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Adults' Cognitive and Socioemotional Skills and their Labor Market Outcomes in Colombia

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Abstract

Previous research has shown that people with higher cognitive skills (mental abilities) and socioemotional skills (behaviors and personality) get better labor market outcomes. It is unclear, however, if this conclusion applies to low- and middle-income countries, given that existing literature builds on studies that are dominantly about high-income countries. In this paper, we explore how cognitive and socioemotional skills of adults, ages 15–64, relate to their labor market outcomes in the context of Colombia. Controlling for a range of confounding factors in a cross-sectional survey, we do find that adults with higher skills also have better outcomes, while cognitive and socioemotional skills correlate with different ones and seemingly through different channels. Adults with higher cognitive skills have better jobs (with higher earnings, more formal, and high-skilled) and are more likely to complete tertiary education. Socioemotional skills correlate more modestly with having a better job but more strongly with labor market participation and tertiary-education completion. Results suggest that adults with both cognitive and socioemotional skills tend to do better in the labor market and that policies boosting the development of both types may be beneficial in Colombia.

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1. Introduction

People with higher socioemotional skills do better on the labor market (Saltiel, Sarzosa, and Urzúa 2017; Acosta and Muller 2018). Once overlooked, people's behaviors and personality traits —their socioemotional skills— have been increasingly seen as essential factors explaining their trajectories in school and the labor market, at least much as their mental abilities —their cognitive skills—, long viewed as the primary determinants of success (Almlund et al. 2011). Three types of evidence sparked this rising interest: first, that beneficiaries of early childhood programs, designed to foster socioemotional development, had strikingly better labor-market and other outcomes decades later when adults (Heckman, Pinto, and Savelyev 2013; Gertler et al. 2014); second, that children and youth with both higher cognitive and socioemotional skills measured by longitudinal surveys had better education, labor-market, and a range of other desirable outcomes later in life (Heckman, Stixrud, and Urzúa 2006; OECD 2015); and third, employers in various countries think that socioemotional skills are of primary importance and lament the lack of them for their employees (Cunningham and Villaseñor 2016).

It is unclear, however, how much socioemotional skills matter for people in low- or middle-income countries. The consensus about the positive influence of these skills on the labor market is almost exclusively based on data from high-income countries.[1] Plus, although differences in skills measures and surveyed populations often challenge comparability, multi-country studies suggest that the returns to cognitive and socioemotional skills vary across countries (Hanushek et al. 2015, 2017; OECD 2015). Indeed, the estimated wage returns to comparable measures of cognitive skills of adults in 32 countries range from 0.11 in Greece to 0.47 in Singapore (Hanushek et al. 2017).[2] For socioemotional skills, for example, the impact of raising adolescents' self-confidence in Norway and Switzerland from the lowest to the highest decile on the probability of being in the top income quartile in adulthood is as different as 35 and 15 percent, respectively (OECD 2015).

A handful of studies on the topic in low- and middle-income countries confirm the unpredictability of results in a given country. Two longitudinal studies in rural China (Glewwe, Huang, and Park 2017) and Madagascar (Sahn and Villa 2016) suggest that both types of skills measured in childhood correlate with better labor market outcomes in early adulthood, mostly through their influence on education trajectories and sorting in employment sectors, rather than on productivity. A few cross-sectional studies in

[1] Empirical research on the influence of socioemotional skills on labor market outcomes include studies on the Netherlands (Nyhus and Pons 2005), the United States (Heckman, Stixrud, and Urzúa 2006), Great Britain (Carneiro, Crawford, and Goodman 2007), Germany (Heineck and Anger 2010), Australia (Cobb-Clark and Tan 2011), and Sweden (Lindqvist and Vestman 2011), among others. OECD (2015) studies data for nine countries that also includes Belgium's Flemish Community, Canada, Korea, New Zealand, Norway, and Switzerland.

[2] The estimates correspond to a measure of cognitive skills based on numeracy. The cross-country patterns are similar using alternative measures such as literacy and problem solving.

Bangladesh (Nordman, Sarr, and Sharma 2019) and Latin American contexts such as Argentina and Chile (Bassi *et al.* 2012), Mexico (Campos-Vazquez 2017), Peru (Cunningham, Parra Torrado, and Sarzosa 2016), and ten of its cities (Berniell et al. 2016), confirm that both cognitive and socioemotional skills also relate to labor market outcomes but with important variations in correlations magnitude across types of skills, outcomes, and countries.

We are interested in examining whether socioemotional skills might be valued differently in the labor market of Colombia, a Latin American middle-income country. There is a range of potential reasons why it could be the case: first, due to differences in the types of employment available. As a typical country of this income level, about half of Colombia's labor force works informally: off regulations and benefits. That could mean that informal workers with higher socioemotional skills such as resilience and social skills would do better in such adverse settings; or, on the contrary, it could mean that such labor markets have not yet produced more jobs requiring more adaptability and social skills as much as seen in the United States in the past forty years (Deming 2017). Second, due to differences in levels of human development. In Colombia, about 25 percent of the population is poor, and 40 percent is vulnerable —they have a high chance of falling back in poverty in case of a shock—, which means that most children grow up in adverse contexts that hamper their lifelong cognitive and socioemotional development (Rubio-Codina et al. 2015); there might thus be a higher premium for both types of skills if the average stock of them is low. Third, due to differences in economic growth: the estimated returns to cognitive skills are larger in countries with faster prior economic growth, suggesting that workers with higher skills are more able to adapt and gain from economic changes (Hanushek et al. 2017). This may also be the case for socioemotional skills, which are about personal and social adaptation. Finally, some cultures might reward more some skills than others. For example, a having self-confidence might be viewed positively in one country and negatively in another.

We rely on two methods, both with advantages and limitations, to estimate the extent to which measures of adults' cognitive and socioemotional skills correlate with their contemporaneous labor market outcomes using a 2012 cross-sectional survey. We study six labor market outcomes: earnings, formality, type of occupation (i.e., high- versus low- and medium-skilled), employment, being active or studying, and tertiary education attainment.[3] Our first method uses standard ordinary least square (OLS) and logit regressions on our raw measure of cognitive skills, a test score that capture the ability to understand and reason from texts, and eight measures of socioemotional skills, survey-based measures of the Big Five

[3] High- and low- and medium-skilled occupations are categorization of ILO's 1988 classification of occupations. High-skilled ones include senior officials and managers, professionals, and technicians while low- and middle-skilled ones includes occupations such as clerks, service workers, machine operators, and laborers.

personality traits and three other measures of attitudes, controlling for background factors.[4] This method has the advantage of assessing the links between skills and outcomes for a range of specific skills; the drawback is its survey-based measures of personality traits that are likely poor and may not capture the intended ones (Laajaj et al. 2019). Our second method rests on structural estimations of latent cognitive and socioemotional skills that treat survey-based skills measures as manifest scores that are a product of those skills (Bartholomew, Knott, and Moustaki 2011; Sarzosa and Urzúa 2016). This method avoids the common measurement error of skills, but it comes at the cost of only estimating one factor for each type of them, which prevents us from observing the diversity of influence of various socioemotional skills. With both methods, our estimates could suffer from reverse causality (better outcomes could also cause better skills because of their simultaneous observation). Our results are thus best interpreted as conditional correlations, rather than causal estimates.

We find that both cognitive and socioemotional skills correlate with favorable labor market outcomes in the Colombian context but with distinct roles and seemingly through different channels. Cognitive skills, both measured and estimated as latent, systematically correlate with all outcomes but employment—likely because employment also captures informal and poor-quality employment. For example, raising latent cognitive skills from the bottom to the top decile is correlated with an increase in hourly labor earnings of US$ 2 in 2011 purchasing power parity (around 50 percent more), being 28 percentage point more likely to work formally, and 60 percentage point more likely to have attended tertiary education. Estimated latent socioemotional skills have virtually no link with earnings, formality, and high-skilled jobs, but likely because the raw disaggregated measures tend to correlate differently and in opposite directions with these outcomes. However, both measured and estimated latent socioemotional skills strongly correlate with studying or being active in the labor market (working or looking for a job) and having attended tertiary education, more than latent cognitive ones for the former outcome and less for the latter. Raising latent socioemotional skills from the bottom to the top decile is correlated with an increase of 9 percentage points in the probability of being active or studying, and 16 percentage points more likely to have attended tertiary education. When considered jointly, highest levels of cognitive and socioemotional skills correlate more highly than highest levels for one or the other for most outcomes. For example, a switch from the bottom to the top decile in both skills raise the probability to having attended tertiary education from virtually zero (only 1.5 percent) to 83 percent. Controlling for education drastically reduces the correlations between measures of cognitive skills and outcomes, suggesting that cognitive skills may also be indirectly linked to outcomes, through its links with higher levels of education

[4] Personality traits are somewhat different than socioemotional skills because they are broad, relatively-fixed facets characterizing individuals along a continuum, rather than learned abilities for which the more is better. However, personality traits influence the attitudes and behaviors that are socioemotional skills and thus are a common approach to study them.

attainment, while socioemotional-skills measures seem independent from education. In addition, while the link between both types of skills with labor earning is consistent across subgroups, the link between socioemotional skills and labor-force participation is particularly strong for women, the youth, and the less educated.

The remainder of this paper is organized as follows: section 2 describes the data set and the measures of cognitive and socioemotional skills, section 3 introduces the empirical strategy with its limitations, and section 4 presents the results. The final section offers our conclusions.

2. Data

2.a. Data set

We use a cross-sectional survey of adults called Skills Toward Employment and Productivity (STEP), which was collected in Colombia in 2012. The STEP is a cross-sectional household survey implemented in around twenty low- and middle-income countries by the World Bank since 2012 (Pierre et al. 2014). The survey covers a wide range of background information (demographics, education, employment, etc.) and randomly selects one individual in each household between the ages of 15 and 64 to be further surveyed and tested on information related to cognitive skills, socioemotional skills, health, and other characteristics.

Colombia STEP Household Survey is representative of most of the country's adults. It is formally representative of the country's thirteen main cities and their metropolitan areas, which are used by the national statistical agency for its labor market and household surveys.[5] The thirteen cities represent the large majority of Colombia's urban population, which represents 80 percent of the country's population. The sample size is 2,617. The age, gender, and education attainment distribution are similar to that for national household surveys for the same urban areas.

2.b. Measures of cognitive and socioemotional skills

We have two types of measures of cognitive and socioemotional skills, which correspond to our two methods, OLS/Logit and structural estimations of latent skills. The first type is raw measures of cognitive skills from the survey, one for cognitive, eight for socioemotional skills. The second type are estimated factors of latent skills, one for cognitive skills and one for socioemotional skills.

[5] The 13 main metropolitan areas are: Bogotá (the capital), Medellín, Cali, Barranquilla, Bucaramanga, Cúcuta, Cartagena, Pasto, Ibagué, Pereira, Manizales, Montería, and Villavicencio.

