitive measure	-0.088*** for agreeableness, 0.057* for emotional stability	Not included	None
Glewwe, Huang & Park (2013)	China (Gansu Province)	Gansu Survey of Children and Families (GSCF), 402 males and females aged 17-21	OLS	Log hourly earnings, with selectivity bias correction	0.059** for years of schooling	0.028 for literacy score	0.027 for self-esteem; -0.086* for depression scale; 0.097** for noncognitive factor	-0.396*** for female dummy	Years of work experience, parents' education, Inverse Mills ratio
Gunewardena (2015)	Sri Lanka	STEP (Skills Measurement Survey); 779 men aged 20-64	OLS	Log hourly earnings	Not included	0.108*** for numeracy, 0.073** for reading, 0.056 for writing, 0.039 for core literacy	Agreeableness***, risk-taking***	Not relevant	Experience, experience-squared; location (region dummy, urban/rural dummy); informal employment, full-time employment
Gunewardena (2015)	Sri Lanka	STEP (Skills Measurement Survey); 510 women, aged 20-64	OLS	Log hourly earnings	Not included	-0.000 for numeracy, -0.009 for reading, 0.134*** for writing, 0.070 for core literacy	Openness ***, emotional stability**, decisionmaking (-)*	Not relevant	Experience, experience-squared; location (region dummy, urban/rural dummy);

									informal employment, full-time employment
Herrera-Sosa, Valerio, Monroy-Taborda, & Chen (2015)	Georgia	STEP (Skills Measurement Survey) 2012; 663 men and women, aged 15-65	OLS	Log hourly earnings; gender as dummy variable	0.0540*** for years of schooling	0.0021*** for reading proficiency	0.0843** (emotional stability), 0.0900** (hostile bias attribution)		Potential experience and experience-squared, mother's edcuation, and indicator variables for wage earners, occupations and economic sector
Liang & Chen (2014)	Yunnan Province, China	STEP (Skills Measurement Survey) for Urban Yunnan, 2012; 1,007 men and women	OLS	Log hourly earnings; gender as dummy variable	0.0802*** for years of schooling without cognitive or noncognitive measures	0.124* if reading at work is 11-25 pages, 0.173* if writing at work is >25 pages, 0.199** if thinking required at work every day	0.0666* - 0.174*** for openness for specifications without and with schooling and cognitive measures; no other significant noncognitive skills	Included but not reported	Potential experience, experience-squared; gender; sector of employment; occupation
Linz & Semykina (2010)	Transition countries (Armenia, Kazakhstan, Kyrgyzstan, Russian Federation, Serbia)	Employee surveys in five formerly socialist economies; 7,860 observations, men aged 16-70 and women aged 16-65	OLS	Log earnings	0.046*** for years of schooling without noncognitive skills (pooled country samples)	None	Armenia: 0.091*** (locus of control), 0.054*** (Challenge-affiliation); Russian Federation: 0.075*** (LOC); Serbia: 0.027*** (LOC), 0.016** (C-A); not significant for other countries	-0.145*** for female dummy (pooled country samples)	Tenure and tenure-squared; dummy variables for type of occupation and for sector of employment
Valerio, Herrera-Sosa, Monroy-Taborda, & Chen (2015)	Armenia	STEP (Skills Measurement Survey)	OLS	Log hourly earnings	0.0178** - 0.0246***	-0.0001 - - 0.0002 for	-0.0756** - - 0.0872** for agreeableness,	-0.3307*** for female dummy	Potential experience and

		2012; 743 men and women, aged 15-65				reading proficiency	0.0648* - 0.0861** for grit, 0.0522* - 0.0672** for hostile bias, -0.0845** - -0.0901** for decisionmaking, 0.0408** - 0.0448** for risk aversion		experience-squared, mother's edcuation, and indicator variables for wage earners, occupations and economic sector
Valerio, Sanchez Puerta, Tognatta & Monroy-Taborda (2015)	Armenia, Bolivia, Colombia, Georgia, Kenya, Ukraine, Vietnam	STEP (Skills Measurement Survey) 2012; men and women, aged 15-65, wage and self-employed workers; sample ranging from 846 in Bolivia to 1,948 in Vietnam	Heckman-correction for selection bias	Log hourly earnings; gender as dummy variable	0.025 (Ukraine) - 0.050*** (Bolivia) for years of schooling	-0.008 (Armenia) - 0.096** (Kenya) for standardized literacy	-0.052* (Colombia) - 0.0378* (Armenia) for extraversion, -0.025 (Colombia) - 0.075*** (Vietnam) for openness, -0.0684*** (Armenia) - 0.020 (Colombia) for agreeableness, -0.025 (Colombia) - 0.0483* (Armenia) for grit	0.035 (Kenya), -0.198*** (Vietnam), -0.256*** (Colombia), -0.402*** (Ukraine), -0.4471*** (Bolivia), -0.479*** (Armenia), and -0.564*** (Georgia)	Potential experience and experience-squared, indicator variable for self employment

Footnotes: Estimation results are statistically significant as reported by the author(s): *** at 1% level; ** at 5% level; * at 10% level. This survey of the literature includes only those studies that estimate log wages or log earnings functions, published after or in 2000, that include measures of cognitive and noncognitive skills and information on gender. From these studies, we selected the results of specifications that include also years of schooling and other covariates.

We note some caveats regarding our approach. First, measures of noncognitive skills do not necessarily capture true, or latent, skills (Heckman and Kautz, 2012; Almlund et al., 2011; Borghans et al., 2011), potentially resulting in biased estimates of the returns to those skills,[17] and second, individual noncognitive skills may be closely associated with other skills, also resulting in biased estimates of the returns to specific skills.[18]

Moreover, skills and years of schooling are likely to be correlated with each other and possibly even causally related. Cognitive and noncognitive skills acquired in childhood likely affect educational success; in turn, with more years of schooling, an individual may acquire more and different skills.[19] To test this causal relationship would require measuring skills at different points in the schooling cycle which our data do not allow us to do, as skills are measured only at the time of the survey of adults, at the same time that earnings and employment were observed.[20]

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[17] One approach used by Acosta, Muller and Sarzosa (2015) for Colombia and by Cunningham, Torrado and Sarzosa (2016) for Peru is to estimate a simultaneous equations model in which noncognitive skills are a latent variable with specific components (or factors) that are allowed to differ in relative importance with respect to the latent variable. For example, Cunningham, Torrado and Sarzosa (2016) impose an a priori ordering of the noncognitive skills; a skill is selected as an "alpha" (higher order) personality trait and two other skills are selected as the "beta" traits that influence the alpha skill.

[18] Pairwise correlations of cognitive and noncognitive skills and schooling are presented in Appendix Tables 2 and 3 and Appendix Figures 1 and 2, and indicate weak, though significant correlations among noncognitive skills and between noncognitive skills and cognitive skills and schooling. However, the correlation between cognitive skills and schooling is stronger, as is to be expected.

[19] The literature on child development supports this assumption: while cognitive and noncognitive skills are not immutable, they develop and take root in childhood and youth. Eisenberg et al. (2014) reviews the accumulated evidence on this relationship and concludes that the elements of conscientiousness and self-regulation emerge in early childhood and that these skills foster conscientiousness that is evident later in life, both directly and via academic motivation and compliance with norms. Neuroscience research has shown that brain development during a child's first few years forms the basis of cognitive and emotional development for a lifetime (Shonkoff and Phillips, 2000). A growing body of evidence shows that after age two, the damage done by chronic malnutrition, or stunting, neglect, and disease becomes irreversible, limiting linguistic, cognitive, and socioemotional development (Cunha and Heckman, 2008; Carneiro and Heckman, 2003; Naudeau et al., 2011).

[20] Innate cognitive ability, as measured typically (and more narrowly) by IQ, is a strong predictor of academic performance, from primary school to tertiary level, and of educational level more generally. In a meta-analysis of over 3,000 studies, Walberg (1984) found a high correlation of 0.7 between initial cognitive ability and academic performance at the lower school level. However, this correlation declines at the higher educational levels, indicating that other factors become more important in later schooling. In one study, for example, it fell from 0.7 in elementary school to as low as 0.4 at the tertiary level (Jensen, 1998).

This raises a further econometric issue: Assuming that cognitive and noncognitive skills continue to develop beyond adolescence and depend on accumulated work and life experience, then equation [2] is subject to simultaneous equations bias, i.e., earnings and employment depend on skills, and skills also depend on a person's work experience.[21] The implicit assumption in using cross-section data as we do is that some skills are relatively unchanged over the work life, or that a permanent component of skills developed early in life dominates later development and is a good enough measure of current skills.[22]

As discussed in the previous section, this potential source of simultaneity bias implies that noncognitive skills acquired in childhood and adolescence determine adults' earnings and employment also through their impact on academic performance.[23,24] As we do not have earlier

[21] Using data on skills at a young age may minimize the problem of reverse causation, of work experience itself contributing to the formation of observed cognitive or noncognitive skills, but studies have also found that some noncognitive skills continue to develop throughout the life cycle. Several studies on advanced countries—for example, Heckman, Stixrud and Urzua (2006), Fortin (2008), Hall and Farkas (2011), and Mueller and Plug (2006) for the U.S., Braakmann (2010) for Germany, and Viinikainen et al. (2014) for Finland—use data on cognitive and/or noncognitive skills that were collected at an earlier time than when earnings were observed (e.g., end of high school or at labor market entry). Keeping in mind that individual noncognitive skills are correlated and that there may indeed be an ordering of skills, we conducted an exploratory principal components analysis to draw out this ordering. However, our results indicated the variables of nine distinct noncognitive skills were characterized more by "uniqueness" rather than being correlated.

[22] While there is evidence that people do change, there is also evidence that personality traits are relatively stable among adults. In a meta-analysis of longitudinal studies, Roberts, Walton and Viechtbauer (2006) examine cumulative lifetime change in the components of the Five-Factor Model, disaggregating the five components into social dominance (assertiveness, dominance) and social vitality (talkativeness, gregariousness, and sociability), and find that people become more socially dominant, conscientious, and emotionally stable as they age, whereas social vitality and openness to experience increase early in life and then fall in old age. In contrast, according to Blonigen et al. (2006) and Roberts and Del Vecchio (2000), personality traits appear to be well-established by the mid- to late-30s and remain relatively stable among adults. Exceptions may occur if there is a sufficiently large or permanent change in one's circumstances (Borghans et al., 2008). Our analysis includes only adults aged 25 and over, so it is reasonable to assume that their personality traits are already established. Linz and Semykina (2009) use this same reason, plus the fact that they exclude those adversely affected by the changes in the former socialist republics in Europe in their analysis to argue that it is possible to examine the general association between personality and performance using cross-section, rather than longitudinal, data.

[23] Several studies also show that early noncognitive skills can influence schooling attainment and cognitive skills (for example, Heckman, Stixrud and Urzua, 2006; Borghans et al., 2008; Almlund et al., 2011; Behncke, 2012).

[24] These might differ by gender; for example, the frequency with which boys argue, fight, or act impulsively has been shown to affect their early school performance, with consequences for their academic success (Goldin, Katz, and

data on cognitive performance or noncognitive skills, nor sufficient background data that can be used as instruments to estimate a simultaneous equations model, we do not explore this relationship. By controlling for *C* and *NC* in the log-earnings equation, however, we assume that the estimated returns to years of schooling (and experience) are purged of the covariation of skills and schooling (and experience), an approach that has been used previously in the literature.[25]

Expanding the measure of gender disadvantage

A typical approach used by many of the studies in Table 1 is to estimate the gender difference in earnings by the coefficient δ on a dummy variable (*G* in equation [3] below), where *G* signifies whether or not the worker is female. Because the function already controls for the level of human capital which is assumed to determine earnings, a negative sign is indicative of female disadvantage.

$$\ln y_i = \beta_0 + \beta_1 S_i + \beta_2 E_i + \beta_3 E_i^2 + \Upsilon_1 C_i + \Upsilon_2 NC_i + \beta_4 R_i + \delta_1 G_i + \varepsilon_i \qquad [3]$$

The studies reviewed in Table 1 show that in low-income and middle-income countries, on average, women earn 4 to 58 percent less than men do, controlling for a set of covariates that include schooling, skills, work experience, as well as socioeconomic background, demographic characteristics, and location of residence. However, this approach captures only the gender differences in the intercept. It constrains the structural coefficients to be the same for men and women, whereas there are theoretical grounds and considerable empirical evidence that the effects of schooling, cognitive skills and noncognitive skills on earnings are likely to be different for men

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Kuziemko, 2006; Buchmann, diPrete and McDaniel, 2008). In some classroom settings, this disruptive behavior results in boys receiving greater, not less, attention from teachers (and parents) than girls (King and Winthrop, 2015).

[25] Estimates from 24 studies on the U.S., for example, indicate that the return to schooling, holding constant a measure of cognitive skills, is 20 percent smaller than the unconditioned return, implying that part of the return attributed to years of schooling is indeed due to the effect of skills on earnings (Bowles, Gintis and Osborne, 2001).

and women. Briefly, men and women with the same schooling may make different labor supply and occupational choices, resulting in sometimes largely different earnings, and men and women with the same schooling and other observable characteristics may face different wage structures even within the same occupation because of gender discrimination (Altonji and Blank, 1999; Bertrand, 2011; and Blau and Kahn, 2017).[26]

As to noncognitive skills, studies, especially in the early childhood literature, reveal that skills such as conscientiousness, self-esteem and self-regulation emerge in childhood and persist in life, and that they differ by gender.[27] Studies further show that even when men and women have similar noncognitive skills, their skills may be rewarded differently by employers. For example, Mueller and Plug (2006) find that being intellectually open is rewarded for both men and women, but men earn a premium for being antagonistic while women earn a premium for being conscientious. In addition, gender differences in noncognitive skills affect not only whom employers hire but also who self-selects into different jobs. For these reasons, we estimate gender-specific slope coefficients for schooling and skills by estimating equation [2] separately for men and women, after testing for equality of the structural coefficients.

$$\ln y_i = \beta_{0j} + \beta_{1j}S_i + \beta_{2j}E_i + \beta_{3j}E_i^2 + \beta_{4j}X_i + \Upsilon_{1j}C_i + \Upsilon_{2j}NC_i + \beta_{4j}R_i + \varepsilon_i \qquad [4]$$

where $j = m, f,$ subscripts denoting male and female, respectively.

Further, because a nontrivial proportion of women are typically not in the labor market or are in nonformal employment for which earnings data are not available, we estimate equation [4]

[26] This last case is explored by the Blinder-Oaxaca (1973) framework and its variants, where unexplained wage gaps are indicative of 'discrimination' in a model that accounts for all wage determinants.

[27] See Eisenberg et al. (2014), Heckman et al. (2008), Else-Quest et al. (2006), Bertrand and Pan (2013). Other studies also find that agreeableness and neuroticism are most consistently associated with gender differences (women more than men) (e.g., Bouchard and Loehlin, 2001); and others find gender differences mostly in extraversion and openness (e.g., Mueller and Plug, 2006).

with a Heckman selection bias correction (Heckman, 1979). Ignoring the differences in the relative participation of men and women in the labor market when estimating the returns to schooling and skills has been found to result in biased estimates. We use this approach also to address the measurement error due to the unobserved wages of men and women who are unpaid workers. Depending on the size of the nonformal sector, this source of selection bias can be significant.[28] We use marital status, the number of young children, and the presence of other workers in the household as instruments to identify the labor force participation function.[29] Previous studies have concluded that, for women, being married and having young children reduce labor force participation and the probability of paid employment, whereas, for men, being married increases labor force participation and the probability of paid work and having young children does not have a significant impact.[30]

Heterogenous effects: Quantile regressions

There is a considerable empirical literature that explores heterogenous effects of covariates along the earnings distribution, based on quantile regressions introduced by Koenker and Bassett

[28] In developing countries, ILO (2014) reports that more than half of all non-agricultural jobs are in the informal economy, and in many South Asian and Sub-Saharan African countries, the share is as high as 90 percent. These jobs employ mostly low-skilled workers and women, and typically these jobs offer modest earnings, limited security, and hardly any social protection (Adams, de Silva, and Razmara, 2013).

[29] While our paper does not attempt to explain marriage and childbearing choices, we examine how marriage and fertility choices affect earnings through labor market choices. We acknowledge that marriage, fertility and labor market choices may be determined simultaneously, but we treat the number of children and marital status as pre-determined.

[30] The cross-country study of Bloom et al. (2009) finds that fertility has a large negative effect on female labor force participation, with this direct effect being concentrated among women aged 20-39. Their results imply that with each additional child, female labor force participation decreases by about 10–15 percentage points in the age group 25–39, and by about 5–10 percentage points in the age group 40–49. These results imply a reduction of about four years of paid work over a woman's lifetime for each birth (Bloom et al., 2007). Other studies have questioned what OLS results show. This skepticism about the causal interpretation of associations between fertility and labor supply stems from the fact that fertility and labor supply could be jointly determined. See, for example, Agüero and Marks (2008) on Latin American countries, and Jensen (2012) on India.

(1978).[31] Heterogeneity in returns at different segments of the earnings distribution may arise because the wage structure itself is likely to be nonlinear, reflecting the different occupations (and types of employment) that correspond to different segments of the earnings spectrum. As a result, occupations that are clustered in the lower end of the earnings distribution could yield lower returns to post-secondary schooling than those that are represented by the upper end of the distribution.[32] Coefficients of quantile regressions are interpreted in the usual way. Standard errors are bootstrap standard errors.

Gender earnings gaps, glass ceilings and sticky floors

Finally, we explore the effect of gender differences in schooling and skills on the gender earnings gap. The conventional method of measuring discrimination developed independently by Blinder (1973) and Oaxaca (1973) begins with the following framework

$$ln y_m = \boldsymbol{\beta}_m \mathbf{X}_m + \varepsilon_m \quad [5]$$

$$ln y_f = \boldsymbol{\beta}_f \mathbf{X}_f + \varepsilon_f \quad [6]$$

---

[31] Quantile regressions are a natural extension of classical least squares estimation of conditional mean models to the estimation of an ensemble of models for conditional quantile functions—of which the central special case is the median regression estimator or Least Absolute Deviations (LAD) estimator that minimizes a sum of absolute errors (Koenker and Hallock, 2000). The θth quantile of y_i conditional on X_i is given by

$Q_\theta (y_i|X_i) = X_i\beta_\theta$, $\theta \in (0,1)$

where the coefficient β_θ is the slope of the quantile line giving the effects of changes in X covariates on the θth conditional quantile of y. As shown by Koenker and Basset (1978), the quantile regression estimator of β_θ solves the following minimization problem: $\beta_\theta = argmin \left[\sum_{i:y_i \geq X_i\beta} \theta|y_i - X_i\beta| + \sum_{i:y_i < X_i\beta} (1-\theta)|y_i - X_i\beta| \right]$.

[32] However, this leaves unexplained why women might be disproportionately overrepresented in the lower end occupations and under-represented in the upper end occupations. A theory of occupational choice—or occupational segregation—drawing on, *inter alia,* the role of social norms that restrict women's access to certain occupations, is required to explain gender differences in occupations, which we do not attempt in this paper. A related explanation drawing on dual labor market theory posits that when labor markets are segmented, and there are two or more groups of unequal status in the labor market, the subordinate group will have earnings distributions which look similar to the dominant group over ordinary jobs, but are comparatively thin over high-paying jobs (Pendakur and Pendakur, 2007), which can in the case of women, lead to a glass ceiling.

where *lny* is the natural logarithm of a measure of earnings such as the hourly wage; **X** is a vector of observed characteristics of the *i*th individual, **β** is a vector of coefficients, and ε is an error term. As in Blau and Kahn (2017), the subscript *i* is suppressed to simplify the notation. The mean earnings gap is then decomposed as follows

$$ln\bar{y}_m - ln\bar{y}_f = (\bar{\mathbf{X}}_m - \bar{\mathbf{X}}_f)\boldsymbol{b}_m + \bar{\mathbf{X}}_f(\boldsymbol{b}_m - \boldsymbol{b}_f) \qquad [7]$$

where the b_m and b_f coefficients are OLS estimates of $\boldsymbol{\beta}_m$ and $\boldsymbol{\beta}_f$, respectively. The first term on the right side of the equation is the impact of *mean* gender differences in the observed variables ($\bar{\mathbf{X}}_m - \bar{\mathbf{X}}_f$), evaluated using the estimated slope coefficients for men, $\boldsymbol{\beta}_m$. The second term is the unexplained gender differential, evaluated at the mean earnings-generating characteristics of women, $\mathbf{X}^*_f$, resulting from differences in coefficients ($\boldsymbol{\beta}_m - \boldsymbol{\beta}_f$). In its original exposition, the second term is taken to measure the extent of discrimination, that is, unequal pay for equally productive workers. In the absence of discrimination, the estimated coefficients of individuals' observed characteristics would be identical for men and women, that is, $\boldsymbol{\beta}^m = \boldsymbol{\beta}^f$, and the second term would disappear from the wage gap equation. On the one hand, this component could overstate discrimination if it reflects unmeasured productivity or compensating differentials. On the other hand, it could understate discrimination if differences in explanatory variables (e.g. schooling and skills) are themselves the (endogenous) result of discrimination. Social norms and gender-stereotyping that place the burden of care and household work on girls and young women—and that assign the role of homemaker to women and breadwinner to men—raise the opportunity cost of schooling for girls relative to boys, with long-lasting effects on their human capital accumulation and future labor market outcomes (Bertrand, 2011; Fortin, 2005).

Assuming that the model is correctly specified, the explanatory variables are all exogenously determined, and there are no unobserved relevant productive characteristics giving rise to omitted variable bias; the second term in equation [7] can be described in terms of a treatment effect, or, in the words of Blau and Kahn (2017), an experiment in which we "take a woman, given her characteristics, and reward her according to the male reward system".[33,34]

Finally, the second right-side term in [7] can be decomposed further into the intercept (b_{0m} and b_{0f}) and slope coefficients, denoted by ($\boldsymbol{b}'_m$ and $\boldsymbol{b}'_f$), yielding three terms, as in [8] below.

$$ln\bar{y}_m - ln\bar{y}_f = (\bar{\mathbf{X}}_m - \bar{\mathbf{X}}_f)\boldsymbol{b}_m + \bar{\mathbf{X}}_f(b_{0m} - b_{0f}) + \bar{\mathbf{X}}_f(\boldsymbol{b}'_m - \boldsymbol{b}'_f) \qquad [8]$$

This decomposition shows that studies that have estimated only a gender dummy, in effect, ignore the third term; they restrict the coefficients to be equal for men and women while allowing for the intercept coefficients to differ by gender. We find this to be counter-intuitive and thus use equation [8] in decomposing the wage gap.

A quite considerable literature explores gender wage differentials across the distribution of wages.[35] We use a method developed by Chernozhukov, Fernández-Val, and Melly (2013) to estimate counterfactual distributions based on regression methods, in which the counterfactual scenarios consist of *ceteris paribus* changes in either the distribution of covariates related to the outcome of interest or the conditional distribution of the outcome, given covariates.[36] Following

[33] Blau and Kahn (2017) posit that such an experiment could be thought of as the outcome of a discrimination case in which a firm that was previously found to have discriminated against women is now required to treat women the same way as it treats men.

[34] While the decomposition in [7] can be performed using the coefficients estimated for women and the mean observed characteristics of men, early extensions of the Blinder-Oaxaca decomposition (Cotton, 1988; Neumark, 1988) also suggest a wage regression estimated using a pooled sample of men and women, which may apply in a labor market with no discrimination. Blau and Kahn (2017) argue persuasively that there would be likely general equilibrium changes if discrimination were eradicated, so it is not possible to know *ex ante* what the resulting reward structure would look like. We find the Blau and Kahn (2017) scenario of taking a woman and valuing her characteristics using the male coefficients to be sufficiently realistic, and therefore limit our analysis to this specification.

[35] Among them are Albrecht, Navarro, and Vroman (2009; Arulampalam, Booth, and Bryan (2007); Blau and Kahn (2017); Nordman, Sarr, and Sharma (2015); and Tognatta, Valerio, and Sanchez Puerta (2015).

[36] This method is similar to that proposed by Machado and Mata (2004) and used by Melly (2006). It is the method used by Blau and Kahn (2017) and Tognatta et al. (2016).

their example, we estimate [9] for a population of men, denoted by 0, and women, denoted by 1, the conditional distribution functions $F_{Y0}|X_0(y|x)$ and $F_{Y1}|X_1(y|x)$ which describe the stochastic assignment of wages to workers with characteristics X_0 and X_1 for men and women, respectively. $F_{Y0}|_0$ and $F_{Y1}|_1$ represent the observed distribution function of wages for men and women, and $F_{Y0}|_1$ represents the counterfactual distribution function of wages that would have prevailed for women had they faced the men's wage structure, $F_{Y0}|X_0$:

$$F_{Y}^{0|1)}(y) := \int_{\mathcal{X}_1} F_{Y_0|X_0}(y\,|x)\; dF_{X1}(x) \qquad [9]$$

This is constructed by integrating the conditional distribution of wages for men with respect to the distribution of characteristics for women.[37]

The difference in the observed wage distributions between men and women can be decomposed in the spirit of Oaxaca (1973) and Blinder (1973) as

$$F_{Y1|1} - F_{Y0|0} = [F_{Y0|1} - F_{Y0|0}] + [F_{Y1|1} - F_{Y0|1}] \qquad [10]$$

where the first term in brackets is a composition effect due to differences in characteristics (evaluated at the male structure) and the second term is due to differences in the wage structure (holding the characteristics of females constant). The decomposition into covariates and coefficients (structure) components in [10] corresponds to the decomposition in [7]. The literature has used this type of decomposition to explore glass ceilings (larger structure components in the upper part of the earnings distribution) and sticky floors (larger structure components in the lower part of the earnings distribution) (Albrecht, Navarro, and Vroman, 2009; Arulampalam, Booth, and Bryan, 2007).

