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Beyond Qualifications

Returns to Cognitive and Socio-Emotional Skills in Colombia

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Abstract

This paper examines the relationship between individuals' skills and labor market outcomes for the working-age population of Colombia's urban areas. Using a 2012 unique household survey, the paper finds that cognitive skills (aptitudes to perform mental tasks such as comprehension or reasoning) and socio-emotional skills (personality traits and behaviors) matter for favorable labor market outcomes in the Colombian context, although they have distinct roles. Cognitive skills are greatly associated with higher earnings and holding a formal job or a high-qualified occupation. By contrast, socio-emotional skills appear to have little direct influence on these outcomes, but play a stronger role in labor market participation. Both types of skills, especially cognitive skills, are largely associated with pursuing tertiary education. The analysis applies standard econometric techniques as a benchmark and structural estimations to correct for the measurement error of skill constructs.

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Beyond Qualifications

Returns to Cognitive and Socio-Emotional Skills in Colombia*

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1. Introduction

The rise in educational attainment in Colombia and Latin America since the 1990s has failed to deliver its expected payoffs: better employment outcomes and productivity. Although the share of Latin Americans with at least a secondary education increased from 40 to 60 percent between 1990 and 2010, returns to secondary and tertiary education fell in most countries of the region over the same period (Gasparini *et al.* 2011). In Colombia, 20 percent of college students and 41 percent of technical and technological students even face negative returns (Gonzalez-Velosa *et al.* 2015).

Part of this disenchantment with educational outcomes stems from the fact that educational attainment or diplomas do not necessarily guarantee a given level knowledge and skills. Student achievement tests, conducted across the world, suggest that Colombian students have levels of basic cognitive skills— academic knowledge such as math, reading, and writing—approximating the Latin American average but significantly below that of students at the same educational level from high-income countries.[1] The low and degrading quality of education in the region is regarded as one of the main causes of the mismatch between skills and educational levels (Bassi *et al.* 2012; Levy and Schady 2013).

A large body of evidence has documented that direct measures of skills provide more adequate estimations of individuals' differences in potential productive capacity than the quantity of education they receive. People are distinguished by the broad sets of abilities, accumulated over their life course, that shape their decisions and success in the labor market (Almlund *et al.* 2011; Borghans *et al.* 2008). These broad sets of skills fall into two categories: (1) cognitive skills—aptitudes to perform mental tasks such as comprehension or reasoning—and (2) socio-emotional skills—personality traits, behaviors, attitudes, and beliefs. Common proxies such as years of education do not capture well cross-country differences in skills acquisition at school and the development of these skills outside the classroom (Hanushek and Woessman 2008). Meanwhile, employer surveys from Latin America and beyond confirm that socio-emotional and advanced cognitive skills are valued, not just qualifications (Cunningham and Villaseñor 2014; Bassi *et al.* 2012).

This paper examines the impact of individuals' skills on labor outcomes in the context of Colombia, an upper-middle-income country. Using a unique cross-sectional household survey providing direct measures of skills and rich background information, we investigate (1) the current levels and distribution of cognitive and socio-emotional skills in Colombia's urban working-age population, and (2) the degree to which certain types of cognitive and socio-emotional skills affect a range of labor market outcomes and educational trajectories in the

[1] For example, see OECD (2014) for the results of secondary students from the 2012 Programme for International Student Assessment (PISA), and see UNESCO (2014) for the results of pupils at the primary level from the 2014 Third Regional Comparative and Explanatory Study (TERCE).

Colombian context. The findings complement evidence from high-income countries (mostly Western Europe and the United States) and a fistful of developing countries.

One value added of our analysis is the use of structural estimations of latent cognitive and socio-emotional skills, which identifies unobserved heterogeneity and corrects for any measurement error of skill indexes.[2] Survey measures of skills-based, self-reported items or tests have proven to be fallible in capturing individuals' true, or latent, skills (Heckman and Kautz 2012; Almlund *et al.* 2011; Borghans *et al.* 2011). For that reason, our preferred approach is to use a structural estimation of latent skills that corrects for measurement error. However, because of its high data requirements and our data set, this technique can only be performed by aggregating the skill constructs, our variables of interest. Thus we also present estimations from ordinary least squares (OLS), logit, and instrumental variables (IV) approaches that provide a more nuanced exploration of the influence of more specific types of skills at the cost of a larger potential estimation bias. Besides, structural estimations of latent skills do not solve the concerns of reverse causality; both labor outcomes and measures of skills are observed simultaneously because of the cross-sectional nature of our data set (Carneiro and Heckman 2004).

We find that both cognitive and socio-emotional skills matter for favorable labor market outcomes in the Colombian context, although they have distinct roles. Cognitive skills are greatly associated with higher earnings and holding a formal job or a high-qualified occupation. By contrast, socio-emotional skills appear to have little direct influence on these outcomes but play a stronger role in labor market participation. Both types of skills, especially cognitive, are largely associated with a tertiary education. These inferences are generally consistent across types of estimates for approaches using both disaggregated measures of skills (OLS, logit, and IV) and aggregated measures (structural estimations of latent skills).

The remainder of this paper is organized as follows. Section 2 provides definitions of the concepts of cognitive and socio-emotional skills. Section 3 reviews the empirical literature on the relationship between these skills and labor market outcomes; section 4 describes the data; and section 5 introduces the empirical strategy. The results are presented in section 6 for descriptive statistics on the levels and distributions of skills and in section 7 for OLS, IV estimates, and the structural estimations. The final section offers our conclusions.

2. Concepts and Definitions

One outstanding fact from the economic and psychology literature addressing skills is the plethora of definitions and taxonomies surrounding this concept. Economists have long considered educational levels to be the main indicator of skills. Then studies began to recognize that competencies and abilities are part of a broader scope and are also influenced by extra-school factors such as family background, work, extracurricular activities, and environment. Nowadays,

[2] Structural estimations of latent skills are used by Heckman, Stixrud, and Urzúa (2006) and Urzúa (2008), among others.

the term *skills* is used broadly to include "competencies, attitudes, beliefs and behaviors that are malleable (modifiable) across an individual's development and can be learned and improved through specific programs and policies" (Guerra, Modecki, and Cunningham 2014).

Cognitive skills are generally defined as intelligence or mental abilities. Two levels can be distinguished: (1) lower-order (basic) cognitive skills are foundational skills or basic academic knowledge such as literacy or numeracy, and (2) higher-order (advanced) cognitive skills involve more complex thinking such as critical thinking or problem solving (Neisser *et al.* 1996; Cattell 1987).[3]

The term *socio-emotional skills* refers to a distinct set of skills that enable individuals to navigate interpersonal and social situations effectively (Guerra, Modecki, and Cunningham 2014). These skills encompass behaviors and attitudes that are consistent patterns of thoughts, feeling, and conduct (such as commitment, discipline, or the ability to work in a team) and personality traits (such as self-confidence, perseverance, and emotional stability) that are broad facets relatively stable over time (Borghans, Duckworth, Heckman, and ter Weel 2008; Almlund *et al.* 2011).[4]

3. Literature Review

The primary approach to assessing the relationship between an individual's skills (cognitive, socio-emotional) and schooling and labor market outcomes is based on longitudinal data. It consists of linking the cognitive test scores and personality constructs, generally from self-reported items, of individuals in their youth with their outcomes as adults. Regrettably, panel data are rare, especially in low- and middle-income countries, and even fewer data provide direct assessments of skills. Thus most evidence comes from the United States and other high-income countries.

A few caveats related to methodological shortcomings and data limitation must be highlighted prior to discussion of the evidence. First, studies may not offer the full picture of the effect of an individual's true skills; results are conditional on the dimensions of the skills set measured in the survey, which may not reflect the full range of an individual's abilities, and survey instruments are subject to measurement error of the skill construct (Almlund *et al.* 2011). Second, causal analyses of the impact of skills and traits on employment often suffer from endogeneity bias when including education in the analysis, casting doubt on the reliability of the estimations (Heckman, Stixrud, and Urzúa 2006). Moreover, cross-sectional studies are subject to a risk of reverse

[3] Technical skills, associated with the specific knowledge needed to carry out one's occupation, can be thought of as a subset of cognitive skills (Almlund *et al.* 2011). They are not specifically addressed in this paper.

[4] In the economic literature, the term *socio-emotional skills* is often used interchangeably with the terms of *behavioral skills*, *life skills*, *non-cognitive skills*, or *soft skills*. Nonetheless, these terms differ slightly and merit clarification. *Non-cognitive skills* refers to a broad range of behaviors, abilities, and traits that are not induced by intelligence or achievement. *Soft skills* and *life skills* usually include more technical skills such as language fluency and computer literacy (Guerra, Modecki, and Cunningham 2014). Psychologists argue that many of the abilities and traits that economists intend to capture by use of the term *non-cognitive skills* are a result of cognition (Borghans, Duckworth, Heckman, and ter Weel 2008).

causality between the measures of skills and labor outcomes because they are observed simultaneously.[5] Studies also vary greatly in the reported magnitude of skills effects, samples, research questions, and statistical methodologies, which may challenge meaningful comparisons between them.

3.a The Role of Skills and Traits in Labor Earnings

According to studies conducted since the mid-1990s, both cognitive skills and personality traits affect the labor earnings of the overall population, although with relatively larger effects for cognitive skills.

In the United States, cognitive abilities have long been the dominant factor determining labor earnings. In a large number of studies, higher levels of cognitive skills measured by intelligence quotient (IQ) or standardized tests of lower-order cognitive skills such as mathematics, reading, and vocabulary predicted higher wages, even when taking into account other factors that might also influence earnings (see Herrnstein and Murray 1994; Murnane, Willett, and Levy 1995; Gottfredson 1997; Mulligan 1999; Murnane *et al.* 2000; Altonji and Pierret 2001; Cawley, Heckman, and Vytlacil 2001; Lazear 2003; Hanushek and Woessmann 2008). Similar results were found in other high-income countries such as the United Kingdom (McIntosh and Vignoles 2001), Canada (Finnie and Meng 2001), and in more than 20 other member countries of the Organisation for Economic Co-operation and Development, or OECD (Hanushek *et al.* 2013).

In light of findings from program experiments and employer surveys, studies have begun to account for measures of socio-emotional abilities and personality traits, in addition to cognition ones, in order to investigate their influence on labor earnings.[6] This burgeoning literature reveals that socio-emotional abilities are at least as important as cognitive skills in determining labor earnings in many high-income countries such as the United States, Germany, the Netherlands, and Sweden.[7] And yet recent longitudinal studies for 11 OECD countries suggest that raising cognitive skills outweighs raising socio-emotional skills to increase income in most countries, especially in Nordic countries and Switzerland but not in Canada and the United Kingdom (OECD 2015). Among the "Big Five traits" used in the majority of empirical studies, conscientiousness and traits related to emotional stability (locus of control and self-esteem) are

[5] In the case of cross-sectional studies such as this paper, evidence can a priori only be interpreted as correlations, controlling for other factors, rather than causal relationships.

[6] For example, studies of General Educational Development (GED) recipients in the United States (high school dropouts who, by passing the GED exams, are certified as having a high school equivalent education) have served as an ideal natural experiment to confirm the crucial role of s*ocio-emotional* skills. GED recipients show higher basic cognitive skills than non-GED high school dropouts but earn, on average, the same wages. The poor labor market performances of GED beneficiaries are interpreted to originate from lower levels of s*ocio-emotional* skills, which are valued by the labor market. Being a GED graduate is a mixed signal that characterizes its recipients as smart but unreliable (Heckman and Rubinstein 2001).