Raw measures of skills

Measures of cognitive skills. The measure is based on a test of reading proficiency administrated with the survey by the Educational Testing Service (ETS) (ETS 2014; Pierre et al. 2014).[6] Reading proficiency refers to not only being able to read a text but also to understand it and be able to reason from it (OECD 2012). Instead of a single score, individuals have a set of 10 scores ranging from 0 to 500, called "plausible values," which is an estimation of the plausible range of his reading proficiency level given his performance on the test and his background characteristics (Von Davier, Gonzalez, and Mislevy 2009; OECD 2013; ETS 2014).[7] The OLS/Logit regressions are repeated ten times for each plausible value and the average coefficients and standard errors of the ten estimations reported.

Measures of socioemotional skills. The survey provides measures of the Big Five personality traits (the most used set of personality measures including: agreeableness, conscientiousness, emotional stability, extraversion, and openness to experience (John and Srivastava, 1999), grit —perseverance and passion for long-term goals— (Duckworth *et al.*, 2007), hostile attribution bias —tendency to interpret others' intents as hostile, which in turn fosters one's antisocial and aggressive behavior— (Dodge, 2003), and the Melbourne Decision Making Scale —coping strategies for decisional conflict— (Mann *et al.*, 1997). Surveyed adults responded to 24 questions, designed by psychologists, corresponding to those domains. Response categories range from 1 ("almost never") to 4 ("almost always"). Scores for each domain is the average of the responses to the two to four survey questions corresponding to it. Table 1 presents the definitions and items of the socioemotional skills of the survey. Correlations among socioemotional measures are often significant but modest in magnitude, ranging from 0 (emotional stability and grit) to 0.28 (decision making and openness to experience) (table 2). Correlations between socioemotional measures and reading proficiency —the cognitive measure— range from 0.02 (with grit) to 0.21 (openness to experience).

[6] The reading proficiency test is comparable to the one produced by the Program for the International Assessment of Adult Competencies (PIAAC), another large-scale survey covering 24 OECD countries (OECD 2013).
[7] Plausible values are multiple imputations, drawn after data collection, generated by combining test results with all available background information such as gender, age, and education. This procedure, based on item response theory, allows to reduce the measurement error inherent in large-scale surveys and to report comparable performance scales because survey participants respond only to a subset of the assessment items.

Table 1. Inventory of Socioemotional Skills in the 2012 Colombia STEP Household Survey

Skill / Personality trait	Definition	Questionnaire item
Openness to experience	Appreciation for art, learning, unusual ideas, and variety of experience	Do you come up with ideas other people haven't thought of before?
		Are you very interested in learning new things?
		Do you enjoy beautiful things such as nature, art, and music?
Conscientiousness	Tendency to be organized, responsible, and hardworking	When doing a task, are you very careful?
		Do you prefer relaxation more than hard work? R
		Do you work very well and quickly?
Extraversion	Sociability, tendency to seek stimulation in the company of others, talkativeness	Are you talkative?
		Do you like to keep your opinions to yourself? Do you prefer to keep quiet when you have an opinion? R
		Are you outgoing and sociable—for example, do you make friends very easily?
Agreeableness	Tendency to act in a cooperative, unselfish manner	Do you forgive other people easily?
		Are you very polite to other people?
		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	Are you relaxed during stressful situations?
		Do you tend to worry? R
		Do you get nervous easily? R
Grit	Perseverance with long-term goals	Do you finish whatever you begin?
		Do you work very hard? For example, do you keep working when others stop to take a break?
		Do you enjoy working on things that take a very long time (at least several months) to complete?
Decision making	Way in which individuals approach decision situations	Do you think about how the things you do will affect you in the future?
		Do you think carefully before you make an important decision?
		Do you ask for help when you don't understand something?
		Do you think about how the things you do will affect others?
Hostile attribution bias	Tendency to perceive hostile intents in others	Do people take advantage of you?
		Are people mean/not nice to you?

Source: Authors' elaboration based on Almlund *et al.* (2011); John and Srivastava (1999); World Bank (2014).

Note: 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 trait domain (e.g. extraversion) is the average of the individual scores on items of this trait. "R" refers to items that are reversely coded for the aggregation.

Table 2. Correlations Between Measures of Skills

	REA	EXT	CONS	OPE	EMO	AGR	GRI	DMG
Reading proficiency (REA)	1							
Extraversion (EXT)	0.08***	1						
Conscientiousness (CONS)	0.06***	0.07***	1					
Openness to experience (OPE)	0.21***	0.19***	0.16***	1				
Emotional stability (EMO)	0.11***	0.11***	0.05***	0.08***	1			
Agreeableness (AGR)	-0.02	0.12***	0.14***	0.19***	0.04**	1		
Grit (GRI)	0.02	0.08***	0.22***	0.21***	0.00	0.20***	1	
Decision making (DMG)	0.20***	0.09***	0.17***	0.28***	-0.07***	0.16***	0.21***	1
Hostile attribution bias (HAB)	-0.18***	-0.03	-0.04**	0.00	-0.16***	0.01	-0.02	-0.06***

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

Estimated latent skills

We estimate latent skills using structural estimation methods to mitigate skills measurement error and acknowledge that skills are latent rather than observable, as developed in Keane and Wolpin (1997), Hansen, and Heckman (2003), Heckman, Stixrud, and Urzúa (2006), and Sarzosa and Urzúa (2016). In this method, individual scores in cognitive tests or in socioemotional survey questions are treated as results of the individual's latent skills, rather than its direct measures. Latent skills are estimated from a measurement system that gives a single score for each dimension of skills, one for cognitive and one for socioemotional ones. The identification of the measurement system requires at least three scores for each dimension explored (Kotlarski 1967; Carneiro¸ Hansen, and Heckman 2003).

The three scores used for the measurement system identifying the factor of latent cognitive skills are the following: (1) a plausible value of reading proficiency, the raw measure of cognitive skills from the test, randomly chosen among the 10 available; (2) a measure of language abilities that is an average of additional dimensions of reading proficiency measured by the test but that are not used for the main score of reading proficiency. These additional dimensions are: average print vocabulary, sentence processing, and passage comprehension (ETS 2014, Pierre et al. 2014); (3) a measure of how much adults use reading at work and outside and the length of these reading, which is based on survey questions that are not linked to the reading-proficiency test.

The three scores used for the measurement system identifying the factor of latent socioemotional skills are based on the aggregation of the eight raw measures of socioemotional skills. We group the measures based on the correlations among them and the similar dimensions they capture to ensure the smoothness needed in the measurement system given that all these measures come from categorical answers. The three scores are measures of: (1) extraversion and openness to experience, (2) emotional stability and hostile attribution bias, and (3) conscientiousness, grit, and decision making.

3. Empirical Strategy

Our objective is to investigate the distinct correlations of cognitive and socioemotional skills with labor market outcomes (earnings, formality, skill level of occupation, employment, being active or studying) and tertiary education attainment. We use two complementary approaches in our analysis: a reduced form (OLS/logit regressions), and a structural model of latent skills. For both methods, the risks of reverse causality between outcomes and skills, and endogeneity due to the interrelations between education and skills, prevent us from claiming causal relationships. Our estimations should be considered as conditional correlations controlling for a range of confounding factors.

3.a Reduced Form

The first empirical approach follows standard Mincer-like regressions (Mincer 1958) to estimate the following relationship between a labor market or schooling outcome and a set of skills:

$$Y_i = \alpha + \beta_1^Y C_i + \beta_2^Y SE_i + \beta_3^Y X_i + \varepsilon_i \tag{1}$$

where Y_i is a labor market outcome (e.g. wage); C_i and SE_i represent, respectively, cognitive skills (such as reading proficiency) and socioemotional skills (such as conscientiousness) that affect the labor market outcome; and X_i is a set of background factors other than skills that affect Y_i (e.g. age, gender, place of living, mother's education).

Our survey gives us a set of measures—we call them here test scores, T_i—, one for cognitive skills and eight for socioemotional skills. As such, we run the following equation (2), using OLS or logit regressions, to estimate β_1 and β_2, the return to each skill captured by the scores T_i^C and T_i^{SE}:

$$Y_i = \alpha + \beta_1^Y T_i^C + \beta_2^Y T_i^{SE} + \beta_3^Y X_i + \vartheta_i \tag{2}$$

While this method allows us to observe the relationship between labor market outcomes and the nine disaggregated measures of skills, estimations could be biased because of measurement error. Survey-based measures of skills can be poor, especially in low- and middle-income countries (Almlund et al. 2011; Laajaj and Macours 2018; Laajaj et al. 2019). Respondents may give socially desirable answers rather than answer how they truly behave, respond under the influence of how the exact questions are asked and how much response options they have, or constantly agree or disagree with the series of questions. Plus, they are not always consistent over short periods of time: a study in rural Colombia reveals that respondents tend to change their answers for survey questions related to the Big Five personality traits and other attitudes when asked two times with a three-week interval (Laajaj and Macours 2018).[8] In addition, using STEP surveys including the Colombia one we use in this paper, Laajaj et al. (2019) show that the scores of the Big Five personality traits based on survey questions do not always measure them as they are supposed to by design and thus cannot be confidently interpreted as measures of them. One of the factors generating the measurement errors could be the limited number of questions on socioemotional skills (24; three in average for each skill measure). That is much lower than usual inventory aiming to capture personality traits and socioemotional skills. The measurement error of skills would produce estimates of β_1 and β_2 biased towards zero.

3.b Structural Estimation

As an alternative to the reduced-form estimations, we run structural estimations of latent skills based on a measurement system of test scores to solve measurement error and omitted variable bias (Keane and Wolpin 1997; Cameron and Heckman 2001; Heckman, Stixrud, and Urzúa 2006; Sarzosa and Urzúa 2016). These structural estimations give us the level of unobserved heterogeneity linked to latent skills, the distributions of the latent skills, and simulations of how these distributions relate to labor market outcomes.[9]

In this setting, the outcomes of interest, Y, are a function of the latent skills and other factors influencing them, as depicted by the following equation:

$$Y = \alpha_C^Y \theta_C + \alpha_{SE}^Y \theta_{SE} + \beta^Y X_Y + e^Y \qquad (3)$$

where, θ_C and θ_{SE} are the latent factors that capture the unobserved heterogeneity of cognitive and socioemotional skills; β^Y, α_C, and α_{SE}^Y are coefficients to estimate; X_Y is observable controls (e.g. gender, age), and e^Y is a vector of independently distributed error terms orthogonal to X_Y, θ_C, and θ_{SE}.

We incorporate the latent factors θ_C and θ_{SE} by treating the available survey measures of cognitive and socioemotional skills only as proxies, or results, of them (Bartholomew, Knott, and Moustaki 2011). Formally, the latent factors are treated as realizations of the following score-production function:

[8] The test-retest correlation between the fifteen scores of socioemotional skills measured in this study in a three-week interval is 0.7. The test-retest for the underlying survey questions varies between 0.21 and 0.66.

[9] For more details about identification and estimation, see Sarzosa and Urzúa (2016).

$$T = \alpha_C^T \theta_C + \alpha_{SE}^T \theta_{SE} + X_T \beta^T + e^T \tag{4}$$

where T is an $L \times 1$ vector of skills measures we call "scores" (e.g. measures of reading proficiency, emotional stability, or grit); X_T is a matrix of observable controls; and e^T is a vector of independently distributed error terms orthogonal to X_Y, θ_C, θ_{SE}, and e^Y. X_T includes exogenous controls such as age, gender, mother's education, and city of residence to estimate the components of the unobserved heterogeneity free of these characteristics that can affect the scores we observe.