[37] This quantity is well defined if X_0, the support of men's characteristics, includes X_1, the support of women's characteristics, namely $X_1 \subseteq X_0$.

III. Data Sources and Descriptive Statistics

Survey data on adults in middle-income countries

Our study uses a survey database on nine middle-income countries collected over the period 2012-13 under the Skills toward Employment and Productivity (STEP) program of the World Bank.[38] The countries are Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Serbia, Ukraine and Vietnam. One adult aged 15-64 years was randomly selected as the respondent from about 3,000 randomly selected households, but we restrict our analysis to the subsample of adults aged 25-54 as our focus is labor market behaviors and outcomes.[39] With a few exceptions, the same household survey instruments were administered in all countries and the data have been harmonized. The survey collected details on skill acquisition (i.e., early childhood education, schooling attainment, training and apprenticeships), measures of skills (cognitive, noncognitive and other job-relevant skills), labor force participation and occupation, family background and socioeconomic status.

Cognitive skills have been measured through a literacy assessment, developed specifically for use in the context of developing countries.[40] These values are not assessment scores of individuals in themselves, but are values imputed from a conditional distribution of assessment scores based on population characteristics. Thus, our estimated returns to cognitive skills indicate

[38] The STEP project included a total of 14 countries as of 2016, but data on our preferred measure of cognitive skills are not available for five countries (Lao PDR, Macedonia, the Philippines, Sri Lanka, and China (Yunnan Province)), so we drop them in this paper.
[39] Survey respondents aged 15-24 are more likely to be enrolled in an educational institution or training course or looking for a first job, while respondents 55 and over may have stopped working for pay for a variety of reasons, including voluntary retirement and ill health. To address estimation issues associated with outliers, we estimate our models using 1%-trimmed samples.
[40] The assessment includes sets of questions taken from the OECD's International Program for Assessing Adult Competencies (PIAAC), the International Adult Literacy Survey, and the Adult Literacy and Life Skills to produce Reading Literacy Assessment Scores and derived "plausible values" of literacy proficiency (see Pierre et al., 2014).

the change in log-earnings that is associated with a one-standard deviation increase in an individual's relative position in the population's distribution of cognitive skills.

To measure noncognitive skills, the surveys include questions about the Five Factor Model skills of extraversion, agreeableness, conscientiousness, neuroticism, and openness, as well as measures of grit, hostile attribution bias, decision-making, risk aversion, and time preference. The measures of noncognitive skills are indices constructed from a battery of questions with score categories ranging from 1 ("almost never") to 4 ("almost always"). The STEP questions used to elicit personality and behavior traits are given in Appendix Table 1.[41]

Country background and descriptive statistics

The nine STEP countries in our sample span four world regions with per-capita GDP levels ranging from PPP$ 12,700 in Serbia in 2015 to less than PPP$ 3,000 in Kenya. They reflect significant variation in levels of economic productivity, industrial structure, and market orientation, with implications for what one might expect about the economic returns to education and skills. The countries also differ with respect to the relative labor force participation and earnings of men and women. For example, in the former socialist/communist economies in Europe and Asia, the link between productivity and reward might be weaker because their market-orientation had been relatively more limited for decades (Linz and Semykina, 2009). In these

[41] Measures were recoded such that each index increases in the characteristic. For example, a greater score of extraversion implies a more extroverted personality, while higher hostile attribution indicates a greater tendency to think of others as being hostile to oneself. Risk aversion (or risk-taking in the converse) was elicited by giving each respondent a series of choices involving receiving a constant amount of money or participating in a lottery which offers different higher amounts and the constructed index increases in risk-taking. Time preference was similarly elicited using a hypothetical payoff in which each respondent was given a series of choices involving different payment sizes and different timing of payments (e.g., willingness to receive a smaller payment sooner versus a larger payment later). Scores increase as responses imply delayed gratification. All skills measures (cognitive and noncognitive) are standardized with mean zero and a standard deviation of one. This standardization allows for ease of interpretation: Coefficients can be interpreted as a percentage "return" to a given measured skill.

countries, we might also expect that more egalitarian policies at that time about educating girls and employing women would have led to narrower gender gaps in schooling, employment and wages.

Table 2. Descriptive Statistics, regression samples

	Armenia			Bolivia			Colombia		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	Male	Female	All	Male	Female	All	Male	Female	All
Log of hourly earnings in USD (trimmed)	1.229	0.828	0.979	1.392	1.033	1.195	1.283	1.007	1.144
	(0.631)	(0.611)	(0.648)	(0.905)	(0.957)	(0.950)	(0.798)	(0.845)	(0.834)
Female	--	--	0.625	--	--	0.550	--	--	0.504
	--	--	(0.484)	--	--	(0.498)	--	--	(0.500)
Age, years	39.028	40.083	39.687	37.067	36.927	36.990	37.547	38.486	38.021
	(9.149)	(9.010)	(9.070)	(8.069)	(8.015)	(8.036)	(8.563)	(8.754)	(8.668)
# of years of education <=9 years	8.919	8.949	8.938	8.314	7.818	8.041	8.009	7.842	7.925
	(0.443)	(0.473)	(0.462)	(1.614)	(2.181)	(1.961)	(1.883)	(2.065)	(1.978)
# of years of education 10-13 years	3.142	3.337	3.264	2.621	2.259	2.422	2.043	1.980	2.012
	(1.394)	(1.256)	(1.312)	(1.613)	(1.702)	(1.672)	(1.598)	(1.643)	(1.621)
# of years of education > 13 years	1.988	1.930	1.951	1.617	1.305	1.445	0.536	0.467	0.501
	(2.025)	(2.030)	(2.027)	(2.099)	(1.969)	(2.033)	(1.210)	(1.109)	(1.160)
Literacy assessment (plausible values Z score)	0.026	0.100	0.072	0.107	-0.187	-0.054	0.103	-0.002	0.050
	(0.636)	(0.606)	(0.618)	(0.850)	(1.001)	(0.947)	(0.763)	(0.794)	(0.780)
Extraversion (Z score)	-0.072	0.105	0.038	0.028	-0.019	0.002	0.115	-0.017	0.049
	(0.948)	(1.053)	(1.018)	(0.963)	(0.994)	(0.980)	(0.910)	(1.018)	(0.968)
Conscientiousness (Z score)	0.082	0.215	0.165	0.111	0.113	0.112	0.171	0.180	0.175
	(1.025)	(0.914)	(0.959)	(0.945)	(0.971)	(0.959)	(0.952)	(0.970)	(0.961)
Openness (Z score)	0.070	0.188	0.144	0.100	0.016	0.054	0.120	-0.027	0.046
	(0.990)	(0.970)	(0.979)	(0.978)	(0.996)	(0.988)	(0.971)	(1.038)	(1.007)
Emotional stability (Z score)	0.231	0.004	0.089	0.335	-0.211	0.035	0.330	-0.234	0.046
	(0.921)	(0.969)	(0.957)	(0.932)	(0.996)	(1.005)	(0.929)	(0.952)	(0.982)
Agreeableness, cooperation (Z score)	-0.100	0.136	0.047	0.095	0.025	0.057	-0.000	-0.005	-0.003
	(0.952)	(0.962)	(0.964)	(0.955)	(1.030)	(0.997)	(0.962)	(1.021)	(0.992)
Grit (Z score)	-0.013	0.143	0.085	0.139	0.133	0.136	0.159	0.079	0.119
	(0.957)	(0.958)	(0.960)	(0.950)	(0.996)	(0.975)	(0.942)	(0.959)	(0.951)
Decision making (Z score)	0.059	0.084	0.075	-0.037	0.110	0.044	-0.048	0.080	0.016
	(0.961)	(0.946)	(0.951)	(1.010)	(0.980)	(0.996)	(1.015)	(1.014)	(1.016)
Hostile attribution bias (Z score)	0.038	-0.059	-0.022	0.025	0.220	0.133	-0.096	0.152	0.029
	(1.038)	(0.970)	(0.996)	(0.996)	(0.994)	(0.999)	(0.927)	(1.027)	(0.986)

Risk taking (Z score)	-0.021	0.013	0.000	-0.001	0.052	0.028	0.005	-0.019	-0.007
	(0.987)	(1.031)	(1.014)	(1.026)	(1.006)	(1.015)	(1.041)	(1.014)	(1.027)
Time preference (Z score)	-0.049	-0.050	-0.050	-0.131	0.046	-0.034	--	--	--
	(0.925)	(0.990)	(0.966)	(1.010)	(0.998)	(1.007)	--	--	--
Metropolitan area of residence	0.555	0.604	0.586	0.623	0.613	0.618	0.344	0.377	0.360
	(0.498)	(0.490)	(0.493)	(0.485)	(0.487)	(0.486)	(0.475)	(0.485)	(0.480)
Observations	247	412	659	491	600	1,091	579	589	1,168

	Georgia			**Ghana**			**Kenya**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	Male	Female	All	Male	Female	All	Male	Female	All
Log of hourly earnings in USD (trimmed)	1.239	0.984	1.079	0.689	0.298	0.519	0.720	0.540	0.642
	(0.764)	(0.750)	(0.765)	(1.062)	(1.229)	(1.153)	(0.968)	(1.044)	(1.005)
Female	--	--	0.628	--	--	0.435	--	--	0.433
	--	--	(0.484)	--	--	(0.496)	--	--	(0.496)
Age, years	39.102	40.128	39.746	35.133	34.297	34.770	33.599	33.264	33.454
	(8.831)	(7.894)	(8.263)	(8.033)	(7.106)	(7.651)	(7.430)	(7.031)	(7.260)
# of years of education <=9 years	9.000	9.000	9.000	8.688	8.724	8.704	7.544	6.927	7.277
	(0.000)	(0.000)	(0.000)	(1.361)	(1.219)	(1.300)	(2.582)	(2.931)	(2.754)
# of years of education 10-13 years	3.636	3.757	3.712	2.387	1.989	2.214	2.138	1.700	1.948
	(0.768)	(0.675)	(0.713)	(1.964)	(2.003)	(1.990)	(1.735)	(1.741)	(1.751)
# of years of education > 13 years	2.809	3.251	3.087	1.135	0.795	0.987	0.677	0.424	0.567
	(2.230)	(2.111)	(2.164)	(1.816)	(1.515)	(1.699)	(1.266)	(1.036)	(1.178)
Literacy assessment (plausible values Z score)	0.009	0.195	0.126	0.381	0.041	0.233	0.126	-0.070	0.041
	(0.691)	(0.685)	(0.692)	(0.926)	(0.970)	(0.959)	(0.863)	(0.891)	(0.881)
Extraversion (Z score)	-0.035	0.160	0.087	-0.018	-0.019	-0.019	0.053	-0.002	0.029
	(0.919)	(0.987)	(0.966)	(0.974)	(0.983)	(0.977)	(1.013)	(1.017)	(1.015)
Conscientiousness (Z score)	0.152	0.267	0.224	0.223	-0.105	0.080	0.122	0.063	0.096
	(0.887)	(0.888)	(0.889)	(0.920)	(0.946)	(0.945)	(0.974)	(0.998)	(0.985)
Openness (Z score)	0.006	0.203	0.130	0.061	-0.176	-0.042	0.060	-0.147	-0.029
	(0.994)	(0.851)	(0.911)	(0.994)	(0.974)	(0.992)	(0.988)	(1.014)	(1.004)
Emotional stability (Z score)	0.225	0.063	0.123	0.136	-0.166	0.004	0.107	-0.015	0.054
	(0.914)	(0.992)	(0.966)	(0.926)	(1.035)	(0.986)	(1.013)	(0.971)	(0.996)
Agreeableness, cooperation (Z score)	-0.021	0.129	0.073	0.013	-0.076	-0.025	0.022	0.053	0.035

	(1.050)	(0.986)	(1.012)	(1.005)	(0.986)	(0.997)	(0.963)	(0.973)	(0.967)
Grit (Z score)	0.169	0.302	0.252	0.113	-0.059	0.038	0.083	0.012	0.052
	(0.886)	(0.960)	(0.935)	(0.951)	(0.990)	(0.972)	(1.004)	(1.010)	(1.007)
Decision making (Z score)	-0.001	0.258	0.162	0.106	-0.138	0.000	0.079	0.054	0.068
	(0.927)	(0.937)	(0.941)	(1.042)	(1.004)	(1.032)	(0.992)	(0.950)	(0.974)
Hostile attribution bias (Z score)	-0.081	0.060	0.008	-0.036	-0.016	-0.027	-0.011	-0.033	-0.021
	(0.905)	(0.964)	(0.945)	(0.954)	(0.950)	(0.951)	(1.013)	(0.962)	(0.991)
Risk taking (Z score)	0.050	0.060	0.056	0.100	0.036	0.072	0.052	0.005	0.031
	(1.022)	(1.037)	(1.031)	(1.106)	(1.012)	(1.066)	(1.038)	(1.010)	(1.026)
Time preference (Z score)	0.020	-0.001	0.007	-0.045	-0.147	-0.089	-0.006	0.000	-0.003
	(0.971)	(1.001)	(0.990)	(1.009)	(0.873)	(0.953)	(0.993)	(0.993)	(0.993)
Metropolitan area of residence	0.496	0.451	0.468	0.351	0.397	0.371	0.251	0.280	0.264
	(0.501)	(0.498)	(0.499)	(0.478)	(0.490)	(0.483)	(0.434)	(0.449)	(0.441)
Observations	236	399	635	481	370	851	900	686	1,586

	Serbia			Ukraine			Vietnam		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	Male	Female	All	Male	Female	All	Male	Female	All
Log of hourly earnings in USD (trimmed)	1.282	1.426	1.357	1.374	1.006	1.139	1.240	0.942	1.066
	(1.117)	(0.825)	(0.977)	(0.584)	(0.491)	(0.555)	(0.767)	(0.826)	(0.815)
Female	--	--	0.524	--	--	0.637	--	--	0.583
	--	--	(0.500)	--	--	(0.481)	--	--	(0.493)
Age, years	39.842	40.300	40.082	37.445	40.857	39.619	39.518	38.754	39.073
	(7.986)	(8.002)	(7.993)	(9.134)	(8.791)	(9.060)	(8.182)	(8.083)	(8.131)
# of years of education <=9 years	8.891	8.899	8.895	8.965	9.000	8.987	8.121	8.066	8.089
	(0.436)	(0.582)	(0.517)	(0.565)	(0.000)	(0.340)	(1.931)	(1.942)	(1.937)
# of years of education 10-13 years	2.830	3.172	3.009	3.114	3.491	3.354	2.238	2.088	2.151
	(1.182)	(1.080)	(1.142)	(1.005)	(0.837)	(0.919)	(1.762)	(1.790)	(1.780)
# of years of education > 13 years	0.476	0.888	0.692	0.969	1.267	1.159	1.076	0.948	1.001
	(1.038)	(1.293)	(1.196)	(1.583)	(1.579)	(1.586)	(1.611)	(1.457)	(1.524)
Literacy assessment (plausible values Z score)	0.146	0.241	0.196	0.070	0.182	0.142	-0.006	-0.025	-0.017
	(0.831)	(0.663)	(0.749)	(0.784)	(0.749)	(0.763)	(0.858)	(0.860)	(0.859)
Extraversion (Z score)	-0.005	0.140	0.071	-0.182	0.098	-0.004	-0.032	0.070	0.027

	(0.939)	(0.933)	(0.938)	(1.089)	(0.918)	(0.992)	(0.989)	(1.000)	(0.996)
Conscientiousness (Z score)	0.070	0.199	0.138	-0.086	0.265	0.138	0.193	0.081	0.128
	(0.906)	(0.832)	(0.870)	(0.951)	(0.915)	(0.943)	(0.942)	(0.930)	(0.936)
Openness (Z score)	0.159	0.172	0.166	0.004	0.125	0.081	0.138	-0.088	0.006
	(0.923)	(0.866)	(0.893)	(1.043)	(0.928)	(0.972)	(0.977)	(1.010)	(1.003)
Emotional stability (Z score)	0.248	-0.064	0.084	0.396	-0.147	0.050	0.412	-0.174	0.070
	(0.911)	(0.871)	(0.903)	(0.953)	(0.969)	(0.997)	(0.909)	(0.924)	(0.962)
Agreeableness, cooperation (Z score)	0.031	0.134	0.085	-0.208	0.114	-0.003	0.016	-0.007	0.003
	(0.928)	(0.897)	(0.913)	(1.071)	(0.966)	(1.017)	(1.009)	(0.990)	(0.997)
Grit (Z score)	0.111	0.175	0.145	0.006	0.098	0.065	0.140	0.093	0.113
	(0.882)	(0.855)	(0.868)	(1.036)	(0.935)	(0.973)	(1.014)	(0.915)	(0.957)
Decision making (Z score)	0.007	0.162	0.088	-0.115	0.198	0.084	0.058	0.015	0.033
	(1.009)	(0.893)	(0.952)	(0.999)	(0.908)	(0.953)	(1.018)	(0.983)	(0.998)
Hostile attribution bias (Z score)	--	--	--	0.056	-0.007	0.016	0.055	0.020	0.034
	--	--	--	(1.080)	(0.947)	(0.997)	(1.001)	(0.982)	(0.990)
Risk taking (Z score)	--	--	--	0.133	-0.101	-0.016	0.024	-0.029	-0.007
	--	--	--	(1.076)	(0.918)	(0.984)	(1.011)	(0.997)	(1.003)
Time preference (Z score)	--	--	--	0.039	0.001	0.014	-0.040	-0.078	-0.062
	--	--	--	(1.018)	(1.002)	(1.007)	(0.976)	(0.956)	(0.965)
Metropolitan area of residence	0.284	0.335	0.311	0.264	0.200	0.223	0.499	0.504	0.502
	(0.451)	(0.472)	(0.463)	(0.442)	(0.400)	(0.416)	(0.500)	(0.500)	(0.500)
Observations	412	454	866	254	446	700	713	995	1,708

Notes: The sample is of men and women between the ages of 25-54 in urban Armenia, Boliva, Colombia, Georgia, Ghana, Kenya, Serbia, Ukraine and Vietnam for whom observations for all variables included in the full regression model are available.

Labor force participation rates by gender differ quite widely across the nine countries. In our regression samples, women's share of the remunerated workforce ranges from 43% in Kenya to 64% in Ukraine.[42,43] The distribution of workers in formal wage, informal wage and self-employment is starkly different across the nine STEP countries,[44] and there are key differences in the employment distribution of men and women. Men are more likely than women to be employed in the formal wage sector, although this is not the case in the former socialist countries in Europe where the share of women in formal wage employment exceeds that of men and a larger share of men than women are self-employed.[45] Women are more likely to be employed in the informal wage sector in the lower-income countries. Among those in the informal wage sector, men are more likely to be self-employed, a pattern that may be due to unequal access to savings and capital between men and women.

Education levels have risen significantly over the past two generations (1950-2010) in the STEP countries, but those levels have progressed differently for men and women.[46] The STEP data show not only gender gaps in years of schooling but also gender differences in cognitive and

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42 Using cross-country data, men's average participation rates are within 20 percentage points of each other (with Colombia falling far lower with men's participation rate at just 60 percent); women's labor force participation rates differ more widely, ranging from 32 percent in Colombia to 80 percent in Vietnam.
43 Women's labor force participation rate is influenced by the pull on women's time of marriage and caring for young children. While the mean singular age at marriage for women in these countries is similar at 22-24 years, their total fertility rate ranges from 1.4 in Serbia to 4.4 in Kenya.
44 While 80-90 percent of employment is in the formal sector in Ukraine, formal wage employment accounts for less than 30 percent in Ghana and Kenya. Formal wage employment is highest in the former socialist countries in Europe; in the lower-income countries, informal wage employment and self-employment together far exceeds half of all employment.
45 Georgia is an exception, where more men are self-employed than women.
46 Data presented in Barro and Lee (2015) show that Colombia has consistently shown the smallest education gender gap over that 60-year period. In the countries with the highest completed years of schooling in 2010 (Armenia, Ukraine, and Serbia), gender differences have greatly narrowed since 1950. In the rest of the countries, the gender difference in years of schooling has tended to rise first before declining, indicating that boys' schooling rose first and faster than girls' schooling as school enrollment expanded in those countries.

noncognitive skills. Table 3 summarizes the results of two gender difference tests, a comparison of means and Kolmogorov-Smirnoff (K-S) tests of the kernel densities of these skills. With respect to cognitive skills (literacy proficiency), men in Bolivia, Colombia, Ghana and Kenya do significantly better than women. In contrast, in Georgia and Ukraine, women significantly outscore men, likely reflecting the greater gender equality in schooling in these countries.[47] That Colombian men outperform women with respect to cognitive skills is also noteworthy because education levels of men and women have been at near parity over the past decades (Barro and Lee, 2015).

With respect to noncognitive skills, the countries do not show clear, significant gender differences in the distribution of the FFM measures of these skills, especially when comparing distributions and not just means. Two striking patterns emerge, however: First, in all countries, men outscore women with respect to emotional stability using both comparisons; using the comparison of distributions only, women outscore men in extraversion and agreeableness in four of the nine countries; in no country do men outscore women. Second, women in only the post-transition countries of Europe outscore men in four of the five FFM skills (excepting emotional stability). Overall, these results are consistent with other studies.[48]

Gender patterns with respect to grit and decision-making skills are similar to those for conscientiousness and openness in Ghana, Kenya and Vietnam where men outscore women and

[47] When comparing distributions only, women in Armenia do better than men as well.
[48] See Bouchard Jr. and Loehlin (2001) and Mueller and Plug (2006). In addition, a meta-study by Piccinelli and Wilkinson (2000) suggests how the result relating to emotional stability may be explained. They conclude that women are "more likely to report physical and psychological symptoms and to seek medical help, although few gender differences have been detected in illness behavior, sick role or defence style," and that "social roles and cultural influences contribute to a female preponderance in depression rates." The gender-specific demands posed by marriage, child-rearing and the resulting limited number of roles available to women compels them to rely for identity and self-esteem on their role as housewife and mother. Women in paid employment, on the other hand, may face economic discrimination and job inequality along with their family responsibilities for household chores and child care. Studies that have controlled for socioeconomic differences are not able to explain away the gender differences in depression prevalence rates. The authors conclude that genetic and biological factors and poor social support have few or no effects in the emergence of gender differences in the prevalence rates and that the gender differences are genuine.

in Ukraine where women outscore men, using both comparison methods. The results for the other countries are less clear. In no country do women outscore men in risk-taking behavior; this male advantage is significant in Kenya, Ukraine and Vietnam, according to both comparison methods.[49] This gender pattern comports with the results of a meta-analysis of 150 risk experiments which find that women are significantly more averse to risk (Byrnes, Miller and Schafer, 1999) as well as with other studies (Croson and Gneezy, 2009; Charness and Gneezy, 2012).[50] With respect to time preference, there is no significant gender difference in six of the seven countries.

[49] Note that there are no data for hostile attribution bias, risk-taking and time preference in the Serbia data set, and no data on time preference also for Colombia.
[50] Note that Nelson (2015) challenges the conclusion reached by the latter studies.

Table 3. Summary of results from significance tests of gender differences in cognitive and noncognitive skills, all adults aged 25-54

	Comparison of means[1]			Comparison of distributions [2]		
Skills	**Higher male**	**No significant gender difference**	**Higher female**	**Higher male**	**No significant gender difference**	**Higher female**
Literacy proficiency (plausible values)	Bolivia, Colombia, Ghana, Kenya	Armenia, Serbia, Vietnam	Georgia, Ukraine	Bolivia, Colombia, Ghana, Kenya	Serbia, Vietnam	Armenia, Georgia, Ukraine
Extraversion	Bolivia, Colombia, Kenya	Ghana	Armenia, Georgia, Serbia, Ukraine, Vietnam		Bolivia, Colombia, Ghana, Kenya, Vietnam	Armenia, Georgia, Serbia, Ukraine
Conscientiousness	Ghana, Kenya, Vietnam	Bolivia, Colombia	Armenia, Georgia, Serbia, Ukraine	Ghana, Kenya, Vietnam	Armenia, Bolivia, Colombia	Georgia, Serbia, Ukraine
Openness	Bolivia, Colombia, Ghana, Kenya, Serbia, Vietnam	Armenia	Georgia, Ukraine	Ghana, Kenya, Vietnam	Armenia, Bolivia, Colombia, Serbia	Georgia, Ukraine
Emotional Stability	Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Serbia, Ukraine, Vietnam			Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Serbia, Ukraine, Vietnam		
Agreeableness	Bolivia, Ghana	Colombia, Kenya, Vietnam	Armenia, Georgia, Serbia, Ukraine		Bolivia, Colombia, Georgia, Ghana, Kenya, Vietnam	Armenia, Serbia, Ukraine
Grit	Ghana, Kenya, Vietnam	Bolivia, Serbia	Armenia, Colombia, Georgia, Ukraine	Ghana, Kenya, Vietnam	Armenia, Bolivia, Colombia, Georgia, Serbia	Ukraine
Decision making	Colombia, Ghana, Kenya, Vietnam	Armenia	Bolivia, Georgia, Serbia, Ukraine	Ghana, Kenya, Vietnam	Armenia	Bolivia, Colombia, Georgia, Serbia, Ukraine
Hostile attribution bias	Vietnam	Armenia, Ghana, Kenya, Ukraine	Bolivia, Colombia, Georgia	Vietnam	Georgia, Ghana, Kenya, Ukraine	Armenia, Bolivia, Colombia
Risk taking	Armenia, Ghana, Kenya, Ukraine, Vietnam	Bolivia, Colombia, Georgia		Kenya, Ukraine, Vietnam	Armenia, Bolivia, Colombia, Georgia, Ghana	
Time preference	Vietnam	Armenia, Georgia, Ghana, Kenya, Ukraine	Bolivia		Armenia, Georgia, Ghana, Kenya, Ukraine, Vietnam	Bolivia

IV. Results – Pooled Sample

Our first set of results uses the pooled sample of eight STEP countries for which we have comparable measures for nine noncognitive skills.[51] We examine if men and women in this sample have different returns to the same covariates, and we explore the effect of covariates on selection into remunerated work. We then explore if the results vary along the earnings distributions for this same sample. In order to allow for non-linearity in the returns to schooling, we use spline variables that define three education segments corresponding roughly to basic education (less than or equal to nine years of schooling), secondary education (10 to 13 years of schooling), and tertiary education (greater than 13 years).[52] For cognitive skills, we use plausible values computed from literacy assessment scores. We include individual noncognitive skills, and we test for the joint significance of those skills.