[7] The following is a non-exhaustive list of sources claiming this result in the United States and Western Europe: Bowles, Gintis, and Osborne (2001b); Nyhus and Pons (2005); Osborne-Groves (2005); Heckman, Stixrud, and Urzúa (2006); Mueller and Plug (2006); Borghans, ter Weel, and Weinberg (2008); Heineck and Anger (2010); Lindqvist and Vestman (2011); and Segal (2013).

the most associated with job performance and wages in the United States and Western European countries (Barrick and Mount 1991; Bowles, Gintis, and Osborne 2001a, Heckman, Stixrud, and Urzúa 2006).[8] Using measures of socio-emotional skills based on school evaluations, Carneiro, Crawford, and Goodman (2007) and Segal (2013) find positive and significant associations between behaviors in childhood and adult wages in the United Kingdom and the United States. The same relationship was found between leadership abilities in youth and adult wages in the United States and Sweden (Kuhn and Weinberger 2005; Lindqvist and Vestman 2011).

Evidence from the urban areas of a few Latin American countries allow extending the general statement that both cognitive and socio-emotional skills are related to higher labor earnings. Pioneer work by Psacharopoulos and Velez (1992) showed that reasoning abilities and cognitive achievement (general knowledge) was strongly associated with earnings of Colombian workers in Bogota in 1988, mostly through higher educational attainment. Bassi *et al.* (2012), based on cross-sectional data for young adults in their late 20s in Argentina and Chile, found that self-efficacy is the ability that predominates the association with higher wages in both countries, with stronger effects for workers with postsecondary degrees. Díaz, Arias, and Tudela (2012) found that factors of lower-order cognitive skills—capturing language abilities and mathematical problem solving—and personality traits are equality valued in the Peruvian labor market for the working-age population. Specifically, grit (perseverance and passion for reaching long-term goals) and emotional stability have a high positive influence on earnings, while agreeableness shows a negative association. Although employers report valuing interpersonal skills such as teamwork, the Peruvian urban labor market does not seem to reward cooperation.

The returns to higher levels of cognitive and socio-emotional abilities differ across population subgroups and job types. There are often sizable differences across gender in the key personality traits with the highest rewards, although it is difficult to draw common patterns over studies.[9] For example, Osborne-Groves (2005) finds that locus of control, aggression, and withdrawal are strong predictors of wages for white women in the United States and the United Kingdom. Mueller and Plug (2006) find that agreeableness and conscientiousness seem to be more rewarding for women in the United States, while Heineck and Anger (2010) find that extraversion and agreeableness negatively affect women's wages in Germany.

Evidence suggests that skills that could be put at use across a broader array of occupations are more greatly rewarded when considering the whole population. For example, personality traits

[8] The Big Five personality traits are openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (opposite of emotional stability. This taxonomy summarizes a large number of distinct, more specific personality traits, behaviors, and beliefs (Goldberg 1993). The locus of control is defined as "the extent to which individuals believe they have control over their lives, i.e., self-motivation and self-determination (internal control) as opposed to the extent that the environment (i.e., chance, fate, luck) controls their lives (external control)" (Heckman, Stixrud, and Urzúa 2006).

[9] Heckman, Stixrud, and Urzúa (2006) find only slight variations in the effect of locus of control and self-esteem on earnings. Differences in the Big Five traits and locus of control between men and women explain only modestly the gender wage gap in Australia, Germany, the Netherlands, the Russian Federation, and the United States (Mueller and Plug 2006; Fortin 2008; Linz and Semykina 2008; Manning and Swaffeld 2008; Braakmann 2009; Cobb-Clark and Tan 2011).

such as conscientiousness and grit seem to matter for a wide spectrum of job complexity (Barrick and Mount 1991; Duckworth *et al.* 2007). And yet more complex jobs—that is, more demanding in information processing such as scientists and senior managers—require high-order cognitive skills that could not be used in other occupations (Schmidt and Hunter 2004). Using data for siblings in the United States, Fletcher (2013) found that extraversion shows a large and robust association with earnings that could reflect the recent change in the composition of occupations in the United States—namely, the increase in service jobs and the requirement for social interactions in the workplace. This finding is in line with that of Borghans, ter Weel, and Weinberg (2013) who document the importance of people skills in the labor markets of the United States, Germany, and the United Kingdom.[10] Higher levels of socio-emotional abilities appear even more important for occupations requiring low-order cognitive skills, especially in the services sector (Bowles, Gintis, and Osborne 2001b).

The returns to skills differ across type of work as well—namely, between salaried workers and the self-employed. Individuals with high-order cognitive skills (learning aptitudes and success as a salaried worker), a tendency to break the rules, and high self-esteem in adolescence are more likely to become successful long-term entrepreneurs in the United States (Levine and Rubinstein 2013). In the Netherlands, language and clerical abilities have a stronger impact on employees' wages, whereas mathematical ability, technical ability, and extraversion in early childhood are more valuable for entrepreneurs (Hartog, van Praag, and van der Sluis 2010). Moreover, entrepreneurs with a balance in abilities across different fields—that is, a jack of all trades—have higher incomes vis-à-vis salaried workers (Lazear 2005; Hartog, van Praag, and van der Sluis 2010).

3.b The Role of Skills and Traits in Labor Supply Outcomes

Skills, especially socio-emotional ones, influence individuals' participation in the labor market and probability of holding a job. As on earnings, conscientiousness has a large positive effect on labor participation in the United States and Germany as does extraversion and locus of control (Barrick and Mount 1991; Gallo *et al.* 2003; Caliendo, Cobb-Clark, and Uhlendorff 2010; Wichert and Pohlmeier 2010). By contrast, neuroticism and openness to experience have a negative effect in Germany, whereas agreeableness has a negative effect only on the labor force participation decisions of married women and no effect on other population subgroups (Wichert and Pohlmeier 2010). In the United States, a man who moves from the 25th to the 75th percentile of the distribution of locus of control and self-esteem would increase his probability of being employed at age 30 by 15 percent (Heckman, Stixrud, and Urzúa 2006). Behaviors of children in the United Kingdom affect significantly the probability of having work as an adult. Although hostility toward adults in childhood has a negative impact on the probability of being in employed in one's adult years, anxiety toward acceptance by adults has a positive and significant impact on

[10] People skills are defined as "the ability to effectively interact with or handle interactions with people, ranging from communication with to caring for to motivating them" (Borghans, ter Weel, and Weinberg 2013).

employment status (Carneiro, Crawford, and Goodman 2007). A potential explanation is that children who are maladjusted on this dimension are judged by their teachers to be overzealous, which may be better rewarded in the labor market. In Sweden, men with a lower level of leadership skills have a higher probability of being unemployed than men with lower low-order cognitive abilities (Lindqvist and Vestman 2011).

In Argentina and Chile, self-efficacy is the socio-emotional skill associated with higher labor force participation and the probability of being employed in both countries (Bassi *et al.* 2012). Other skills do not show strong association with labor force participation except that high-order cognitive skills are also associated with higher participation in the Argentine labor force. Patterns are almost entirely similar across the two countries.

Personality traits also drive occupational choices. Individuals partly select occupations that correspond to their orientations such as being a caring or a direct person in adolescence (Borghans, ter Weel, and Weinberg 2008, 2013). Cobb-Clark and Tan (2011) find that personality traits have a substantial effect on the probability of employment in many occupations, with gender specificities. The combination of skills and traits rather than single attributes also determines occupational outcomes. Kern *et al.* (2013) found that disagreeable intelligent individuals achieved higher occupational status, whereas disagreeable low-intelligent men were more likely to be unemployed or to work at a lower-status job.

3.c The Role of Skills in Schooling Decisions

Measures of cognitive and socio-emotional skills influence schooling decisions and a range of educational outcomes (Almlund *et al.* 2011). Cunha, Heckman, and Schennach (2010) estimate that 12 percent of the variance in educational attainment is explained by personality measures, and 16 percent is accounted for by cognitive ability measures. Using longitudinal surveys of children in the United Kingdom, the United States, and Canada, Duncan *et al.* (2007) discovered that mathematics, reading, and attention skills were strong predictors of later academic achievements. By contrast, measures of socio-emotional skills at school entry had limited power in explaining educational success.[11]

Among personality traits, conscientiousness is the main determinant of overall attainment and achievement, such as college grades (Almlund *et al.* 2011). Self-discipline and grit are also better predictors of the academic performance in the United States than IQ (Duckworth and Seligman 2005; Duckworth *et al.* 2007). Openness to experience also affects educational attainment, but predicts attendance and the difficulty of courses selected as well. Emotional stability—as captured by self-esteem and locus of control—also influences educational attainment such as graduating from a four-year college (Heckman, Stixrud, and Urzúa 2006).

[11] This could be explained by the fact that those measures of s*ocio-emotional* skills influence measures of cognitive skills and therefore underestimate their effect.

Misbehavior at a young age drives lower probabilities of staying longer in school in the United Kingdom and the United States (Carneiro, Crawford, and Goodman 2007; DiPrete and Jennings 2012; Segal 2013). Technical abilities, a subset of cognitive skills, influence the probability of going to college. By contrast to cognitive and socio-emotional skill levels, in the United States a higher level of vocational ability is associated with a lower probability of attending a four-year college because individuals with higher technical skills expect higher returns from a vocational education (Prada 2013; Prada and Urzúa 2014).

Finally, there are substantial differences between young boys and girls in their acquisition of skills from kindergarten to fifth grade. Boys and girls have roughly the same academic return to socio-emotional skills, but girls begin school with more advanced social and behavioral skills and their skill advantage grows over time (DiPrete and Jennings 2012).

4. Data

The analysis in this paper is based on the Skills toward Employment and Productivity (STEP) Household Survey, a multicountry study led by the World Bank. The survey covers a wide range of background information, similar to a standard household survey, which includes demographics, education, employment and compensation, household wealth, and household size and composition (World Bank 2014). In addition, a randomly selected individual in each household between the ages of 15 and 64 is further surveyed and tested on information related to basic cognitive skills, socio-emotional skills, personal health, and use of skills on and off the job.

The STEP Household Survey of Colombia is representative of the country's 13 main cities and their metropolitan areas—that is, it covers the large majority of Colombia's urban population and is the area widely used by labor market household surveys in the country. The sample size is 2,617. The distribution in age, gender, and education attainment is similar to that for national household surveys for the same urban areas.

Measures of cognitive skills. Unless otherwise stated, the following sections of this paper use a measure of reading proficiency, a lower-order cognitive skill, produced from an advanced test developed by the Educational Testing Service (ETS).[12] *Reading proficiency* is defined as the ability to "understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (OECD 2012). In this respect, reading proficiency is a broader construct than "reading," narrowly understood to be a set of strategies for decoding written text. It is intended to encompass the range of cognitive strategies (including decoding) that adults must bring into play to respond appropriately to a variety of texts of different formats and types in the range of situations or contexts in which they read (OECD 2013). To increase the accuracy of the cognitive measurement, the survey provides a set of 10

[12] 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.

"plausible values" that are unbiased estimations of the plausible range of reading proficiency for groups of individuals (Von Davier, Gonzalez, and Mislevy 2009; OECD 2013; ETS 2014). Plausible values are multiple imputations, drawn after data collection, by combining test results with all available background information such as gender, age, and education. This procedure, based on item response theory, allows one 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. The scale of plausible values ranges from 0 to 500. A higher score signifies a higher measured proficiency. In practice, each estimation is repeated 10 times for each plausible value. The average coefficients and standard errors of the 10 estimations are reported.