The model forms a measurement system—including outcomes, test scores, observable controls, and error terms—that is linked by latent factors θ_C and θ_{SE}. The identification assumption takes e_Y and e_T as mutually independent conditional on (θ_C, θ_{SE}, X).

Carneiro¸ Hansen, and Heckman (2003) and Sarzosa and Urzúa (2016) show that the system of production functions of test scores in equation (4) can be used to non-parametrically identify the distributions of the latent abilities $f_{\theta_C}(\cdot)$ and $f_{\theta_{SE}}(\cdot)$, their loading matrices (α_C and α_{SE}), and the diagonal matrix of their variance, Σ_θ.[10] The loading matrices of latent factors α_C and α_{SE} can be identified up to one normalization—that is, one loading per factor is set to equal to one and the rest of them will be interpreted relative to the one chosen as nummeraire. Kotlarski (1967) and Carneiro¸ Hansen, and Heckman (2003) show that two assumptions are needed for identification: (i) that latent skills factor θ_s for $s = \{C, SE\}$ are orthogonal to each other, and (ii) that the system includes at least three test scores per skill dimension. Because we estimate two factors of latent skills requires a minimum of six test scores ($L = 6$).

In practice, the test scores measurement system allows us to identify the distributions $f_{\theta_C}(\cdot)$ and $f_{\theta_{SE}}(\cdot)$ associated to the unobserved heterogeneity in order to integrate it away in a maximum likelihood procedure.[11] The likelihood function is then:

$$\begin{aligned}\mathcal{L} = \prod_{i=1}^{N} \int \int f_{e^Y}(X_Y, Y, \varrho_1, \varrho_2) \times f_{e^{T_1}}(X_{T_1}, T_1, \varrho_1, \varrho_2) \cdots \\ \times f_{e^{T_6}}(X_{T_6}, T_6, \varrho_1, \varrho_2) dF_{\theta_1}(\varrho_1) dF_{\theta_2}(\varrho_2).\end{aligned} \tag{5}$$

[10] The estimated distributions $f_{\theta_A}(\cdot)$ and $f_{\theta_B}(\cdot)$ are not assumed to follow any particular distribution. The procedure uses a mixture of normals, which are known to be able to re-create a wide range of distributions (Frühwirth-Schnatter 2006).

[11] Integrals are calculated using the Gauss-Hermite quadrature (Judd 1998).

From which we retrieve all the parameters of interest, β_Y, β_{T_τ}, α_C^Y, α_{SE}^Y, $\alpha_C^{T_\tau}$, $\alpha_{SE}^{T_\tau}$ for $\tau = \{1, 2, 3, 4, 5, 6\}$, and the parameters (means, standard deviations, and mixing probabilities) that describe the distributions $f_{\theta_C}(\cdot)$ and $f_{\theta_{SE}}(\cdot)$.

Given that skills are unobservable, we must rely on simulations of the expected outcome as a function of this unobserved heterogeneity. Given that we estimate two dimensions of such heterogeneity, we present the simulations using three-dimensional graphs that plot:

$$E[Y|\theta_C, \theta_{SE}] = E[X\beta] + \alpha_C\theta_{SE} + \alpha_C\theta_{SE} \tag{6}$$

In that sense, we randomly draw θ_C and θ_{SE} from the distributions, $f_{\theta_C}(\cdot)$ and $f_{\theta_{SE}}(\cdot)$, estimated in the first-step estimations and construct $E[Y|\theta_C, \theta_{SE}]$. This way, from the simulated graphs, we clearly see how the unobserved skills relate to the outcome variable.[12]

3.c. Beyond measurement errors: limitations due to reverse causality and endogeneity of schooling and skills

Whatever method considered, the risk of reverse causality between skills and labor market outcomes prevent us from interpreting our estimates as causal. In our cross-sectional data set, we observe the measures of skills and labor outcomes simultaneously. While we are interested in assessing the impact of having higher skills on a given desirable outcome, it could be that this outcome also raises skills. For example, people who are more able to manage their stress and emotions —more emotional stable— are more likely to be employed and have higher wages, the stability their job and steady wage give them can reinforce their emotional stability.

Another source of bias could come from the endogeneity of schooling. Skills and schooling are interrelated: children with higher cognitive and socioemotional skills are more likely to have better school performance and complete more schooling, and the latter tend to raise both cognitive and socioemotional skills (Hansen, Heckman, and Mullen 2004). Unfortunately, our cross-sectional data set does not allow us to empirically distinguish between these two relations. Therefore, our preferred approach is to leave education out of the estimations to avoid its endogeneity clouding our understanding of the link between skills and outcomes. By not controlling for schooling we allow our estimates to represent the total effect of skills on outcomes, even if it is directly or indirectly through schooling (Heckman, Stixrud, and Urzúa

[12] For the probit case the expected outcome equation follows the same logic. Therefore, it becomes: $E[Y|\theta_C, \theta_{SE}] = \Pr(E[X\beta] + \alpha_C\theta_{SE} + \alpha_C\theta_{SE} + \zeta > 0)$ where $\zeta \sim \mathcal{N}(0,1)$.

2006).[13] Controlling for education attainment may be relevant if we consider our setting to be one in which schooling is exogenous and we are interested in measuring inframarginal returns to skills (Willis and Rosen 1979). Although we consider schooling to be endogenous in our case, for comparison purposes, we present both sets of results---controlling and not controlling for education---for the OLS and Logit regressions.

4. Results

4.a OLS-Logit estimates

In this section, we explore OLS and logit estimates of the relationship between six labor market outcomes (labor earnings, job formality, skill level of occupation, employment, being active or studying, and tertiary education attainment) with one measure of cognitive skills (reading proficiency) and eight socioemotional ones (extraversion, openness to experience, emotional stability, conscientiousness, grit, hostility bias, and decision making), controlling for a range of background characteristics (such as gender, age, mother's education, and place of living). These estimates allow us to appreciate the diversity of correlations across the eight measured skills, even if they are based on likely noisy measures of socioemotional skills. Thus, one should not overinterpret these results as true differences in labor-market returns for the different traits referenced by their labels.

Abstracting from their level of schooling, adults with higher measures of cognitive skills are much more likely to also have better jobs (formal, higher-skilled, and with higher earnings) than those with higher measures of socioemotional skills. The correlation between reading proficiency, the single raw measure of cognitive skills, and log hourly labor earnings from the main job —which include wages for salaried workers and net profits for self-employed— is double than that from any measure of socioemotional skills. While a one standard deviation increase in the measure of reading proficiency is related to a 16-percent increase in hourly labor earnings from one's main job, an equally sized increase in the measure of openness to experience (reflecting creativity, curiosity, and appreciation for beauty), the only socioemotional measure significantly correlated with earnings, is associated with an 8-percent increase in hourly earnings (see figure 1 and table 3). Consistently, adults with one more standard deviation of reading proficiency also are 6 and 14 percent more likely to have a formal job and a job in a high-skilled occupation.[14] For socioemotional skills measures, only having less hostile-attribution bias—the perception that other's intents are hostile, which leads in return to more hostility—is significantly correlated with 3 percent more

[13] The latter includes aspects of schooling influencing outcomes not necessarily linked to education increasing skills, but skills affecting education attainment. For example, education attainment being a signal of productivity or the creation of professional networks that help navigate the labor market.
[14] A worker is defined here as formal if he or she benefits from social security through his or her job.

chance to have a formal job; no socioemotional skills measure correlates with having a high-skilled occupation.

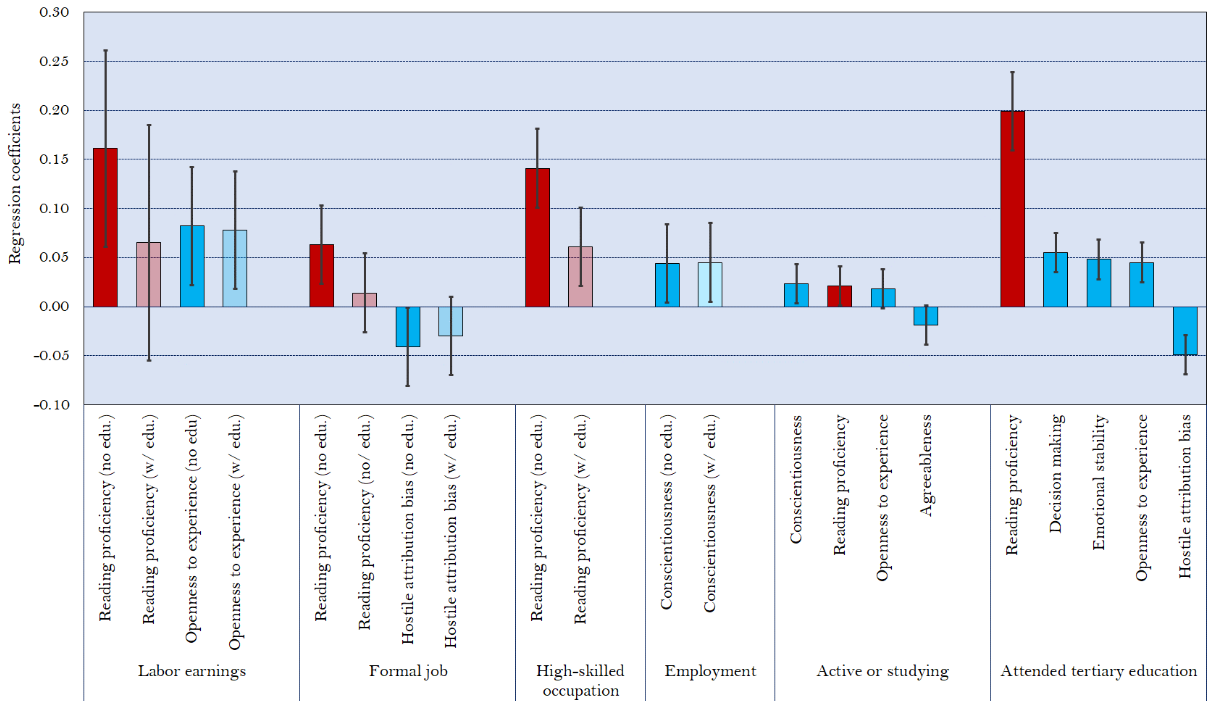
However, adults with some higher measures of socioemotional skills are less likely to be idle. Adults scoring one standard deviation more in the conscientiousness (tendency to be organized and hardworking) and openness to experience scales are 2-percent more likely to be active in the labor market (working or looking for a job) or studying, as opposed to being inactive and not studying. By contrast, adults scoring one more standard deviation in the agreeableness scale (being forgiven, polite, and generous) are 2-percent less likely to be active in the labor market. Among those who do not study over age 18, those who score one standard deviation more in the conscientiousness scale are also 4 percent more likely to be employed. While one standard deviation in reading proficiency is also correlated with a 2-percent probability to be active in the labor market or studying, it is not significantly correlated with being employed.

One should note that employment, in the context of Colombia, could imply working in poor conditions and/or informally. Informal employment is often the last resort for Colombians as many of them cannot afford to be unemployed for long spells because of the lack of assets or savings. As such, the unemployed may include some more well-off fellows that can afford to be in this situation for some time until they find a good job. Given that cognitive skills are positively associated with formal and better jobs, it may be the case that it does not make a difference for employment, undiscriminating between formal and informal.