[51] This set of results excludes Serbia which does not have data for three measures of noncognitive skills.
[52] Previous studies find that the returns to each school cycle do differ—on average, higher for the tertiary level than for the lower cycles—but that these returns can shift with massive increases in school enrollments and educational levels (Montenegro and Patrinos, 2014).

Table 4: Earnings functions with cognitive and noncognitive skills, individuals, ages 25-54

	OLS			Selectivity corrected		First-Stage	
VARIABLES	All	Males	Females	Males	Females	Males	Females
Female	-0.257***	--	--	--	--	--	--
	(0.018)	--	--	--	--	--	--
Age, years	0.026**	0.040***	0.016	0.035**	0.070***	-0.013	0.131***
	(0.010)	(0.015)	(0.014)	(0.016)	(0.016)	(0.025)	(0.017)
Age squared/1000	-0.286**	-0.455**	-0.142	-0.394*	-0.797***	0.042	-1.604***
	(0.134)	(0.198)	(0.183)	(0.205)	(0.204)	(0.318)	(0.219)
# of years of education <=9 years	0.027***	0.037***	0.020**	0.036***	0.014	0.010	-0.001
	(0.006)	(0.009)	(0.008)	(0.009)	(0.009)	(0.015)	(0.010)
# of years of education 10-13 years	0.050***	0.045***	0.056***	0.045***	0.068***	-0.003	0.039***
	(0.008)	(0.012)	(0.011)	(0.012)	(0.012)	(0.019)	(0.014)
# of years of education > 13 years	0.132***	0.121***	0.143***	0.118***	0.177***	0.062***	0.100***
	(0.007)	(0.010)	(0.009)	(0.010)	(0.010)	(0.015)	(0.011)
Literacy assessment (plausible values Z score)	0.037***	0.029	0.046***	0.030	0.063***	0.017	0.027
	(0.013)	(0.019)	(0.018)	(0.019)	(0.019)	(0.029)	(0.020)
Extraversion (Z score)	0.017*	0.018	0.018	0.015	0.034**	0.040*	0.038**
	(0.009)	(0.013)	(0.012)	(0.014)	(0.014)	(0.021)	(0.015)
Conscientiousness (Z score)	0.003	0.005	0.004	-0.001	0.030**	0.098***	0.067***
	(0.010)	(0.015)	(0.014)	(0.015)	(0.015)	(0.023)	(0.016)
Openness (Z score)	0.041***	0.055***	0.031**	0.055***	0.030**	0.004	0.018
	(0.010)	(0.015)	(0.014)	(0.015)	(0.015)	(0.023)	(0.016)
Emotional stability (Z score)	0.021**	0.008	0.028**	0.006	0.041***	0.044**	0.036**
	(0.009)	(0.014)	(0.013)	(0.014)	(0.014)	(0.022)	(0.015)
Agreeableness, cooperation (Z score)	-0.000	0.013	-0.011	0.015	-0.021	-0.058***	-0.021
	(0.009)	(0.014)	(0.013)	(0.014)	(0.014)	(0.022)	(0.016)
Grit (Z score)	-0.012	-0.018	-0.005	-0.019	0.011	0.012	0.041***
	(0.010)	(0.014)	(0.013)	(0.014)	(0.015)	(0.023)	(0.016)
Decision making (Z score)	0.011	0.005	0.017	0.004	0.015	0.005	-0.005
	(0.010)	(0.014)	(0.013)	(0.014)	(0.014)	(0.023)	(0.016)
Hostile attribution bias (Z score)	-0.029***	-0.030**	-0.028**	-0.031**	-0.023*	0.012	0.006
	(0.009)	(0.013)	(0.013)	(0.013)	(0.014)	(0.022)	(0.015)
Risk taking (Z score)	0.035***	0.042***	0.028**	0.042***	0.043***	0.004	0.029**
	(0.009)	(0.012)	(0.012)	(0.012)	(0.013)	(0.020)	(0.015)
Number of own children under 6 years						0.051	-0.135***
						(0.037)	(0.021)
Married						0.383***	-0.179***
						(0.054)	(0.031)
# of other employed/hh_size						-1.414***	-0.594***
						(0.092)	(0.067)
Athro						-0.168	0.911***
						(0.144)	(0.065)
Lnsigma						-0.225***	-0.061***
						(0.014)	(0.021)
Observations	8,425	3,911	4,514	5,223	8,304	5,223	8,304
R-squared	0.225	0.229	0.211				

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: The sample is of men and women between the ages of 25-54 in urban Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam. The estimations do not include Serbia which does not have data on risk taking or hostile attribution bias. The dependent variable is the natural logarithm of gross hourly earnings in 2011 $PPP, top and bottom 1% trimmed. Other controls included years of schooling at basic, upper-secondary and tertiary levels, a measure of cognitive skill (literacy), country fixed effects and a country-specific location indicating metropolitan area of residence.

Returns to schooling and skills

The first column of Table 4 presents ordinary least squares results for a pooled sample of 8,425 men and women who are engaged in remunerated work, including wage work and self-employment, in eight countries. On average, women earn 26 percent lower hourly earnings than men do, controlling for the full set of covariates. The OLS returns to schooling are positive and significant, but highly non-linear, increasing from 3 percent for basic education to 5 percent for secondary education and to 13 percent for post-secondary education. With respect to cognitive skills, a one-standard deviation gain in cognitive performance, controlling for schooling and other covariates, increases log-earnings by 4 percent. Using a joint significance test, we test whether the noncognitive skills taken *together* affect individual earnings, and we find that these skills are jointly statistically significant. We find that openness, the degree to which a person seeks intellectual stimulation and variety, emotional stability and risk-taking have significantly positive returns, while hostile attribution bias has a negative return.

We then test if the model that constrains structural coefficients for men and women to be the same (that is, with only gender intercepts) is correctly specified. The Wald test, however, rejects joint equality of the coefficients, suggesting that separating the sample by gender is justified. We also test for selection bias and find evidence of selection bias for women, but not for men.[53] In the discussion that follows we focus on OLS results for men and selectivity-corrected results for women.

[53] We perform OLS estimates on separate samples of 3,911 men and 4,514 women and using the entire sample of active and inactive individuals, obtain selectivity corrected estimates from a sample of 5,223 men and 8,304 women.

Gender differences in returns to schooling and skills

Both men and women have the expected returns to experience, proxied by age. Gender differences in the non-linear pattern of returns to schooling are remarkable (Table 4): The estimated returns to basic years of schooling, controlling for country fixed effects and for measures of cognitive and noncognitive skills, are statistically significant for men (4 percent), but not for women; however, at higher levels of schooling, there is a much larger return per year of schooling for women (7 percent for secondary and 18 percent for post-secondary) than for men (4 percent and 12 percent, respectively). Higher levels of schooling also have a significant positive effect on selection into remunerated work for women, which is consistent with the literature on the determinants of labor force participation for women.

Gender differences in the effects of cognitive skill are also notable: a one-standard deviation gain in cognitive performance, controlling for schooling and noncognitive skills, has no effect on men's log-earnings, but a similar gain increases women's log-earnings by 6 percent, an effect larger than the effect of basic education (which is effectively zero) and comparable in magnitude to the effect of 10-13 years of education. While this raises concern as to why learning does not appear to benefit boys, it lends empirical support to the conversation about the benefits of learning for girls.[54] We look to country-specific results to better understand this gender difference.

We next turn to gender differences in the returns to noncognitive skills. We find that both men and women are rewarded for openness and for risk-taking, while they are both penalized for hostile attribution bias. However, women are also rewarded for emotional stability,

[54] Note that cognitive skills have no effect on the selection into participation in remunerated work for either men or women.

conscientiousness and extraversion, while men are not. In the case of emotional stability, it could be argued that it is rewarded in the population where it is rarer (among women) and not rewarded for those who have more of it (among men). The same argument does not apply to the results for conscientiousness and extraversion, and the reason for this gender difference remains a puzzle.

In addition to being associated with higher earnings, risk taking is associated with the higher probability that women will engage in remunerated work. Similarly, women with higher grit scores are more likely to be engaged in remunerated work. Conscientiousness and emotional stability are associated with participation in remunerated work for both men and women, although the effect is greater for men than for women. Extraversion has a similar association with participation for both sexes, while agreeableness is associated with lower participation by men in remunerated work.

Gender differences in returns to schooling and skills along the earnings distribution

We next explore if returns to schooling and skills vary along the earnings distribution, and are different for men and women, by estimating quantile regressions in addition to the mean regressions discussed above. By estimating quantile-specific effects, we are able to examine the relationship between earnings and skills not only at the center of the earnings distribution, but also at its tails. Past studies that have found heterogeneous returns to schooling attribute this result to unobserved skills being correlated with schooling, with this correlation being stronger or weaker at different parts of the earnings distribution.[55]

[55] That is, more able individuals become better educated because they expect a higher rate of return from schooling. Since our estimation model controls not only for schooling but also for cognitive and noncognitive skills, which proxy innate ability to some extent, a further explanation for heterogenous returns is needed.

We estimate the returns to schooling and skills at the .10, .25, .50, .75 and .90 points of the earnings distributions. We do not correct for selectivity bias in the quantile regressions as we did in the mean regressions.[56]

[56] While several approaches to correcting for sample selection in quantile regression models have been adopted, decomposition in the context of quantile regressions is more complex (Buchinsky 1998, 2001; Arellano and Bonhomme, 2017). Like ours, other studies do not correct for selectivity bias in their quantile regressions (e.g., Tognatta, Valerio, and Sanchez Puerta, 2015; and Blau and Kahn, 2017).

Table 5. QR estimates of earnings functions with schooling, cognitive and noncognitive skills, individuals aged 25-54

	Males						**Females**					
Variables	**OLS**	**q10**	**q25**	**q50**	**q75**	**q90**	**OLS**	**q10**	**q25**	**q50**	**q75**	**q90**
Age, years	0.040**	0.073**	0.047***	0.044***	0.029	0.012	0.016	0.020	0.019	0.006	0.021	0.018
	(0.016)	(0.029)	(0.018)	(0.016)	(0.021)	(0.035)	(0.014)	(0.020)	(0.015)	(0.015)	(0.017)	(0.025)
Age squared/1000	-0.455**	-0.968***	-0.594**	-0.499**	-0.271	-0.027	-0.142	-0.208	-0.211	-0.029	-0.215	-0.150
	(0.202)	(0.371)	(0.241)	(0.204)	(0.278)	(0.433)	(0.181)	(0.258)	(0.193)	(0.197)	(0.228)	(0.327)
# of years of education <=9 years	0.037***	0.016	0.019*	0.035***	0.052***	0.036*	0.020**	0.001	0.007	0.015*	0.032**	0.037*
	(0.009)	(0.015)	(0.012)	(0.008)	(0.011)	(0.019)	(0.009)	(0.014)	(0.013)	(0.009)	(0.012)	(0.021)
# of years of education 10-13 years	0.045***	0.053***	0.062***	0.044***	0.033**	0.020	0.056***	0.074***	0.057***	0.064***	0.061***	0.036
	(0.013)	(0.019)	(0.016)	(0.013)	(0.016)	(0.026)	(0.012)	(0.020)	(0.017)	(0.014)	(0.015)	(0.029)
# of years of education > 13 years	0.121***	0.106***	0.108***	0.127***	0.137***	0.139***	0.143***	0.123***	0.143***	0.140***	0.143***	0.134***
	(0.010)	(0.016)	(0.009)	(0.013)	(0.013)	(0.021)	(0.009)	(0.014)	(0.012)	(0.010)	(0.010)	(0.023)
Literacy	0.029	0.063*	0.042*	0.037*	0.024	0.031	0.046**	0.070***	0.065***	0.058***	0.031	-0.012
	(0.020)	(0.033)	(0.023)	(0.022)	(0.026)	(0.041)	(0.018)	(0.025)	(0.021)	(0.020)	(0.022)	(0.045)
Openness (Z score)	0.055***	0.054**	0.067***	0.057***	0.035*	0.047	0.031**	0.008	0.026	0.031**	0.046***	0.052*
	(0.015)	(0.026)	(0.018)	(0.014)	(0.021)	(0.033)	(0.014)	(0.018)	(0.018)	(0.016)	(0.014)	(0.027)
Conscientiousness (Z score)	0.005	0.033	0.024	0.001	-0.017	-0.011	0.004	0.002	0.025	0.012	0.003	-0.015
	(0.015)	(0.023)	(0.017)	(0.016)	(0.017)	(0.029)	(0.014)	(0.023)	(0.018)	(0.015)	(0.016)	(0.030)
Extraversion (Z score)	0.018	0.006	0.020	0.008	0.040**	0.034	0.018	0.043***	0.017	0.005	0.023	0.017
	(0.014)	(0.021)	(0.016)	(0.016)	(0.017)	(0.025)	(0.012)	(0.017)	(0.014)	(0.013)	(0.017)	(0.032)
Agreeableness, cooperation (Z score)	0.013	-0.030	-0.034**	-0.010	0.038**	0.089***	-0.011	-0.036*	-0.010	-0.020	-0.008	0.007
	(0.014)	(0.022)	(0.015)	(0.017)	(0.017)	(0.026)	(0.013)	(0.021)	(0.014)	(0.013)	(0.015)	(0.030)
Emotional stability (Z score)	0.008	0.027	0.011	-0.003	0.013	0.019	0.028**	0.023	0.033**	0.031**	0.031*	0.034
	(0.014)	(0.022)	(0.017)	(0.016)	(0.017)	(0.025)	(0.013)	(0.021)	(0.016)	(0.012)	(0.017)	(0.029)
Grit (Z score)	-0.018	-0.011	-0.037**	-0.020	-0.006	-0.011	-0.005	-0.010	-0.016	0.001	0.002	0.033
	(0.014)	(0.023)	(0.017)	(0.013)	(0.017)	(0.029)	(0.014)	(0.019)	(0.021)	(0.016)	(0.019)	(0.028)
Decision making (Z score)	0.005	0.020	-0.002	0.008	-0.014	0.001	0.017	0.005	0.014	0.016	0.014	0.009
	(0.014)	(0.020)	(0.017)	(0.016)	(0.021)	(0.028)	(0.013)	(0.023)	(0.017)	(0.015)	(0.018)	(0.025)
Hostile attribution bias (Z score)	-0.030**	-0.082***	-0.053***	-0.026*	-0.000	-0.005	-0.028**	-0.071***	-0.031*	-0.025**	-0.020	0.027
	(0.014)	(0.022)	(0.019)	(0.015)	(0.015)	(0.025)	(0.013)	(0.024)	(0.016)	(0.012)	(0.014)	(0.027)
Risk taking (Z score)	0.042***	0.039*	0.044***	0.037**	0.040***	0.065**	0.028**	0.037*	0.025*	0.020	0.029*	0.004
	(0.013)	(0.020)	(0.013)	(0.015)	(0.015)	(0.027)	(0.012)	(0.019)	(0.014)	(0.015)	(0.017)	(0.022)
Observations	3911	3911	3911	3911	3911	3911	4514	4514	4514	4514	4514	4514
R-squared	0.229						0.211					

Notes: These results derive from the full model with country fixed effects and an additional control for metropolitan area of residence. Statistical significance is denoted as *** p<0.01, ** p<0.05, * p<0.1 ; robust standard errors are in parenthesis. The estimations do not include Serbia which does not have data on risk taking or hostile attribution bias. Data sources: STEP data for 8 countries, 2012-13

The quantile regression results in Table 5 identify in which part of the earnings distribution the returns to schooling and skills are higher or lower and how these patterns differ between men and women. We focus our discussion on the differences between the 25th and 75th percentiles (hereon represented as q25 and q75, respectively), but examining the entire distribution is instructive because switches could happen at a lower or higher quantile.

Starting with the schooling splines, we note that for men and women those at the lower tail of the conditional distribution of earnings see zero returns to basic education, but the returns to basic education increase at higher quantiles, increasing to 5 percent at q75 for men and 4 percent at q90 for women. The return to secondary education for men at q10 is comparable to the average return of 5 percent, and for women at q10 is 7 percent.[57] The estimated returns to post-secondary schooling are between 11 percent for men and 14 percent for women providing rather tight bounds on the true return to post-secondary schooling.[58]

The returns to cognitive skills are only weakly significant for men across the earnings distribution but are strongly significant for women at the lower and middle end of the distribution. In fact, for women, the returns to a one-standard deviation gain in literacy proficiency (6-7 percent) are comparable to the returns to an additional year of secondary education in the lower half of the earnings distribution.[59]

With respect to noncognitive skills, in the quantile regressions, the coefficients for openness are significant for men in the bottom three-fourths of the distribution, and for women

[57] Although it appears that they decrease in the case of 10-13 years of education, our test of equality of the coefficients at the 25th, 50th and 75th percentiles, and at the 25th and 75th percentiles could not be rejected.
[58] At basic education, the upper bounds are 4 and 5 percent for women and men respectively, and for 10-13 years of education, they are 6 and 7 percent for men and women, respectively.
[59] We note this with a caveat that gains in literacy proficiency and additional years of schooling are likely correlated, we are not implying there is a trade-off.

only in the top half of the distribution. However, for both men and women, tests of equality of the coefficients for openness across the conditional distribution could not be rejected. Risk-taking is strongly significant for men across the distribution but shows no variation across the quantiles; it is only weakly significant for women across the distribution. Hostile attribution bias has significant coefficients only at the lower half of the distribution for both men and women.

Finally, three other noncognitive skills show significant returns at different parts of the earnings distributions: (1) Agreeableness is associated with lower earnings (3 percent) for men at q25 but with higher earnings (9 percent) at q90, and these differences are statistically significant. (2) Extraversion rewards men at q75 and women at q10. (3) Women are rewarded for emotional stability at the mean, median and q25. These quantile regressions results for the pooled sample of countries have been estimated with country fixed effects that are meant to control for cross-country differences in earnings and assume that the relationship between earnings and schooling and skills within each country is the same. Because the distribution of earnings differs across countries, our quantile regressions results could be reflecting the wage structures specific to different countries. We now turn to the results of the models estimated for each country.

V. Country-Specific Results

In this section, we turn to country-specific results, expanding the analysis to include a ninth country, Serbia, for which we have comparable measures for seven of the nine noncognitive skills. We first explore if the returns to schooling and skills differ by gender. We then turn to the gender earnings gap, first examining the effect of the unconstrained model on the extent of the unexplained/coefficients/structure gap and then estimating the effect of expanding the definition of human capital from schooling to skills on this gap. For ease of presentation, we present only summary tables of our results by country and gender in the text; Appendix Table 4 presents the complete results. Also, for the sake of comparison, we include the estimates from Table 4 on the pooled sample.

Gender differences in the returns to schooling

First, we turn to the estimates of the returns to schooling. For all samples but women in Armenia and Bolivia and men in Ghana and Ukraine, the estimated return to basic education is not significant, whereas the estimated returns to post-secondary education in all countries tend to be positive, larger and statistically significant.[60] These results show a steep gradient in log earnings with increasing education. We note too that the returns to women's schooling are higher than the returns to men's schooling but that this gender difference is largest at the post-secondary level.[61,62] These results are consistent with our findings for the pooled sample.

[60] Note that the returns to basic education in the pooled sample of all countries is significant. Our country-specific results suggest that this arises from variation between countries, rather than from variation within countries.

[61] Montenegro and Patrinos (2014) find average returns to tertiary education in over 30 countries in Sub-Saharan Africa to be 21 percent for both men and women.

[62] The returns to schooling, measured as years, are significantly higher for women in Ghana, Ukraine and Vietnam, and for men in Colombia and Kenya. The gender differences in the return to years of schooling are not statistically different between men and women in half of the countries—Armenia, Bolivia, Georgia, and Serbia. Correcting for selection bias does not change any of these findings. Consistent with Glewwe (1996) and Hanushek et al. (2015), in Kenya controlling for skills reduces the estimated returns to years of schooling by 1-2 percentage points for men and women.

Table 6. Log earnings returns to schooling

Countries	Completed schooling years and education splines	Men OLS	Men Selectivity-corrected	Women OLS	Women Selectivity-corrected
All countries					
	<10 years	0.037***	0.036***	0.020**	0.014
	10-13 years	0.045***	0.045***	0.056***	0.068***
	>13 years	0.121***	0.118***	0.143***	0.177***
Armenia					
	<10 years	-0.014	0.045	0.064**	0.082***
	10-13 years	0.022	0.005	-0.027	-0.040
	>13 years	0.036	-0.003	0.101***	0.086***
Bolivia					
	<10 years	0.037	0.036	0.068***	0.072***
	10-13 years	-0.038	-0.038	-0.035	-0.034
	>13 years	0.121***	0.121***	0.161***	0.172***
Colombia					
	<10 years	0.015	0.017	0.017	0.011
	10-13 years	0.069**	0.066**	0.050	0.080**
	>13 years	0.182***	0.182***	0.194***	0.210***
Georgia					
	<10 years	--	--	--	--
	10-13 years	-0.072	-0.103	-0.004	-0.003
	>13 years	0.076***	0.065**	0.118***	0.160***
Ghana					
	<10 years	0.105***	0.102***	-0.055	-0.056
	10-13 years	-0.001	0.003	0.073*	0.070*
	>13 years	0.172***	0.173***	0.256***	0.257***
Kenya					
	<10 years	-0.005	-0.005	0.024	0.016
	10-13 years	0.113***	0.112***	0.022	0.032
	>13 years	0.289***	0.286***	0.379***	0.382***
Serbia					
	<10 years	0.083	0.161	-0.015	0.241
	10-13 years	0.044	0.041	0.155***	-0.003
	>13 years	0.105*	0.106*	0.132***	0.148**
Ukraine					
	<10 years	0.069***	0.106***	--	--
	10-13 years	0.005	0.002	0.003	0.004
	>13 years	0.007	0.011	0.120***	0.120***
Vietnam					
	<10 years	0.009	0.009	-0.007	-0.015
	10-13 years	0.054**	0.056**	0.092***	0.106***
	>13 years	0.086***	0.082***	0.129***	0.161***

Note: Results are from the full model estimates that include also measures of cognitive and noncognitive skills. All-countries pooled results are estimated with country fixed effects. See Table 4 and Appendix Table 4 for complete results. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data sources: STEP data for 9 countries, 2012-13.

Gender differences in the returns to cognitive skills

Whereas the estimated return to cognitive skills based on literacy assessments is positive and significant in the pooled sample, the estimates for individual countries are very mixed. The estimates are not significant for all but one country in the case of men and are only significant in one-third of the countries in the case of women. However, a one-standard deviation gain in cognitive skills increases log-earnings by as much as 12 percent for men in Bolivia, and by 10, 14 and 19 percent for women in Vietnam, Kenya, and Georgia (Table 7). We obtain significant findings with large returns for women in Kenya and Vietnam, even when controlling for both schooling and noncognitive skills. The striking gender difference observed in the pooled sample results are less obvious in individual countries and are restricted to the aforementioned countries.

