Beyond qualifications: labor market returns to cognitive skills and personality traits in urban Colombia[1]

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Abstract

The objective of this paper is to estimate the returns to cognitive skills (a scaled reading proficiency score), personality traits (Big 5 model, Grit, Hostile bias, and decision-making scales) and educational levels on labor outcomes in urban Colombia. The analysis is based on an original dataset collected in 2012 by the World Bank, representative of Colombia 13 main metropolitan areas. Average results for the total working-age population (15-64) indicate a stronger role for cognitive skills as predictor of labor earnings than personality traits. Cognitive skills matter also for holding a formal job, being a white collar worker, a wage worker, but not for being employed. Generally, these effects no longer hold when controlling for education levels. Personality traits have mixed effects on these outcomes and across groups of interests (gender, wage worker and self-employed, but their effects generally hold when controlling for schooling. Methodologies to accurately estimate causal relationships in the face of these multiple and complex challenges are still under development in the academic literature, and it is expected that the next version of this draft will include regressions using instrumental variables (IV) to correct for endogeneity of schooling, and experiment more sophisticated techniques to overcome current methodology. The empirical evidence will also provide insights to guide broad directions for policy recommendations.

JEL Codes: J24, J31, I24.

Key words: Colombia, returns to cognitive skills, personality traits, schooling.

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1. Introduction

A central priority for policy makers is to increase the productivity of their country's economy and provide economic opportunities to their population by fostering the employability of the labor force. A better use and investment on skills have great implications regarding to labor productivity, innovation and growth (Banerji et al. 2010, Fiszbein 2012, OECD 2013a). Beyond that, providing vulnerable workers and the young with the type of skills that would improve their employability, cope with the economic transformations occurring in a global economy, and ultimately help them to find a quality job with sufficient income is a central policy issue from a human development perspective.

The main objective of this paper is to investigate (i) the current levels and distribution of skills in the Colombian labor force, (ii) which skills (or skill sets) are most important for labor market and school success, and (iii) through which channels they impact on outcomes. It complements empirical evidence from high-income countries (United States, Western European countries) and a few cases for Latin American countries on the impact of cognitive, socio-emotional and technical skills on schooling and labor market outcomes. These skills encompass respectively intelligence, behaviors and attitudes, and skills specifically developed to perform a range of tasks. Deeper knowledge on which abilities to foster, at what age, and through which interventions, would have major implications for the design of efficient education policies and active labor market programs such as trainings.

Employers across the globe value more a certain set of skills, not only qualifications. Recent studies using employers' surveys for Argentina, Brazil and Chile confirm that, while technical skills are valued[2], also are socio-emotional skills and higher-order cognitive skills (Bassi et al. 2012). Socio-emotional skills appear to be even more important for low-wage workers in predicting their labor market outcomes. In the meantime, Latin American employers lament that potential recruits lack an adequate set of skills (of work ethics and teamwork stands out), especially for the young. A strong mismatch exists between the skills required by employers and those provided to students (World Bank 2011, Aedo and Walker 2012, Bassi et al. 2012, Mourshed et al. 2012, OECD 2012).

Among other explanations, this disconnection could root in the degradation of education in the region. A current research agenda in the Latin America region aims to explain the patterns that drive overall declining returns to education during the last two decades while schooling attainment has generally increased. Recent evidence for the region shows that while between 1990 and 2010 the proportion of the labor force in the region with at least secondary education increased from 40 to 60 percent, returns to secondary education completion fell throughout the last two decades in the vast majority of countries, while the 2000s saw a reversal in the increase in the returns to tertiary education experienced in the 1990s (Gasparini et al. 2011). While

[2] Top valuable technical skills include adaption to computer technologies; even it could arguably be characterized as a combination of high-order cognitive skills and socio-emotional skills (Guerra and Modecki forthcoming).

several elements could explain this pattern3, a degradation of higher education is considered as one of the main factor at stake (Bassi and Urzúa 2010, Gasparini et al. 2011, Bassi et al. 2012, Castro and Yamada 2012, Levy and Schady 2013). Looking at the current distribution of skills and traits rather than qualifications would bring important insights to this debate.