Adults with higher of types of measured skills, especially cognitive ones, are also more likely to have attended tertiary education.[15] A range of measured socioemotional skills correlate with this outcome, including openness to experience and less hostile-attribution bias—consistently with their positive correlations with higher earnings and probability to have a formal job—but also emotional stability (management of stress and emotions) and decision making (way in which individuals approach decision situations) that do not correlate with other outcomes. All socioemotional skills correlate around 5 percent. By comparison, the correlation with reading proficiency is a high 20 percent.

[15] The results are similar when considering completion instead of attainment.

Figure 1. Selected regression coefficients of skills measures, with or without controlling for education



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: The figure shows regression coefficients for measures of skills significantly correlated with outcomes (at least at the 90-percent level) from tables 3 and 4. The bars represent the regression coefficients and the error bars the confidence interval at 95 percent. Red and blue bars represent measures of cognitive and socioemotional skills, respectively. Transparent-colored bars represent the regression coefficient when controlling for education. Regressions include one disaggregated measure of cognitive skills (reading proficiency) and eight socioemotional ones (extraversion, openness to experience, emotional stability, conscientiousness, grit, hostility bias, and decision making); all are standardized (Definitions of skills are in table 1). A worker is defined here as formal if he or she benefits from social security through his job. High-skilled workers hold occupations categorized as senior officials and managers, professionals, or technicians, as opposed to low- and medium-skilled workers such as clerks, service workers, machine operators, or laborers (jobless having held a job in the past year are also included). The classification is based on the International Labour Organization's 1988 International Standard Classification of Occupations (ISCO). Conditional correlations are computed from ordinary least squares (OLS) regressions for labor earnings and logit regressions for labor supply outcomes. The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. OLS calculations control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Logit regressions control for the same variables and a self-reported categorical variable on parents' involvement in one's education at the age of 12 (three levels). Average marginal effects are reported for logit regressions and reflect the changes in the probability of being observed in a labor or school participation situation with respect to the variables evaluated at the mean. Regressions coefficients and standards errors of reading proficiency are the averages of the ten estimations using plausible values.

Table 3. Conditional Correlations of Measures of Cognitive and Socioemotional Skills with Labor Outcomes

	Log hourly labor earning	Being a formal worker	Being a high-skilled worker	Being employed	Being active or in school	Having attended tertiary education
Method	OLS	Logit	Logit	Logit	Logit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
Reading proficiency	**0.161*** **	**0.063*** **	**0.141*** **	0.003	**0.021* **	**0.199*** **
	(0.05)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Extraversion	-0.009	0.001	-0.004	-0.007	0.009	-0.009
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Conscientiousness	-0.034	-0.003	0.001	**0.044*** **	**0.023** **	0.002
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Openness to experience	**0.082** **	-0.020	0.020	0.011	**0.018* **	**0.045*** **
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Emotional stability	0.008	0.027	0.006	0.018	0.009	**0.048*** **
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Agreeableness	0.023	-0.011	-0.007	-0.016	**-0.019* **	0.001
	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Grit	-0.030	-0.020	0.013	0.005	0.003	0.003
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Hostile attribution bias	-0.003	**-0.041** **	-0.019	-0.010	-0.009	**-0.049*** **
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Decision making	0.013	0.012	0.019	-0.031*	-0.003	**0.055*** **
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	1,372	1,576	1,801	2,117	2,356	1,717
R-squared	0.11					

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: A worker is defined here as formal if he or she benefits from social security through his job. High-skilled workers hold occupations categorized as senior officials and managers, professionals, or technicians, as opposed to low- and medium-skilled workers such as clerks, service workers, machine operators, or laborers (jobless having held a job in the past year are also included). The outcomes of being employed and having attended tertiary education are restricted to adults ages 19–64 and ages 25–64, respectively. The classification is based on the International Labour Organization's 1988 International Standard Classification of Occupations (ISCO). Standard errors are in parentheses. Conditional correlations are computed from ordinary least squares (OLS) regressions for labor earnings and logit regressions for labor supply outcomes. The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. OLS calculations control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Logit regressions control for the same variables and a self-reported categorical variable on parents' involvement in one's education at the age of 12 (three levels). Average marginal effects are reported for logit regressions and reflect the changes in the probability of being observed in a labor or school participation situation with respect to the variables evaluated at the mean. Measures of reading proficiency and socioemotional skills are standardized. Regressions coefficients and standards errors of reading proficiency are the average of the 10 estimations using plausible values.

$^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$

The relationship between measures of cognitive skills and outcomes indicating better jobs is sensitive to the inclusion of schooling. When holding fixed the educational level completed by surveyed adults, the net correlation between the measures of reading proficiency and formal, better-paid, and high-skilled jobs is reduced by at least half (figure 1). The correlation coefficient with working in a high-skilled occupation decreases from 14 percent to 6 percent after controlling for schooling (table 4). The coefficient for labor earnings and having a formal job decrease from 16 to 6 percent and from 6 to 1 percent, respectively, and become non-significant when controlling for schooling. Given that completing higher levels of education is correlated with higher probabilities of having formal, better-paid, and high-skilled jobs, we may interpret that cognitive skills relate to these outcomes because adults who have higher levels of them have completed more schooling. That might also reflect the signaling power of education: employers, when hiring, would seek in educational levels a candidate who has completed them as a guarantee of its levels reading proficiency levels. However, our data do not allow us to formally disentangle the respective effects of skills and schooling on labor outcomes and explore further their mediating effects, and as we explained in section 3.c., the results controlling for schooling should be taken with caution since education is not exogenous.

By contrast, the relationship between measures of socioemotional skills and outcomes is almost the same when considering adults of the same level of education. The regression coefficients of the measures of socioemotional skills that are significant when not controlling for schooling barely change when controlling for it. This may reflect that most socioemotional skills development happen out of school, in families, with friends, in the living environment, and in the workplace (Heckman and Mosso 2014).

While the link between both types of skills with labor earning is consistent across subgroups, the link between socioemotional skills and labor-force participation is particularly strong for women, the youth, and the less educated.[16] Not considering schooling, reading proficiency has a similar correlation with earnings of about 13-18 percent across subgroups (by gender, age, and educational level), except for the less educated (table 5). This absence of significant relationships for the less educated might come from the smaller sample (438 observation). The positive relationship between openness and earnings is driven by men, older adults (35+), and more educated workers, suggesting that other factors matter for the earnings of women, youth, and less educated. For being active or in school, however, it is women, youth, and less educated that drive the relationships with conscientiousness (table 6). Younger adults who are more extroverted and open to experience are also more likely to also be active or in school. For these outcomes, the socioemotional skills of men and the more educated do not seem to play any role.

[16] We consider only two outcomes for subgroups for brevity. Results for other labor market outcomes for subgroups are available upon request.

Table 4. Conditional Correlations of Measures of Cognitive and Socioemotional Skills with Labor Outcomes, Controlling for Schooling

Outcomes	Log hourly labor earning	Being a formal worker	Being a high-skilled worker	Being employed
Method	OLS	Logit	Logit	Logit
	(1)	(2)	(3)	(4)
Reading proficiency	0.065	0.014	**0.061*** **	-0.009
	(0.06)	(0.02)	(0.02)	(0.02)
Extraversion	0.000	0.005	-0.000	-0.007
	(0.04)	(0.02)	(0.01)	(0.02)
Conscientiousness	-0.034	-0.003	-0.002	**0.045*** **
	(0.04)	(0.02)	(0.01)	(0.02)
Openness to experience	**0.078** **	-0.022	0.017	0.010
	(0.03)	(0.02)	(0.01)	(0.01)
Emotional stability	-0.015	0.016	-0.007	0.015
	(0.04)	(0.02)	(0.01)	(0.02)
Agreeableness	0.015	-0.014	-0.003	-0.016
	(0.03)	(0.02)	(0.01)	(0.02)
Grit	-0.043	-0.025	0.007	0.004
	(0.04)	(0.02)	(0.01)	(0.02)
Hostile attribution bias	0.023	**-0.030* **	-0.003	-0.008
	(0.03)	(0.02)	(0.01)	(0.01)
Decision making	-0.007	0.002	-0.002	**-0.033** **
	(0.04)	(0.02)	(0.01)	(0.02)
Education: below primary	0.015	0.103	0.091	-0.063
	(0.11)	(0.08)	(0.07)	(0.06)
Education: upper secondary	**0.289*** **	**0.198*** **	**0.163*** **	0.003
	(0.10)	(0.05)	(0.04)	(0.04)
Education: vocational tertiary	**0.371*** **	**0.263*** **	**0.278*** **	0.053
	(0.11)	(0.05)	(0.04)	(0.05)
Education: general tertiary	**0.880*** **	**0.348*** **	**0.566*** **	0.066
	(0.15)	(0.06)	(0.05)	(0.07)
Observations	1,372	1,576	1,801	2,117
R-squared	0.16			

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Standard errors are in parentheses. Conditional correlations are computed from ordinary least squares (OLS) regressions for labor earnings and logit regressions for labor supply outcomes. The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. The outcomes of being employed and having attended tertiary education are restricted to adults ages 19–64 and ages 25–64, respectively.. OLS calculations control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Logit regressions control for the same variables and a self-reported categorical variable on parents' involvement in one's education at the age of 12 (three levels). Average marginal effects are reported for logit regressions and reflect the changes in the probability of being observed in a labor or school participation situation with respect to the variables evaluated at the mean. Measures of reading proficiency and socioemotional skills are standardized. Regressions coefficients and standards errors of reading proficiency are the average of the 10 estimations using plausible values.

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

Table 5. Conditional Correlations of Labor Earnings with Measures of Skills, across Subsamples

Outcome	Log hourly labor earning					
Method	OLS					
Subsample	Men	Women	Younger (15–34)	Older (35–64)	Less educated (maximum, incomplete secondary)	More educated (minimum, complete secondary)
	(1)	(2)	(3)	(4)	(5)	(6)
Reading proficiency	**0.160****	**0.140****	**0.134***	**0.173*****	0.019	**0.180****
	(0.07)	(0.06)	(0.07)	(0.06)	(0.05)	(0.08)
Extraversion	-0.030	0.024	0.011	-0.011	0.007	0.008
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Conscientiousness	-0.037	-0.017	**-0.102***	0.044	-0.040	-0.004
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Openness to experience	**0.130*****	0.046	0.030	**0.152*****	0.065	**0.066***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Emotional stability	-0.031	0.047	-0.013	0.036	0.011	-0.050
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Agreeableness	0.028	0.013	-0.006	0.037	-0.003	0.050
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Grit	-0.033	-0.040	-0.040	-0.059	-0.015	-0.084
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Hostile attribution bias	-0.044	0.029	0.048	-0.053	0.036	-0.008
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Decision making	0.046	-0.030	0.033	0.019	-0.024	0.006
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Observations	686	686	678	694	438	934
R-squared	0.12	0.09	0.13	0.16	0.06	0.14

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Standard errors are in parentheses. The bottom and top 1 percent of the log hourly labor earnings distribution are trimmed. Ordinary least squares (OLS) calculations control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Measures of reading proficiency and socioemotional skills are standardized. Regression coefficients and standard errors of reading proficiency are the average of the 10 estimations using plausible values.