Measures of socio-emotional skills. The survey provides six measures of personality traits (relatively enduring patterns of thinking, feeling, and conduct) and two measures of behaviors and attitudes (how individuals manage interpersonal and social situations). The core of the socio-emotional skills inventory is based on the Big Five model, a widely used taxonomy of broad families of personality traits, which include the following dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability (John and Srivastava 1999). The inventory also includes items that allows one to measure the following: grit, a trait of perseverance and motivation to meet long-term goals (Duckworth *et al.* 2007); hostile attribution bias, a tendency to interpret others' intents as hostile, which in return fosters one's antisocial and aggressive behavior (Dodge 2003); and the Melbourne Decision Making Scale, which captures coping strategies for decisional conflict (Mann *et al.* 1997)—see table 1 for brief definitions of the socio-emotional skills in the survey and items used for the construction of scores of these skills. Like most surveys aiming to measure socio-emotional skills, the STEP Household Survey includes a battery of 24 self-reported items, designed by developmental and personality psychologists, that are mapped to the eight domains (skills) just listed. For example, one questionnaire item mapped to conscientiousness asks, "When doing a task, are you very careful?" Each socio-emotional skills score is the result of the aggregation of these predefined items (three on average for this survey). The response categories for each item range from 1, "almost never," to 4, "almost always." The aggregation of items onto domains is done through an inter-item average—that is, a weighted average of pre-assigned items based on all possible pairs.[13]

5. Empirical Strategy

The objective of this research is to investigate the distinct contribution of cognitive and socio-emotional skills to labor market outcomes—labor earnings, labor force participation, and occupational choices—and a measure of educational trajectory—pursuing a tertiary education.

[13] Empirical studies often perform exploratory factor analyses or the like to produce s*ocio-emotional* skills factors from the inventory of questions. However, the limited number of items available in the STEP survey prevented us from using such a method. The inter-item average approach has been empirically validated by lead psychologists who advised the World Bank STEP Core team and was performed with Stata's *alpha* command (World Bank 2014). Ultimately, it eases the interpretation of skill domain scores because items are preassigned to specific skills.

In other words, this study examines how those skills, however acquired, matter for these outcomes.

We draw our analysis from three types of estimates. The preferred approach uses a structural estimation of latent skills that corrects for possible measurement error in our survey-based measures of skills—see, for example, Carneiro, Hansen, and Heckman (2003) and Heckman, Stixrud, and Urzúa (2006). Because of its high data requirements and our data set, this technique can only be performed by aggregating skill measures into two factors: latent cognitive skills and socio-emotional skills. We therefore also present conventional approaches based on OLS and logit estimations to appreciate the effect of nine disaggregated measures of skills (one cognitive, eight socio-emotional) at the cost of the larger potential estimation bias. Finally, we also explore instrumental variable techniques, as a robustness check, to correct for potential measurement error and reverse causality between outcomes and measures of skills.

In view of our research question, we do not investigate the distinct effects of education and skill stocks on outcomes. Schooling, cognitive skills, and socio-emotional skills are interrelated and influence each other. Distinguishing their respective effects is technically challenging and can lead to severe estimation bias when considered simultaneously in a standard regression model—an issue not addressed in the literature of the early 2000s (see Cawley, Heckman, and Vytlacil 2001; Heckman, Stixrud, and Urzúa 2006). Not controlling for schooling in linear estimations, such as a wage equation, can lead to overestimations of the net effects of measures of skills on wages but capture the whole effect of skills, independently of where they were formed (Heckman, Stixrud, and Urzúa 2006). We present both results controlling and not controlling for education, but we prioritize the approach excluding schooling for the interpretation.

5.a Conventional Approach

The first empirical approach follows a standard Mincer-like specification 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 socio-emotional skills (such as conscientiousness) that affect the labor market outcome; and X_i is a set of factors (other than skills) that affect Y_i.

True skills C_i and SE_i are unobserved (latent). A common proxy for skills is years of schooling or school levels. However, educational attainment is a poor measure of actual scholastic ability because (1) many of the skills and personality traits that shape an individual's success are acquired outside the classroom, and (2) students acquire skills at each level of schooling very differently across schools and countries (Hanushek and Woessmann 2008). Nonetheless, the Colombia

STEP Household Survey provides a set of measures, or test scores, T_i, that capture various dimensions of cognitive and socio-emotional skills.

Assuming that T_i measures all skills that are captured in equation (1), we can rewrite the equation as

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

Under the assumption that our sets of T_i perfectly measure all C_i and SE_i, we can estimate equation (2) using OLS or logit regressions without any ability bias, and β1 and β2 will give us the return to each skill captured by the vectors T_i^C and T_i^{SE}. However, a growing literature shows that measured skills, captured by the vector T_i, capture C_i and SE_i with error, so $\mathrm{Cov}(T_i, \vartheta_i) \neq 0$ could be possible (Borghans, Duckworth, Heckman, and ter Weel 2008; Hansen, Heckman, and Mullen 2004). In that case, measurement error and omitted variable bias produce biased estimates of $\square_1$ and $\square_2$.[14] The estimations featured in the next sections use the OLS and logit specifications as a benchmark for comparison with alternative methods.

5.b Structural Estimation

An alternative to OLS and logit estimations to solve measurement error and omitted variable bias is to conduct a structural estimation of latent skills based on a measurement system of test scores (Keane and Wolpin 1997; Cameron and Heckman 2001; Heckman, Stixrud, and Urzúa 2006; Urzúa 2008; Sarzosa and Urzúa 2013, 2014). The outcomes of interest, Y, are a function of the latent skills and other factors influencing them, as depicted by the reduced-form equation

$$Y = \alpha_A^Y \theta_A + \alpha_B^Y \theta_B + X_Y \beta^Y + e^Y \tag{3}$$

where, θ_A and θ_B are the latent factors or dimensions of unobserved heterogeneity; β^Y, α_A, and α_B^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_A, and θ_B.

The need for a structural estimation relies in the assumption that θ_A and θ_B are unobservable—that is, the measures or scores available in the data are only proxies of the true latent variables that we want to use for the estimation (Bartholomew, Knott, and Moustaki 2011). They are treated as realizations of the "score-production function" presented in (4), whose inputs are observable and unobservable characteristics, which is written as

$$T = X_T \beta^T + \alpha_A^T \theta_A + \alpha_B^T \theta_B + e^T \tag{4}$$

[14] Test scores are sensitive to the amount of schooling completed at the time of the test and family background (Hansen, Heckman, and Mullen 2004). Furthermore, the measures of ability are known to be very noisy. Thus using test scores as an independent variable in regression model analysis could lead to measurement error bias.

where T is an $L \times 1$ vector of 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_A, θ_B, and e^Y. In this sense, the model comprises a measurement system (i.e., outcomes, test scores, observable controls, and error terms) that is linked by latent factors or unobserved heterogeneity (i.e., θ_A and θ_B). In this case, the identification assumption takes e_Y and e_T as mutually independent conditional on (□, *X*).

The system of production functions of test scores (6) can then be used to non-parametrically identify the distributions of the latent abilities $f_{\theta_A}(\cdot)$ and $f_{\theta_B}(\cdot)$, their coefficients (α_A and α_B), and the diagonal matrix of their variance, Σ_θ.[15] The coefficients of latent factors, α_A and α_B, can be identified up to one normalization—that is, one coefficient is set to equal to 1 and the rest will be interpreted relative to the one chosen as numeraire. The two main restrictions to this procedure are (1) the assumption that latent skills factor θs are orthogonal and independent of each other, and (2) that the system includes at least three test scores per skill (Carneiro, Hansen, and Heckman 2003; Kotlaski 1967).[16] Estimating 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 that are followed by the unobserved heterogeneity in order to be able to integrate it away in a maximum likelihood procedure.[17] The likelihood function is then

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

Maximizing (5), we can retrieve all the parameters of interest, β_Y, β_{T_τ}, α_A^Y, α_B^Y, $\alpha_A^{T_\tau}$, $\alpha_B^{T_\tau}$ for $\tau = \{1, 2, 3, 4, 5, 6\}$, and the parameters (i.e., the means, standard deviations, and mixing probabilities) that describe the distributions $f_{\theta_A}(\cdot)$ and $f_{\theta_B}(\cdot)$.

5.c Robustness Checks: Exploring Instrumental Variable Estimations

In both conventional and advanced methods, the causal effects of our measures of skills on labor market outcomes can hardly be claimed because of the simultaneity of the observation of both the outcomes of interest and the measures of skills. Because we use cross-sectional data, reverse

[15] 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).

[16] Carneiro, Hansen, and Heckman (2003) actually propose a slightly milder condition, $L > 2k + 1$, where *k* is the number of latent factors in the system.

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

causality could be at play if a labor market outcome of interest would also influence its expected determinants such as measured skills (Carneiro and Heckman 2004). For example, although personality is often viewed as fairly stable over the life course, evidence from the United States and Germany suggests that participation in the labor market affects personality traits such as emotional stability, agreeableness, conscientiousness, and openness to experience (Gottschalk 2005; Boyce *et al.* 2015).

One approach to providing a consistent estimate even in the presence of measurement error and simultaneity is to perform an instrumental variable method (Angrist and Krueger 2001). This two-stage procedure relies on the use of an instrumental variable, Z_i, that is correlated with T_i^C and T_i^{SE} but not with the error term ϑ_i. For example, the proximity to school might be correlated with skills acquired through schooling but not with wages. The first stage estimates

$$T_i = \pi_0 + \pi_1^T Z_i + \pi_2^T X_i + u_i \tag{6}$$

and relates to the reduced-form equation as

$$Y_i = \pi_0 + \pi_1^Y Z_i + \pi_2^Y X_i + \varphi_i. \tag{7}$$

The IV approach is not straightforward and can also generate a number of pitfalls. The weaknesses of the approach are multiple, including the difficulty in selecting a meaningful instrument, highly correlated with T_i, and the need to select an IV for each T_i (many of which are produced through similar processes).[18] Invalid or weak instruments can lead to severe result bias (Murray 2006). For that reason, we use IV results as a robustness check—to inquire whether the relationships between labor outcomes and skill measures are generally consistent over estimation methods holding distinct sets of assumptions.

6. Descriptive Statistics

This section presents some descriptive statistics on the distribution of skills across gender, age groups, and educational levels of the working-age population. These distributions are not conditional on other observable and unobservable characteristics of individuals.

Reading proficiency levels are significantly different across educational level and generations but not gender. The distribution of scores is highly correlated (as expected) with educational level, though not perfectly (figure 1). In particular, the difference in mean levels between those with a secondary and tertiary education is not as pronounced as that between those with a primary and secondary education. On top of that, there are significant overlaps across education levels, suggesting that the completion of a schooling level does not necessarily guarantee a certain level of cognitive skills. The heterogeneity of reading proficiency within educational levels justifies

[18] For a discussion of these challenges, see Heckman, Stixrud, and Urzúa (2006), Heckman and Urzúa (2010), and the sources cited therein.

the focus on individuals' skills, rather than educational achievement. While gender differences in reading proficiency are negligible, the distribution of scores among the young (15–24) is higher than among adults (25–49), a signal that suggests improvement over generations in the ability to understand and analyze written texts (also possibly correlated with educational levels) or that this ability tends to depreciate with aging.