Table 7. Log earnings returns to cognitive skills

	Men				Women			
	OLS		Selectivity corrected		OLS		Selectivity corrected	
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
All countries	0.039**	0.029	0.041**	0.030	0.055***	0.046**	0.075***	0.063***
Armenia	0.073	0.054	0.092	0.073	0.059	0.068	0.045	0.056
Bolivia	0.122**	0.124**	0.121*	0.116*	-0.031	-0.022	-0.045	-0.042
Colombia	-0.047	-0.044	-0.047	-0.037	-0.038	-0.051	-0.032	-0.039
Georgia	0.080	0.076	0.081	0.064	0.118**	0.103**	0.218***	0.192***
Ghana	-0.019	-0.053	-0.043	-0.067	-0.024	-0.022	0.029	-0.018
Kenya	0.049	0.052	0.058	0.062	0.110**	0.104*	0.152**	0.143**
Serbia	0.019	0.029	0.022	0.031	0.002	-0.000	-0.104	-0.129
Ukraine	-0.002	-0.007	-0.062	-0.057	0.005	-0.002	0.004	-0.001
Vietnam	0.059	0.037	0.051	0.030	0.117***	0.087**	0.136***	0.100***

Note: Specifications [1] and [3] do not include noncognitive skills; specifications [2] and [4] are full models that include noncognitive skills. Schooling is measured as spline variables. Results for all countries pool the samples of Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam and are estimated with country fixed effects. See Appendix Table 4 for complete results. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Data sources: STEP data, 2012-13

Gender differences in the returns to noncognitive skills

With the exception of Serbia for which noncognitive skills are not jointly significant in any specification, and Ghana and Kenya for which noncognitive skills are not jointly significant for all specifications related to women, we find that noncognitive skills together do affect the log-earnings of men and women (Table 8). Correcting for selection bias switches the joint significance of these skills from not-significant to significant for women in Armenia, Colombia and Georgia.[63]

Table 8. Joint significance of noncognitive skills in log earnings regression estimates, adults aged 25-54

	Men		Women	
	OLS	**Selectivity-corrected**	**OLS**	**Selectivity-corrected**
All countries	S***	S***	S***	S***
Armenia	S**	S***	NS	S***
Bolivia	S**	S*	NS	S*
Colombia	S**	S***	NS	S**
Georgia	S**	S***	NS	S***
Ghana	S*	S**	NS	NS
Kenya	S***	S***	NS	NS
Serbia	NS	NS	NS	NS
Ukraine	NS	NS	S**	S***
Vietnam	S*	NS	S***	S***

Note: These are based on the full model results using schooling splines as a measure of education. The complete results are contained in Appendix Table 4. Results for all countries pool the samples of Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam and are estimated with country fixed effects. No data on time preference for Colombia; no data on hostile attribution bias, risk-taking and time preference for Serbia. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Data sources: STEP data for 9 countries, 2012-13

[63] In an effort to understand the interrelationships among individual noncognitive skills and to find a more parsimonious measure of this aspect of human capital, we estimated a principal components model for noncognitive skills using the pooled sample of countries and repeated the analysis for individual countries. We find no individual noncognitive skill that explains a large enough share of the variation in the log-earnings of either men or women to justify a principal components approach, so we continue to include the full list of noncognitive skills in addition to schooling and cognitive skills as a reduced-form specification of human capital. Our results indicated the variables of nine distinct noncognitive skills were characterized more by “uniqueness” rather than being correlated. We also implemented the approach developed by Sarzosa and Urzua (2015); see footnote 16.

The analysis of returns to individual noncognitive skills in the analysis of individual countries presents a more complex picture compared with the pooled sample regressions, as patterns across countries differ regarding which skills are valued in the labor market and which skills obtain different returns for men and women. For example, while openness is strongly significant in the pooled sample of countries, its coefficient is significantly positive and varies for either men or women in only five countries. We find that taking risks increases log-earnings for men and women, but not in the same countries. Hostile attribution bias is negatively associated with log-earnings, except in Georgia, where hostile attribution bias raises men's log earnings.[64] For cognitive skills, some of the results obtained in the pooled sample disappear or are significant only in a few countries. Similarly, skills which did not yield significant returns in the pooled sample of all countries are significant in country-specific estimations (e.g. grit has a negative return in Ghana). We consider that these differences support a composition effect when all countries are combined, but note *that our results relating to openness, risk-taking and hostile attribution bias are robust across several countries.*

Table 9. Log earnings returns to noncognitive skills, adults aged 25-54

		Men		**Women**	
		OLS	**Selectivity-corrected**	**OLS**	**Selectivity-corrected**
All countries	Openness	0.055***	0.055***	0.031**	0.030**
	Conscientiousness	0.005	-0.001	0.004	0.030**
	Extraversion	0.018	0.015	0.018	0.034**
	Agreeableness	0.013	0.015	-0.011	-0.021
	Emotional stability	0.008	0.006	0.028**	0.041***
	Grit	-0.018	-0.019	-0.005	0.011
	Decision making (1)	0.005	0.004	0.017	0.015
	Hostile attribution bias (1)	-0.030**	-0.031**	-0.028**	-0.023*

[64] Emotional stability is statistically significant in four countries, but with mixed positive and negative returns for men and women. Agreeableness and conscientiousness are statistically significant in two countries each, with no overlap in the countries for men and women and also a mix of positive and negative returns, and extraversion is statistically significant in just two countries and is positively associated with hourly earnings in both. Finally, grit is statistically significant in two countries, with no overlap in the countries for men and women and mixed positive and negative returns.

Table 9. Log earnings returns to noncognitive skills, adults aged 25-54

	Risk taking	0.042***	0.042***	0.028**	0.043***
Armenia	Openness	0.109**	0.106**	0.019	0.004
	Conscientiousness	0.020	-0.014	-0.029	-0.040
	Extraversion	0.045	0.022	0.029	0.025
	Agreeableness	-0.104**	-0.111**	-0.003	-0.012
	Emotional stability	0.042	0.056	0.061**	0.049
	Grit	0.022	0.017	0.040	0.036
	Decision making	-0.005	0.009	-0.014	-0.002
	Hostile attribution bias	0.055	0.027	0.023	0.030
	Risk taking	0.069*	0.091**	-0.012	-0.016
	Time preference	0.040	0.054	0.002	0.007
Bolivia	Openness	-0.035	-0.034	-0.009	-0.003
	Conscientiousness	-0.099**	-0.098**	-0.042	-0.046
	Extraversion	0.039	0.040	-0.018	-0.005
	Agreeableness	0.037	0.037	-0.026	-0.029
	Emotional stability	-0.005	-0.001	0.000	0.001
	Grit	-0.013	-0.012	-0.037	-0.040
	Decision making	-0.091**	-0.093**	0.028	0.017
	Hostile attribution bias	-0.078*	-0.075*	-0.096**	-0.090**
	Risk taking	0.036	0.033	0.083**	0.086**
	Time preference	-0.061	-0.060	0.029	0.027
Colombia [1]	Openness	0.065*	0.068**	0.038	0.030
	Conscientiousness	0.002	0.004	-0.020	0.020
	Extraversion	-0.024	-0.019	0.073**	0.082**
	Agreeableness	0.020	0.014	-0.042	-0.079**
	Emotional stability	-0.069**	-0.068**	0.018	0.024
	Grit	-0.014	-0.012	-0.057	-0.053
	Decision making	0.013	0.014	-0.027	-0.059
	Hostile attribution bias	-0.103***	-0.103***	-0.015	-0.009
	Risk taking	0.066**	0.067**	0.038	0.047
Georgia	Openness	0.059	0.072	0.052	0.068
	Conscientiousness	0.060	0.045	0.017	0.031
	Extraversion	-0.021	-0.035	0.004	0.041
	Agreeableness	0.039	0.053	-0.057	-0.055
	Emotional stability	0.065	0.067	0.009	0.046
	Grit	0.008	-0.019	0.013	0.090
	Decision making	-0.002	-0.017	0.016	0.027
	Hostile attribution bias	0.119**	0.138**	-0.004	-0.000
	Risk taking	0.104**	0.109**	-0.054	-0.037
	Time preference	-0.131***	-0.141***	0.070*	0.075*
Ghana	Openness	0.045	0.038	0.021	0.019
	Conscientiousness	0.055	0.070	-0.085	-0.083
	Extraversion	-0.010	-0.009	0.052	0.054

Table 9. Log earnings returns to noncognitive skills, adults aged 25-54

	Agreeableness	0.057	0.051	-0.011	-0.007
	Emotional stability	-0.041	-0.039	0.058	0.056
	Grit	-0.115**	-0.119**	0.017	0.018
	Decision making	0.061	0.059	0.061	0.060
	Hostile attribution bias	-0.026	-0.026	-0.130**	-0.127**
	Risk taking	0.084*	0.081*	-0.004	-0.003
	Time preference	-0.063	-0.058	-0.076	-0.072
Kenya	Openness	0.091***	0.092***	0.027	0.007
	Conscientiousness	0.003	-0.000	0.070*	0.095**
	Extraversion	0.033	0.033	0.018	0.026
	Agreeableness	-0.020	-0.026	0.020	0.000
	Emotional stability	0.045*	0.047*	0.014	0.037
	Grit	-0.019	-0.019	-0.016	0.000
	Decision making	-0.010	-0.013	0.009	0.016
	Hostile attribution bias	-0.033	-0.035	-0.004	-0.014
	Risk taking	0.017	0.016	0.009	0.033
	Time preference	0.054*	0.054*	0.040	0.049
Serbia [1]	Openness	0.004	0.038	0.016	0.218*
	Conscientiousness	0.131*	0.118	0.014	-0.046
	Extraversion	-0.026	-0.049	-0.018	-0.103
	Agreeableness	-0.026	0.043	0.078*	0.104
	Emotional stability	0.029	0.007	-0.023	0.004
	Grit	-0.081	-0.151	-0.010	-0.015
	Decision making	0.058	0.012	-0.004	-0.005
Ukraine	Openness	0.076*	0.066	0.072***	0.072***
	Conscientiousness	0.019	-0.032	0.005	0.006
	Extraversion	-0.018	-0.016	-0.033	-0.033
	Agreeableness	-0.028	-0.015	-0.007	-0.008
	Emotional stability	-0.016	-0.001	-0.044*	-0.044*
	Grit	0.013	-0.008	0.065**	0.065**
	Decision making	0.051	0.027	-0.038	-0.038
	Hostile attribution bias	0.021	0.022	-0.020	-0.020
	Risk taking	-0.022	-0.021	-0.021	-0.022
	Time preference	-0.001	-0.028	0.015	0.015
Vietnam	Openness	0.026	0.026	0.054**	0.041
	Conscientiousness	0.027	0.023	0.034	0.043
	Extraversion	0.054*	0.052*	0.026	0.044*
	Agreeableness	0.031	0.032	-0.013	-0.015
	Emotional stability	0.031	0.027	0.059**	0.060**
	Grit	-0.011	-0.011	0.003	0.015
	Decision making	0.050*	0.048*	0.033	0.055**
	Hostile attribution bias	-0.008	-0.008	-0.056**	-0.034
	Risk taking	-0.006	-0.007	0.041*	0.063**

Table 9. Log earnings returns to noncognitive skills, adults aged 25-54

Time preference	0.002	0.004	-0.025	-0.023

Notes: These results derive from the full specifications (Table 4, columns 2-5 and Appendix Table 4, columns 3 and 6 for men and women). Those specifications control for age, age-square, education (measured as spline variables), and cognitive skills (measured as plausible values of literacy assessments). Results for all countries pool the samples of Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam and are estimated with country fixed effects. [1] No data on time preference for Colombia; no data on hostile attribution bias, risk-taking and time preference for Serbia. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Data sources: STEP data for 9 countries, 2012-13

VI. Decomposing the Gender Earnings Gaps and the Role of Skills

Finally, in this section, we draw upon the above results to explore three questions that focus on gender differences: Does estimating a model that allows the slope coefficients of the elements of human capital to differ by gender (that is, moving from a constrained model to an unconstrained model) change our estimates of the conditional gender earnings gap? Does expanding women's fuller set of skills, beyond completed years of schooling, help to close the gender gap? What could be the effects on the gender earnings gap of policies that equalize observed covariates versus policies that equalize wage structure? We explore these questions here.

Estimating gender disadvantage: Constrained and unconstrained models

Using the pooled sample of men and women in all countries to estimate the log-earnings functions, with gender as a dummy variable, we find that women's log earnings are 31 percent lower than men's in the basic model (only schooling, without skills), with selection bias correction, and 28 percent lower in the full model (with skills) (Table 4). Turning to individual countries, we also estimate a constrained model in which gender enters as a dummy variable, first with just schooling and then with both schooling and skills (columns 1 and 2, Table 10). Except in Serbia and Kenya, women are paid significantly less than men, whether or not we control for skills, with the largest gender gap being in Armenia and Ukraine (37-40 percent).[65] As with the all-countries regressions, the gender coefficient for Bolivia, Colombia, Georgia, and Vietnam loses a few percentage points when measures of skills are taken into account, suggesting that it takes higher cognitive and noncognitive skills for women in those countries to narrow the gender wage gap.

Table 10. Female disadvantage in log earnings regressions, constrained and unconstrained models

	Constrained		Unconstrained	
	[1]	[2]	[3]	[4]
Armenia	-0.360***	-0.368***	-0.089	-0.104
	(0.060)	(0.065)	(0.162)	(0.163)
Bolivia	-0.312***	-0.296***	-0.452***	-0.441***
	(0.063)	(0.068)	(0.164)	(0.167)
Colombia	-0.437***	-0.418***	-0.488***	-0.527***
	(0.060)	(0.063)	(0.132)	(0.136)
Georgia	-0.674**	-0.647***	-0.961***	-1.008***
	(0.304)	(0.217)	(0.356)	(0.358)
Ghana	-0.337***	-0.337***	-0.255	-0.265
	(0.081)	(0.083)	(0.211)	(0.212)
Kenya	-0.088	-0.041	-0.175	-0.176
	(0.123)	(0.052)	(0.154)	(0.154)
Serbia	0.068	0.070	0.120	0.172
	(0.100)	(0.104)	(0.275)	(0.282)
Ukraine	-0.394***	-0.417***	-0.341***	-0.352***
	(0.044)	(0.046)	(0.081)	(0.085)
Vietnam	-0.258***	-0.215***	-0.291***	-0.295***
	(0.038)	(0.039)	-0.098	-0.097

Notes: The full results are contained in Appendix Table 4. Specification [1] is the basic model, with no controls for cognitive or noncognitive skills variables. Specification [2] is the full model, with controls for age, age-square, schooling, cognitive skills (measured as plausible values of literacy assessments), and noncognitive skills. Specifications [3] and [4] present the mean "coefficients" gender earnings gap from Blinder-Oaxaca decomposition of regressions where the controls in [3] are the same as in [1] and the controls in [4] are the same as in [2].All estimates are corrected for selection bias, with marital status, number of children and other adults in the household as instruments for selection into the paid work. Statistical significance is denoted as * p < 0.10, ** p < 0.05, *** p < 0.01. Data sources: STEP data for 9 countries, 2012-13

[65] The coefficients do not change significantly between the comparable simple OLS estimates and the selectivity-corrected specifications.

In the unconstrained model, the slope coefficients for men and women are allowed to differ from each other.[66] We compare the slope coefficients from the constrained model with the slope coefficients estimated at the mean of the earnings distribution in the unconstrained model, using first the basic model with just schooling (column 3) and then with both schooling and skills (column 4). Using the mean counterfactual coefficients indicates that the "true" estimate of the gender disadvantage is larger than that implied by the constrained model in all but three countries (Armenia, Ghana and Ukraine).[67] The constrained model underestimates female disadvantage most in Georgia; in Ghana, moving from the constrained model to the unconstrained model turns a significant male-favoring gap to an insignificant one at the 5-percent level. The inclusion of controls for skills (selection-bias corrected estimates) does not reduce the gender gap, except in Bolivia.

The role of covariates, including skills, in closing the gender earnings gap

The full set of results from estimating the gender decomposition described by equation [9] are given in Table 11. The top panel describes the overall estimated gap between men and women at nine quantiles, from 0.10 to 0.90, where 0.50 refers to the median gap. The middle panel presents the gap due to gender differences in observed characteristics such as schooling and skills (covariates gap), and the bottom panel presents the gap due to differences in the returns to schooling and skills, as well as other covariates (the coefficients gap or the gender gap that is due to differences in the wage structures for men and women).

[66] Except for Serbia and Kenya, the equality of the coefficients is rejected at the 1-percent level, justifying a model estimated separately by gender.

[67] The results of columns (3) and (4) in table 10 stem from estimating equation [9], using first the basic model without skills and then the model with skills. The counterfactual (coefficients/structure) gap refers to the gap that would exist if covariates were equalized and only the coefficients differed between men and women.

Table 11. Wage gap decompositions, quantile regressions

Quantiles	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Serbia	Ukraine	Vietnam
				Conditional wage gap: $F_{Y[m,m]}$ - $F_{Y[f,f]}$					
0.10	0.334***	0.479***	0.400***	0.331***	0.679***	0.282***	-0.138	0.214***	0.357***
	(0.0772)	(0.0830)	(0.0766)	(0.112)	(0.123)	(0.0818)	(0.268)	(0.0631)	(0.0511)
0.20	0.382***	0.395***	0.329***	0.309***	0.511***	0.232***	-0.0124	0.347***	0.355***
	(0.0721)	(0.0666)	(0.0546)	(0.0789)	(0.114)	(0.0641)	(0.0650)	(0.0534)	(0.0435)
0.50	0.482***	0.338***	0.270***	0.172***	0.417***	0.187***	-0.0247	0.406***	0.306***
	(0.0583)	(0.0688)	(0.0382)	(0.0630)	(0.0981)	(0.0621)	(0.0398)	(0.0500)	(0.0422)
0.80	0.370***	0.298***	0.171**	0.244***	0.161	0.141*	-0.0634	0.444***	0.234***
	(0.0618)	(0.0881)	(0.0794)	(0.0895)	(0.109)	(0.0733)	(0.0519)	(0.0574)	(0.0623)
0.90	0.329***	0.327***	0.168*	0.359***	0.122	0.0826	-0.0555	0.476***	0.253***
	(0.0813)	(0.101)	(0.0903)	(0.113)	(0.120)	(0.0894)	(0.0589)	(0.0663)	(0.0853)
				Covariates gap: $F_{Y[m,m]}$ - $F_{Y[m,f]}$					
0.10	0.0422	0.129**	-0.00274	-0.0542	-0.000536	0.105***	-0.0226	-0.0344	0.0398
	(0.0461)	(0.0542)	(0.0358)	(0.0635)	(0.0579)	(0.0266)	(0.112)	(0.0584)	(0.0321)
0.20	-0.00319	0.112**	0.0192	-0.0497	0.0250	0.108***	-0.0428	-0.0317	0.0489*
	(0.0373)	(0.0501)	(0.0253)	(0.0514)	(0.0499)	(0.0253)	(0.0376)	(0.0499)	(0.0260)
0.50	-0.00852	0.117**	0.0181	-0.0791*	0.0664	0.145***	-0.0916***	-0.0289	0.0351
	(0.0297)	(0.0513)	(0.0267)	(0.0436)	(0.0519)	(0.0297)	(0.0270)	(0.0410)	(0.0241)
0.80	-0.0226	0.108**	0.0316	-0.0842	0.0720	0.201***	-0.0881***	0.0198	0.0425
	(0.0360)	(0.0511)	(0.0442)	(0.0548)	(0.0514)	(0.0453)	(0.0307)	(0.0490)	(0.0300)
0.90	-0.0175	0.0953	0.0246	-0.0659	0.0932	0.210***	-0.0804**	0.0389	0.0477
	(0.0427)	(0.0599)	(0.0524)	(0.0576)	(0.0605)	(0.0503)	(0.0363)	(0.0549)	(0.0355)
				Coefficients gap: $F_{Y[m,f]}$ - $F_{Y[f,f]}$					
0.10	0.291***	0.351***	0.403***	0.385***	0.679***	0.177**	-0.116	0.249***	0.318***
	(0.0810)	(0.0986)	(0.0786)	(0.117)	(0.129)	(0.0879)	(0.318)	(0.0745)	(0.0495)
0.20	0.385***	0.283***	0.310***	0.358***	0.486***	0.124*	0.0304	0.379***	0.306***
	(0.0696)	(0.0783)	(0.0565)	(0.0937)	(0.115)	(0.0655)	(0.0781)	(0.0655)	(0.0427)
0.50	0.491***	0.221***	0.252***	0.251***	0.351***	0.0415	0.0670	0.435***	0.271***
	(0.0617)	(0.0704)	(0.0388)	(0.0662)	(0.0919)	(0.0544)	(0.0420)	(0.0647)	(0.0422)
0.80	0.393***	0.190**	0.140*	0.329***	0.0892	-0.0596	0.0247	0.425***	0.191***
	(0.0701)	(0.0896)	(0.0815)	(0.0902)	(0.110)	(0.0644)	(0.0520)	(0.0640)	(0.0643)
0.90	0.346***	0.232**	0.144	0.425***	0.0284	-0.128	0.0249	0.437***	0.205**
	(0.0918)	(0.110)	(0.0918)	(0.114)	(0.125)	(0.0824)	(0.0635)	(0.0753)	(0.0875)
Observations	660	1,093	1,168	636	851	1,586	866	723	1,708

These results derive from the full model, with controls for schooling, cognitive and noncognitive skills. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Focusing first on results at the median, the wage gap ranges from 48 percent of the male wage in Armenia (women earn only 52 percent of what men earn) to -2 percent in Serbia, a female-favoring wage gap. With the exception of Serbia and Kenya, in all countries the coefficients gap dominates the covariates gap. The coefficients gap is not significant at any decile. In Georgia, women at the median also have better covariates than men, but this covariate gap is not significant at any other decile. However, in Georgia the coefficients gap is significant at all deciles, leading to an overall female disadvantage across the earnings distribution. In Ukraine and Armenia as well, while there is no significant gap in covariates at any decile, the coefficient gap is significant, leading to a female disadvantage across the earnings distribution. These results are consistent with previous studies on Ukraine (Ganguli and Terrell, 2009) and Georgia (Khitarishvili, 2009).

Colombia, Ghana, and Vietnam also do not have a significant covariates gap but have significant coefficients gaps. By contrast, in Kenya, the gender earnings gap is due largely to better covariates for men than women, with the coefficients gap being small and insignificant. The results for Bolivia are different from Kenya's in that there are significant male-favoring covariates gaps, except at the 90^{th} percentile, as well as a significant male-favoring coefficients gap throughout the distribution.

As mentioned in Section III, relatively larger coefficients gaps at the top of the earnings distribution are indicative of glass ceilings, while larger coefficients gaps at the bottom of the distribution have been termed 'sticky floors'. Here we observe distinctly different results for the FSU countries and for all other countries. Starting with the FSU countries, in Armenia and Ukraine, the largest coefficient gaps are found at the middle of the earnings distribution. Ganguli and Terrell (2006, 2009) find that in Ukraine the minimum wage policy reduced gender wage gaps at the bottom of the distribution. By contrast, in Georgia the smallest coefficient gap is at the median, with this gap increasing toward both the bottom and top of the distribution, indicative of sticky floors *and* glass ceilings.

In all the other countries, there is evidence of sticky floors. In Bolivia, Colombia and Vietnam, the largest coefficient gaps are at the 10th percentile and the smallest are at the 80th percentile. In Ghana, the coefficient gap is significant only up to the median of the distribution; in Kenya, this is the case only up to the 20th percentile. The results presented in Table 11 suggest that women with earnings at the bottom of the distribution are disadvantaged not only by gaps in human capital (as in Bolivia and Kenya), but also by institutional factors such as wage structures that reward human capital systematically less for women than for men. In these countries, women are disproportionately engaged in informal work. By contrast, in the FSU countries a larger share of women are in formal employment, and minimum wage laws mitigate gender wage gaps that are not due to gender differences in human capital.

Finally, we simulate the implication of our gender decomposition results for policy by estimating what women would earn if either their covariates were similar to those of men in the same country or if the wage structure that applies to men also applied to women. As implied by the covariates gap, or the second panel in Table 11, the effect of equalizing covariates is likely to be small except in Bolivia and Kenya where women's schooling levels and skills are significantly lower than men's. In Serbia, equalizing the covariates will result in a male advantage in the upper part of the distribution, as men catch up with women in schooling and skills.

VII. Concluding Remarks

Much of the literature on estimating the determinants of earnings and, in particular, the returns to human capital, focuses on the contribution of work experience (as measured by age) and education attainment (as measured by years of schooling). In this paper, we unbundle the human capital variable further using assessments of skills that are typically not available for a large sample of adults in developing and transition countries—cognitive skills (literacy proficiency) and a number of noncognitive or socioemotional skills. Our analyses of the data on adults aged 25-54 from comparable surveys in nine middle-income countries reveal that men and women differ not only with respect to how much schooling they have completed but also with regard to how much cognitive and noncognitive skills they possess. In addition, we note that the size and direction of these gender differences vary across our sample of countries.

Our sample countries span four world regions and vary widely with respect to their GDP per capita, average schooling levels, demographic characteristics such as fertility rate, and economic structures such as the employment shares of their informal and formal sectors and their industrial composition. Three of the countries were formerly part of the Soviet Union (FSU) and together with another former socialist country, Serbia, have education levels and employment rates that are generally more equal between men and women, as compared with other countries, reflecting past socialist policies in those countries. The other five countries are low-middle to middle-income countries in Africa, Asia and South America. The country differences are evident from the gender gaps in schooling, skills and earnings and in the relationship between earnings and the different measures of human capital.

Starting with the pooled sample of countries, we find that estimating the log-hourly earnings function separately for men and women is justified, given statistical significance tests. These gender differences arise in part because labor markets in these countries value the schooling and skills of men and women differently, a product of social norms and institutions that shape gender identity, attitudes, and behaviors.[68] Although there is a growing literature on the relationships between schooling and noncognitive skills and between noncognitive skills and labor market outcomes, this literature is still small outside advanced countries and deserves more rigorous research.

Besides estimating separate earnings functions for men and women at the mean, we also examine the differences in returns to schooling and skills across their earnings distribution using quantile regressions. Our results suggest that the relative benefits of schooling and skills may be different for men and women at different parts of the earnings distribution.

In the final part of this paper, using a decomposition method similar to Blau and Khan's (2017), we explore the relative potential of two broad types of policies, those that focus on equalizing the human capital endowments of men and women and those that focus on "leveling the playing field" by ensuring that the employment and wage structures in the workplace do not discriminate between men and women who have comparable endowments (schooling, experience and skills). The global efforts on education have largely succeeded in raising enrollment and completion rates for girls and women, especially in middle-income countries. Our results are a reminder too that the learning outcomes that matter in the workplace encompass different types of knowledge and skills.