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

Table 6. Conditional Correlations of Being Active or in School with Skills, across Subsamples

Outcome	Being active or in school (versus nonstudent inactive)					
Method	Logit					
Subsample	Men	Women	Younger (15–34)	Older (35–64)	Less educated (maximum, incomplete secondary)	More educated (minimum, complete secondary)
	(1)	(2)	(3)	(4)	(5)	(6)
Reading proficiency	-0.001	**0.039****	**0.030****	0.012	**0.035****	0.015
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Extraversion	-0.002	0.017	**0.023*****	-0.016	**0.029***	0.003
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Conscientiousness	0.003	**0.043*****	**0.020****	**0.027***	**0.046*****	0.004
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Openness to experience	0.004	**0.029***	**0.022****	**0.027***	0.010	0.016
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Emotional stability	-0.008	0.021	0.007	0.017	0.007	0.011
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Agreeableness	-0.011	**-0.027***	-0.010	**-0.029***	**-0.045*****	-0.002
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Grit	0.006	0.003	-0.003	0.012	0.004	0.006
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Hostile attribution bias	-0.009	-0.012	-0.006	-0.009	0.018	**-0.018****
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Decision making	-0.013	-0.000	-0.005	0.002	-0.000	-0.007
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	933	1,369	1,233	1,123	864	1,492

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

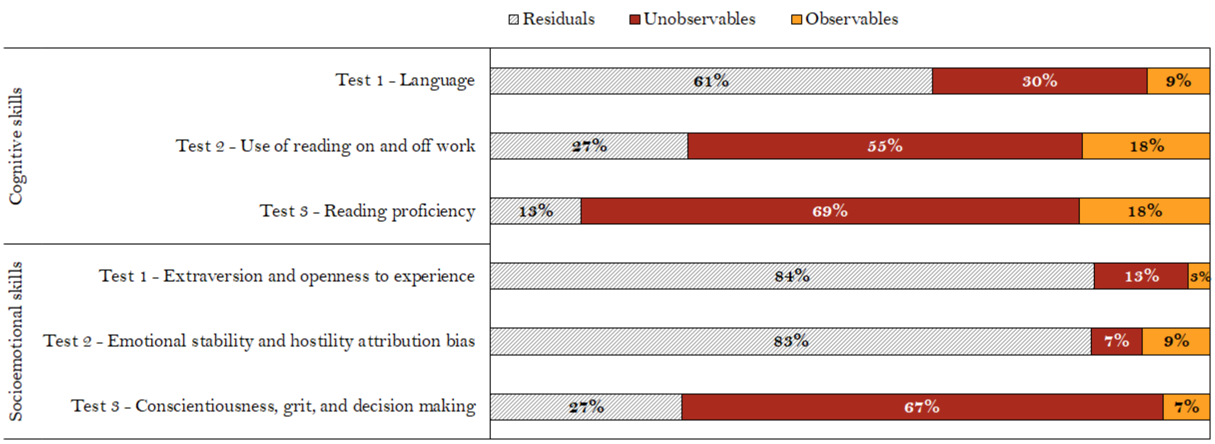
Note: Standard errors in parentheses. Regressions control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category), and a self-reported categorical variable on parental involvement in one's education at the age of 12 (three levels). Average marginal effects are reported and reflect the changes in the probability of being observed in a labor or school participation situation with respect to the variables evaluated at the mean. Measures of reading proficiency and socioemotional skills are standardized. Regression coefficients and standard errors of reading proficiency are the average of the 10 estimations using plausible values.

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

4.b Structural Estimation

In this section, we estimate the links between latent skills and labor market outcomes using structural estimation methods.[17] As opposed to the OLS and logit estimates, this method mitigates measurement errors but gives estimates for only one dimension of the latent cognitive skills and one of latent socioemotional skills. The estimated distributions of unobserved heterogeneity show that the latent factors of skills explain large proportions of the variance of many of the scores (figure 2). These distributions are used to structurally model the latent skills in the outcome equations.

Figure 2. Variance Decomposition of the Tests Scores of Cognitive and Socioemotional and Used for the Structural Estimation of Latent Skills



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Factors of latent cognitive and socioemotional skills are obtained from a measurement system of three "test scores" for each. Given that measures of socioemotional skills are built from categorical answers with limited variability, they were averaged into three tests to satisfy the necessary smoothness in the measurement system; the measures were paired based on the correlations among them and the similarity of the dimensions they aim to capture (see table 2). Definitions of skills are in table 1. The first test used for the measurement system identifying the factor of latent cognitive skills, is a measure of language skills that is an average of additional dimensions of reading proficiency measured by the test but that are not used for the main score of reading proficiency: average print vocabulary, sentence processing, and passage comprehension (ETS 2014, Pierre et al. 2014). The second test for latent cognitive skills is a measure of how much adults use reading at work and outside and the length of these reading, which are based on survey questions not linked to the reading-proficiency test.

Like in our OLS and logit results, latent cognitive skills are highly correlated with working in better-paid, formal and high-skilled jobs, far more than latent socioemotional ones. All else being held constant, an increase in one standard deviation in latent cognitive skills is associated with an increase of 13 percent in log hourly labor earnings, while latent socioemotional skills have a nonsignificant correlation (figure 3

[17] All the estimations presented in this section were implemented using the *heterofactor* command in Stata developed by Sarzosa and Urzúa (2016).

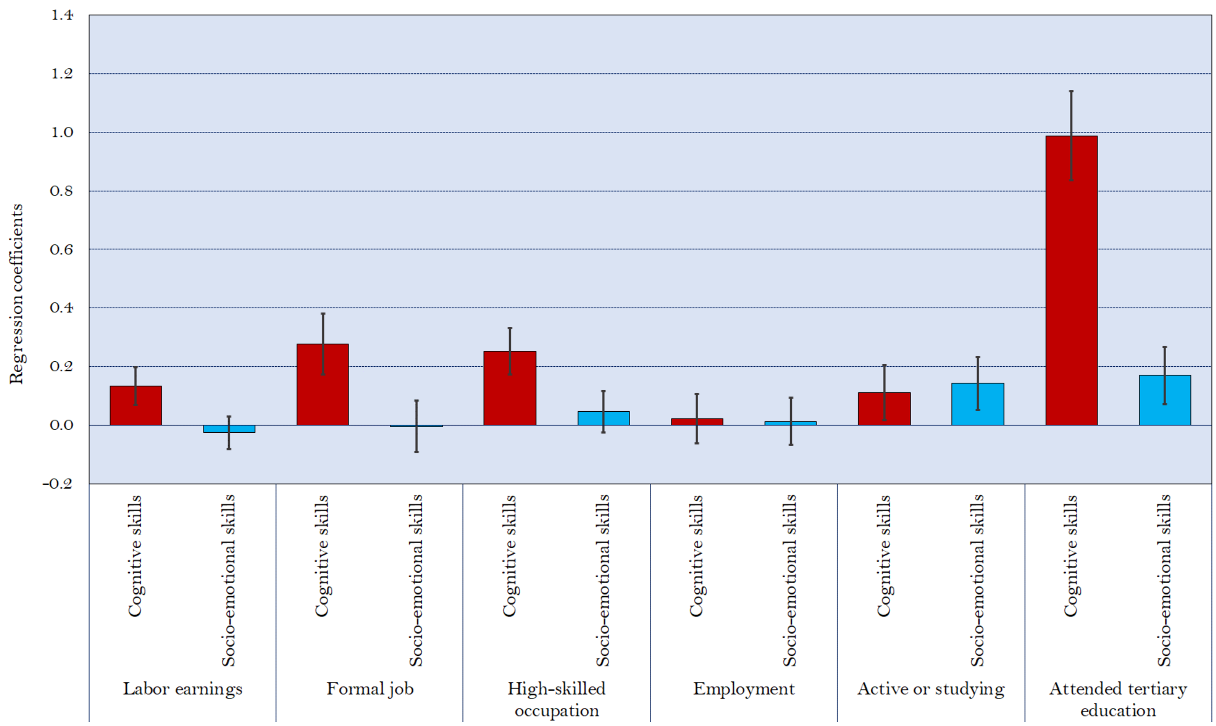
and table 7). The high correlation of latent skills with earnings can also be appreciated along the distribution: workers who belong to the top decile of the cognitive skill can earn up to US$ 2 (in 2011 purchasing power parity) more per hour than those in the lowest decile of the cognitive skills distribution, which is roughly 50 percent more (figure 4). Likewise, those in the top decile of the distribution of latent cognitive are 28 percentage points more likely to have a formal job —more than the double— (figure 5) and 27 percentage points more likely to have a high-skilled job than those in the bottom decile (figure 6). Latent socioemotional skills are only marginally associated with these outcomes, although a bit more with working in a high-skilled occupation.

However, higher latent socioemotional skills are a lot more correlated with participating fully in the labor market, more than cognitive ones. An increase of one standard deviation of latent socioemotional skills correlates with a 14-percentage-point increase in the probability of being working, studying, or looking for job, compared to 11 percentage points for latent cognitive ones (figure 3 and table 7). Although adults with the lowest level of latent socioemotional skills, from the bottom decile, already have an 85 percent probability of being active or studying, adults with the highest levels, from the top decile, have a 93 percent probability of being so. Both types of latent skills do not correlate significantly with being employed. The distribution remains flat — about 75 percent— in the entire skills space, which reflects that being employed in a labor market with high informality is not a synonym to better conditions and higher skills (figure 8).

With tertiary-education attendance, the relationship with latent cognitive skills is especially strong and more modest with latent socioemotional ones. Those with the lowest levels of cognitive skills have virtually no chance of having attended tertiary education—only 2 percent. However, those with the highest levels of latent cognitive skills have a 62 percent probability of having done so (figure 9). For latent socioemotional skills, it goes from 21 percent to 37 percent.

Latent cognitive and socioemotional skills often compound their correlations with outcomes. Take the probability of being active or studying, for example. Adults with the lowest level of both latent cognitive and socioemotional skills already have a probability of 80 percent of being active or studying. However, adults with the highest levels of both types have a 95 percent probability of being so. That is a 15-percentage-point increase, more than the 6- and 9-percentage-point increases when raising latent socioemotional and cognitive skills, respectively, from their bottom to top levels while the level of the other is held constant at its average. The joint relationship of both types of latent skills is even higher with tertiary-education attendance: switching from the bottom to the top deciles of both latent cognitive and socioemotional skills is associated with an 81-percent point increase in tertiary education enrollment. This is consistent with the idea that a solid knowledge base and cognitive skills are better used in education trajectories when accompanied by certain traits. Joint relationships of skills with outcomes are not always higher than their individual relationships though. For example, the 50 percent increase in hourly labor earning correlated with raising latent cognitive skills from the bottom to the top deciles is higher than the corresponding 39 percent increase for joint latent cognitive and socioemotional skills.