In terms of socio-emotional skills (figures 2, 3, and 4), differences across gender, age, and educational level are less noticeable. Across gender, and among all possible dimensions covered by the survey, men and women show slight differences in distribution of the conscientiousness, emotional stability, grit, decision-making, and hostile attribution bias scores. The most noticeable is the fact that males tend to score higher on the emotional stability scale than women, that is, reporting to be more able to manage emotions and stressful situations. By age, the only differences are registered for agreeableness, emotional stability, grit, and hostile attribution bias, with the young scoring lower than adults across these dimensions. Finally, there are significant differences in socio-emotional skill scores by educational level; in all cases except for hostile attribution bias (which is the opposite), less educated workers score lower on the scale.

Correlations among measures of cognitive and socio-emotional skills are often significant but rather modest. As shown in table 2, the correlation between reading proficiency and socio-emotional dimensions differs substantially, with openness to experience, decision making, and hostile attribution bias among the ones with a higher correlation but never higher than 0.25. Some socio-emotional dimensions are also relatively higher correlated among themselves—for example, extraversion with openness to experience (0.17); emotional stability with hostile attribution bias (–0.17); conscientiousness with grit (0.21), decision making (0.17), agreeableness (0.16), and openness to experience (0.16); openness to experience with decision making (0.29), agreeableness (0.20), and grit (0.20); agreeableness with grit (0.21) and decision making (0.17); and decision making with grit (0.21).

7. Results

7.a OLS Estimates

Our first set of results explores OLS estimates of the relationship between disaggregated measures of cognitive and socio-emotional skills and labor market outcomes. The first set of outcomes is for log hourly labor earnings (wage for salaried workers and net profits for self-employed), and these results are presented in table 3. The sample includes individuals between 15 and 64 years of age (both men and women).

The main conclusion is that, controlling for other observable characteristics such as gender, age, mother's education, and regional indicators, reading proficiency is positive and statistically significantly related to labor earnings. As for socio-emotional skills, only openness to experience seems to be significantly related to labor earnings. These results remain when all skill dimensions are included in the same regression. It is important to note that the estimates in table 3 do not control for educational level, and so the coefficients capture the full association between different skills dimensions and labor earnings, irrespective of whether these skills were formed at school, at work, or at home (Heckman, Stixrud, and Urzúa 2006).

Beyond labor earnings, skills dimensions also have distinctive relationships regarding labor participation outcomes and occupational choices, including the likelihood of being a formal worker, of being a high-skilled worker, of being employed, of being active or studying, or of having pursued a tertiary education. Reading proficiency is again positively related with the probability of being a formal or high-skilled worker, but socio-emotional skills seem to play no role in these outcomes—except for more hostile individuals having a higher probability of holding an informal job (table 4). However, some of these socio-emotional characteristics seem to be relevant for labor or educational choice paths. For example, conscientiousness and decision making are positively related with being employed and being active or in school (table 5). A higher scale in openness to experience, emotional stability, decision making, and hostile attribution bias seem to matter for pursuing a tertiary education. For comparison purposes, tables 4 and 5 also include regressions that control for the educational level of the individual, the only difference being in the role of reading proficiency, which becomes nonsignificant (except for being a high-skilled worker), suggesting that educational level is the signal to which the job market responds and that it serves as a guarantee of the reading proficiency the employer is buying when hiring an individual with a given educational level.

Tables 6 and 7 present results for different gender, age, and education subgroups.[19] The main findings are that reading proficiency (without controlling for education) remains positive and statistically significant in relation to wages across gender and age, but only among the more educated individuals—that is, those with at least a complete upper secondary education (nine years of schooling). By contrast, it is only related with labor force or school participation among females, young people (less than 35 years old), and less educated workers (maximum incomplete upper secondary education). As for socio-emotional skills, the role of openness to experience in wages seem relevant only among males, older, and more educated workers. The role of socio-emotional skills in explaining labor and schooling decisions also has different effects across subgroups. Strikingly, among males socio-emotional skills do not play any role in occupational decisions.

7.b Structural Estimation

As stated earlier, we can also estimate the effect of latent skills on labor market outcomes using structural estimation methods as developed in Keane and Wolpin (1997); Heckman, Stixrud, and Urzúa (2006); and Sarzosa and Urzúa (2014). As opposed to the OLS and logit estimates presented earlier, this method can mitigate measurement error concerns because it relies on

[19] Only two outcomes are showcased: hourly earnings and being active or in school. Results for other labor market outcomes for subgroups are available upon request.

latent skills that fully capture their relationship with outcomes abstracting from single (and potentially poor) measures of skills.

To apply this method, we constructed an adjunct measurement system that comprises scores in two dimensions: cognitive skills and socio-emotional skills. Identification in this set-up requires at least three test scores per dimension explored—that is, we had to construct three scores that provided information about socio-emotional skills and three scores about cognitive skills.

To obtain the factor of latent socio-emotional skills, we aggregated the scale of extraversion with the measure of openness to experience into one score, the measure of emotional stability with the measure of hostile attribution bias into a second score, and the measures of conscientiousness, grit, and decision making into a third score. The aggregation of these measures into three test scores was needed to secure the necessary smoothness in the measurement system because all of these measures come from categorical answers. The pairing of the measures is based on the correlations among them (table 2).

To obtain the measurement system needed to identify the factor of latent cognitive skills, we used the following scores: (1) a measure of language captured by a weighted average of reading components measured by the reading proficiency test—average print vocabulary, sentence processing, and passage comprehension (ETS 2014, World Bank 2014); (2) a measure of use and length of the reading undertaken on and off the workplace; and (3) a plausible value of reading proficiency, from the direct assessment, randomly chosen among 10.

Using these scores and exogenous controls such as age, gender, mother's education, and city of residence, we estimated the system of equations described in equations (3) and (4) of section 5.b.[20] The purpose of these estimations is to retrieve the components of the unobserved heterogeneity free of the exogenous characteristics that can affect the scores we observe. These estimations are presented in tables 8 and 9. For example, people with more educated mothers are more likely to have a broader vocabulary and thus score higher on the average print vocabulary, even if latent cognitive skills are unchanged.

More important than these coefficients are the estimated distributions of the unobserved heterogeneity obtained from these estimations. These distributions are used to structurally model the unobserved heterogeneity in the outcome equations. Figure 5 presents the variance decompositions of the scores. It shows that the latent factors explain large proportions of the variance of many of the scores. The clean variation is the one we identify as the latent skill or unobserved heterogeneity.

Having estimated the distributions that describe cognitive and socio-emotional skills, we estimate their relationship with labor market outcomes. The results presented in table 10 indicate that the unobserved heterogeneity matters in almost every outcome we analyzed, yet in very

[20] All the estimations presented in this section were implemented using the *heterofactor* command in Stata developed by Sarzosa and Urzúa (2014).

different ways.[21] Socio-emotional skills matter in choices such as participating in the labor market and attending college—that is, socio-emotional skills prevent inactivity among those members of the population working and studying, although the probability of attending college is also highly correlated with cognitive skills. Once in the labor market, cognitive skills are the ones related with higher probabilities of formally working, being a high-skilled worker, and earning more. In fact, our results indicate that an increase in one standard deviation in reading proficiency is associated with an increase of 12.5 percent in earned hourly labor earnings.

Given the unobserved nature of our traits of interest, we must rely on simulations in order to interpret our results and better describe the size of the relations of interest here. We present the expected outcome as a function of the unobserved heterogeneity. Therefore, because we estimated two dimensions of such heterogeneity, we present three-dimensional graphs that represent

$$E[Y|\theta_A, \theta_B] = E[X\beta] + \alpha_A\theta_A + \alpha_B\theta_B \qquad (8)$$

In that sense, we randomly draw θ_A and θ_B from the distributions estimated in the first-step estimations (described in tables 8 and 9) and construct $E[Y|\theta_A, \theta_B]$ based on the draws, the exogenous controls, and the estimates for β, α_A, and α_B. This way, we clearly see how the unobserved skills relate with the outcome variable.[22] Interpretation is also aided by the fact that the scale of the unobserved heterogeneity is presented in terms of the deciles of their respective distribution.

The probability of being active either in the labor force or as a student is higher as socio-emotional and cognitive skills increase (Figure 6). Although the low-skilled population (both in the cognitive and socio-emotional dimension) has a 78 percent probability of being active, the high-skilled population has a 95 percent probability of being so. If focused on only one dimension, we see that, other things being equal, a person gains 9 percentage points in the probability of being active if taken from the first to the 10th decile in the distribution of socio-emotional skills. In the same way, an increase of 5.8 percentage points in the probability of being active is associated with taking a person from the first to the 10th decile of the distribution of cognitive skills.

Figure 7 reveals that the relationship between going to college and skills is even stronger. Those with the lowest levels of skills have almost no chance of going or having gone to college (only 1.5 percent), whereas those with the highest levels of skills have an 83 percent probability. Although both set of skills are correlated with this outcome, the size of such a relationship is dramatically different. Changing a person's socio-emotional skills increase the probability of going or having gone to college by 17.7 percentage points. The increase rises to 71.2 percentage

[21] Consistent with the previous preferred specification, these estimations do not control for education.

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

points when we compare those in the first decile with those in the 10th decile of the cognitive skill distribution, leaving everything else constant.

The size of these relationships contrasts with the ones that arise when we analyze the probability of being employed. Figure 8 shows that the probability of being employed remains unchanged at about 75 percent in the entire skills space. However, once the decision of working is out of the way, the quality of the job does correlate with skills—in particular, with cognitive skills.

Figures 9, 10, and 11 attest to this. For example, figure 9 shows that, all else being held constant, the likelihood of having a formal job increases by 28 percentage points (i.e., more than doubles) when a person in the first decile is compared with one in the 10th decile of the cognitive skill distribution. In the same way, workers with higher cognitive skills are 26.7 percentage points more likely to have (or have had) a high-skilled job than low-skilled workers, who have a 28 percent probability of doing so (figure 10. Also, workers with highest scores in reading proficiency can earn up to Col$3,000 (US$1.50) more per hour than those in the lowest scale, which is roughly 50 percent more (figure 11).

7.c IV Estimates

In order to crosscheck our results from the OLS and structural estimations, we explored IVs in an attempt to provide estimates free of measurement error, omitted variable bias, or reverse causality. For that, we needed a set of instruments Z_i that correlated with the skills set T_i in equation (3), but not with the error term υ_i.

Among the possible instruments that could be appropriate and available in the Colombia STEP Household Survey, we selected the age at which a person started school and the economic situation of the household at age 12 (a self-reported variable based on a scale of from 1 to 10) as suitable instruments for the reading proficiency score. The idea is that reading proficiency is a skill that is likely to be fostered in school at a young age and to be influenced by a child's economic and family environment (Cawley, Heckman and Vytlacil 2001; Carneiro and Heckman 2004,). For each socio-emotional skill, we used the indicator of whether the individual lived with both parents at age 12, and again the economic situation of the household at age 12. As for cognitive skills, socio-emotional ones are greatly shaped by family and social environment (Carneiro, Hansen, and Heckman 2003; Cunha *et al.* 2006). These instruments pass the Sargan-Hansen test of overidentified restrictions, and the first stages show they are not weak, as they are thought to be by Stock, Wright, and Yogo (2002).

Table 11 presents the main results of the IV estimation (second stage) for each labor market outcome, considering just one skill dimension at a time in each regression (for presentational purposes, the coefficients from different regressions for same outcome are presented in one column). Most of the results found using OLS remain, and generally of the aggregated latent factors. In particular, IV estimations seem to confirm that only reading proficiency seems to matter for explaining earnings rather than socio-emotional skills. No set of skills is significant for the probability of being a formal worker, of being employed, or being active or in school. By contrast, reading proficiency and several socio-emotional skills (conscientiousness, emotional stability, grit, and hostile attribution bias) seem to be significantly related with the probability of being a high-skilled worker, or having pursued a tertiary education.