Here we highlight some key findings:

- *The return to schooling is significantly non-linear, a result missed by using a continuous measure of years of schooling.* Using splines, we find modest (or even flat) returns to basic

[68] They may also arise if the type of schooling and skills that men and women have differs systematically, beyond that which we observe.

education, steeper returns to secondary education, and the steepest return to post-secondary education. The returns to post-secondary education for women are notably larger than for men. With increasing enrollment and continuation rates and changing work technologies, especially in middle-income countries, whether boys and girls persist through secondary education and post-secondary education is a crucial decision for families and youth to make and an important indicator for governments to watch.

- *Including measures of cognitive and noncognitive skills to the log-earnings function addresses an omitted variable bias that overstates the return to years of schooling*. The returns attributed to schooling are biased upward when skills are not taken into account—in the pooled sample of countries, women's (conditional) earnings disadvantage relative to men's falls from 31 percent to 28 percent lower when skills are included—suggesting that it takes even better cognitive and noncognitive skills for women to narrow the gender wage gap, holding constant years of schooling. Based on the results from the full model with schooling and skills, all measures of human capital account for as much as 22-24 percent of the total variance in the log-earnings of women and men, respectively. Schooling attainment accounts for much of this explanatory power, implying that schooling is still a smart investment, even in the countries where schooling levels are relatively high.
- *The estimated return to cognitive skills is significantly positive in the pooled sample, especially for women*. Over and above the returns to years of schooling, the return to cognitive skills can be interpreted as a return to improvements in the quality of schooling. Based on quantile regressions, the return to cognitive skills is only weakly significant for men across the earnings distribution but is strongly significant for women at the lower end and middle of the distribution. In fact, for women, the returns to a one-standard deviation gain (6-7 percent) are

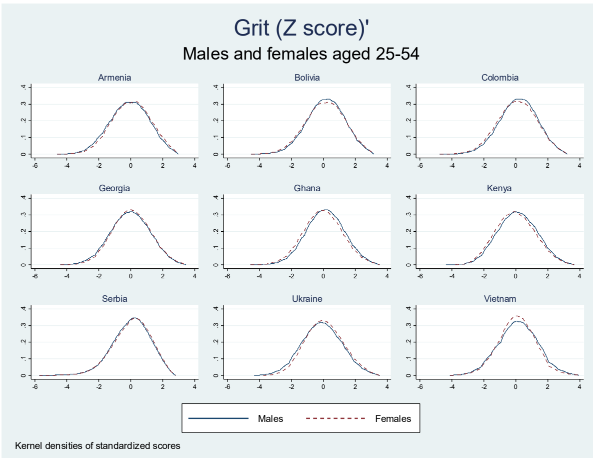
comparable to the estimated return to an additional year of secondary education at the lower half of the earnings distribution. This makes for a compelling argument for more effective investments that improve learning for girls.

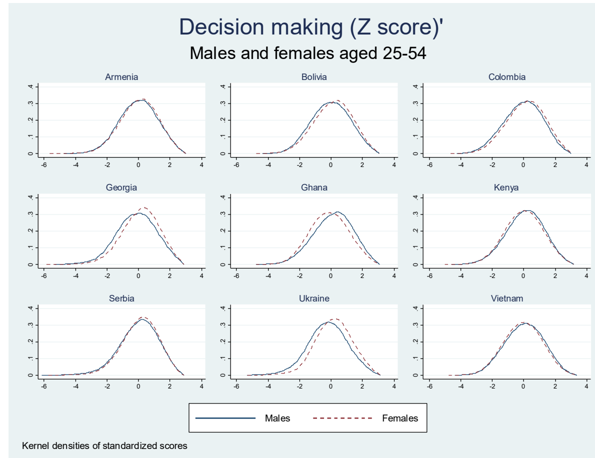
- *While it is difficult to pinpoint specific noncognitive skills that are consistently critical to earnings, the measures of noncognitive skills are jointly significant in the log earnings functions of men and women*. Our results do reveal shared patterns among the countries. For example, openness to experience, the degree to which a person seeks intellectual stimulation and variety, is important for more countries than any other noncognitive skill, and its implied return is significantly positive. For men, the implied return of a one-standard deviation change is 6 percent in the pooled sample; this ranges from 7-11 percent across countries. For women, the estimated return is lower at 3 percent for the pooled sample, but this ranges widely from 5 to 22 percent across countries. Risk-taking, hostile attribution bias and emotional stability are other noncognitive skills that have significant results across our specifications for the pooled sample but are less consistent in the regressions for individual countries. Our findings suggest that noncognitive skills, as a whole, have a significant effect on earnings, in addition to the returns to schooling and to cognitive skills. Our findings also show that the distributions of specific skills differ between men and women, and that the returns to those skills differ by gender and by country.

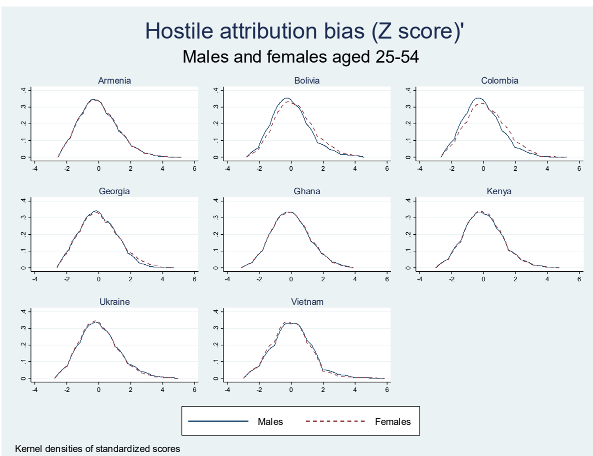
One possible explanation for the difference in the relative role of schooling and skills returns is that skills, unlike schooling, are less easily observed by employers (Blau and Kahn, 2017). While this information asymmetry should affect the returns for both men and women, it seems more of a disadvantage for women than for men. Employers' belief that women have intrinsically weaker labor force attachment than men do may explain their reluctance to hire women, controlling for education levels. Hence, the level of schooling completed, relative to skills, is effectively a stronger signal for women than men.

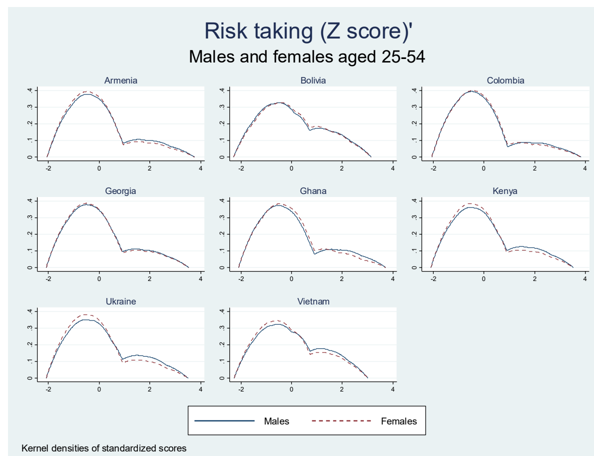
- *Our gender decomposition results show that, especially at the lower end of the earnings distribution, women are disadvantaged not only by having lower human capital than men, but also (and more importantly) by institutional factors such as wage structures that reward women's human capital systematically less than men's.* In the former socialist countries, a larger share of women are in formal employment and policies such as minimum wage laws can mitigate gender wage gaps that may be due to discriminatory behaviors of employers. However, in the other countries, women are more likely engaged in informal work for reasons that include family responsibilities and gender norms and have fewer protections from discrimination. The decomposition of the gender earnings gap into a covariates gap and a coefficients gap indicates that, in the majority of our countries, the coefficients gap dominates the covariates gap. Furthermore, the coefficients gap tends to be higher at the lower end of the earnings distribution, indicating a sticky floor.

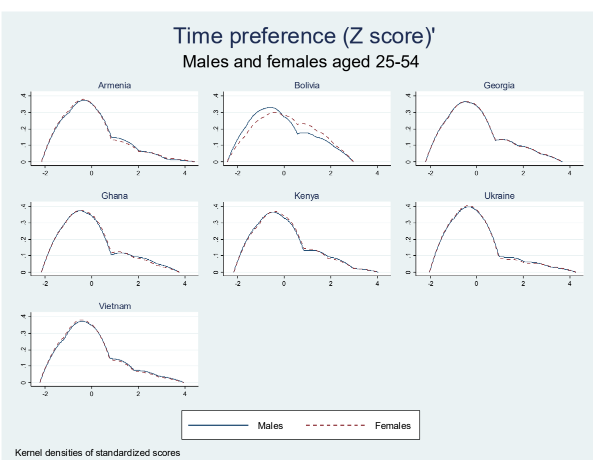
Figure 1. Kernel density functions of standardized cognitive and noncognitive skills


Grit (Z score)'
Males and females aged 25-54
Armenia
Bolivia
Colombia
Georgia
Ghana
Kenya
Serbia
Ukraine
Vietnam
Males
Females
Kernel densities of standardized scores


Decision making (Z score)'
Males and females aged 25-54
Armenia
Bolivia
Colombia
Georgia
Ghana
Kenya
Serbia
Ukraine
Vietnam
Males
Females
Kernel densities of standardized scores


Hostile attribution bias (Z score)'
Males and females aged 25-54
Armenia
Bolivia
Colombia
Georgia
Ghana
Kenya
Ukraine
Vietnam
Males
Females
Kernel densities of standardized scores


Risk taking (Z score)'
Males and females aged 25-54
Armenia
Bolivia
Colombia
Georgia
Ghana
Kenya
Ukraine
Vietnam
Males
Females
Kernel densities of standardized scores


Time preference (Z score)'
Males and females aged 25-54
Armenia
Bolivia
Georgia
Ghana
Kenya
Ukraine
Vietnam
Males
Females
Kernel densities of standardized scores

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Appendix Table 1. Definition of personality traits and behaviors included in the STEP instrument

Domains	Definitions	Question number	Domain items
Openness to experience	Appreciation for art, learning, unusual ideas, and variety of experience	Q1.03	Do you come up with ideas other people haven't thought of before?
		Q1.11	Are you very interested in learning new things?
		Q1.14	Do you enjoy beautiful things such as nature, art, and music?
Conscientiousness	Tendency to be organized, responsible, and hardworking	Q1.02	When doing a task, are you very careful?
		Q1.12	Do you prefer relaxation more than hard work? [R]
		Q1.17	Do you work very well and quickly?
Extraversion	Sociability, tendency to seek stimulation in the company of others, talkativeness	Q1.01	Are you talkative?
		Q1.04 *	Do you like to keep your opinions to yourself? Do you prefer to keep quiet when you have an opinion? [R]
		Q1.20	Are you outgoing and sociable—for example, do you make friends very easily?
Agreeableness	Tendency to act in a cooperative, unselfish manner	Q1.09	Do you forgive other people easily?
		Q1.16	Are you very polite to other people?
		Q1.19	Are you generous to other people with your time or money?
Emotional stability	Predictability and consistency in emotional reactions, with absence of rapid mood changes	Q1.05 *	Are you relaxed during stressful situations?
		Q1.10	Do you tend to worry? [R]
		Q1.18	Do you get nervous easily? [R]
Grit	Perseverance with long-term goals	Q1.06	Do you finish whatever you begin?
		Q1.08	Do you work very hard? For example, do you keep working when others stop to take a break?
		Q1.13	Do you enjoy working on things that take a very long time (at least several months) to complete?
Decision making	Manner of approaching decision situations	Q1.15	Do you think about how the things you do will affect you in the future?
		Q1.21	Do you think carefully before you make an important decision?
		Q1.21	Do you ask for help when you don't understand something?
		Q1.24	Do you think about how the things you do will affect others?
Hostile attribution bias	Tendency to perceive hostile intent in others	Q1.07	Do people take advantage of you?
		Q1.22	Are people mean/not nice to you?

Appendix Table 1. Definition of personality traits and behaviors included in the STEP instrument

Domains	Definitions	Question number	Domain items
Risk taking	Willingness to bear risk		Hypothetical situation: Respondents were asked to choose between joining a lottery for a larger sum and being assured a safe but smaller amount (seven-item risk-preference scale)
Time preference	Willingness to delay gratification		Hypothetical situation: Respondents were asked to choose between receiving a smaller payment sooner and receiving a larger payment later

Sources: Pierre et al. (2014); Gunewardena (2015)

Notes: For each item, response categories range from 1 to 4: (1) almost never; (2) sometimes; (3) most of the time; (4) almost always. The score of each domain is the average of scores for individual items. "R" refers to items that are reversely coded for this aggregation. *In Wave 2, two additional questions were added: Q.1.25, "Do you like to share your thoughts and opinions with other people, even if you don't know them very well?" can be used instead of Q.1.04; and Q.1.26, "Do you get very upset in stressful situations?" can be used instead of Q.1.05.

Appendix Table 2. Pairwise Correlations, Skills and Schooling, Men, ages 25-54

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	zopenness	1												
(2)	zconscientiousness	0.224***	1											
(3)	zextraversion	0.175***	0.099***	1										
(4)	zagreeableness	0.265***	0.193***	0.158***	1									
(5)	zstability	0.073***	0.119***		0.049**	1								
(6)	zgrit	0.249***	0.241***	0.088***	0.202***	0.077***	1							
(7)	zdecision	0.335***	0.260***	0.116***	0.253***	0.055***	0.225***	1						
(8)	zhostile		-0.114***	-0.041*		-0.151***		-0.088***	1					
(9)	zrisk									1				
(10)	zdiscount									0.254***	1			
(11)	zpvlit	0.201***	0.106***	0.064***	0.098***	0.046**		0.171***	-0.083***	0.049**		1		
(12)	educsp1	0.147***	0.065***	0.068***	0.066***	0.055***		0.115***	-0.045**			0.449***	1	
(13)	educsp2	0.240***	0.099***	0.082***	0.088***	0.065***	0.037*	0.177***	-0.050**	0.069***		0.487***	0.594***	1
(14)	educsp3	0.190***	0.072***	0.042**	0.067***	0.070***	0.060***	0.145***	-0.051**	0.072***		0.358***	0.265***	0.590***
	N	3911												

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Empty cells denote correlations not significant at * $p < 0.05$; Estimates are from a pooled sample of eight countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam. Correlations with time preference are only for seven countries (measures of time preference were not available for Colombia).

Appendix Table 3. Pairwise Correlations, Skills and Schooling, Women, ages 25-54

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	zopenness	1												
(2)	zconscientiousness	0.212***	1											
(3)	zextraversion	0.189***	0.082***	1										
(4)	zagreeableness	0.235***	0.209***	0.146***	1									
(5)	zstability	0.048**	0.091***		0.030*	1								
(6)	zgrit	0.257***	0.229***	0.099***	0.208***	0.049**	1							
(7)	zdecision	0.269***	0.221***	0.102***	0.224***		0.175***	1						
(8)	zhostile		-0.082***	-0.048**		-0.137***		-0.059***	1					
(9)	zrisk	0.040**	0.030*	0.032*						1				
(10)	zdiscount									0.197***	1			
(11)	zpvlit	0.210***	0.134***	0.093***	0.052***	0.106***		0.152***	-0.092***		-0.047**	1		
(12)	educsp1	0.190***	0.080***	0.084***	0.047**	0.077***		0.073***	-0.051***			0.476***	1	
(13)	educsp2	0.246***	0.134***	0.117***	0.084***	0.123***	0.032*	0.143***	-0.093***	0.054***		0.504***	0.608***	1
(14)	educsp3	0.225***	0.106***	0.096***	0.075***	0.101***	0.065***	0.133***	-0.082***	0.085***		0.360***	0.284***	0.598***
	N	3911												

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Empty cells denote correlations not significant at * $p < 0.05$; Estimates are from a pooled sample of eight countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine and Vietnam. Correlations with time preference are only for seven countries (measures of time preference were not available for Colombia).

Appendix Table 4. Cognitive and noncognitive skills, male and female: means comparison tests

	Armenia				Bolivia				Colombia			
	Means		Difference		Means		Difference		Means		Difference	
	Male	Female	M-F		Male	Female	M-F		Male	Female	M-F	
Literacy proficiency (plausible values)	0.00	0.02	-0.03		0.16	-0.17	**0.33**	***	0.05	-0.05	**0.10**	***
	(0.03)	(0.02)	(0.04)		(0.04)	(0.03)	**(0.05)**		(0.03)	(0.03)	**(0.04)**	
Extraversion	-0.15	0.05	**-0.20**	***	0.04	-0.09	**0.12**	**	0.07	-0.04	**0.11**	**
	(0.04)	(0.03)	**-0.05**		(0.04)	(0.04)	**(0.05)**		(0.04)	(0.03)	**(0.05)**	
Conscientiousness	-0.05	0.07	**-0.12**	**	0.12	0.11	0.01		0.15	0.12	0.04	
	(0.05)	(0.03)	(0.05)		(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	(0.05)	
Openness	-0.03	0.02	-0.05		0.11	-0.02	**0.13**	***	0.10	-0.04	**0.13**	***
	(0.05)	(0.03)	(0.05)		(0.04)	(0.04)	**(0.05)**		(0.04)	(0.03)	**(0.05)**	
Emotional Stability	0.27	-0.10	**0.37**	***	0.34	-0.24	**0.58**	***	0.32	-0.26	**0.58**	***
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.03)	**(0.05)**		(0.04)	(0.03)	**(0.05)**	
Agreeableness	-0.17	0.04	**-0.20**	***	0.10	0.03	**0.07**	*	0.03	0.05	-0.01	
	0.05	(0.03)	**(0.05)**		(0.04)	(0.04)	**(0.05)**		(0.04)	(0.03)	(0.05)	
Grit	-0.08	0.03	**-0.11**	**	0.15	0.11	0.04		0.16	0.07	**0.09**	**
	(0.05)	(0.03)	(0.05)		(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	**(0.05)**	
Decision making	0.00	0.04	-0.04		-0.02	0.13	**-0.15**	***	-0.05	0.11	**-0.16**	***
	(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	**(0.05)**		(0.04)	(0.03)	**(0.05)**	
Hostile attribution bias	0.00	0.02	-0.02		0.00	0.22	**-0.21**	***	-0.11	0.08	**-0.20**	***
	(0.04)	-0.03	-0.05		(0.04)	(0.04)	**(0.05)**		(0.03)	(0.03)	(0.04)	
Risk taking	0.06	-0.03	**0.09**	*	0.03	0.04	-0.01		0.02	-0.02	0.04	
	(0.05)	-0.03	**(0.05)**		(0.04)	(0.03)	(0.06)		(0.03)	(0.03)	(0.04)	
Time preference	-0.01	-0.02	0.02		-0.14	0.06	**-0.21**	***	--	--	--	
	(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	**(0.05)**		--	--	--	

Appendix Table 4. Cognitive and noncognitive skills, male and female: means comparison tests

	Georgia				Ghana				Kenya			
	Means		Difference		Means		Difference		Means		Difference	
	Male	Female	M-F		Male	Female	M-F		Male	Female	M-F	
Literacy proficiency (plausible values)	-0.12	0.02	**-0.14**	***	0.15	-0.30	**0.44**	***	0.10	-0.14	**0.24**	***
	(0.03)	(0.02)	**(0.04)**		(0.03)	(0.02)	**(0.04)**		(0.03)	(0.03)	**(0.04)**	
Extraversion	-0.12	-0.01	**-0.11**	***	-0.01	-0.04	0.02		0.05	-0.01	**0.06**	*
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	(0.06)		(0.03)	(0.03)	**(0.04)**	
Conscientiousness	-0.04	0.12	**-0.16**	***	0.19	-0.07	**0.26**	***	0.11	-0.02	**0.13**	***
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Openness	-0.09	0.03	**-0.11**	**	0.08	-0.18	**0.26**	***	0.08	-0.15	**0.23**	***
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Emotional Stability	0.15	-0.07	**0.21**	***	0.12	-0.15	**0.27**	***	0.08	-0.05	**0.13**	***
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.05)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Agreeableness	-0.05	0.03	**-0.08**	*	0.04	-0.06	**0.10**	*	0.04	0.03	-0.01	
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.05)	**(0.06)**		(0.05)	(0.03)	(0.04)	
Grit	-0.02	0.05	**-0.07**	*	0.13	-0.03	**0.16**	***	0.10	-0.03	**0.13**	***
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Decision making	-0.12	0.13	**-0.25**	***	0.12	-0.12	**0.24**	***	0.08	0.01	**0.08**	**
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Hostile attribution bias	-0.02	0.07	**-0.09**	**	-0.02	-0.02	0.00		0.00	0.00	0.00	
	(0.04)	(0.03)	**(0.05)**		(0.04)	(0.04)	(0.06)		(0.03)	(0.03)	(0.04)	
Risk taking	0.00	-0.03	0.04		0.04	-0.03	**0.07**	*	0.07	-0.04	**0.11**	***
	(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	**(0.05)**		(0.03)	(0.03)	**(0.04)**	
Time preference	-0.03	-0.02	-0.01		-0.02	-0.05	0.03		-0.02	-0.02	-0.01	
	(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	(0.05)		(0.03)	(0.03)	(0.04)	

Appendix Table 4. Cognitive and noncognitive skills, male and female: means comparison tests

	Serbia				Ukraine				Vietnam			
	Means		Difference		Means		Difference		Means		Difference	
	Male	Female	M-F		Male	Female	M-F		Male	Female	M-F	
Literacy proficiency (plausible values)	0.06	0.08	-0.02		-0.06	0.08	**-0.14**	***	-0.06	-0.10	0.05	
	(0.03)	(0.03)	(0.04)		(0.04)	(0.03)	**(0.05)**		(0.03)	(0.02)	(0.04)	
Extraversion	-0.04	0.06	**-0.11**	***	-0.24	0.12	**-0.36**	***	-0.04	0.03	**-0.08**	**
	(0.03)	(0.03)	**(0.04)**		(0.05)	(0.03)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Conscientiousness	0.03	0.12	**-0.10**	**	-0.21	0.15	**-0.36**	***	0.16	0.04	**0.12**	***
	(0.03)	(0.03)	**(0.04)**		(0.04)	(0.03)	**(0.05)**		(0.03)	(0.03)	**(0.04)**	
Openness	0.11	0.05	**0.06**	*	-0.10	0.09	**-0.20**	***	0.11	-0.14	**0.25**	***
	(0.03)	(0.03)	**(0.04)**		(0.05)	(0.03)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Emotional Stability	0.19	-0.11	**0.29**	***	0.39	-0.18	**0.56**	***	0.38	-0.19	**0.57**	***
	(0.03)	(0.03)	**(0.04)**		(0.04)	(0.03)	**(0.05)**		(0.03)	(0.03)	**(0.04)**	
Agreeableness	-0.05	0.07	**-0.12**	***	-0.26	0.07	**-0.33**	***	0.01	-0.02	0.03	
	(0.03)	(0.03)	**(0.04)**		(0.05)	(0.03)	**(0.06)**		(0.04)	(0.03)	(0.04)	
Grit	0.04	0.08	-0.04		-0.09	0.07	**-0.16**	***	0.13	0.06	**0.07**	*
	(0.03)	(0.03)	(0.04)		(0.05)	(0.03)	**(0.06)**		(0.04)	(0.02)	**(0.04)**	
Decision making	0.02	0.10	**-0.08**	**	-0.22	0.16	**-0.37**	***	0.03	-0.05	**0.08**	**
	(0.03)	(0.03)	**(0.04)**		(0.05)	(0.03)	**(0.06)**		-0.04	-0.03	**-0.04**	
Hostile attribution bias	--	--	--		0.07	0.01	0.05		0.06	-0.03	**0.09**	**
	--	--	--		(0.05)	(0.03)	(0.06)		(0.04)	(0.03)	**(0.04)**	
Risk taking	--	--	--		0.11	-0.04	**0.15**	***	0.01	-0.08	**0.09**	**
	--	--	--		(0.05)	(0.03)	**(0.06)**		(0.03)	(0.03)	**(0.04)**	
Time preference	--	--	--		0.00	-0.03	0.02		-0.03	-0.09	**0.06**	*
	--	--	--		(0.05)	(0.03)	(0.06)		(0.03)	(0.03)	**(0.04)**	

Note: The third column denotes differences between mean male and female skills. Statistical significance is denoted as *p< 0.10, , **p<0.05, and *** p<0.01 respectively.