Figure 1. Regression coefficients of latent skills measures



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: The figure shows the effect size for measures of latent skills. The bars stand for the regression coefficients and the error bars for the confidence interval at 95 percent. Red and blue bars stand for measures of cognitive and socioemotional skills, respectively. A worker is defined here as formal if he or she benefits from social security through his job. Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions. High-skilled workers hold occupations categorized as senior officials and managers, professionals, or technicians, as opposed to low- and medium-skilled workers such as clerks, service workers, machine operators, or laborers (jobless having held a job in the past year are also included). The classification is based on the International Labour Organization's 1988 International Standard Classification of Occupations (ISCO). Conditional correlations are computed from ordinary least squares (OLS) regressions for labor earnings and logit regressions for labor supply outcomes. The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. OLS calculations control for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Logit regressions control for the same variables and a self-reported categorical variable on parents' involvement in one's education at the age of 12 (three levels). Average marginal effects are reported for logit regressions and reflect the changes in the probability of being observed in a labor or school participation situation with respect to the variables evaluated at the mean. Measures of reading proficiency and socioemotional skills are standardized.

Table 7. Structural Estimates of Correlations between Labor Market Outcomes on Latent Skills Factors

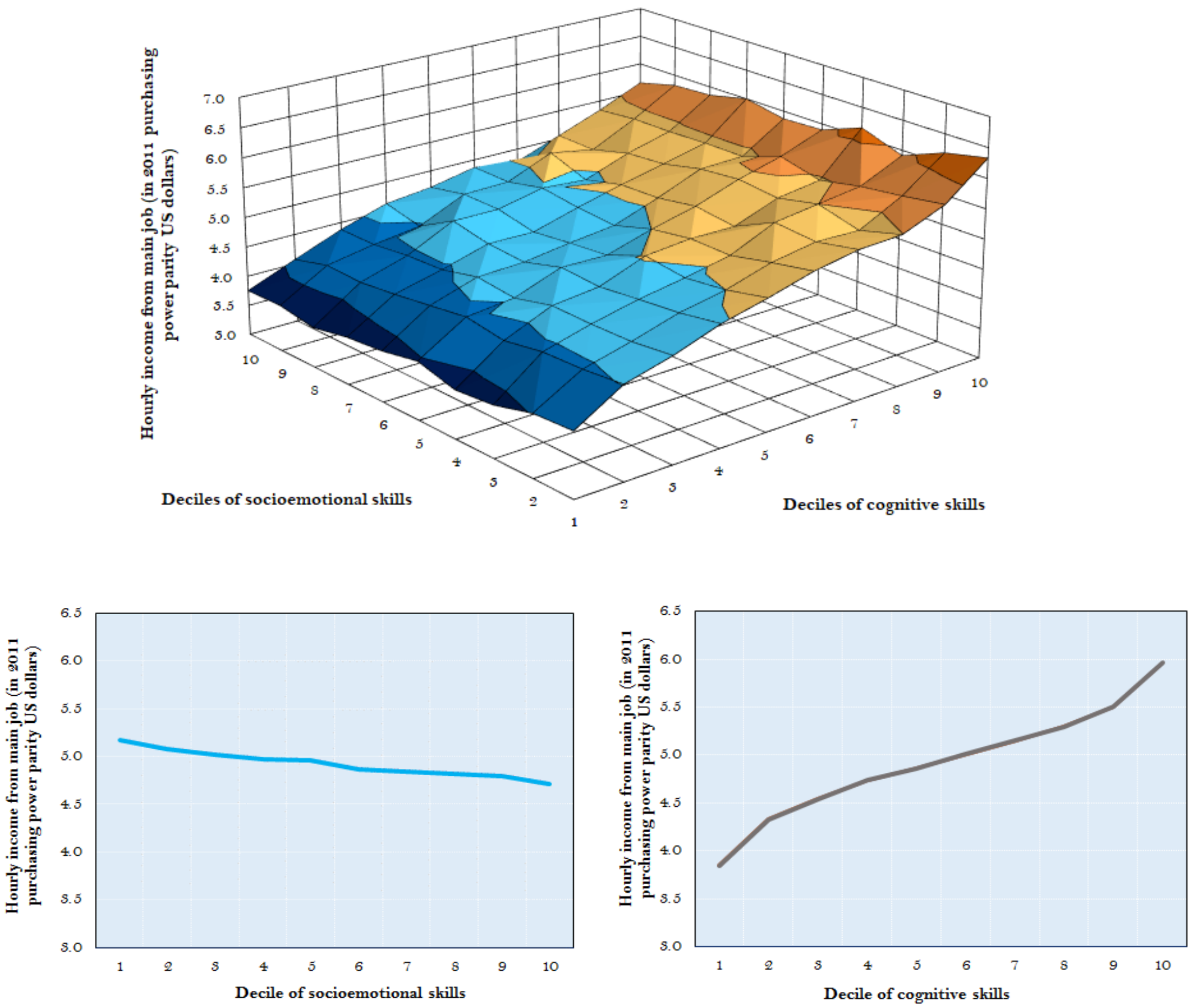
	Log hourly labor earning	Being a formal worker	Being a high-skilled worker	Being employed	Being active or in school	Having attended tertiary education
	(1)	(2)	(3)	(4)	(5)	(6)
Latent cognitive skills	**0.134*** **	**0.276*** **	**0.252*** **	0.023	**0.112** **	**0.988*** **
	(0.032)	(0.052)	(0.04)	(0.042)	(0.047)	(0.076)
Latent socioemotional skills	-0.026	-0.004	0.046	0.013	**0.143*** **	**0.170*** **
	(0.028)	(0.044)	(0.035)	(0.04)	(0.045)	(0.049)
Observations	1,363	1,560	2,328	2,089	2,328	1,692

Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Standard errors are in parentheses. Estimated using Sarzosa and Urzúa (2016). The estimations presented in columns (2) t0 (6) assume a probit structure, hence the presented coefficients are not marginal effects. The regression in column (1) controls for being a woman (dummy), age, age-squared, mother's education (dummies; primary education is the reference category), and cities of living and their metropolitan areas (dummies; Bogota-Barranquilla-Villavicencio is the reference category). Regressions with probit structure (columns 2-6) control for the same variables and a self-reported categorical variable on parents' involvement in one's education at the age of 12 (three levels). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of personality traits (extraversion, openness to experience, emotional stability, conscientiousness, and grit) and behaviors (hostility bias and decision-making styles). All the estimations include city dummies and an index of parental involvement that refers to a parent's regularity in checking a primary student's grades and exams. A worker is defined here as formal if he or she benefits from social security through his or her job. High-skilled workers hold occupations categorized as senior officials and managers, professionals, or technicians, as opposed to low- and medium-skilled workers such as clerks, service workers, machine operators, or laborers (jobless having held a job in the past year are also included). The classification is based on the International Labour Organization's 1988 International Standard Classification of Occupations (ISCO). The outcomes of being employed and having attended tertiary education are restricted to adults ages 19–64 and ages 25–64, respectively.

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

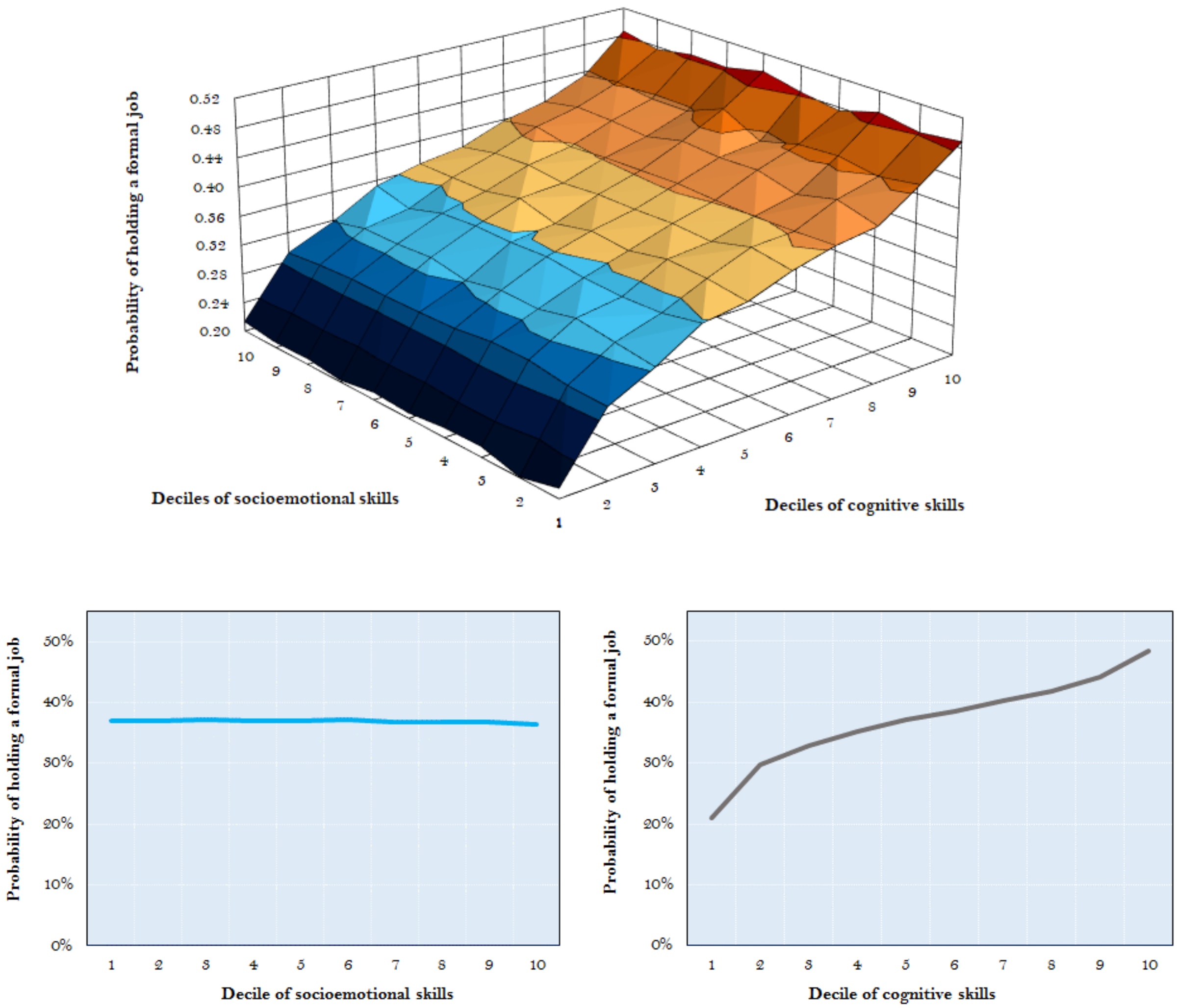
Figure 2. Hourly Income from Main Job by Skill Deciles: in 2011 PPP US dollars