Colombia is a country with one of the highest income inequality in the most unequal region in the world according to Gini coefficients.). Labor is the primary source of income and of income inequality (Lustig et al. 2013, OECD 2013, SEDLAC 2013). The sources of labor income inequality are multifold (incentives structures, labor market barriers, etc.) but skills might be one central. The wage premium declined for primary and secondary education between 1997 and 2008. Returns to university education fell during between 1997 and 2003 but increased in 2003-2008 (Aedo and Walker 2012). National unemployment rate is also the highest in the region, especially for the youth. While it might paradoxically be partly a good sign (some individual can afford to be unemployed, dedicate more time to look for better job that match better their skills), it also highlights that jobs are not filled, despite employers' demand. A skills assessment may allow shedding light on persistent inequalities and labor market challenges in the country.

This paper will also contribute to the literature by using a unique dataset revealing information on cognitive skills, personality traits, skills used at work and rich background information. This is the first of the kind in Colombia, and one of the fewest worldwide for developing countries. This data can go beyond most previous studies that use education as proxy for human capital.

2. Concepts and definitions

One outstanding fact from the literature addressing skills, be it economic or psychology, is the plethora of definitions and taxonomies surrounding this concept. Economists have long considered educational levels as the main aspect capturing skills. Later on, studies have recognized that competencies and abilities are part of a broader scope and are also influenced by extra-school factors such as family background, work, extra-curricular activities and environment. Nowadays, 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 and Modecki forthcoming). Nonetheless, a variety of denominations have been used to designate these aspects.

Cognitive skills are generally defined as intelligence or mental abilities. Lower- and higher-orders of intelligence are distinguished. Firstly, lower-order cognitive skills are basic skills such as literacy and numeracy. It relates to *crystallized intelligence* (knowledge and developed skills)[4]. Secondly, higher-order cognitive skills defines can be defined as the ability to

[3] Potential factors are: over-supply of workers with higher educational attainment, reduction in the demand for labor requiring higher educational level, modified institutional policies like minimum wage.
[4] The latter is more malleable than the former and it is affected by formal schooling as well as for other stimuli that enhance mental capacity (Díaz et al. 2012).

understand complex ideas, adapt to the environment, learn from experience, engage in various forms of reasoning and overcome obstacles through thinking (Neisser et al. 1996). It relates to *fluid intelligence* (ability to solve novel problems) (Horn 1970, Cattell 1987). Cognitive skills are usually measured by Intelligence Quotient (IQ) tests, other tests of intelligence[5] and standardized test scores (reading, math and science). One dominant factor is commonly used to summarize the effect of cognitive skills ("g").

Social-emotional skills refer to a distinct set of skills that enable individuals to navigate interpersonal and social situations effectively (Guerra and Modecki forthcoming). Economists commonly consider behavioral characteristics and personality traits under the umbrella of "non-cognitive skills" or leave the distinction unexplained. Socio-emotional skills are understood here as behaviors and attitudes (commitment, discipline, ability to work in a team and determination) while personality traits designate a range of personal facets that are relatively stable over time (self-confidence, sociability, emotional stability, among others)[6]. Personality traits are broad facets defining an individual. They influence socio-emotional skills as reactions. They are relatively stable over time (Borghans et al. 2008, Almlund et al. 2011). A widely used method to capture an individual's facets is to perform a factor analysis of Big-Five model based on the Goldberg's questionnaire (Goldberg 1993). Each of the five personality factors - openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (opposite of emotional stability) - summarizes a large number of distinct, more specific personality traits, behaviors, and beliefs[7]. Another trait stands out from the literature: Grit, a narrower trait capturing one's inclination and motivation to achieve long term goals. The perseverance of effort and consistency of interest is characteristic of high-achieving individuals (Duckworth et al. 2007).

Technical skills, also called professional skills or vocational abilities, can be defined as those abilities that are associated with the specific knowledge to carry out one's occupation. Measures of technical skills derive typically from an observed assessment of a person performs a task and the related skills. Alternative measurements can be drawn from test batteries related to

[5] The United States Army uses such tests for its recruitment procedures: the Armed Forces Qualifying test (AFQT), which measures *crystallized intelligence* (knowledge and developed skills) and the Raven Progressive Matrices, which measure *fluid intelligence* (the ability to solve novel problems).