Data sources: STEP data for 9 countries, 2012-13

Appendix Table 5. Cognitive and noncognitive skills, male and female: Two-sampled Kolgomorov-Smirnov tests for equality of distributions

	Armenia				**Bolivia**				**Colombia**			
	Diff				**Diff**				**Diff**			
	Max(F-M)	**Min(F-M)**	**Combined K-S**		**Max(F-M)**	**Min(F-M)**	**Combined K-S**		**Max(F-M)**	**Min(F-M)**	**Combined K-S**	
Literacy proficiency (plausible values)	**0.055**	-0.010	**0.055**	*	0.004	**-0.090**	**0.090**	***	0.000	**-0.053**	**0.053**	*
	(0.026)	(0.885)	(0.052)		0.982	(0.000)	(0.000)		(1.000)	(0.028)	(0.056)	
Extraversion	**0.096**	0.000	**0.095**	***	0.000	-0.053	0.053		0.009	-0.058	0.058	
	(0.002)	(1.000)	(0.003)		(1.000)	(0.153)	(0.305)		(0.935)	(0.077)	(0.154)	
Conscientiousness	0.054	-0.003	0.054		0.019	-0.034	0.034		0.002	-0.016	0.016	
	(0.129)	(0.996)	(0.258)		(0.786)	(0.460)	(0.833)		(0.996)	(0.816)	(1.000)	
Openness	0.030	-0.009	0.030		0.000	-0.052	0.052		0.000	-0.043	0.043	
	(0.526)	(0.945)	(0.905)		(1.000)	(0.160)	(0.318)		(1.000)	(0.242)	(0.477)	
Emotional Stability	0.000	**-0.155**	**0.155**	***	0.000	**-0.247**	**0.247**	***	0.000	**-0.242**	**0.242**	***
	(1.000)	(0.000)	(0.000)		(1.000)	(0.000)	(0.000)		(1.000)	(0.000)	(0.000)	
Agreeableness	**0.096**	0.000	**0.096**	***	0.008	-0.051	0.051		0.030	-0.017	0.030	
	(0.001)	(1.000)	(0.003)		(0.960)	(0.173)	(0.345)		(0.493)	(0.802)	(0.871)	
Grit	0.048	0.000	0.048		0.020	-0.033	0.033		0.008	-0.053	0.053	
	(0.195)	(1.000)	(0.387)		(0.772)	(0.484)	(0.861)		(0.951)	(0.109)	(0.218)	
Decision making	0.055	-0.006	0.055		**0.074**	-0.004	**0.074**	**	**0.056**	-0.001	0.056	
	(0.116)	(0.977)	(0.232)		(0.024)	(0.992)	(0.048)		(0.087)	(0.999)	(0.173)	
Hostile attribution bias	**0.049**	0.000	0.049	*	**0.072**	0.000	**0.072**	***	**0.102**	0.000	**0.102**	***
	(0.055)	(1.000)	(0.109)		(0.002)	(1.000)	(0.004)		(0.000)	(1.000)	(0.000)	
Risk taking	0.000	-0.030	0.030		0.026	-0.023	0.026		0.005	-0.027	0.027	
	(1.000)	(0.336)	(0.647)		(0.465)	(0.549)	(0.838)		(0.963)	(0.386)	(0.728)	
Time preference	0.010	-0.024	0.024		**0.093**	0.000	**0.093**	***	--	--	--	
	(0.890)	(0.497)	(0.876)		(0.000)	(1.000)	(0.000)		--	--	--	

	Georgia				**Ghana**				**Kenya**			
	Diff				**Diff**				**Diff**			
	Max(F-M)	**Min(F-M)**	**Combined K-S**		**Max(F-M)**	**Min(F-M)**	**Combined K-S**		**Max(F-M)**	**Min(F-M)**	**Combined K-S**	
Literacy proficiency (plausible values)	**0.078**	-0.004	**0.078**	***	0.000	**-0.257**	**0.257**	***	0.001	**-0.094**	**0.094**	***
	(0.000)	(0.976)	(0.000)		(1.000)	(0.000)	(0.000)		(0.999)	(0.000)	(0.000)	
Extraversion	**0.072**	-0.002	**0.072**	**	0.035	-0.020	0.035		0.007	-0.039	0.039	
	(0.017)	(0.997)	(0.034)		(0.509)	(0.808)	(0.888)		(0.939)	(0.169)	(0.336)	
Conscientiousness	**0.079**	0.000	**0.079**	**	0.002	**-0.121**	**0.121**	***	0.000	**-0.073**	**0.073**	***
	(0.007)	(1.000)	(0.015)		(0.997)	(0.000)	(0.001)		(1.000)	(0.002)	(0.004)	
Openness	**0.070**	-0.009	**0.070**	**	0.003	**-0.121**	**0.121**	***	0.000	**-0.089**	**0.089**	***
	(0.021)	0.945	(0.042)		(0.995)	(0.000)	(0.001)		(1.000)	(0.000)	(0.000)	
Emotional Stability	0.000	**-0.115**	**0.115**	***	0.000	**-0.110**	**0.110**	***	0.000	**-0.060**	**0.060**	**
	(1.000)	(0.000)	(0.000)		(1.000)	(0.001)	(0.003)		(1.000)	(0.015)	(0.031)	
Agreeableness	0.037	-0.007	0.037		0.001	-0.047	0.047		0.028	-0.009	0.028	
	(0.342)	(0.958)	(0.656)		(0.999)	(0.299)	(0.581)		(0.395)	(0.920)	(0.742)	
Grit	0.039	0.000	0.039		0.002	**-0.077**	**0.077**	*	0.003	**-0.074**	**0.074**	***
	(0.305)	(1.000)	(0.593)		(0.999)	(0.038)	(0.076)		(0.991)	(0.002)	(0.004)	
Decision making	**0.120**	-0.001	**0.120**	***	0.005	**-0.134**	**0.134**	***	0.005	**-0.057**	**0.057**	**
	(0.000)	(1.000)	(0.000)		(0.987)	(0.000)	(0.000)		(0.970)	(0.022)	(0.044)	
Hostile attribution bias	0.034	0.000	0.034		0.034	-0.008	0.034		0.026	-0.010	0.026	

Appendix Table 5. Cognitive and noncognitive skills, male and female: Two-sampled Kolgomorov-Smirnov tests for equality of distributions

	(0.217)	(1.000)	(0.430)		(0.335)	(0.947)	(0.646)		(0.288)	(0.817)	(0.561)	
Risk taking	0.000	-0.029	0.029		0.015	-0.034	0.034		0.000	**-0.052**	**0.052**	**
	(1.000)	(0.342)	(0.656)		(0.714)	(0.192)	(0.381)		(1.000)	(0.006)	(0.012)	
Time preference	0.042	0.000	0.042		0.016	-0.015	0.016		0.008	-0.023	0.023	
	(0.109)	(1.000)	(0.217)		(0.691)	(0.723)	(0.993)		(0.878)	(0.373)	(0.707)	

	Serbia				Ukraine				Vietnam			
	Diff				Diff				Diff			
	Max(F-M)	Min(F-M)	Combined K-S		Max(F-M)	Min(F-M)	Combined K-S		Max(F-M)	Min(F-M)	Combined K-S	
Literacy proficiency (plausible values)	0.019	-0.021	0.021		**0.056**	-0.017	**0.056**	*	0.005	-0.075	0.075	
	(0.577)	(0.493)	(0.872)		(0.039)	(0.741)	(0.078)		(0.960)	(0.000)	(0.000)	
Extraversion	**0.064**	-0.015	**0.064**	**	**0.188**	-0.009	**0.188**	***	0.043	0.000	0.043	
	(0.018)	(0.806)	(0.036)		(0.000)	(0.945)	(0.000)		(0.149)	(1.000)	(0.296)	
Conscientiousness	**0.061**	-0.006	**0.061**	**	**0.156**	0.000	**0.156**	***	0.000	**-0.067**	**0.067**	**
	(0.024)	(0.968)	(0.048)		(0.000)	(1.000)	(0.000)		(1.000)	(0.010)	(0.020)	
Openness	0.007	-0.036	0.036		**0.103**	-0.013	**0.103**	***	0.000	**-0.108**	**0.108**	***
	(0.951)	(0.283)	(0.554)		(0.001)	(0.905)	(0.002)		(1.000)	(0.000)	(0.000)	
Emotional Stability	0.000	**-0.157**	**0.157**	***	0.000	**-0.259**	**0.259**	***	0.000	**-0.245**	**0.245**	***
	(1.000)	(0.000)	(0.000)		(1.000)	(0.000)	(0.000)		(1.000)	(0.000)	(0.000)	
Agreeableness	**0.059**	-0.002	**0.059**	*	**0.129**	0.000	**0.129**	***	0.005	-0.035	0.035	
	(0.032)	(0.997)	(0.064)		(0.000)	(1.000)	(0.000)		(0.976)	(0.283)	(0.553)	
Grit	0.040	-0.014	0.040		**0.072**	0.000	**0.072**	*	0.021	**-0.058**	**0.058**	*
	(0.212)	(0.835)	(0.421)		(0.039)	(1.000)	(0.077)		0.622	0.030	0.061	
Decision making	**0.051**	-0.014	0.051		**0.161**	0.000	**0.161**	***	0.003	**-0.052**	0.052	
	(0.075)	(0.832)	(0.150)		(0.000)	(1.000)	(0.000)		0.988	0.064	0.127	
Hostile attribution bias	--	--	--		0.012	-0.024	0.024		0.002	**-0.056**	**0.056**	**
	--	--	--		(0.852)	(0.543)	(0.920)		(0.992)	(0.006)	(0.012)	
Risk taking	--	--	--		0.000	**-0.063**	**0.063**	**	0.000	**-0.055**	**0.055**	**
	--	--	--		(1.000)	(0.018)	(0.037)		(1.000)	(0.007)	(0.014)	
Time preference	--	--	--		0.003	-0.015	0.015		0.001	-0.027	0.027	
	--	--	--		(0.994)	(0.791)	(1.000)		(0.999)	(0.316)	(0.613)	

Note: The first column denotes the hypothesis that *x* for males contains smaller values than for females, the second that *x* for males contains larger values than for females. The third column denotes the combined test. *p*-values are given in parenthesis. Statistical significance is denoted as *p< 0.10, , **p<0.05, and *** p<0.01 respectively. Data sources: STEP data for 9 countries, 2012-13

Appendix Table 6. Earnings Functions (OLS and Selection Corrected), Ages 25-54, using education splines

		Men						Women						All					
		OLS			Selectivity-corrected			OLS			Selectivity-corrected			OLS			Selectivity-corrected		
		[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]
Armenia																			
	Female													-0.409***	-0.413***	-0.407***	-0.360***	-0.366***	-0.368***
														(0.049)	(0.049)	(0.050)	(0.060)	(0.060)	(0.065)
	Schooling <10 years	0.026	0.017	-0.014	0.077	0.067	0.045	0.069***	0.068***	0.064**	0.084***	0.084***	0.082***	0.059**	0.057**	0.043	0.070**	0.068**	0.052
		(0.060)	(0.063)	(0.062)	(0.070)	(0.073)	(0.071)	(0.026)	(0.026)	(0.027)	(0.030)	(0.030)	(0.031)	(0.027)	(0.027)	(0.030)	(0.030)	(0.030)	(0.033)
	Schooling 10-13 years	0.022	0.020	0.022	0.010	0.008	0.005	-0.019	-0.026	-0.027	-0.036	-0.042	-0.040	-0.015	-0.019	-0.021	-0.024	-0.028	-0.027
		(0.039)	(0.040)	(0.040)	(0.041)	(0.041)	(0.041)	(0.027)	(0.027)	(0.027)	(0.029)	(0.028)	(0.028)	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)
	Schooling >13 years	0.058**	0.052**	0.036	0.030	0.021	-0.003	0.106***	0.104***	0.101***	0.089***	0.088***	0.086***	0.091***	0.088***	0.080***	0.079***	0.077***	0.072***
		(0.025)	(0.026)	(0.026)	(0.028)	(0.029)	(0.029)	(0.016)	(0.016)	(0.017)	(0.018)	(0.018)	(0.018)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
	Literacy (Plausible values)		0.073	0.054		0.092	0.073		0.059	0.068		0.045	0.056		0.051	0.057		0.046	0.054
			(0.060)	(0.062)		(0.063)	(0.064)		(0.047)	(0.047)		(0.048)	(0.047)		(0.037)	(0.037)		(0.038)	(0.037)
	Extraversion			0.045			0.022			0.029			0.025			0.039*			0.036
				(0.040)			(0.042)			(0.026)			(0.026)			(0.022)			(0.022)
	Conscientiousness			0.020			-0.014			-0.029			-0.040			-0.015			-0.022
				(0.040)			(0.043)			(0.032)			(0.031)			(0.025)			(0.026)
	Openness			0.109**			0.106**			0.019			0.004			0.050*			0.045*
				(0.051)			(0.052)			(0.031)			(0.032)			(0.027)			(0.027)
	Emotional stability			0.042			0.056			0.061*			0.049			0.055**			0.052**
				(0.046)			(0.047)			(0.031)			(0.031)			(0.025)			(0.025)
	Agreeableness			-0.104**			-0.111**			-0.003			-0.012			-0.034			-0.039
				(0.047)			(0.049)			(0.031)			(0.031)			(0.026)			(0.026)
	Grit			0.022			0.017			0.040			0.036			0.036			0.034
				(0.049)			(0.052)			(0.031)			(0.031)			(0.026)			(0.026)
	Decision making			-0.005			0.009			-0.014			-0.002			-0.016			-0.011
				(0.046)			(0.048)			(0.028)			(0.029)			(0.023)			(0.024)
	Hostile attribution bias			0.055			0.027			0.023			0.030			0.035			0.036
				(0.042)			(0.043)			(0.029)			(0.028)			(0.024)			(0.024)
	Risk taking			0.069*			0.091**			-0.012			-0.016			0.015			0.017
				(0.041)			(0.043)			(0.028)			(0.028)			(0.023)			(0.023)
	Time preference			0.040			0.054			0.002			0.007			0.027			0.029
				(0.045)			(0.049)			(0.031)			(0.030)			(0.024)			(0.024)
	Prob > F (noncognitive)			S**			S***			NS			S***			S**			S***
	Joint sig of gender																		
	r=0				NS	S*	S**				S*	S*	S*				NS	NS	NS
	N	247	247	247	470	470	470	412	412	412	1,345	1,345	1,345	659	659	659	1815	1815	1815
Bolivia																			
	Female													-0.294***	-0.289***	-0.273***	-0.312***	-0.298***	-0.296***
														(0.054)	(0.055)	(0.056)	(0.063)	(0.066)	(0.068)
	Schooling <10 years	0.057	0.047	0.037	0.057	0.047	0.036	0.058**	0.059**	0.068***	0.061**	0.064***	0.072***	0.058***	0.055***	0.057***	0.059***	0.057***	0.058***
		(0.037)	(0.038)	(0.039)	(0.037)	(0.038)	(0.038)	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.025)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)
	Schooling 10-13 years	-0.033	-0.051	-0.038	-0.034	-0.051	-0.038	-0.037	-0.028	-0.035	-0.040	-0.027	-0.034	-0.034	-0.041	-0.039	-0.035	-0.042	-0.039
		(0.047)	(0.048)	(0.049)	(0.047)	(0.048)	(0.048)	(0.040)	(0.043)	(0.045)	(0.040)	(0.043)	(0.045)	(0.030)	(0.032)	(0.032)	(0.030)	(0.032)	(0.032)
	Schooling >13 years	0.128***	0.117***	0.121***	0.128***	0.117***	0.121***	0.160***	0.162***	0.161***	0.167***	0.170***	0.172***	0.146***	0.143***	0.143***	0.147***	0.144***	0.145***
		(0.024)	(0.024)	(0.025)	(0.023)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)
	Plausible values		0.122**	0.124**		0.121*	0.116*		-0.031	-0.022		-0.045	-0.042		0.036	0.041		0.033	0.034
			(0.062)	(0.062)		(0.063)	(0.070)		(0.046)	(0.047)		(0.050)	(0.051)		(0.037)	(0.037)		(0.038)	(0.039)
	Extraversion			0.039			0.040			-0.018			-0.005			0.008			0.010
				(0.044)			(0.043)			(0.039)			(0.041)			(0.029)			(0.030)
	Conscientiousness			-0.099**			-0.098**			-0.042			-0.046			-0.066**			-0.065**
				(0.043)			(0.043)			(0.036)			(0.036)			(0.027)			(0.027)
	Openness			-0.035			-0.034			-0.009			-0.003			-0.022			-0.021
				(0.050)			(0.050)			(0.043)			(0.043)			(0.033)			(0.033)
	Emotional stability			-0.005			-0.001			0.000			0.001			-0.011			-0.010
				(0.045)			(0.050)			(0.036)			(0.036)			(0.028)			(0.028)
	Agreeableness			0.037			0.037			-0.026			-0.029			0.005			0.004
				(0.042)			(0.043)			(0.038)			(0.038)			(0.028)			(0.028)
	Grit			-0.013			-0.012			-0.037			-0.040			-0.030			-0.032
				(0.045)			(0.044)			(0.039)			(0.039)			(0.029)			(0.029)
	Decision making			-0.091**			-0.093**			0.028			0.017			-0.028			-0.031
				(0.042)			(0.042)			(0.036)			(0.038)			(0.028)			(0.028)
	Hostile attribution bias			-0.078*			-0.075*			-0.096**			-0.090**			-0.084***			-0.082***
				(0.043)			(0.044)			(0.040)			(0.041)			(0.030)			(0.030)
	Risk taking			0.036			0.033			0.083**			0.086**			0.055**			0.054**
				(0.038)			(0.041)			(0.036)			(0.036)			(0.026)			(0.026)
	Time preference			-0.061			-0.060			0.029			0.027			-0.013			-0.012
				(0.038)			(0.038)			(0.038)			(0.039)			(0.027)			(0.027)
	Prob > F (noncognitive)			S**			S*			NS			S*			S***			S***
	Joint sig of gender																		
	r				NS	NS	NS				NS	NS	NS				NS	NS	NS
	N (uncensored obs)	491	491	491	560	560	560	600	600	600	841	841	841	1,401	1,401	1,401	1,401	1,401	1,401
Colombia																			
	Female													-0.253***	-0.255***	-0.250***	-0.437***	-0.441***	-0.418***
														(0.045)	(0.045)	(0.046)	(0.060)	(0.059)	(0.063)
	Schooling <10 years	0.003	0.010	0.015	0.002	0.010	0.017	0.013	0.019	0.017	0.010	0.015	0.011	0.009	0.015	0.014	0.014	0.018	0.015
		(0.025)	(0.026)	(0.027)	(0.025)	(0.027)	(0.026)	(0.022)	(0.024)	(0.024)	(0.023)	(0.025)	(0.026)	(0.016)	(0.018)	(0.018)	(0.017)	(0.019)	(0.018)

	Schooling 10-13 years	0.078**	0.083***	0.069**	0.079**	0.084**	0.066**	0.050	0.053	0.050	0.076**	0.079**	0.080**	0.062***	0.066***	0.063***	0.072***	0.074***	0.072***
		(0.032)	(0.032)	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.037)	(0.037)	(0.036)	(0.023)	(0.023)	(0.023)	(0.025)	(0.025)	(0.025)
	Schooling >13 years	0.191***	0.196***	0.182***	0.191***	0.196***	0.182***	0.189***	0.193***	0.194***	0.200***	0.204***	0.210***	0.194***	0.199***	0.189***	0.198***	0.201***	0.192***
		(0.032)	(0.033)	(0.034)	(0.032)	(0.033)	(0.034)	(0.029)	(0.029)	(0.030)	(0.033)	(0.034)	(0.035)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)	(0.025)
	Plausible values		-0.047	-0.044		-0.047	-0.037		-0.038	-0.051		-0.032	-0.039		-0.044	-0.052		-0.025	-0.034
			(0.064)	(0.065)		(0.063)	(0.065)		(0.056)	(0.059)		(0.062)	(0.064)		(0.042)	(0.043)		(0.045)	(0.046)
	Extraversion			-0.024			-0.019			0.073**			0.082**			0.032			0.050*
				(0.034)			(0.034)			(0.035)			(0.037)			(0.024)			(0.027)
	Conscientiousness			0.002			0.004			-0.020			0.020			-0.015			0.006
				(0.035)			(0.035)			(0.036)			(0.039)			(0.024)			(0.026)
	Openness			0.065*			0.068**			0.038			0.030			0.054**			0.056**
				(0.034)			(0.034)			(0.034)			(0.036)			(0.023)			(0.025)
	Emotional stability			-0.069**			-0.068**			0.018			0.024			-0.027			-0.024
				(0.033)			(0.033)			(0.038)			(0.041)			(0.025)			(0.026)
	Agreeableness			0.020			0.014			-0.042			-0.079**			-0.019			-0.050*
				(0.036)			(0.038)			(0.032)			(0.036)			(0.024)			(0.027)
	Grit			-0.014			-0.012			-0.057			-0.053			-0.035			-0.031
				(0.032)			(0.031)			(0.037)			(0.040)			(0.024)			(0.026)
	Decision making			0.013			0.014			-0.027			-0.059			-0.001			-0.018
				(0.034)			(0.034)			(0.036)			(0.039)			(0.025)			(0.027)
	Hostile attribution bias			-0.103***			-0.103***			-0.015			-0.009			-0.057**			-0.055**
				(0.034)			(0.034)			(0.036)			(0.038)			(0.025)			(0.026)
	Risk taking			0.066**			0.067**			0.038			0.047			0.048**			0.053**
				(0.031)			(0.031)			(0.030)			(0.033)			(0.022)			(0.023)
	Prob > F (noncognitive)			S**			S***			NS			S**			S**			S***
	Joint sig of gender r				NS	NS	NS				S**	S**	S***				S***	S***	S***
	N (uncensored obs)	579	579	579	667	667	667	589	589	589	929	929	929	1,168	1,168	1,168	1,596	1,596	1,596
Georgia	Female													-0.294***	-0.310***	-0.321***	-0.674**	-0.738**	-0.647***
														(0.058)	(0.058)	(0.059)	(0.304)	(0.335)	(0.217)
	Schooling <10 years	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Schooling 10-13 years	-0.008	-0.018	-0.072	-0.003	-0.015	-0.103	0.004	-0.002	-0.004	0.019	0.010	-0.003	-0.009	-0.017	-0.022	0.075	0.063	0.015
		(0.059)	(0.062)	(0.070)	(0.082)	(0.082)	(0.086)	(0.063)	(0.062)	(0.069)	(0.066)	(0.066)	(0.067)	(0.044)	(0.044)	(0.046)	(0.108)	(0.111)	(0.075)
	Schooling >13 years	0.095***	0.089***	0.076***	0.097**	0.091***	0.065**	0.129***	0.119***	0.118***	0.179***	0.169***	0.160***	0.118***	0.109***	0.107***	0.257**	0.244**	0.194***
		(0.027)	(0.027)	(0.028)	(0.039)	(0.030)	(0.031)	(0.020)	(0.021)	(0.022)	(0.034)	(0.032)	(0.030)	(0.016)	(0.016)	(0.017)	(0.104)	(0.101)	(0.056)
	Plausible values		0.080	0.076		0.081	0.064		0.118**	0.103**		0.218***	0.192***		0.104**	0.095**		0.325*	0.239**
			(0.085)	(0.082)		(0.072)	(0.072)		(0.053)	(0.052)		(0.074)	(0.071)		(0.046)	(0.046)		(0.181)	(0.107)
	Extraversion			-0.021			-0.035			0.004			0.041			-0.007			0.080
				(0.054)			(0.053)			(0.041)			(0.045)			(0.032)			(0.070)
	Conscientiousness			0.060			0.045			0.017			0.031			0.032			0.101
				(0.061)			(0.063)			(0.045)			(0.049)			(0.037)			(0.070)
	Openness			0.059			0.072			0.052			0.068			0.040			0.035
				(0.052)			(0.054)			(0.045)			(0.050)			(0.033)			(0.054)
	Emotional stability			0.065			0.067			0.009			0.046			0.024			0.085
				(0.051)			(0.053)			(0.036)			(0.043)			(0.029)			(0.059)
	Agreeableness			0.039			0.053			-0.057			-0.055			-0.024			-0.052
				(0.045)			(0.050)			(0.037)			(0.042)			(0.029)			(0.051)
	Grit			0.008			-0.019			0.013			0.090			0.004			0.169
				(0.067)			(0.067)			(0.040)			(0.056)			(0.035)			(0.109)
	Decision making			-0.002			-0.017			0.016			0.027			0.017			0.058
				(0.052)			(0.058)			(0.040)			(0.044)			(0.031)			(0.056)
	Hostile attribution bias			0.119**			0.138**			-0.004			-0.000			0.040			0.018
				(0.052)			(0.058)			(0.038)			(0.041)			(0.031)			(0.051)
	Risk taking			0.104**			0.109**			-0.054			-0.037			0.004			0.030
				(0.043)			(0.046)			(0.036)			(0.039)			(0.028)			(0.048)
	Time preference			-0.131***			-0.141***			0.070**			0.075*			0.001			0.026
				(0.050)			(0.051)			(0.034)			(0.039)			(0.028)			(0.049)
	Prob > F (noncognitive)			S**			S***			NS			S***			NS			S***
	Joint sig of gender r l				NS	NS	NS				S**	S**	S*				NS	NS	S*
	N (uncensored obs)	236	236	236	568	568	568	399	399	399	1,262	1,262	1,262	635	635	635	1,830	1,830	1,830
Ghana	Female													-0.304***	-0.306***	-0.312***	-0.337***	-0.336***	-0.337***
														(0.075)	(0.075)	(0.077)	(0.081)	(0.082)	(0.083)
	Schooling <10 years	0.105***	0.105***	0.105***	0.100***	0.101***	0.102***	-0.058	-0.060	-0.055	-0.061	-0.062	-0.056	0.039	0.039	0.043	0.041	0.041	0.044
		(0.034)	(0.034)	(0.033)	(0.034)	(0.034)	(0.033)	(0.061)	(0.062)	(0.063)	(0.062)	(0.062)	(0.064)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.032)
	Schooling 10-13 years	0.008	0.012	-0.001	0.008	0.018	0.003	0.071**	0.067*	0.073*	0.069*	0.064	0.071*	0.040*	0.042	0.036	0.038*	0.041	0.035
		(0.029)	(0.034)	(0.034)	(0.029)	(0.034)	(0.034)	(0.036)	(0.039)	(0.039)	(0.036)	(0.040)	(0.040)	(0.023)	(0.026)	(0.026)	(0.023)	(0.026)	(0.025)
	Schooling >13 years	0.179***	0.182***	0.172***	0.175***	0.181***	0.173***	0.274***	0.269***	0.256***	0.275***	0.269***	0.257***	0.210***	0.212***	0.197***	0.211***	0.213***	0.198***
		(0.031)	(0.033)	(0.033)	(0.031)	(0.033)	(0.033)	(0.041)	(0.043)	(0.044)	(0.042)	(0.044)	(0.045)	(0.025)	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)
	Plausible values		-0.019	-0.053		-0.043	-0.067		0.024	-0.022		0.029	-0.018		-0.010	-0.043		-0.013	-0.043
			(0.065)	(0.069)		(0.066)	(0.069)		(0.077)	(0.082)		(0.077)	(0.081)		(0.051)	(0.053)		(0.051)	(0.053)
	Extraversion			-0.010			-0.009			0.052			0.054			0.017			0.020
				(0.049)			(0.048)			(0.060)			(0.060)			(0.038)			(0.038)
	Conscientiousness			0.055			0.070			-0.085			-0.083			-0.002			0.001
				(0.054)			(0.055)			(0.075)			(0.076)			(0.046)			(0.046)
	Openness			0.045			0.038			0.021			0.019			0.032			0.030
				(0.051)			(0.050)			(0.072)			(0.070)			(0.043)			(0.043)
	Emotional stability			-0.041			-0.039			0.058			0.056			-0.004			-0.006