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

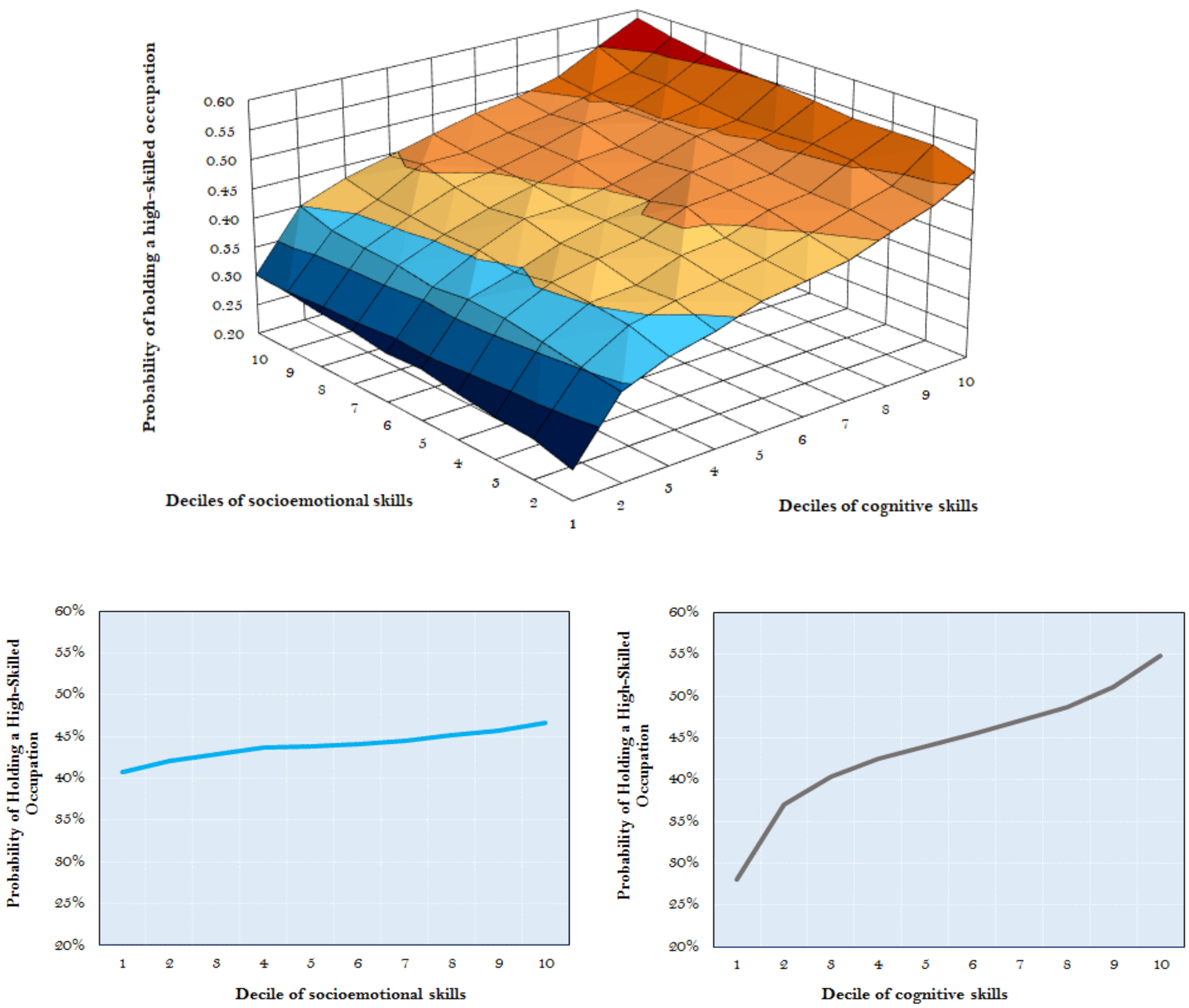
Figure 5. Probability of Holding a Formal Job by Skill Deciles



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

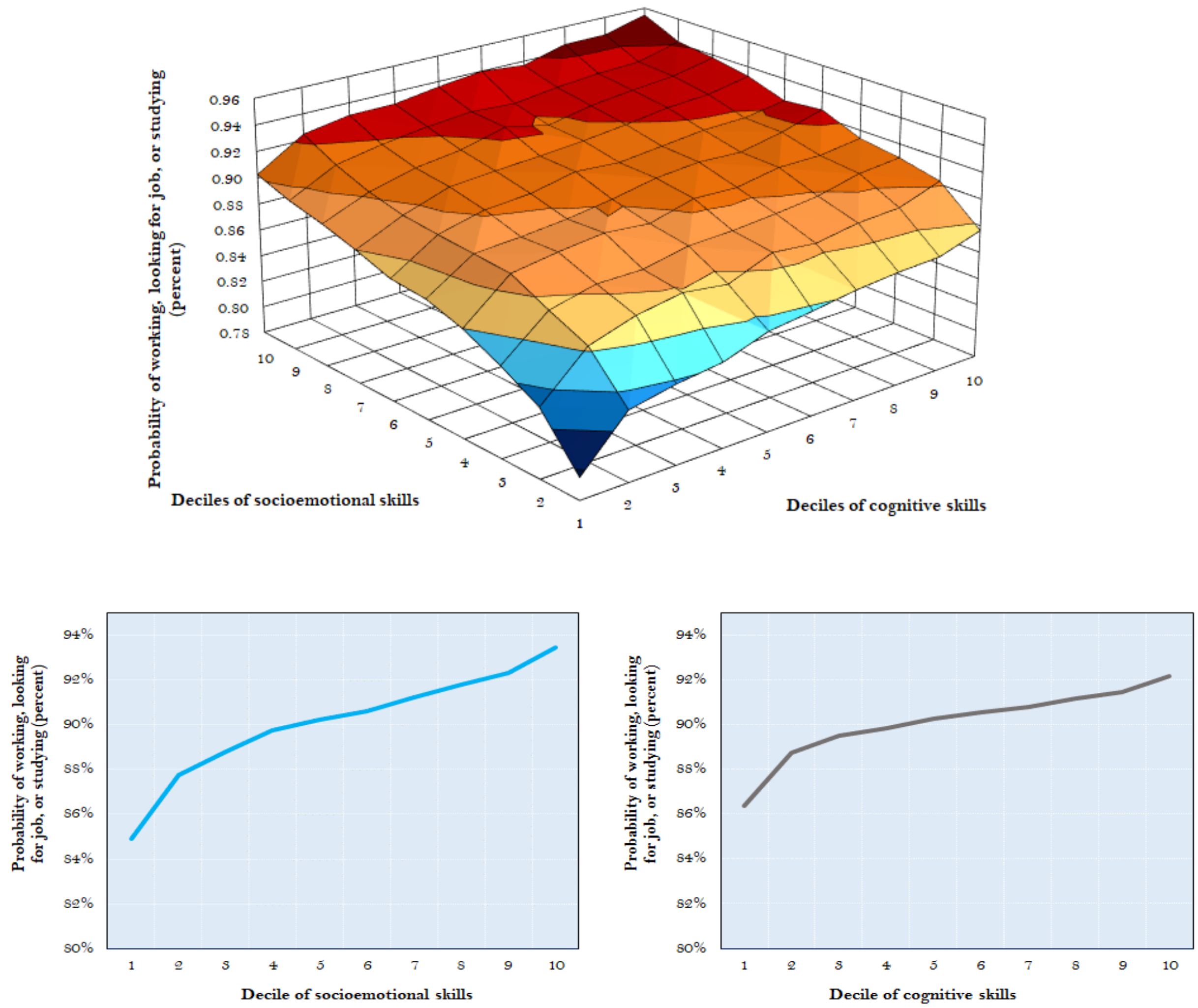
Figure 6. Probability of Holding a High-Skilled Occupation (versus Holding a Low- or Medium-skilled Occupation) by Skill Deciles



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

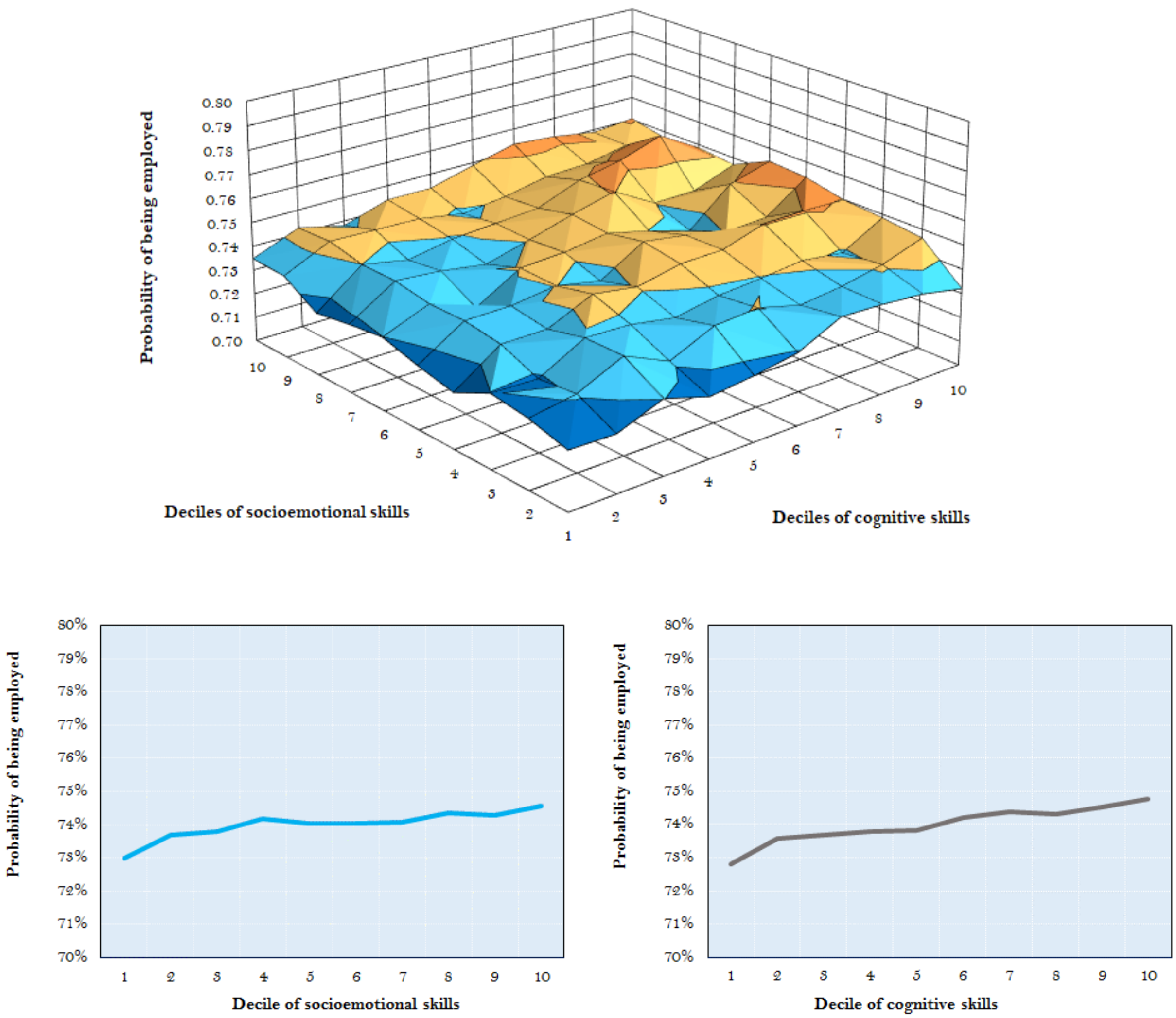
Figure 7. Probability of Being Active or in School by Skill Deciles