8. Conclusion

Using a unique data set that measures cognitive (reading proficiency) and socio-emotional skills (personality traits and behaviors) for Colombia, we have documented the role that these skills play in the labor market by looking at different outcomes for different subsets of the population and different methodologies (OLS, IVs, structural estimation of latent skills). Our preferred approach, structural estimation of latent skills, can estimate more accurate conditional correlations between labor market outcomes and cognitive and socio-emotional skills in an aggregated form.

Across all methods, one result came up quite consistently: cognitive skills (in particular, reading proficiency) are an important predictor of earnings and quality job. For example, using our preferred methodology one standard deviation in the scale of reading proficiency can increase hourly wages by 12.5 percent. Reading proficiency is also an important predictor of being a formal or high-skilled worker. This result is consistent with previous findings such as Murnane, Willett, and Levy (1995); Murnane *et al.* (2000); Altonji and Pierret (2001); Cawley, Heckman, and Vytlacil (2001); and Hanushek and Woessmann (2008) for the United States.

By contrast, the role of socio-emotional skills seems quite different. Across all the methodologies explored, they do not seem to play any significant role in explaining wage levels or job quality, although this finding is at odds with previous literature for the United States such as Bowles, Gintis, and Osborne (2001a, 2001b) and Drago (2011). But they do seem to play an important role as a predictor of labor force participation and schooling decisions, along with cognitive skills, as found in Carneiro, Crawford, and Goodman (2007) and Almlund *et al.* (2011).

Some results emerge as differential for different subgroups (because of data limitations, it was only possible to perform this breakdown using OLS methods). For example, socio-emotional skills are a more important predictor of labor force participation among women, younger people (under 35), and less educated workers (less than a complete secondary education). By contrast, cognitive skills seem more relevant for explaining wage levels among males, older people, and more educated workers.

These results have important policy implications for school and vocational training programs in terms of curricula, where the combination of development modules of cognitive and socio-emotional skills would play quite distinctive roles, depending on the immediate policy objective— namely, improving job quality or fostering higher labor market participation or tertiary education. Given the influence of family environments on skill formation, there is also a great role to play for parenting and extra-curricular activities to foster cognitive and socio-emotional skills. In any case, further research is needed on the optimal combination of packages for different demographic and socioeconomic population groups, rarely systematically incorporated into the education system, particularly in developing countries.

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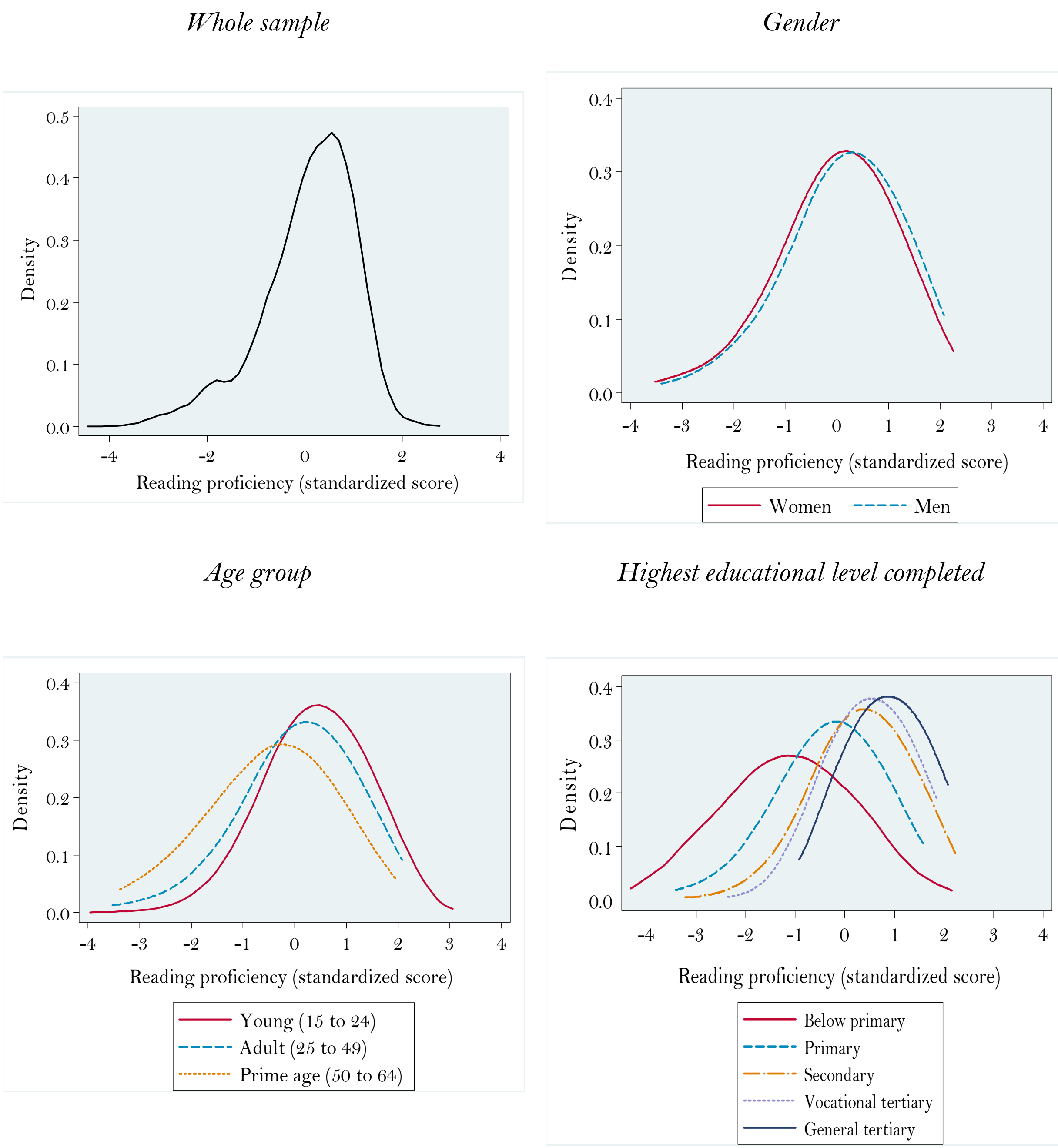
Figure 1 Distribution of Reading Proficiency across Groups of Interest, Colombia

Kernel densities of standardized reading proficiency scores

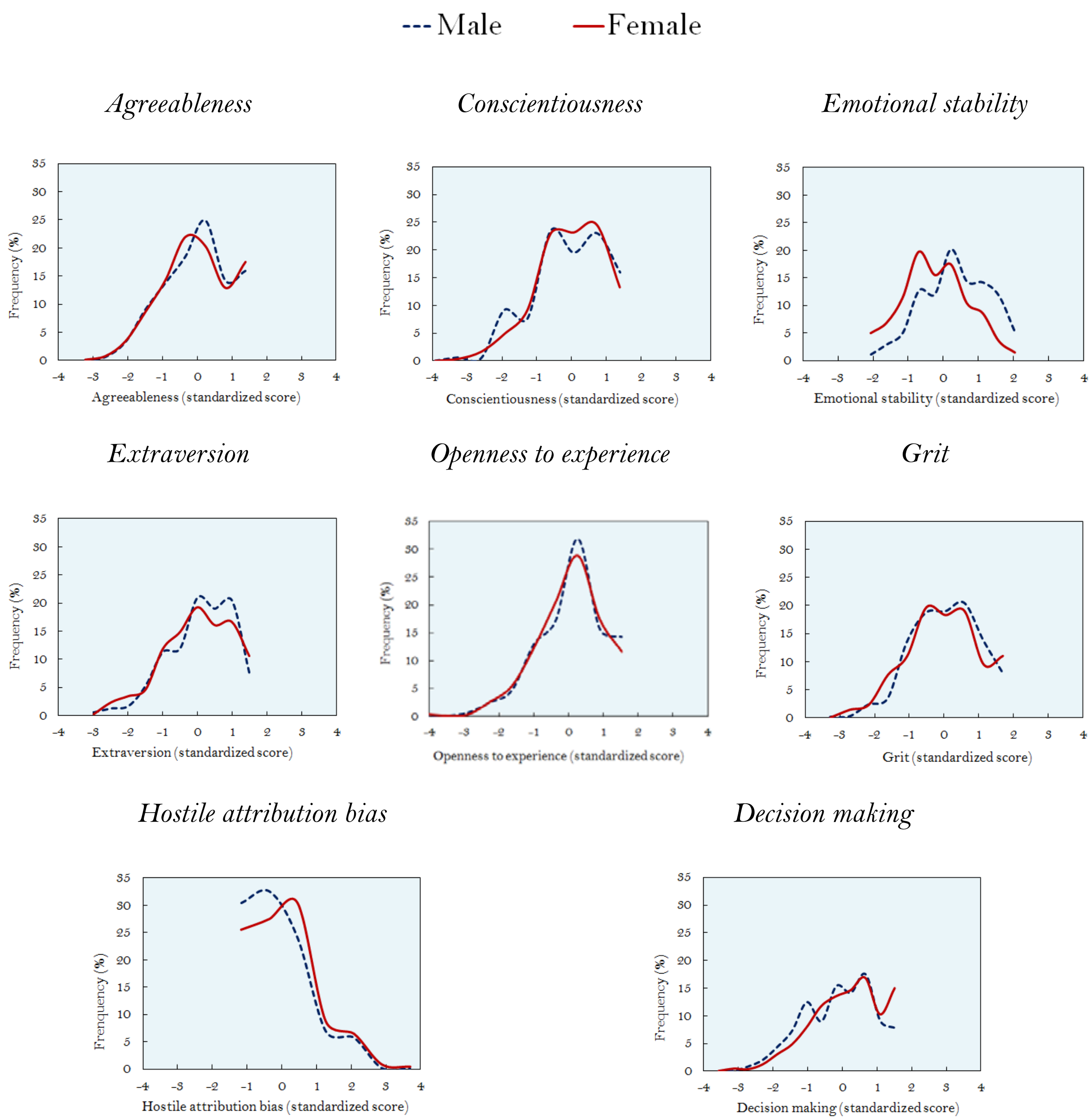


Source: Authors' calculations based on Colombia STEP Household Survey (2012).

Note: Differences in the distribution of reading proficiency scores are significant at the 95 percent level for age and educational levels (not across gender), based on two-sample Kolmogorov-Smirnov tests.