				(0.056)			(0.055)			(0.057)			(0.057)			(0.041)			(0.040)
	Agreeableness			0.057			0.051			-0.011			-0.007			0.026			0.025
				(0.049)			(0.049)			(0.065)			(0.065)			(0.040)			(0.040)
	Grit			-0.115**			-0.119**			0.017			0.018			-0.055			-0.059
				(0.051)			(0.051)			(0.063)			(0.067)			(0.041)			(0.040)
	Decision making			0.061			0.059			0.061			0.060			0.058			0.056
				(0.052)			(0.052)			(0.059)			(0.058)			(0.040)			(0.040)
	Hostile attribution bias			-0.026			-0.026			-0.130**			-0.127*			-0.075*			-0.074*
				(0.057)			(0.056)			(0.066)			(0.065)			(0.044)			(0.044)
	Risk taking			0.084*			0.081*			-0.004			-0.003			0.050			0.049
				(0.043)			(0.043)			(0.059)			(0.058)			(0.034)			(0.034)
	Time preference			-0.063			-0.058			-0.076			-0.072			-0.067*			-0.068*
				(0.044)			(0.044)			(0.065)			(0.079)			(0.036)			(0.036)
	Prob > F (noncognitive)			S*			S*						NS			NS			NS
	Joint sig of gender																		
	r				S*	NS	NS					NS					NS		
	l												NS					NS	NS
	N (uncensored obs)	481	481	481	575	575	575	370	370	370	502	502	502	851	851	851	1,077	1,077	1,077
Kenya																			
	Female													-0.043	-0.040	-0.029	-0.088	-0.079	-0.041
														(0.044)	(0.044)	(0.044)	(0.123)	(0.123)	(0.052)
	Schooling <10 years	0.004	-0.003	-0.005	0.007	-0.002	-0.005	0.042**	0.023	0.024	0.041**	0.016	0.016	0.022**	0.009	0.007	0.021*	0.008	0.005
		(0.013)	(0.014)	(0.014)	(0.015)	(0.016)	(0.014)	(0.017)	(0.019)	(0.019)	(0.018)	(0.020)	(0.020)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
	Schooling 10-13 years	0.131***	0.128***	0.113***	0.129***	0.126***	0.112***	0.029	0.029	0.022	0.041	0.041	0.032	0.086***	0.084***	0.072***	0.086***	0.083***	0.071***
		(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.033)	(0.033)	(0.033)	(0.036)	(0.036)	(0.036)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)
	Schooling >13 years	0.300***	0.292***	0.289***	0.299***	0.291***	0.286***	0.404***	0.386***	0.379***	0.414***	0.391***	0.382***	0.341***	0.329***	0.324***	0.340***	0.326***	0.321***
		(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.040)	(0.041)	(0.041)	(0.042)	(0.043)	(0.043)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)	(0.022)
	Plausible values		0.049	0.052		0.058	0.062		0.110**	0.104*		0.152**	0.143**		0.079**	0.080**		0.088***	0.089***
			(0.041)	(0.041)		(0.041)	(0.040)		(0.052)	(0.054)		(0.059)	(0.060)		(0.033)	(0.033)		(0.033)	(0.033)
	Extraversion			0.033			0.033			0.018			0.026			0.023			0.024
				(0.028)			(0.027)			(0.036)			(0.038)			(0.022)			(0.022)
	Conscientiousness			0.003			-0.000			0.070*			0.095**			0.037			0.038
				(0.032)			(0.031)			(0.041)			(0.044)			(0.025)			(0.025)
	Openness			0.091***			0.092***			0.027			0.007			0.059**			0.057**
				(0.031)			(0.031)			(0.036)			(0.041)			(0.023)			(0.023)
	Emotional stability			0.045*			0.047*			0.014			0.037			0.036*			0.037*
				(0.025)			(0.026)			(0.037)			(0.039)			(0.021)			(0.021)
	Agreeableness			-0.020			-0.026			0.020			0.000			-0.000			-0.001
				(0.031)			(0.031)			(0.038)			(0.042)			(0.024)			(0.024)
	Grit			-0.019			-0.019			-0.016			0.000			-0.015			-0.015
				(0.029)			(0.029)			(0.037)			(0.041)			(0.023)			(0.023)
	Decision making			-0.010			-0.013			0.009			0.016			-0.003			-0.006
				(0.031)			(0.031)			(0.041)			(0.043)			(0.025)			(0.025)
	Hostile attribution bias			-0.033			-0.035			-0.004			-0.014			-0.020			-0.023
				(0.028)			(0.027)			(0.039)			(0.040)			(0.023)			(0.022)
	Risk taking			0.017			0.016			0.009			0.033			0.017			0.021
				(0.029)			(0.029)			(0.034)			(0.036)			(0.022)			(0.022)
	Time preference			0.054*			0.054*			0.040			0.049			0.045**			0.046**
				(0.030)			(0.030)			(0.036)			(0.037)			(0.023)			(0.023)
	Prob > F (noncognitive)			S***			S***			NS			NS			S***			S***
	Joint sig of gender																		
	r				NS	NS	NS				NS	S*	S*						
	l																NS	NS	NS
	N (uncensored obs)	906	906	900	1099	1099	1089	690	690	686	1216	1216	1203	1596	1596	1586	2315	2315	2264
Serbia																			
	Female													0.056	0.056	0.048	0.068	0.068	0.070
														(0.068)	(0.068)	(0.070)	(0.100)	(0.100)	(0.104)
	Schooling <10 years	0.110	0.106	0.083	0.209	0.202	0.161	-0.019	-0.019	-0.015	0.097	0.160	0.241	0.020	0.019	0.017	0.168	0.169	0.169
		(0.099)	(0.098)	(0.108)	(0.131)	(0.130)	(0.141)	(0.039)	(0.041)	(0.041)	(0.112)	(0.135)	(0.162)	(0.047)	(0.049)	(0.050)	(0.105)	(0.106)	(0.107)
	Schooling 10-13 years	0.046	0.040	0.044	0.036	0.029	0.041	0.160***	0.160***	0.155***	0.036	0.037	-0.003	0.105***	0.104***	0.101**	0.042	0.043	0.036
		(0.058)	(0.065)	(0.069)	(0.074)	(0.074)	(0.075)	(0.047)	(0.048)	(0.049)	(0.083)	(0.082)	(0.092)	(0.038)	(0.039)	(0.040)	(0.060)	(0.057)	(0.059)
	Schooling >13 years	0.106*	0.105*	0.105*	0.109*	0.108*	0.106*	0.134***	0.134***	0.132***	0.161***	0.168***	0.148***	0.128***	0.128***	0.126***	0.134***	0.134***	0.132***
		(0.060)	(0.060)	(0.061)	(0.059)	(0.059)	(0.059)	(0.024)	(0.023)	(0.024)	(0.041)	(0.040)	(0.055)	(0.027)	(0.027)	(0.028)	(0.036)	(0.037)	(0.036)
	Plausible values		0.019	0.029		0.022	0.031		0.002	-0.000		-0.104	-0.129		0.005	0.007		-0.004	-0.014
			(0.101)	(0.101)		(0.094)	(0.097)		(0.056)	(0.058)		(0.103)	(0.095)		(0.063)	(0.063)		(0.076)	(0.075)
	Extraversion			-0.026			-0.049			-0.018			-0.103			-0.019			-0.060
				(0.077)			(0.092)			(0.038)			(0.083)			(0.040)			(0.068)
	Conscientiousness			0.131*			0.118			0.014			-0.046			0.072*			0.065
				(0.069)			(0.078)			(0.048)			(0.086)			(0.042)			(0.060)
	Openness			0.004			0.038			0.016			0.218*			0.002			0.086
				(0.070)			(0.089)			(0.053)			(0.125)			(0.044)			(0.070)
	Emotional stability			0.029			0.007			-0.023			0.004			0.006			0.001
				(0.075)			(0.092)			(0.041)			(0.123)			(0.042)			(0.074)
	Agreeableness			-0.026			0.043			0.078			0.104			0.035			0.068
				(0.079)			(0.098)			(0.048)			(0.092)			(0.045)			(0.070)
	Grit			-0.081			-0.151**			-0.010			-0.015			-0.039			-0.095*
				(0.074)			(0.073)			(0.048)			(0.075)			(0.042)			(0.057)
	Decision making			0.058			0.012			-0.004			-0.005			0.020			-0.001
				(0.087)			(0.100)			(0.052)			(0.126)			(0.052)			(0.080)
	Prob > F (noncognitive)			NS			NS			NS			NS			NS			NS
	Joint sig of gender																		

	r				NS	NS	NS				NS	NS	NS				NS	NS	NS
	N (uncensored obs)	412	412	412	608	608	608	454	454	454	286	286	286	886	866	866	894	894	894
Ukraine																			
	Female													-0.393***	-0.393***	-0.415***	-0.394***	-0.394***	-0.417***
														(0.043)	(0.043)	(0.045)	(0.044)	(0.044)	(0.046)
	Schooling <10 years	0.078***	0.079***	0.069***	0.107***	0.117***	0.106***	--	--	--	--	--	--	0.083***	0.082***	0.077***	0.082***	0.081***	0.076***
		(0.016)	(0.018)	(0.024)	(0.033)	(0.032)	(0.034)							(0.010)	(0.010)	(0.013)	(0.011)	(0.013)	(0.014)
	Schooling 10-13 years	0.017	0.017	0.005	-0.007	-0.001	0.002	0.010	0.009	0.003	0.008	0.009	0.004	0.004	0.003	-0.002	0.005	0.004	-0.001
		(0.041)	(0.041)	(0.041)	(0.047)	(0.045)	(0.045)	(0.026)	(0.026)	(0.026)	(0.029)	(0.029)	(0.029)	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)	(0.023)
	Schooling >13 years	0.014	0.015	0.007	0.006	0.011	0.011	0.124***	0.123***	0.120***	0.123***	0.123***	0.120***	0.085***	0.085***	0.078***	0.086***	0.085***	0.078***
		(0.032)	(0.032)	(0.034)	(0.034)	(0.035)	(0.037)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)
	Plausible values		-0.002	-0.007		-0.062	-0.057		0.005	-0.002		0.004	-0.001		0.006	-0.001		0.008	0.001
			(0.048)	(0.050)		(0.059)	(0.056)		(0.028)	(0.027)		(0.029)	(0.028)		(0.025)	(0.025)		(0.028)	(0.027)
	Extraversion			-0.018			-0.016			-0.033			-0.033			-0.027			-0.027
				(0.039)			(0.042)			(0.025)			(0.025)			(0.022)			(0.022)
	Conscientiousness			0.019			-0.032			0.005			0.006			0.012			0.014
				(0.040)			(0.050)			(0.026)			(0.030)			(0.022)			(0.025)
	Openness			0.076*			0.066			0.072***			0.072***			0.073***			0.073***
				(0.044)			(0.046)			(0.026)			(0.027)			(0.023)			(0.023)
	Emotional stability			-0.016			-0.001			-0.044*			-0.044*			-0.034			-0.034
				(0.046)			(0.049)			(0.025)			(0.024)			(0.022)			(0.022)
	Agreeableness			-0.028			-0.015			-0.007			-0.008			-0.012			-0.012
				(0.038)			(0.044)			(0.024)			(0.024)			(0.020)			(0.020)
	Grit			0.013			-0.008			0.065**			0.065**			0.040*			0.040*
				(0.039)			(0.044)			(0.028)			(0.027)			(0.022)			(0.022)
	Decision making			0.051			0.027			-0.038			-0.038			0.001			0.001
				(0.047)			(0.055)			(0.027)			(0.026)			(0.024)			(0.024)
	Hostile attribution bias			0.021			0.022			-0.020			-0.020			-0.006			-0.006
				(0.037)			(0.039)			(0.025)			(0.024)			(0.021)			(0.021)
	Risk taking			-0.022			-0.021			-0.021			-0.022			-0.027			-0.027
				(0.038)			(0.041)			(0.026)			(0.025)			(0.021)			(0.021)
	Time preference			-0.001			-0.028			0.015			0.015			0.015			0.016
				(0.040)			(0.043)			(0.022)			(0.022)			(0.020)			(0.020)
	Prob > F (noncognitive)			NS			NS			S**			S***			S***			S***
	Joint sig of gender																		
	r				NS	NS	S*				NS	NS	NS				NS	NS	NS
	N (uncensored obs)	254	254	254	441	441	441	446	446	446	834	834	834	700	700	700	1,275	1,275	1,275
Vietnam																			
	Female													-0.265***	-0.266***	-0.228***	-0.258***	-0.261***	-0.215***
														(0.036)	(0.036)	(0.038)	(0.038)	(0.038)	(0.039)
	Schooling <10 years	0.023	0.012	0.009	0.021	0.012	0.009	0.013	-0.006	-0.007	0.007	-0.015	-0.015	0.016	-0.000	-0.003	0.016	-0.000	-0.002
		(0.018)	(0.020)	(0.020)	(0.018)	(0.020)	(0.020)	(0.013)	(0.015)	(0.015)	(0.014)	(0.016)	(0.016)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
	Schooling 10-13 years	0.071***	0.064**	0.054**	0.071***	0.066**	0.056**	0.115***	0.099***	0.092***	0.132***	0.114***	0.106***	0.100***	0.088***	0.078***	0.099***	0.087***	0.077***
		(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.021)	(0.021)	(0.021)	(0.023)	(0.023)	(0.023)	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.016)
	Schooling >13 years	0.085***	0.082***	0.086***	0.080***	0.078***	0.082***	0.147***	0.139***	0.129***	0.181***	0.171***	0.161***	0.115***	0.109***	0.107***	0.113***	0.108***	0.104***
		(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
	Plausible values		0.059	0.037		0.051	0.030		0.117***	0.087**		0.136***	0.100***		0.097***	0.073***		0.096***	0.069**
			(0.042)	(0.042)		(0.042)	(0.042)		(0.036)	(0.036)		(0.039)	(0.039)		(0.027)	(0.027)		(0.027)	(0.027)
	Extraversion			0.054*			0.052*			0.026			0.044*			0.040**			0.038**
				(0.028)			(0.027)			(0.025)			(0.026)			(0.019)			(0.019)
	Conscientiousness			0.027			0.023			0.034			0.043			0.032			0.030
				(0.032)			(0.032)			(0.026)			(0.028)			(0.020)			(0.020)
	Openness			0.026			0.026			0.054**			0.041			0.046**			0.047**
				(0.033)			(0.033)			(0.025)			(0.027)			(0.020)			(0.020)
	Emotional stability			0.031			0.027			0.059**			0.060**			0.051**			0.050**
				(0.032)			(0.032)			(0.029)			(0.030)			(0.021)			(0.021)
	Agreeableness			0.031			0.032			-0.013			-0.015			0.003			0.003
				(0.029)			(0.029)			(0.025)			(0.026)			(0.019)			(0.019)
	Grit			-0.011			-0.011			0.003			0.015			-0.002			-0.003
				(0.028)			(0.027)			(0.028)			(0.030)			(0.019)			(0.019)
	Decision making			0.050*			0.048*			0.033			0.055*			0.034*			0.032*
				(0.028)			(0.028)			(0.026)			(0.028)			(0.019)			(0.019)
	Hostile attribution bias			-0.008			-0.008			-0.056**			-0.034			-0.036**			-0.038**
				(0.027)			(0.027)			(0.023)			(0.025)			(0.018)			(0.018)
	Risk taking			-0.006			-0.007			0.041*			0.063**			0.020			0.018
				(0.030)			(0.030)			(0.024)			(0.026)			(0.018)			(0.019)
	Time preference			0.002			0.004			-0.025			-0.023			-0.013			-0.013
				(0.030)			(0.030)			(0.024)			(0.025)			(0.019)			(0.019)
	Prob > F (noncognitive)			S*			NS			S***			S***			S***			S***
	Joint sig of gender																		
	r				NS	NS	NS				S**	S**	S**				NS	NS	NS
	N (uncensored obs)	713	713	713	833	833	833	995	995	995	1,359	1,359	1,359	1,708	1,708	1,708	2,192	2,192	2,192

Notes: Standard errors are in parentheses. Columns 1-3 are coefficients of (unweighted) least squares estimation, columns 4-6 are coefficients of selectivity-corrected models. The dependent variable is the natural logarithm of gross hourly earnings, top and bottom 1% trimmed. Control variables included are age, age-squared, location and a constant term. M,F=Statistically significant in favor of males (M) or females (F); NS=Not statistically significant. Statistical significance is denoted as * p < 0.10, ** p < 0.05, *** p < 0.01 . Data sources: STEP data for 9 countries, 2012-13

	(0.0418)	(0.0405)	(0.0411)	(0.0561)	(0.0467)	(0.0529)	(0.0524)	(0.0436)	(0.0399)	(0.0389)	(0.0428)
0.70	-0.0438	-0.0468	-0.0524	0.436***	0.438***	0.454***	0.420***	0.229***	0.246***	0.250***	0.247***
	(0.0403)	(0.0422)	(0.0440)	(0.0570)	(0.0517)	(0.0558)	(0.0536)	(0.0509)	(0.0486)	(0.0421)	(0.0485)
0.80	-0.0627	-0.0627	-0.0634	0.482***	0.496***	0.485***	0.444***	0.216***	0.216***	0.228***	0.234***
	(0.0464)	(0.0515)	(0.0519)	(0.0669)	(0.0601)	(0.0585)	(0.0574)	(0.0632)	(0.0594)	(0.0489)	(0.0623)
0.90	-0.0597	-0.0452	-0.0555	0.547***	0.526***	0.511***	0.476***	0.258***	0.258***	0.249***	0.253***
	(0.0618)	(0.0666)	(0.0589)	(0.0681)	(0.0609)	(0.0642)	(0.0663)	(0.0796)	(0.0819)	(0.0654)	(0.0853)
Covariates gap: $F_{Y[m,m]}$ - $F_{Y[m,f]}$											
0.10	-0.00500	0.00176	-0.0226	-0.0344	-0.0358	-0.0143	-0.0344	0.0164	0.0251	0.0507*	0.0398
	(0.111)	(0.0972)	(0.112)	(0.0474)	(0.0472)	(0.0509)	(0.0584)	(0.0152)	(0.0170)	(0.0289)	(0.0321)
0.20	-0.0430*	-0.0387	-0.0428	0.00236	-0.000486	-0.0150	-0.0317	0.0323**	0.0319**	0.0588**	0.0489*
	(0.0233)	(0.0268)	(0.0376)	(0.0317)	(0.0306)	(0.0429)	(0.0499)	(0.0159)	(0.0158)	(0.0250)	(0.0260)
0.30	-0.0643***	-0.0645***	-0.0589**	0.00157	0.000554	-0.0183	-0.0242	0.0287*	0.0310*	0.0497**	0.0421*
	(0.0193)	(0.0221)	(0.0296)	(0.0246)	(0.0245)	(0.0426)	(0.0451)	(0.0149)	(0.0171)	(0.0240)	(0.0256)
0.40	-0.0948***	-0.0885***	-0.0757***	0.00624	0.00340	-0.0212	-0.0277	0.0292*	0.0295*	0.0424*	0.0367
	(0.0223)	(0.0216)	(0.0284)	(0.0257)	(0.0232)	(0.0412)	(0.0426)	(0.0156)	(0.0155)	(0.0237)	(0.0246)
0.50	-0.107***	-0.102***	-0.0916***	0.00325	0.00451	-0.0277	-0.0289	0.0292**	0.0288**	0.0357	0.0351
	(0.0200)	(0.0220)	(0.0270)	(0.0252)	(0.0254)	(0.0397)	(0.0410)	(0.0139)	(0.0142)	(0.0241)	(0.0241)
0.60	-0.101***	-0.0926***	-0.0860***	0.0183	0.0238	-0.00926	-0.0174	0.0290**	0.0264**	0.0266	0.0266
	(0.0191)	(0.0214)	(0.0264)	(0.0292)	(0.0262)	(0.0405)	(0.0433)	(0.0124)	(0.0127)	(0.0253)	(0.0251)
0.70	-0.102***	-0.0960***	-0.0863***	0.0234	0.0362	0.0139	0.00297	0.0282**	0.0260**	0.0192	0.0284
	(0.0202)	(0.0231)	(0.0269)	(0.0322)	(0.0263)	(0.0414)	(0.0461)	(0.0130)	(0.0129)	(0.0284)	(0.0267)
0.80	-0.100***	-0.0980***	-0.0881***	0.0555	0.0499*	0.0223	0.0198	0.0311**	0.0294**	0.0291	0.0425
	(0.0249)	(0.0303)	(0.0307)	(0.0351)	(0.0285)	(0.0438)	(0.0490)	(0.0144)	(0.0145)	(0.0311)	(0.0300)
0.90	-0.0985***	-0.104***	-0.0804**	0.0554	0.0494	0.0271	0.0389	0.0485**	0.0427**	0.0410	0.0477
	(0.0312)	(0.0346)	(0.0363)	(0.0361)	(0.0345)	(0.0463)	(0.0549)	(0.0195)	(0.0186)	(0.0381)	(0.0355)
Coefficients gap: $F_{Y[m,f]}$ - $F_{Y[f,f]}$											
0.10	-0.0772	-0.0691	-0.116	0.245***	0.235***	0.239***	0.249***	0.358***	0.339***	0.317***	0.318***
	(0.277)	(0.246)	(0.318)	(0.0790)	(0.0848)	(0.0747)	(0.0745)	(0.0566)	(0.0546)	(0.0514)	(0.0495)
0.20	0.0280	0.0136	0.0304	0.377***	0.376***	0.362***	0.379***	0.304***	0.305***	0.296***	0.306***
	(0.0641)	(0.0492)	(0.0781)	(0.0599)	(0.0515)	(0.0663)	(0.0655)	(0.0442)	(0.0413)	(0.0447)	(0.0427)
0.30	0.0498	0.0432	0.0490	0.409***	0.414***	0.404***	0.416***	0.310***	0.307***	0.291***	0.306***
	(0.0571)	(0.0430)	(0.0559)	(0.0543)	(0.0433)	(0.0642)	(0.0646)	(0.0394)	(0.0369)	(0.0406)	(0.0397)
0.40	0.0652	0.0579	0.0522	0.419***	0.423***	0.428***	0.432***	0.313***	0.307***	0.283***	0.290***
	(0.0502)	(0.0409)	(0.0454)	(0.0514)	(0.0435)	(0.0631)	(0.0650)	(0.0386)	(0.0388)	(0.0404)	(0.0398)

0.50	0.0845**	0.0706*	0.0670	0.416***	0.419***	0.438***	0.435***	0.297***	0.295***	0.270***	0.271***
	(0.0428)	(0.0390)	(0.0420)	(0.0551)	(0.0481)	(0.0584)	(0.0647)	(0.0413)	(0.0381)	(0.0433)	(0.0422)
0.60	0.0700*	0.0565	0.0530	0.397***	0.394***	0.435***	0.423***	0.245***	0.246***	0.250***	0.243***
	(0.0398)	(0.0390)	(0.0421)	(0.0609)	(0.0476)	(0.0560)	(0.0610)	(0.0400)	(0.0375)	(0.0432)	(0.0436)
0.70	0.0579	0.0491	0.0339	0.413***	0.402***	0.440***	0.417***	0.201***	0.219***	0.230***	0.218***
	(0.0389)	(0.0392)	(0.0456)	(0.0565)	(0.0497)	(0.0571)	(0.0617)	(0.0475)	(0.0453)	(0.0464)	(0.0503)
0.80	0.0378	0.0353	0.0247	0.426***	0.446***	0.462***	0.425***	0.185***	0.186***	0.198***	0.191***
	(0.0444)	(0.0500)	(0.0520)	(0.0681)	(0.0584)	(0.0622)	(0.0640)	(0.0626)	(0.0553)	(0.0515)	(0.0643)
0.90	0.0388	0.0586	0.0249	0.491***	0.477***	0.484***	0.437***	0.210**	0.216***	0.208***	0.205**
	(0.0634)	(0.0697)	(0.0635)	(0.0701)	(0.0592)	(0.0723)	(0.0753)	(0.0817)	(0.0765)	(0.0633)	(0.0875)
Observations	886	866	866	773	769	769	723	1,710	1,710	1,708	1,708