[6] The economic literature refers to socio-emotional skills using the terms "behavioral skills", "life skills", "non-cognitive skills" and "soft skills". However, a distinction has to be made between them. Non-cognitive skills refers to a broad range of behaviors, abilities and traits that are not induced by intelligence or achievement; soft and life skills usually include more technical skills such as language fluency and computer literacy (Guerra and Modecki forthcoming). It is also worth noting that psychologists argue that many of the abilities and traits that economists intend to capture by the term "non-cognitive skills" are a result of cognition (Borghans et al. 2008a).

[7] The predominance of the Big-Five traits in the literature masks the diversity of behaviors and personality traits characterized as non-cognitive skills. No less than one hundred forty different socio-emotional skills have been found in the literature (Cunnigham and Villaseñor forthcoming). In order to propose a more practical taxonomy, a World Bank's initiative has put together a more comprehensive set of socio-emotional skills under eight facets: the PRACTICE skills (see Guerra and Modecki forthcoming).

mechanical, psychomotor abilities and manual dexterity (Prada forthcoming). The psychology literature defines technical skills as a sub-set of cognitive skills (Almlund et al. 2011).

Box 1. Skill formation over the life cycle

The formation of abilities is a cumulative life-cycle process (World Bank 2011). Individuals learn at every stage of the life cycle, from pregnancy and early childhood to adolescence and adult life. A range of family characteristics, environments and experiences shape the development of competencies, behaviors and traits.

The early stages of life are critical for the development of basic cognitive and socio-emotional abilities. Their development during the so-called “first 1,000 days” of the child, from his birth to after his two years, enables individual to learn later at school and in the professional adult life (Heckman 2004). Early childhood environments have great impacts on later life outcomes (Knudsen et al. 2006, Heckman 2008, Almond and Currie 2011, Heckman et al. 2013). Deficits or delays in the development of these skills can lead to long-term and often irreversible effects on education, health, and earnings for individuals (Banerji 2010, World Bank 2011).

Socio-emotional and cognitive skills then evolve over the life cycle and can be altered by experience and investment. Marketable skills are developed after childhood through informal learning, formal schooling, training and on-the-job learning. National institutions such as the health care system and the school system are major components that can alter the skills of an individual (see figure 1). On top of that, the familial environment (household’s living standards, parents’ education, relationships within the family) and home learning environment play a tremendous part in producing cognitive and socio-emotional skills (Carneiro et al. 2003, Carneiro and Heckman 2003, Cunha et al. 2005, Heckman et al. 2006, Carneiro et al. 2007). Hostile social environments such as schools subject to violence and bullying can have high detrimental effects on children’s capacity to develop their traits and behaviors that would matter for their future success (World Bank 2011, Sarzosa and Urzúa 2013). Little evidence exists on the conditions favoring the specific development of technical skills apart that these task-specific skills are meant to be taught in vocational education and trainings.

There is a wide consensus that socio-emotional abilities and personality traits evolve and can be fostered in more malleable way than cognitive one (Carneiro and Heckman 2003, Cunha et al. 2006, Borghans et al. 2008a, Cunha et al. 2010, Heineck and Anger 2010, Almlund et al. 2011). Higher levels of extraversion, conscientiousness and emotional stability are more prevalent as individuals grow older. Conversely, level of openness to experience and the locus of control[8] appear to increase during childhood until young adulthood (age 20 to 30), stabilize during

[8] 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 et al. 2006).

adulthood, and decline in old age (Borghans et al. 2008a, Cobb-Clark and Schurer 2012, 2013). The stability of socio-emotional skills during adulthood seems to be explained by genetic factors. Yet, small-magnitude changes of socio-emotional skills occurring over this period have been associated with changes in socio-economic, family, institutional and social dimensions (Blonigen et al. 2006). Likewise, cognitive abilities are also partly inherited and partly built through education and informal human capital investment (Cawley and al. 2001). They are stable by adulthood and decline at older ages (55 or older) (Borghans et al. 2008a).