Figure 2 Distribution of Socio-emotional Skills across Gender, Colombia

Share of individuals by socio-emotional skills scores across gender

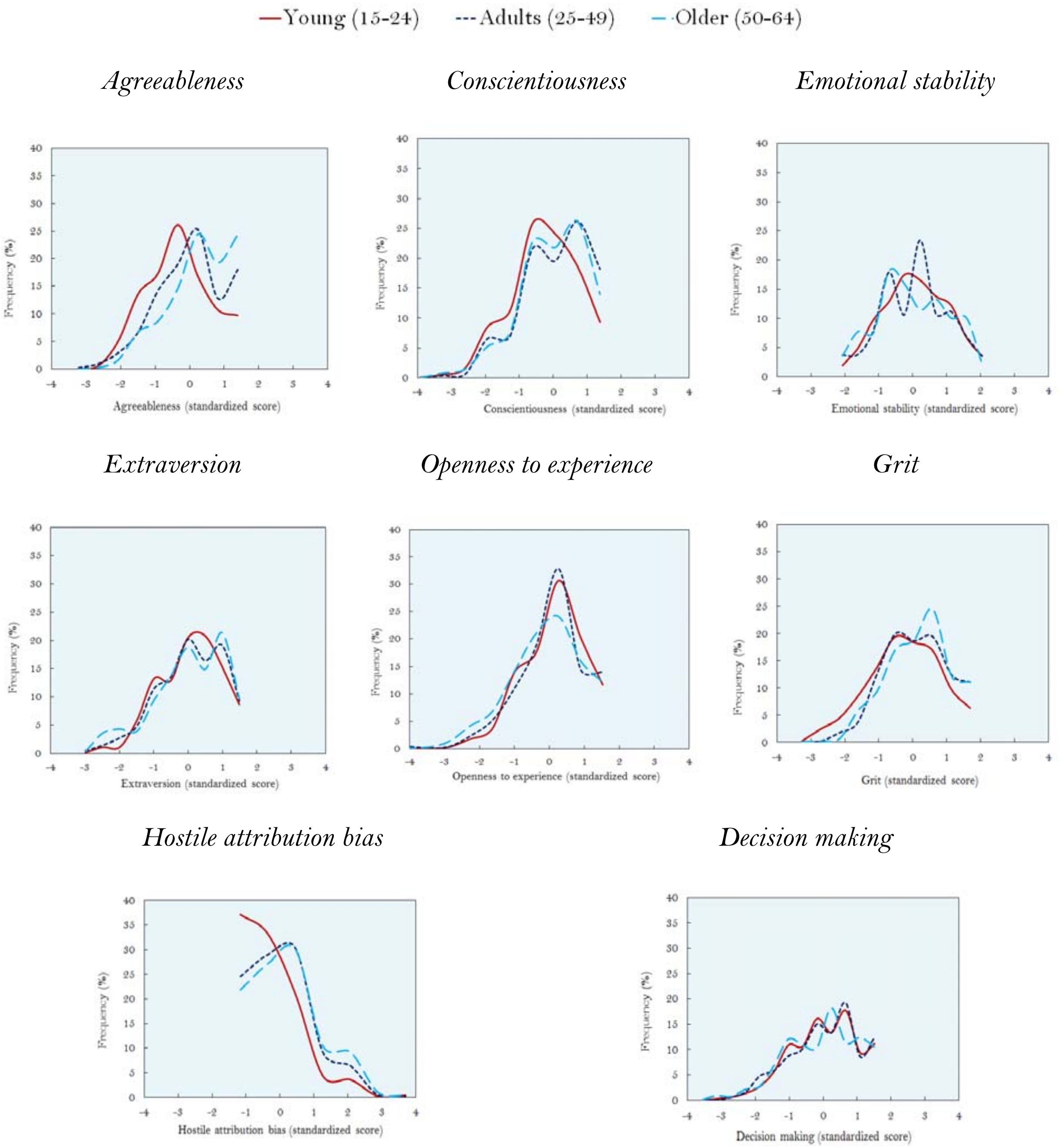


Source: Authors' elaboration based on Colombia STEP Household Survey (2012).

Note: The graphs represent scatter plots with smoothed lines based on tabulations of the standardized scores of socio-emotional skills across gender. Differences in the distribution of conscientiousness, emotional stability, grit, decision making, and hostile attribution bias are significant at the 95 percent level based on Pearson's chi-square tests.

Figure 3 Distribution of Socio-emotional Skills across Age Groups, Colombia

Share of individuals by socio-emotional skills scores across age groups



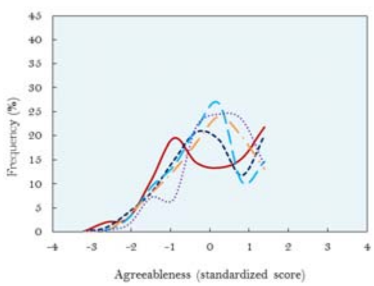
Source: Authors' elaboration based on Colombia STEP Household Survey (2012).

Note: The graphs represent scatter plots with smoothed lines based on tabulations of standardized scores of socio-emotional skills across age groups. Differences in the distribution of agreeableness, emotional stability, grit, and hostile attribution bias are statistically significant at the 95 percent level between at least at two levels based on Pearson's chi-square tests performed two levels by two.

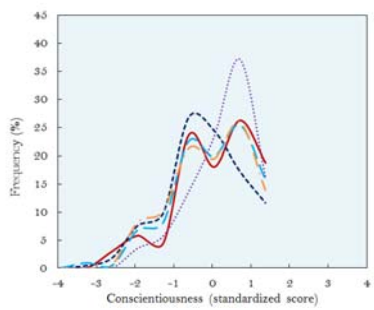
Figure 4 Distribution of Socio-emotional Skills across Highest Educational Level Completed, Colombia

Share of individuals by socio-emotional skills scores across educational levels

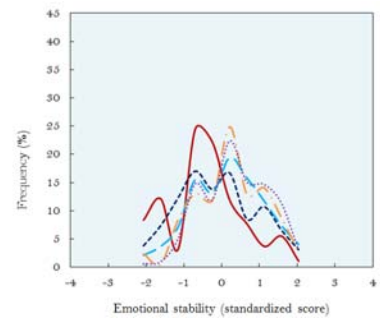
Agreeableness



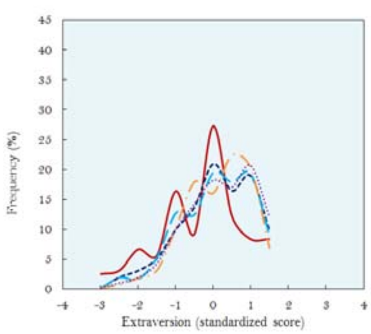
Conscientiousness



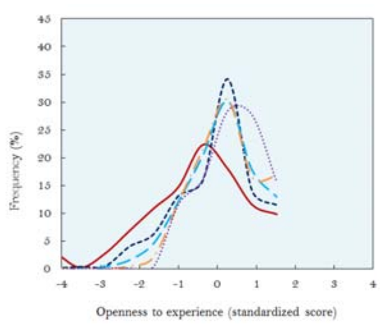
Emotional stability



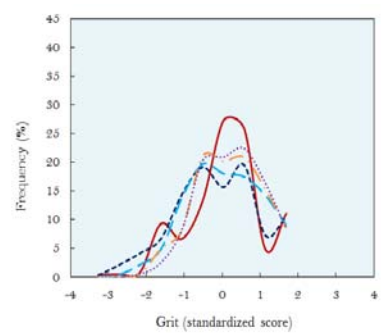
Extraversion



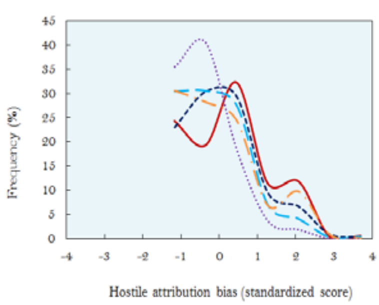
Openness to experience



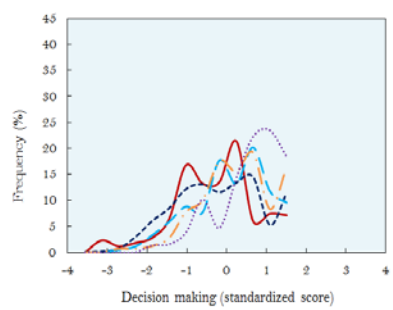
Grit



Hostile attribution bias



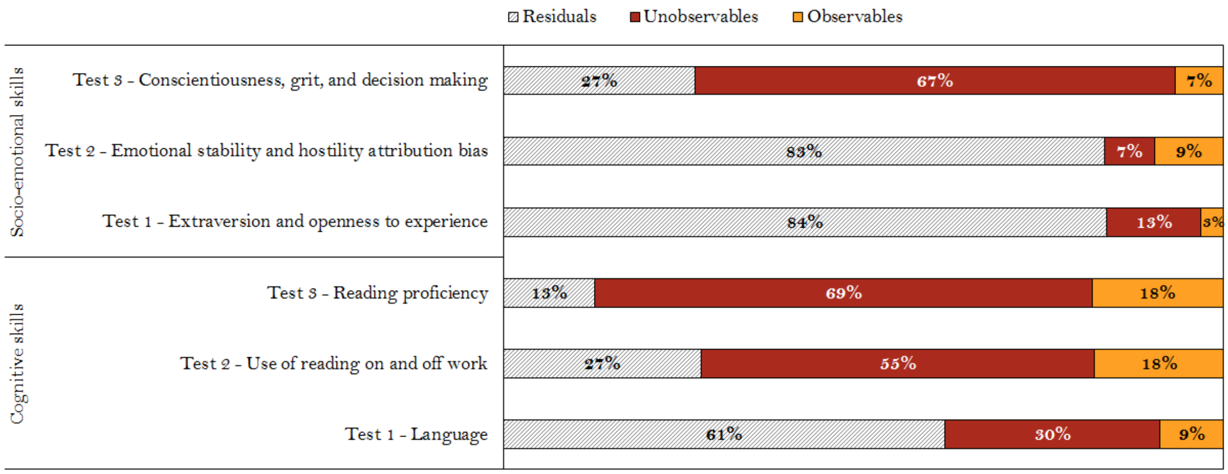
Decision making



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

Note: The graphs represent scatter plots with smoothed lines based on tabulations of standardized scores of socio-emotional skills across highest completed educational level. Differences in the distribution are all statistically significant at the 95 percent between at least at two levels based on Pearson's chi-square tests performed two levels by two.

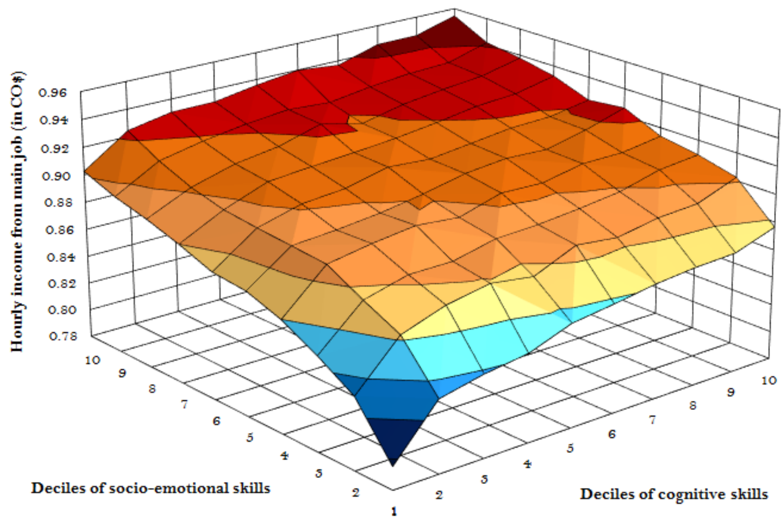
Figure 5 Variance Decomposition of the Tests Forming Socio-emotional and Cognitive Skill Factors Used for Structural Estimation, Colombia



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

Note: Factors of latent cognitive and socio-emotional skills are obtained from a measurement system of three "test scores" for each. Measures of socio-emotional skills were averaged into three tests to satisfy the necessary smoothness in the measurement system because all of these measures come from categorical answers; measures were paired based on the correlations among them (see table 2). To obtain the measurement system identifying the factor of latent socio-emotional skills, the scale of extraversion was aggregated with the measure of openness to experience (test 1), the measure of emotional stability with the measure of hostile attribution bias (test 2), and the measure of conscientiousness with the measures of grit and decision making (test 3)—see definitions in table 1. To obtain the measurement system identifying the factor of latent cognitive skills, we used the following tests: (1) a measure of languages captured by a weighted average of reading components measured by the reading proficiency test—average print vocabulary, sentence processing, and passage comprehension (World Bank 2014); (2) a measure of use and length of the reading done on and off the workplace; and (3) a plausible value of reading proficiency, from the direct assessment, randomly chosen among 10 (ETS 2014).