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

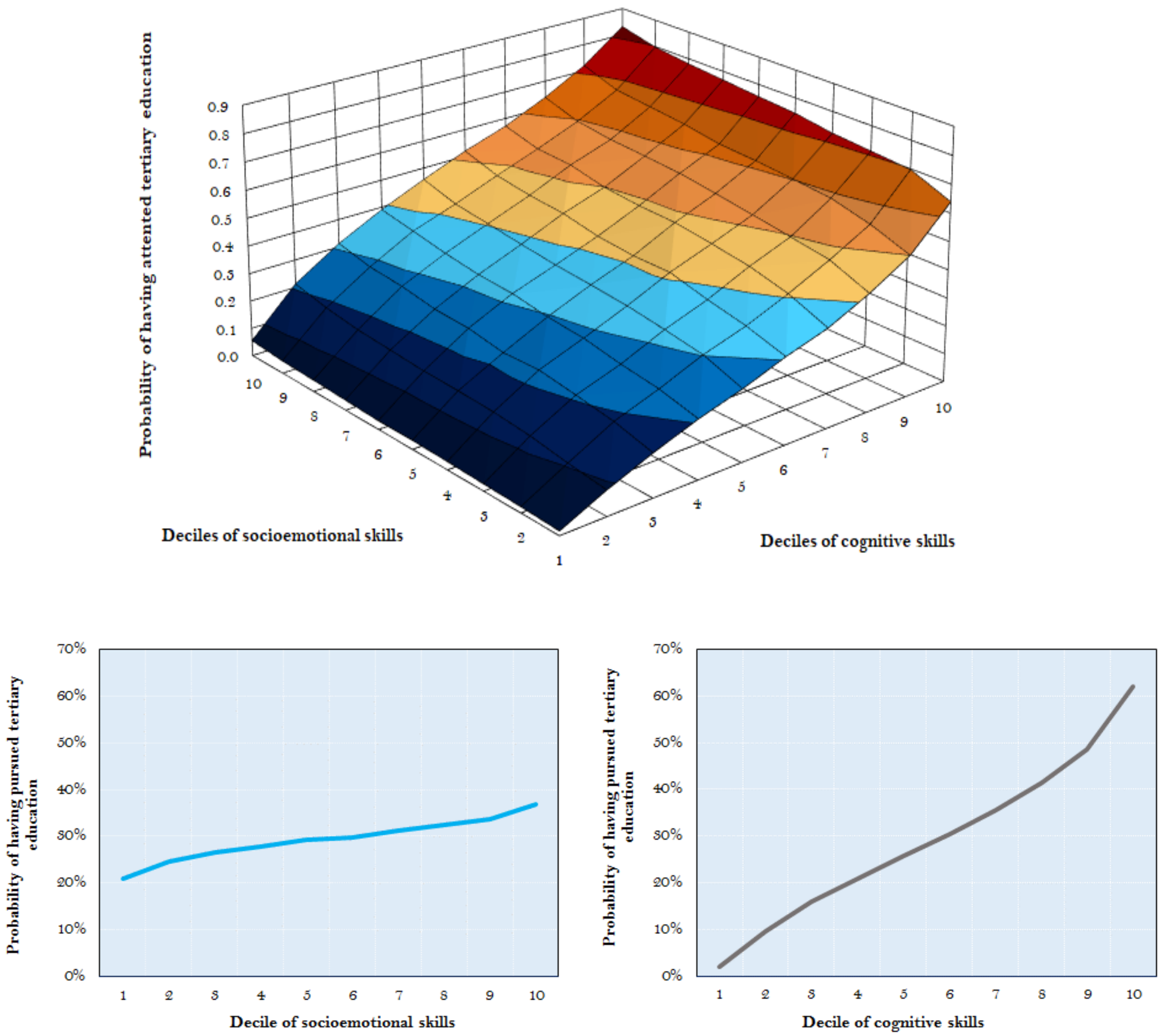
Figure 8. Probability of Being Employed by Skill Deciles for Adults Aged 19–64



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

Figure 9. Probability of Having Attended Tertiary Education by Skill Deciles for Adults Aged 25–64



Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Simulations are based on structural estimations of latent skills factors using Sarzosa and Urzúa (2016). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socioemotional skills are captured by an estimated latent factor using measures of the Big Five personality traits (extraversion, openness to experience, emotional stability, conscientiousness), grit, hostility bias, and decision-making styles. See table 1 for definitions.

4.c. Discussion

Making sense of OLS-Logit and structural estimations of latent skills

Overall, the estimations of OLS-Logit with raw measures of skills and structural estimations of latent ones share similar patterns of relationships with labor outcomes but with amplified differences in the respective links for each type of them. As commonalities, latent cognitive skills correlate with the exact same outcomes than measured cognitive skills—all but employment—and latent socioemotional skills correlate with being active or in school and having attended tertiary education, more than latent cognitive ones for the former outcome and less for the latter. As differences, the magnitude of the correlations of latent cognitive skills with outcomes linked to better jobs (higher earnings, more formal, and high-skilled) and having attended tertiary education is much higher than with latent socioemotional, by a much higher margin than between measured cognitive and socioemotional skills. In particular, while the relationship between better-job outcomes and latent cognitive skills are higher compared to with measured cognitive skills, the relationship with these outcomes and latent socioemotional skills become virtually inexistent—non-significant and even slightly negative for earnings and formality.

The attenuation of the link between socioemotional skills and better-job outcomes may come from their aggregation in only one latent factor. The latent factors of skills reduce measurement error but also the diversity of skills by reducing them to two factors, one for cognitive and one for socioemotional skills. Each latent factor collects the common variation in the measures used. The variation that is unique to each measure, which may be driving the OLS and logit results, is left out. For example, the scores of openness to experience, agreeableness and decision-making correlate positively with earnings, but extraversion, conscientiousness, grit and hostile attribution bias correlate negatively with it. Using the latent factor model, we find that the common variation across all the socioemotional skills has a weak and negative correlation with earnings.

Different socioemotional skills correlate differently with the labor market and education outcomes. Cognitive scores, by contrast, are known to be related to outcomes the same way, which makes more consistent the aggregation in a single latent factor (Almlund et al. 2011). In our data, the measures of cognitive skills and latent factors roughly capture the same dimension, which is using, understanding, and reasoning from reading texts.

The relationships of skills and labor outcomes in Colombia compared to other countries

Our findings unveil a mix of similar and dissimilar patterns of the links between skills and labor outcomes in Colombia with studies on other countries. Unfortunately, we cannot distinguish if those differences are due to actual differences of labor markets, living conditions, or culture, or to differences in studies, including divergence in skills measures (e.g. list of skills, validity) or surveyed populations (e.g. age group, national population or urban settings).

In broad terms, both cognitive and socioemotional skills matter for labor-market outcomes in Colombia, especially cognitive ones, and socioemotional skills have diverse effects, which align with studies on high-income countries. Longitudinal studies on nine high-income OECD countries generally find that children and adolescents with both higher cognitive and socioemotional skills, but particularly higher cognitive skills, are more likely to have better labor market outcomes (income and employment) and attend tertiary education (OECD 2015). In this context, cognitive skills reduce unemployment, which is the mark of those struggling in the labor market, by contrast to Colombia, where fewer people can afford it. The role socioemotional skills seem to play for labor force participation and schooling decisions is also found in some high-income countries (Carneiro, Crawford, and Goodman 2007; Almlund et al. 2011; OECD 2015). In line with our findings for raw measures of skills, while the impact of socioemotional skills can rival those of cognitive skills in some high-income countries, different socioemotional skills in a given country can also have opposite effects.

In this study, we find that, in Colombia, openness to experience correlate with labor earnings, which is in line with research in the United Kingdom (Heineck 2011). Yet, studies on high-income countries usually find that skills and personality traits related to conscientiousness and emotional stability are those impacting more labor-market outcomes such as wages (Nyhus and Pons 2005; Heckman, Stixrud and Urzúa 2006; Almlund et al. 2011). While grit—people's perseverance and passion for long-term goals—is also considered as a predictor of education in the United States (Duckworth et al. 2017), and then possibly of labor outcomes, in Colombia, our measure of grit does not correlate with any outcome we look. Our measure of extroversion was neither correlated with any labor market outcome, but this result is in line with research in other countries, likely because more of this trait is not necessarily needed in a broad range of occupations. That might indicate that across countries' cultures and labor, cognitive skills tend to be more universally rewarded in jobs and that the returns to socioemotional ones may differ across countries in part according to the structure of employment. But, again, we cannot conclude on the specific skills that the Colombian labor market rewards from our results: it is likely that the socioemotional skills measures of our survey do not properly capture what they are intended to, and thus are likely not too comparable with other studies so (Laajaj et al. 2019).

5. Conclusion

Using a cross-sectional data set, we find that Colombian adults with the higher levels of both cognitive and socioemotional skills are also those who have better labor market outcomes and have attended tertiary education, seemingly for different reasons for each type of skill. We use two methods, one showing specific but potentially noisy measures of skills and another showing more accurate estimations of people's actual skills but bundled in one dimension, one for each type of skill. We find that adults with higher cognitive skills are especially more likely to have a job that is better paid, formal, and high-skilled and have attended tertiary education because cognitive skills are highly linked to schooling—children with higher cognitive skills are more likely to do well in school and pursue education, and in turn develop more cognitive skills. Adults with socioemotional skills are particularly more likely to have a productive activity, either work, look actively for a job, or study as opposed to being idle. Socioemotional skills, although they are partly linked with schooling, appear to be built and influence outcomes beyond schooling, especially for labor force participation and tertiary-education attendance, in particular for subgroups such as women, youth, and less educated adults. Adults with the highest levels of both types tend to do better than those who have the highest levels in one or the other. The general importance and channels of cognitive and socioemotional skills seem broadly consistent with evidence from high-income countries. Although with our data we can neither assess how specific skills are differently rewarded in Colombia nor why.

The interpretation of our results should take into account two main empirical challenges: measurement error and reverse causality. First, while our structural estimations of latent skills solve the biases due to noisy survey-based measures of socioemotional skills, the method applied to our data comes at the cost of only being able to estimate a single factor for cognitive and socioemotional skills, each, due to its high data requirements. As such, we cannot observe the possible diverse influence of a range of socioemotional skills on labor market outcomes. Second, because we use a cross-sectional survey in which skills and outcomes are measured at the same time, it is possible that better outcomes also cause higher skills. The link between openness to experience (curiosity and creativity) with tertiary-education attendance might be both the result of more opened youth being eager to study at this level and that they have been through that kind of education raised their openness. For these reasons, our estimates are best interpreted as conditional correlations controlling for confounding factors, rather than causal effects.

The results of this paper may have important policy implications. Although in different ways, both cognitive and socioemotional skills are linked to outcomes and strategies to foster them may be well advised. For example, the curriculum of training programs aiming to raise youth and adults' employment outcomes may combine modules of both cognitive and socioemotional skills. Since the formation of both types of skills is cumulative and start from early childhood, policies to foster them before youth get to tertiary education and the labor market may be of important help, including at school, where they are rarely systematically incorporated, and out of school like in extra-curricular activities. In any case, there is a need for further research on the optimal combination of packages of various dimensions of skills, and on different demographic and socioeconomic population groups, particularly in the context of low- and middle-income countries such as Colombia.

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