Notes: Specification (1) contains only schooling (using spline variables) as the measure of human capital; specification (2) includes schooling and cognitive skills; specification (3) includes both cognitive and only the seven noncognitive skills common to all nine countries; and specification (4) includes cognitive and all the noncognitive skills for which each of the nine countries have data. Standard errors are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 7. Gender earnings gap decomposition, all model specifications

	Armenia				Bolivia				Colombia			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Conditional wage gap: $F_{Y[m,m]}$ - $F_{Y[f,f]}$												
0.10	0.317***	0.305***	0.332***	0.334***	0.543***	0.525***	0.482***	0.479***	0.379***	0.385***	0.405***	0.400***
	(0.0679)	(0.0799)	(0.0766)	(0.0772)	(0.0903)	(0.0957)	(0.0795)	(0.0830)	(0.0798)	(0.0795)	(0.0715)	(0.0766)
0.20	0.384***	0.384***	0.388***	0.382***	0.430***	0.433***	0.404***	0.395***	0.333***	0.327***	0.338***	0.329***
	(0.0698)	(0.0766)	(0.0707)	(0.0721)	(0.0636)	(0.0834)	(0.0565)	(0.0666)	(0.0517)	(0.0538)	(0.0498)	(0.0546)
0.30	0.455***	0.460***	0.439***	0.447***	0.391***	0.381***	0.365***	0.368***	0.303***	0.302***	0.304***	0.310***
	(0.0592)	(0.0656)	(0.0652)	(0.0629)	(0.0580)	(0.0676)	(0.0567)	(0.0611)	(0.0381)	(0.0412)	(0.0406)	(0.0412)
0.40	0.500***	0.500***	0.475***	0.483***	0.362***	0.357***	0.344***	0.354***	0.290***	0.292***	0.276***	0.287***
	(0.0587)	(0.0596)	(0.0622)	(0.0608)	(0.0594)	(0.0677)	(0.0571)	(0.0624)	(0.0394)	(0.0420)	(0.0377)	(0.0357)
0.50	0.500***	0.511***	0.489***	0.482***	0.343***	0.350***	0.334***	0.338***	0.278***	0.282***	0.273***	0.270***
	(0.0535)	(0.0505)	(0.0596)	(0.0583)	(0.0616)	(0.0666)	(0.0564)	(0.0688)	(0.0465)	(0.0474)	(0.0392)	(0.0382)
0.60	0.483***	0.491***	0.473***	0.463***	0.341***	0.348***	0.341***	0.335***	0.256***	0.255***	0.255***	0.245***
	(0.0483)	(0.0454)	(0.0552)	(0.0542)	(0.0672)	(0.0662)	(0.0607)	(0.0737)	(0.0604)	(0.0614)	(0.0489)	(0.0481)
0.70	0.433***	0.421***	0.435***	0.430***	0.311***	0.314***	0.310***	0.310***	0.225***	0.228***	0.222***	0.206***
	(0.0521)	(0.0473)	(0.0526)	(0.0537)	(0.0758)	(0.0704)	(0.0697)	(0.0822)	(0.0725)	(0.0718)	(0.0608)	(0.0627)
0.80	0.366***	0.357***	0.366***	0.370***	0.292***	0.304***	0.304***	0.298***	0.174**	0.169**	0.168**	0.171**
	(0.0595)	(0.0602)	(0.0652)	(0.0618)	(0.0802)	(0.0765)	(0.0781)	(0.0881)	(0.0770)	(0.0797)	(0.0773)	(0.0794)
0.90	0.326***	0.324***	0.314***	0.329***	0.362***	0.367***	0.344***	0.327***	0.140	0.166*	0.175*	0.168*
	(0.0815)	(0.0970)	(0.0903)	(0.0813)	(0.0988)	(0.107)	(0.102)	(0.101)	(0.0922)	(0.0903)	(0.0976)	(0.0903)
Covariates gap: $F_{Y[m,m]}$ - $F_{Y[m,f]}$												
0.10	0.0258	0.0137	0.0126	0.0422	0.0628*	0.103***	0.118**	0.129**	0.0195	0.0174	-0.00720	-0.00274
	(0.0380)	(0.0345)	(0.0515)	(0.0461)	(0.0343)	(0.0364)	(0.0522)	(0.0542)	(0.0201)	(0.0163)	(0.0361)	(0.0358)
0.20	-0.00650	-0.0199	0.00301	-0.00319	0.0597**	0.0880***	0.105**	0.112**	0.0144	0.0131	0.00694	0.0192
	(0.0394)	(0.0361)	(0.0483)	(0.0373)	(0.0271)	(0.0312)	(0.0439)	(0.0501)	(0.0160)	(0.0148)	(0.0288)	(0.0253)
0.30	-0.0219	-0.0292	0.00190	0.0115	0.0696***	0.0935***	0.121***	0.136***	0.0123	0.00988	1.50e-05	0.0221
	(0.0299)	(0.0297)	(0.0404)	(0.0327)	(0.0237)	(0.0299)	(0.0436)	(0.0514)	(0.0144)	(0.0141)	(0.0253)	(0.0239)
0.40	-0.0224	-0.0259	-0.00193	0.00954	0.0743***	0.105***	0.125***	0.132**	0.00608	0.00529	-0.00483	0.0174
	(0.0250)	(0.0255)	(0.0353)	(0.0308)	(0.0225)	(0.0286)	(0.0425)	(0.0523)	(0.0150)	(0.0141)	(0.0249)	(0.0255)
0.50	-0.0159	-0.0237	-0.0124	-0.00852	0.0769***	0.109***	0.126***	0.117**	0.00753	0.00911	0.00457	0.0181
	(0.0198)	(0.0191)	(0.0322)	(0.0297)	(0.0252)	(0.0273)	(0.0413)	(0.0513)	(0.0174)	(0.0153)	(0.0259)	(0.0267)
0.60	-0.00862	-0.0101	-0.0198	-0.0183	0.0909***	0.102***	0.121***	0.119**	0.0132	0.0138	0.00550	0.0202

	(0.0178)	(0.0171)	(0.0307)	(0.0297)	(0.0260)	(0.0271)	(0.0436)	(0.0489)	(0.0228)	(0.0202)	(0.0304)	(0.0298)
0.70	-0.00224	-0.0115	-0.0213	-0.0235	0.0812***	0.0942***	0.108**	0.106**	0.0192	0.0200	0.00706	0.0295
	(0.0161)	(0.0179)	(0.0310)	(0.0332)	(0.0266)	(0.0274)	(0.0453)	(0.0485)	(0.0285)	(0.0262)	(0.0362)	(0.0359)
0.80	0.000742	-0.00774	-0.0149	-0.0226	0.0673**	0.0830***	0.113**	0.108**	0.0229	0.0188	0.0180	0.0316
	(0.0173)	(0.0210)	(0.0355)	(0.0360)	(0.0287)	(0.0317)	(0.0472)	(0.0511)	(0.0307)	(0.0281)	(0.0461)	(0.0442)
0.90	0.00777	0.00736	-0.0352	-0.0175	0.0360	0.0467	0.0951*	0.0953	0.0322	0.0246	0.0146	0.0246
	(0.0307)	(0.0341)	(0.0478)	(0.0427)	(0.0335)	(0.0390)	(0.0547)	(0.0599)	(0.0371)	(0.0348)	(0.0547)	(0.0524)
Coefficients gap: $F_{Y[m,f]}$ - $F_{Y[f,f]}$												
0.10	0.291***	0.291***	0.319***	0.291***	0.480***	0.422***	0.364***	0.351***	0.359***	0.368***	0.412***	0.403***
	(0.0728)	(0.0836)	(0.0792)	(0.0810)	(0.0906)	(0.0993)	(0.0914)	(0.0986)	(0.0859)	(0.0815)	(0.0724)	(0.0786)
0.20	0.391***	0.404***	0.385***	0.385***	0.370***	0.345***	0.300***	0.283***	0.318***	0.314***	0.331***	0.310***
	(0.0786)	(0.0786)	(0.0746)	(0.0696)	(0.0634)	(0.0887)	(0.0754)	(0.0783)	(0.0539)	(0.0552)	(0.0558)	(0.0565)
0.30	0.477***	0.490***	0.437***	0.435***	0.322***	0.288***	0.244***	0.232***	0.291***	0.292***	0.304***	0.288***
	(0.0658)	(0.0672)	(0.0717)	(0.0629)	(0.0539)	(0.0713)	(0.0708)	(0.0704)	(0.0387)	(0.0433)	(0.0478)	(0.0452)
0.40	0.522***	0.526***	0.477***	0.474***	0.288***	0.252***	0.218***	0.222***	0.284***	0.286***	0.281***	0.270***
	(0.0594)	(0.0534)	(0.0678)	(0.0618)	(0.0538)	(0.0698)	(0.0705)	(0.0687)	(0.0394)	(0.0407)	(0.0413)	(0.0382)
0.50	0.516***	0.534***	0.501***	0.491***	0.266***	0.241***	0.208***	0.221***	0.270***	0.273***	0.268***	0.252***
	(0.0523)	(0.0469)	(0.0670)	(0.0617)	(0.0543)	(0.0707)	(0.0683)	(0.0704)	(0.0445)	(0.0448)	(0.0410)	(0.0388)
0.60	0.491***	0.501***	0.492***	0.482***	0.250***	0.246***	0.219***	0.217***	0.242***	0.241***	0.249***	0.225***
	(0.0472)	(0.0432)	(0.0640)	(0.0604)	(0.0609)	(0.0685)	(0.0687)	(0.0726)	(0.0569)	(0.0592)	(0.0496)	(0.0484)
0.70	0.435***	0.432***	0.456***	0.453***	0.230***	0.220***	0.202***	0.204***	0.206***	0.208***	0.215***	0.176***
	(0.0515)	(0.0476)	(0.0640)	(0.0614)	(0.0715)	(0.0699)	(0.0725)	(0.0778)	(0.0690)	(0.0699)	(0.0614)	(0.0638)
0.80	0.365***	0.365***	0.381***	0.393***	0.225***	0.221***	0.191**	0.190**	0.151**	0.150*	0.150*	0.140*
	(0.0596)	(0.0615)	(0.0771)	(0.0701)	(0.0775)	(0.0741)	(0.0791)	(0.0896)	(0.0753)	(0.0782)	(0.0815)	(0.0815)
0.90	0.318***	0.317***	0.349***	0.346***	0.326***	0.320***	0.248**	0.232**	0.108	0.141	0.161	0.144
	(0.0844)	(0.0946)	(0.106)	(0.0918)	(0.0973)	(0.110)	(0.102)	(0.110)	(0.0910)	(0.0892)	(0.112)	(0.0918)
Observations	660	660	660	660	1,105	1,105	1,094	1,093	1,168	1,168	1,168	1,168

	Georgia				**Ghana**				**Kenya**			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Conditional wage gap: $F_{Y[m,m]}$ - $F_{Y[f,f]}$												
0.10	0.393***	0.384***	0.352***	0.331***	0.704***	0.699***	0.675***	0.679***	0.297***	0.304***	0.290***	0.282***
	(0.116)	(0.128)	(0.116)	(0.112)	(0.0956)	(0.0849)	(0.115)	(0.123)	(0.0683)	(0.0704)	(0.0684)	(0.0818)
0.20	0.348***	0.335***	0.301***	0.309***	0.666***	0.669***	0.524***	0.511***	0.233***	0.234***	0.235***	0.232***

	(0.0822)	(0.0867)	(0.0861)	(0.0789)	(0.0898)	(0.0801)	(0.105)	(0.114)	(0.0624)	(0.0605)	(0.0515)	(0.0641)
0.30	0.260***	0.259***	0.247***	0.247***	0.625***	0.621***	0.475***	0.445***	0.225***	0.221***	0.223***	0.232***
	(0.0714)	(0.0705)	(0.0723)	(0.0649)	(0.0826)	(0.0714)	(0.0820)	(0.103)	(0.0641)	(0.0542)	(0.0465)	(0.0572)
0.40	0.200***	0.208***	0.216***	0.210***	0.608***	0.610***	0.460***	0.439***	0.217***	0.201***	0.208***	0.213***
	(0.0709)	(0.0674)	(0.0687)	(0.0596)	(0.0754)	(0.0619)	(0.0769)	(0.0941)	(0.0648)	(0.0546)	(0.0502)	(0.0585)
0.50	0.189**	0.170**	0.187***	0.172***	0.591***	0.588***	0.412***	0.417***	0.173**	0.170***	0.187***	0.187***
	(0.0742)	(0.0736)	(0.0703)	(0.0630)	(0.0745)	(0.0686)	(0.0868)	(0.0981)	(0.0760)	(0.0601)	(0.0533)	(0.0621)
0.60	0.151**	0.157**	0.171**	0.166**	0.550***	0.550***	0.373***	0.362***	0.166**	0.168***	0.172***	0.176***
	(0.0670)	(0.0764)	(0.0752)	(0.0668)	(0.0720)	(0.0718)	(0.0971)	(0.102)	(0.0659)	(0.0611)	(0.0550)	(0.0609)
0.70	0.128	0.163**	0.180**	0.177**	0.464***	0.463***	0.285***	0.272***	0.159**	0.171***	0.174***	0.169***
	(0.0803)	(0.0814)	(0.0822)	(0.0765)	(0.0757)	(0.0772)	(0.104)	(0.106)	(0.0696)	(0.0652)	(0.0617)	(0.0629)
0.80	0.227**	0.248***	0.234***	0.244***	0.361***	0.370***	0.158	0.161	0.126*	0.133*	0.152**	0.141*
	(0.0945)	(0.0909)	(0.0906)	(0.0895)	(0.0756)	(0.0745)	(0.105)	(0.109)	(0.0691)	(0.0699)	(0.0743)	(0.0733)
0.90	0.345***	0.353***	0.349***	0.359***	0.197*	0.209**	0.0899	0.122	0.0722	0.0613	0.0713	0.0826
	(0.102)	(0.104)	(0.109)	(0.113)	(0.111)	(0.102)	(0.114)	(0.120)	(0.0838)	(0.100)	(0.0951)	(0.0894)
Covariates gap: $F_{Y[m,m]}$ - $F_{Y[m,f]}$												
0.10	-0.00386	-0.0186	-0.0426	-0.0542	0.159***	0.145***	-0.00226	-0.000536	0.0609**	0.0704***	0.104***	0.105***
	(0.0526)	(0.0561)	(0.0646)	(0.0635)	(0.0549)	(0.0518)	(0.0568)	(0.0579)	(0.0249)	(0.0231)	(0.0259)	(0.0266)
0.20	-0.00236	-0.0333	-0.0445	-0.0497	0.132***	0.141***	0.0296	0.0250	0.0720***	0.0859***	0.106***	0.108***
	(0.0322)	(0.0456)	(0.0558)	(0.0514)	(0.0426)	(0.0366)	(0.0494)	(0.0499)	(0.0219)	(0.0220)	(0.0251)	(0.0253)
0.30	-0.0111	-0.0405	-0.0661	-0.0715	0.138***	0.140***	0.0225	0.0302	0.0978***	0.0963***	0.116***	0.123***
	(0.0294)	(0.0376)	(0.0512)	(0.0459)	(0.0332)	(0.0356)	(0.0454)	(0.0480)	(0.0250)	(0.0216)	(0.0257)	(0.0265)
0.40	-0.0283	-0.0574	-0.0750	-0.0841*	0.135***	0.138***	0.0350	0.0459	0.106***	0.102***	0.130***	0.131***
	(0.0310)	(0.0351)	(0.0478)	(0.0452)	(0.0389)	(0.0386)	(0.0440)	(0.0481)	(0.0258)	(0.0223)	(0.0261)	(0.0279)
0.50	-0.0312	-0.0664*	-0.0701	-0.0791*	0.134***	0.129***	0.0441	0.0664	0.136***	0.135***	0.150***	0.145***
	(0.0299)	(0.0372)	(0.0481)	(0.0436)	(0.0367)	(0.0384)	(0.0442)	(0.0519)	(0.0294)	(0.0259)	(0.0286)	(0.0297)
0.60	-0.0283	-0.0575	-0.0813*	-0.0695	0.134***	0.132***	0.0609	0.0591	0.155***	0.156***	0.171***	0.177***
	(0.0351)	(0.0392)	(0.0490)	(0.0432)	(0.0378)	(0.0428)	(0.0487)	(0.0550)	(0.0341)	(0.0310)	(0.0341)	(0.0329)
0.70	-0.0384	-0.0534	-0.0840*	-0.0825*	0.143***	0.145***	0.0718	0.0737	0.183***	0.189***	0.204***	0.197***
	(0.0384)	(0.0436)	(0.0498)	(0.0480)	(0.0375)	(0.0404)	(0.0517)	(0.0529)	(0.0418)	(0.0378)	(0.0382)	(0.0393)
0.80	-0.0568	-0.0739	-0.0836	-0.0842	0.175***	0.167***	0.0813	0.0720	0.176***	0.177***	0.202***	0.201***
	(0.0474)	(0.0507)	(0.0542)	(0.0548)	(0.0468)	(0.0507)	(0.0542)	(0.0514)	(0.0450)	(0.0435)	(0.0438)	(0.0453)
0.90	-0.00724	-0.0151	-0.0788	-0.0659	0.138***	0.137***	0.0819	0.0932	0.215***	0.204***	0.211***	0.210***
	(0.0467)	(0.0517)	(0.0505)	(0.0576)	(0.0437)	(0.0498)	(0.0635)	(0.0605)	(0.0544)	(0.0462)	(0.0503)	(0.0503)
Coefficients gap: $F_{Y[m,f]}$ - $F_{Y[f,f]}$												

0.10	0.397***	0.403***	0.394***	0.385***	0.545***	0.555***	0.677***	0.679***	0.236***	0.234***	0.186***	0.177**
	(0.119)	(0.129)	(0.123)	(0.117)	(0.119)	(0.103)	(0.114)	(0.129)	(0.0685)	(0.0733)	(0.0693)	(0.0879)
0.20	0.350***	0.368***	0.345***	0.358***	0.533***	0.529***	0.494***	0.486***	0.161***	0.148**	0.129**	0.124*
	(0.0830)	(0.0890)	(0.0956)	(0.0937)	(0.0953)	(0.0820)	(0.114)	(0.115)	(0.0581)	(0.0600)	(0.0541)	(0.0655)
0.30	0.271***	0.299***	0.313***	0.319***	0.487***	0.481***	0.453***	0.414***	0.127**	0.125**	0.108**	0.109**
	(0.0734)	(0.0714)	(0.0831)	(0.0737)	(0.0885)	(0.0765)	(0.0899)	(0.0983)	(0.0582)	(0.0503)	(0.0475)	(0.0552)
0.40	0.229***	0.265***	0.291***	0.294***	0.473***	0.472***	0.425***	0.393***	0.111*	0.0998**	0.0780	0.0821
	(0.0743)	(0.0694)	(0.0796)	(0.0663)	(0.0903)	(0.0753)	(0.0805)	(0.0893)	(0.0570)	(0.0490)	(0.0484)	(0.0530)
0.50	0.220***	0.236***	0.257***	0.251***	0.458***	0.459***	0.368***	0.351***	0.0365	0.0355	0.0368	0.0415
	(0.0769)	(0.0740)	(0.0825)	(0.0662)	(0.0827)	(0.0720)	(0.0826)	(0.0919)	(0.0633)	(0.0509)	(0.0503)	(0.0544)
0.60	0.179**	0.215***	0.252***	0.236***	0.416***	0.418***	0.312***	0.303***	0.0114	0.0120	0.000352	-0.00122
	(0.0710)	(0.0793)	(0.0863)	(0.0706)	(0.0780)	(0.0782)	(0.0852)	(0.0963)	(0.0565)	(0.0543)	(0.0487)	(0.0566)
0.70	0.166**	0.217**	0.264***	0.260***	0.321***	0.318***	0.213**	0.198**	-0.0237	-0.0181	-0.0301	-0.0278
	(0.0814)	(0.0866)	(0.0924)	(0.0804)	(0.0759)	(0.0806)	(0.0877)	(0.0985)	(0.0611)	(0.0637)	(0.0539)	(0.0589)
0.80	0.283***	0.322***	0.318***	0.329***	0.186**	0.203**	0.0768	0.0892	-0.0505	-0.0442	-0.0503	-0.0596
	(0.0908)	(0.0973)	(0.0956)	(0.0902)	(0.0826)	(0.0837)	(0.0999)	(0.110)	(0.0573)	(0.0630)	(0.0624)	(0.0644)
0.90	0.352***	0.368***	0.428***	0.425***	0.0589	0.0716	0.00797	0.0284	-0.142**	-0.143*	-0.140*	-0.128
	(0.105)	(0.103)	(0.120)	(0.114)	(0.106)	(0.103)	(0.124)	(0.125)	(0.0720)	(0.0836)	(0.0803)	(0.0824)
Observations	646	646	637	636	1,521	1,521	857	851	1,596	1,596	1,586	1,586

	Serbia			**Ukraine**				**Vietnam**			
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Conditional wage gap: $F_{Y[m,m]} - F_{Y[f,f]}$											
0.10	-0.0822	-0.0673	-0.138	0.210***	0.199**	0.225***	0.214***	0.374***	0.364***	0.367***	0.357***
	(0.203)	(0.192)	(0.268)	(0.0733)	(0.0794)	(0.0680)	(0.0631)	(0.0587)	(0.0565)	(0.0492)	(0.0511)
0.20	-0.0150	-0.0251	-0.0124	0.380***	0.376***	0.347***	0.347***	0.336***	0.337***	0.355***	0.355***
	(0.0553)	(0.0478)	(0.0650)	(0.0525)	(0.0491)	(0.0546)	(0.0534)	(0.0476)	(0.0425)	(0.0434)	(0.0435)
0.30	-0.0145	-0.0213	-0.00988	0.410***	0.415***	0.385***	0.391***	0.339***	0.338***	0.341***	0.348***
	(0.0522)	(0.0419)	(0.0485)	(0.0477)	(0.0381)	(0.0513)	(0.0488)	(0.0404)	(0.0388)	(0.0403)	(0.0388)
0.40	-0.0296	-0.0306	-0.0235	0.425***	0.427***	0.406***	0.404***	0.342***	0.336***	0.325***	0.327***
	(0.0499)	(0.0399)	(0.0439)	(0.0466)	(0.0403)	(0.0504)	(0.0502)	(0.0424)	(0.0423)	(0.0408)	(0.0416)
0.50	-0.0224	-0.0309	-0.0247	0.419***	0.424***	0.410***	0.406***	0.326***	0.323***	0.306***	0.306***
	(0.0450)	(0.0392)	(0.0398)	(0.0526)	(0.0471)	(0.0488)	(0.0500)	(0.0453)	(0.0398)	(0.0406)	(0.0422)
0.60	-0.0308	-0.0361	-0.0330	0.416***	0.418***	0.426***	0.405***	0.274***	0.273***	0.277***	0.270***

Figure 1: Scatterplots of skills and schooling, Men, ages 25-54, All countries (8)

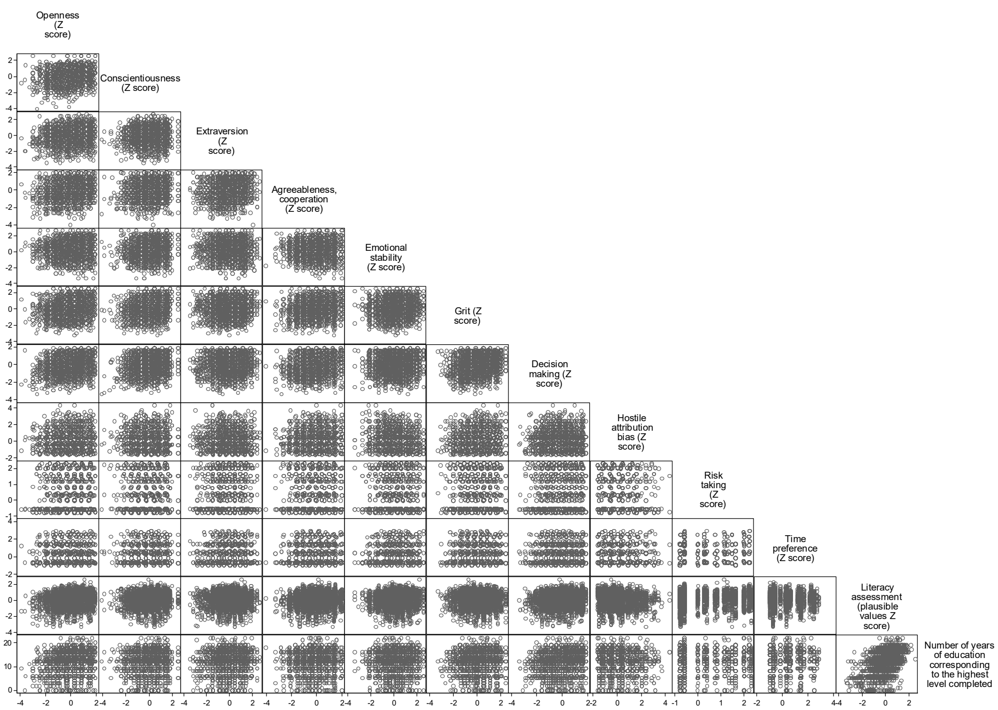

Figure 2: Scatterplots of skills and schooling, Women, ages 25-54, All countries (8)