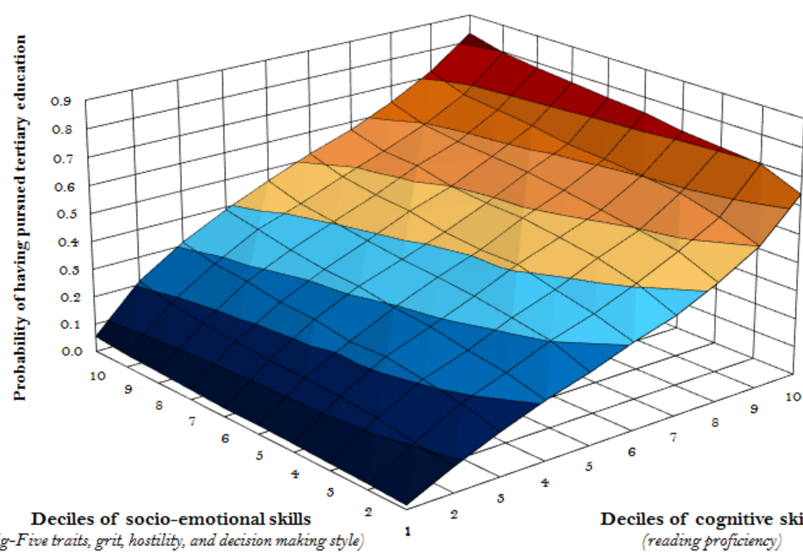
Figure 6 Probability of Being Active or in School by Skill Deciles, Colombia



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 (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

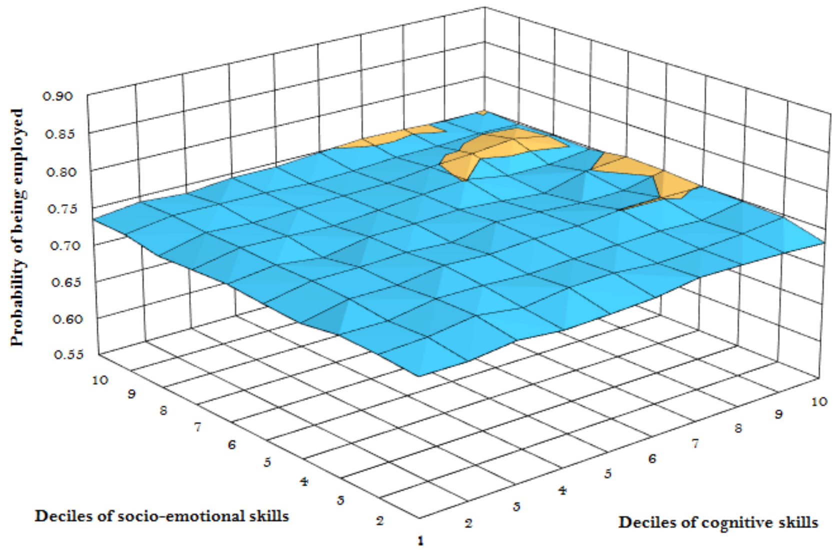
Figure 7 Probability of Having Pursued Tertiary Education by Skill Deciles for Adults Aged 25–64, Colombia



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 (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

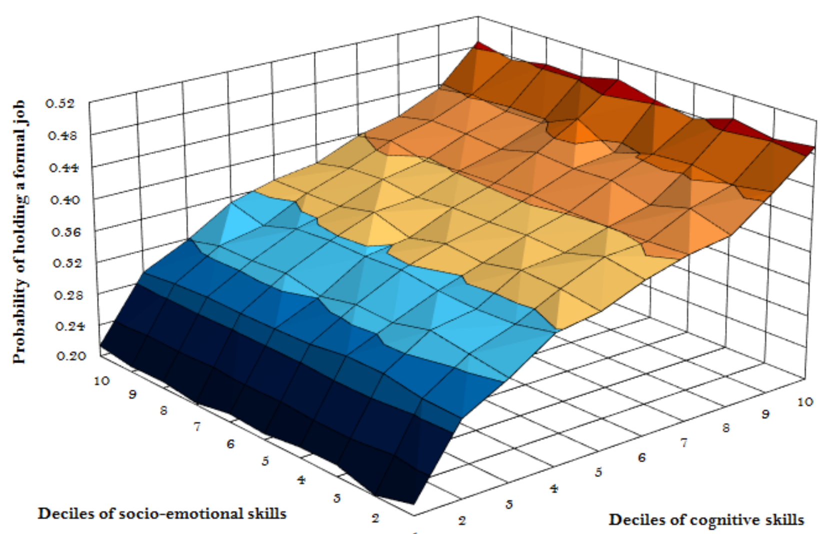
Figure 8 Probability of Being Employed by Skill Deciles for Adults Aged 19–64, Colombia



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 (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

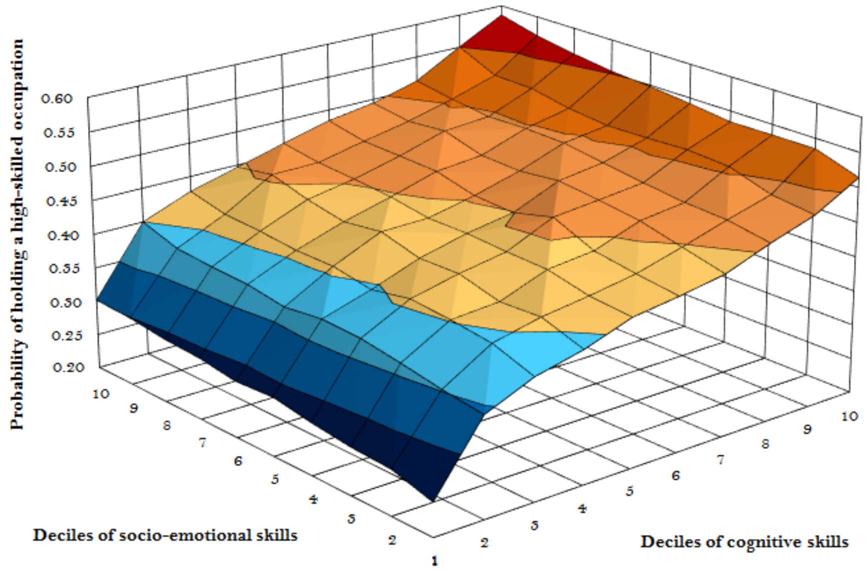
Figure 9 Probability of Holding a Formal Job by Skill Deciles, Colombia



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 (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

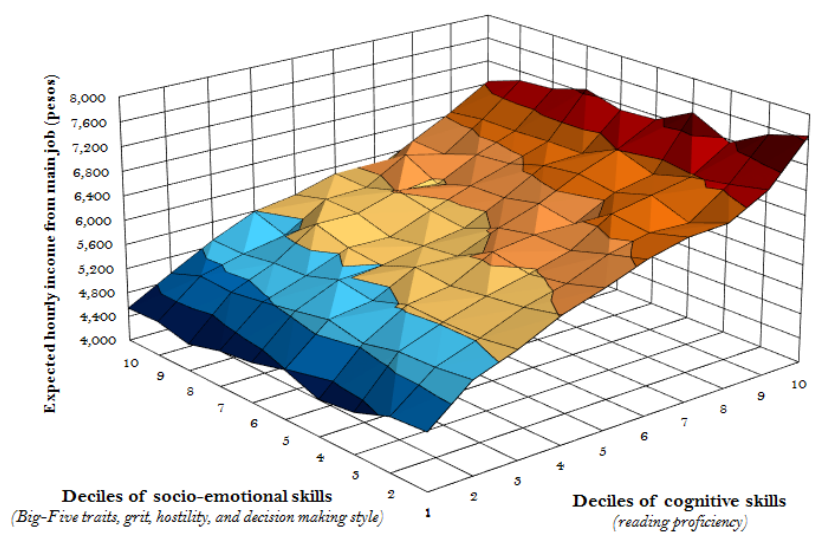
Figure 10 Probability of Holding a High-Skilled Occupation (versus Holding a Low- or Middle-Skilled Occupation) by Skill Deciles, Colombia



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

Note: Simulations based on structural estimations of latent skills factors using Sarzosa and Urzúa (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

Figure 11 Hourly Income from Main Job by Skill Deciles: Colombia (pesos)



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

Note: Simulations based on structural estimations of latent skills factors using Sarzosa and Urzúa (2014). Cognitive skills are captured by an estimated latent factor using measures of reading proficiency, use of reading on and off work, and language. Socio-emotional 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).

Table 1 Inventory of Socio-emotional Skills in the Colombia STEP Household Survey

		Definition	Questionnaire item
Personality traits	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?
Behaviors and attitudes	Decision making	Manner 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 Partial Correlations between Measures of Skills, Colombia

	REA	EXT	CONS	OPE	EMO	AGR	GRI	DMG	HAB
Reading proficiency (REA)	1								
Extraversion (EXT)	0.06	1							
Conscientiousness (CONS)	0.06	0.05	1						
Openness to experience (OPE)	0.20*	0.17*	0.16*	1					
Emotional stability (EMO)	0.10*	0.10*	0.06	0.09*	1				
Agreeableness (AGR)	-0.03	0.11*	0.16*	0.20*	0.04	1			
Grit (GRI)	0.00	0.05	0.21*	0.20*	0.00	0.21*	1		
Decision making (DMG)	0.23*	0.08*	0.17*	0.29*	-0.08*	0.17*	0.21*	1	
Hostile attribution bias (HAB)	-0.17*	-0.01	-0.04	0.00	-0.17*	0.01	-0.02	-0.05	1

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

*$p < 0.001$.

Table 3 OLS Regressions of Log Hourly Labor Earnings on Cognitive Skills and Socio-emotional Skills, Colombia

Dependent variable: log hourly labor earnings										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Reading proficiency	0.178***									0.161***
	(0.05)									(0.05)
Extraversion		0.013								-0.009
		(0.04)								(0.04)
Conscientiousness			-0.023							-0.034
			(0.04)							(0.04)
Openness to experience				0.099***						0.082**
				(0.04)						(0.03)
Emotional stability					0.010					0.008
					(0.04)					(0.04)
Agreeableness						0.042				0.023
						(0.03)				(0.03)
Grit							-0.021			-0.030
							(0.04)			(0.04)
Hostile attribution bias								-0.011		-0.003
								(0.03)		(0.03)
Decision making									0.054	0.013
									(0.04)	(0.04)
Observations	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372
R-squared	0.09	0.07	0.07	0.08	0.07	0.07	0.07	0.07	0.07	0.11

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

Note: Standard errors are in parentheses. All regressions are estimated using OLS and include controls 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). The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. Measures of reading proficiency and socio-emotional 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 4 Conditional Correlations of Labor Earnings, Formality, and Occupational Status with Measures of Skills and Schooling, Colombia

Outcome	Log hourly labor earning		Being a formal worker		Being a high-skilled worker	
Method	OLS		Logit		Logit	
With/without schooling	Without	With	Without	With	Without	With
	(1)	(2)	(3)	(4)	(5)	(6)
Reading proficiency	0.161***	0.065	0.063***	0.014	0.141***	0.061***
	(0.05)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)
Extraversion	-0.009	0.000	0.001	0.005	-0.004	-0.000
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Conscientiousness	-0.034	-0.034	-0.003	-0.003	0.001	-0.002
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Openness to experience	0.082**	0.078**	-0.020	-0.022	0.020	0.017
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Emotional stability	0.008	-0.015	0.027	0.016	0.006	-0.007
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Agreeableness	0.023	0.015	-0.011	-0.014	-0.007	-0.003
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Grit	-0.030	-0.043	-0.020	-0.025	0.013	0.007
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Hostile attribution bias	-0.003	0.023	-0.041**	-0.030*	-0.019	-0.003
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Decision making	0.013	-0.007	0.012	0.002	0.019	-0.002
	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Education: below primary		0.015		0.103		0.091
		(0.11)		(0.08)		(0.07)
Education: upper secondary		0.289***		0.198***		0.163***
		(0.10)		(0.05)		(0.04)
Education: vocational tertiary		0.371***		0.263***		0.278***
		(0.11)		(0.05)		(0.04)
Education: general tertiary		0.880***		0.348***		0.566***
		(0.15)		(0.06)		(0.05)
Observations	1,372	1,372	1,576	1,576	1,801	1,801
R-squared	0.11	0.16				

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 middle-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). 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 socio-emotional 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 Employment, Activity, and Educational Trajectory with Measures of Skills and Schooling, Colombia

Outcome	Being employed		Being active or in school	Having pursued a tertiary education
Method	Logit		Logit	Logit
With/without schooling	Without	With	Without	Without
	(1)	(2)	(3)	(4)
Reading proficiency	0.003	-0.009	0.021*	0.199***
	(0.02)	(0.02)	(0.01)	(0.02)
Extraversion	-0.007	-0.007	0.009	-0.009
	(0.02)	(0.02)	(0.01)	(0.01)
Conscientiousness	0.044***	0.045***	0.023**	0.002
	(0.02)	(0.02)	(0.01)	(0.01)
Openness to experience	0.011	0.010	0.018*	0.045***
	(0.02)	(0.01)	(0.01)	(0.01)
Emotional stability	0.018	0.015	0.009	0.048***
	(0.02)	(0.02)	(0.01)	(0.01)
Agreeableness	-0.016	-0.016	-0.019*	0.001
	(0.02)	(0.02)	(0.01)	(0.01)
Grit	0.005	0.004	0.003	0.003
	(0.02)	(0.02)	(0.01)	(0.01)
Hostile attribution bias	-0.010	-0.008	-0.009	-0.049***
	(0.01)	(0.01)	(0.01)	(0.01)
Decision making	-0.031*	-0.033**	-0.003	0.055***
	(0.02)	(0.02)	(0.01)	(0.01)
Education: below primary		-0.063		
		(0.06)		
Education: upper secondary		0.003		
		(0.04)		
Education: vocational tertiary		0.053		
		(0.05)		
Education: general tertiary		0.066		
		(0.07)		
Observations	2,117	2,117	2,356	1,717

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

Note: Standard errors are in parentheses. Conditional correlations are computed from logit regressions for labor supply and educational outcomes. 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 parents' involvement in ones' 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 socio-emotional 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 Labor Earnings with Measures of Skills, across Subsamples, Colombia

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 socio-emotional 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 7 Conditional Correlations of Being Active or in School with Skills, across Subsamples, Colombia

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 socio-emotional 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 8 Estimation of Socio-emotional Skills Factor for Structural Estimation, Colombia

	Test 1	Test 2	Test 3
Measure of skills included in the test	Extroversion and openness to experience	Emotional stability and hostile attribution bias	Conscientiousness, grit, and decision making
Socio-emotional skills	0.4412**	0.0447	1
	(0.174)	(0.047)	.
Age	0.0183*	-0.0200**	0.1009***
	(0.011)	(0.009)	(0.010)
Age-squared	-0.0001	0.0002	-0.0012***
	(0.000)	(0.000)	(0.000)
Female	-0.0826*	-0.4869***	0.1085**
	(0.048)	(0.041)	(0.047)
Mother ed. < primary	-0.5259***	-0.4857***	-0.3593***
	(0.123)	(0.105)	(0.116)
Mother ed. = primary	-0.2304**	-0.2180**	-0.1803*
	(0.099)	(0.085)	(0.093)
Mother ed. = secondary	-0.1561	-0.0640	-0.1184
	(0.101)	(0.086)	(0.095)
Constant	9.2485***	1.7043***	7.6960***
	(0.197)	(0.169)	(0.189)

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

Note: Factors of latent socio-emotional skills are obtained from the measurement system of the three "test scores" presented in the table. Measures of socio-emotional skills were averaged into three tests to satisfy the necessary smoothness in the measurement system because all of these measures come from categorical answers. The measures were paired based on the correlations among them (see table 2). The scale of extraversion was aggregated with the measure of openness to experience (test 1), the measure of emotional stability with the measure of hostile attribution bias (test 2), and the measures of conscientiousness with grit and decision making (test 3)—(see definitions in table 1). Standard errors are in parentheses. All the estimations include city dummies (coefficients not reported). "Mother ed." refers to mother's education. The omitted category of the mother's education variable is tertiary education and beyond. $N = 2{,}372$.

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

Table 9 Estimation of Cognitive Skills Factor for Structural Estimation, Colombia

	Test 1	Test 2	Test 3
Measure of skills included in the test	Language	Use of reading on and off work	Reading proficiency
Cognitive skills	1.6001***	0.9055***	1
	(0.057)	(0.020)	.
Age	0.0626***	0.0100	0.0240***
	(0.019)	(0.007)	(0.007)
Age-squared	-0.0011***	-0.0002**	-0.0004***
	(0.000)	(0.000)	(0.000)
Female	-0.0506	-0.0376	-0.0272
	(0.086)	(0.033)	(0.031)
Mother ed. < primary	-1.1520***	-1.0506***	-0.9422***
	(0.216)	(0.080)	(0.075)
Mother ed. = primary	-0.5451***	-0.6397***	-0.4983***
	(0.172)	(0.064)	(0.059)
Mother ed. = secondary	-0.1183	-0.3318***	-0.2433***
	(0.175)	(0.065)	(0.060)
Constant	25.2210***	0.6072***	0.3168***
	(0.346)	(0.129)	(0.121)

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

Note: Factors of latent cognitive skills are obtained from the measurement system of three "test scores" presented in the table. The following tests were used: (1) a measure of languages captured by a weighted average of reading components measured by the reading proficiency test—average print vocabulary, sentence processing, and passage comprehension (World Bank 2014); (2) a measure of use and length of the reading done on and off the workplace; and (3) a plausible value of reading proficiency, from the direct assessment, randomly chosen among 10. Standard errors are in parentheses. All the estimations include city dummies (coefficients not reported). "Mother ed." refers to mother's education. The omitted category of the mother's education variable is tertiary education and beyond. $N = 2{,}340$.

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

Table 10 Structural Estimates of Associations between Labor Market Outcomes on Latent Skills Factors, Colombia

	Log hourly labor earning	Being formal worker	Being a high-skilled worker	Being employed	Being active or in school	Having pursued a tertiary education
	(1)	(2)	(3)	(4)	(5)	(6)
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
Socio-emotional 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
Age	0.032***	0.137***	0.123***	0.171***	0.073***	0.027
	-0.012	-0.019	-0.013	-0.017	-0.016	-0.029
Age-squared	-0.000**	-0.002***	-0.002***	-0.002***	-0.001***	0
	0	0	0	0	0	0
Female	-0.198***	-0.396***	0.093*	-0.712***	-0.874***	-0.076
	-0.044	-0.068	-0.055	-0.066	-0.085	-0.075
Mother ed. < primary	-0.810***	-0.104	-0.939***	0.148	-0.476**	-2.559***
	-0.122	-0.18	-0.145	-0.167	-0.232	-0.267
Mother ed. = primary	-0.507***	-0.14	-0.469***	0.033	-0.635***	-1.637***
	-0.103	-0.146	-0.113	-0.138	-0.209	-0.231
Mother Ed. = Secondary	-0.249**	-0.041	-0.214*	0.077	-0.434**	-1.069***
	-0.106	-0.15	-0.114	-0.142	-0.212	-0.236
Parental involvement—medium		0.07	-0.058	-0.03	0.004	0.1
		-0.093	-0.075	-0.082	-0.093	-0.096
Parental involvement—strong		0.035	-0.214**	-0.113	-0.101	-0.023
		-0.113	-0.091	-0.1	-0.114	-0.12
Constant	0.032***	-2.223***	-1.769***	-2.057***	1.425***	0.673
	-0.012	-0.373	-0.245	-0.329	-0.347	-0.625
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. The estimations presented are raw coefficients. All the estimations include city dummies (coefficients not reported). "Parental involvement" refers to a parent's regularity in checking a primary student's grades and exams (reference category is "no, never, or almost never"). "Medium" means "yes, sometimes," and "strong" means "yes, always, or almost always." 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 middle-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).

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

Table 11 IV Estimates (Second-Stage) of Associations between Labor Market Outcomes and Skills, Colombia

	Log hourly labor earning	Being formal worker	Being a high-skilled worker	Being employed	Being active or in school	Having pursued a tertiary education
	(1)	(2)	(3)	(4)	(5)	(6)
Reading proficiency	0.483**	0.119	0.196**	-0.038	0.042	0.612***
	(0.22)	(0.10)	(0.08)	(0.08)	(0.07)	(0.10)
Extraversion	-1.492	-2.384	4.461	-0.061	0.420	1.316
	(2.09)	(10.40)	(36.87)	(0.51)	(0.85)	(1.06)
Conscientiousness	-0.429	-0.143	-0.283**	0.161	0.070	-0.467**
	(0.31)	(0.11)	(0.12)	(0.12)	(0.09)	(0.21)
Openness to experience	-0.020	0.297	-0.564	-0.736	-0.307	1.708
	(0.74)	(0.62)	(1.10)	(1.09)	(0.40)	(1.70)
Emotional stability	0.170	-0.018	0.125	0.104	0.250	0.365*
	(0.34)	(0.16)	(0.17)	(0.25)	(0.25)	(0.19)
Agreeableness	-0.051	0.070	-0.984	0.243	-0.125	-1.025
	(1.19)	(0.67)	(1.37)	(0.33)	(0.25)	(0.85)
Grit	0.419	0.155	0.332**	-0.093	0.022	0.539***
	(0.31)	(0.17)	(0.16)	(0.14)	(0.08)	(0.17)
Hostile attribution bias	-0.554	-0.205	-0.458**	0.112	-0.001	-0.659***
	(0.41)	(0.17)	(0.21)	(0.13)	(0.11)	(0.24)
Decision making	-0.490	-0.052	-0.324	-0.379	-0.288	-0.009
	(0.48)	(0.20)	(0.24)	(0.46)	(0.28)	(0.35)
Observations	1,371	1,575	1,800	2,116	2,355	1,717

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

Note: Standard errors are in parentheses. The bottom and the top 1 percent of the log hourly labor earnings distribution are trimmed. The instrumental variables (IVs) considered for reading proficiency are the age at which a person started school and the economic situation of the household at age 12; for each socio-emotional skill, the indicator of whether the individual lived with both parents at age 12 and the economic situation of household at age 12. These instruments are valid in first stage per the Sargan-Hansen test. Other controls are gender, 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 socio-emotional skills are standardized. Solely for the IV analysis, only the means of the 10 plausible values is used as a score of reading proficiency. For presentational purposes, the coefficients from different regressions for same outcome are presented in one column.

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