3. Review of empirical studies on the role of skills in the labor market

3.1. Evidence from developed countries on returns to skills

Cognitive abilities have long been seen as the dominant factor determining labor earnings in the United States. The primary approach to assess such relationship is based on longitudinal data and consists in linking cognitive test scores (like mathematics) of individuals in high school with their wages once they have graduated from high school. In a large number of economic studies, higher measures of cognitive skills were associated with higher wages and the capacity to deal with complex information processing in a professional environment (Herrnstein and Murray 1994, Murnane et al. 1995, Gottfredson 1997, Mulligan 1999, Murnane et al. 2000, Cawley et al. 2001, Lazear 2003, Hanushek and Woessmann 2008). The net impact of measured cognitive abilities on earnings has been found high when taking into account differences in the quantity of schooling, workers' experience, and other factors that might also influence earnings (Hanushek and Woessmann 2008). Similar results were found in the United Kingdom (McIntosh and Vignoles 2001) and Canada (Finnie and Meng 2001).

More recently, a burgeoning literature reported socio-emotional abilities and personality traits to be of equal importance or more in the determination of labor earnings of US workers[9]. Among the so-called "Big Five traits"[10] used in most empirical studies, conscientiousness is the most associated with job performance (Nyhus and Pons 2005, Almund et al. 2011). Accounting for measures of cognitions, studies found that conscientiousness and traits related to emotional stability (locus of control[11] and self-esteem) play an essential role in determining job performance and wage (Bowles et al. 2001b, Judge and Hurst 2007; Drago 2011). Misbehaviors of eight-grade students in 1988 have been also found to be associated with lower earnings later in 1999 in the United States (Segal 2012). Males who occupied leadership positions in high school earn between 4 percent and 33 percent higher wages as adults (Kuhn and Weinberger 2005).

[9] A non-exhaustive list of sources validating this claim in the United States and Western Europe is: Bowles et al. (2001a), Nyhus and Pons (2005), Osborne-Groves (2005), Heckman et al. (2006), Mueller and Plug (2006), Carneiro et al. (2007), Borghans et al. (2008b), Kniesner and ter Weel (2008), Heineck and Anger (2010), Heckman et al. (2011), Lindqvist and Vestman (2011), Segal (2012).

[10] The Big- Five traits include: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (VandenBos 2007).

[11] See note 6 for the definition.

Studies on high-school second chance programs in the United States provide ideal natural experiments and their evaluation confirm the crucial role of socio-emotional skills. High-school dropout students in the United States who benefit from the GED program[12] exhibit higher levels of low-order cognitive skills than other high-school dropouts. But they have paradoxically relative lower labor market outcomes later in life. In absolute terms, GED graduates have higher hourly wages but when controlling for measured ability, they earn less than other high-school dropouts. This unexplained factor is considered to originate from lower levels of socio-emotional skills that are also valued on the labor market. Being a GED graduate is a mixed signal that characterizes its recipients as smart but unreliable (Heckman and Rubinstein 2001, Heckman et al. 2011).

Differences in abilities between races, like Blacks and Whites in the United States explain earning gaps. Black-white gaps in labor earnings derive main from difference in cognitive skills gap, in addition to more disadvantaged background and lower level of schooling (Neal and Johnson 1996, Carneiro et al. 2005, Urzúa 2008, Segal 2012).

However, the identification of the determinants of earnings featured in most of the previous-mentioned empirical studies faces severe measurement issues. In addition to measurement errors, simple econometric models fail to capture appropriately the effect of skills when accounting both for education and measured skills. Schooling is an endogenous variable as intelligence, personality and other factors determine it and are influenced by it (Heckman et al. 2006). Removing schooling from the wage equation overestimates the net effect of intelligence and personality on wage; meanwhile controlling for schooling in conventional specifications leads to biased, unreliable results. This issue has been unaddressed in the 2000s' literature (Cawley et al. 2001). However, recent work has undertaken this aspect using low dimensional vector[13] to capture latent skills as opposed to measured skills (Heckman et al. 2006, Urzúa 2008, Heckman et al. 2011)[14].

Beyond issues linked to measurement errors, the literature faces the usual challenges inherent to causal analysis. First, empirical explorations of data on skills using are useful to unveil associations but do not allow to assess if variations in skills stock *cause* variations in labor outcomes and schooling decisions. Second, simple econometric models fail to capture appropriately the effect of skills. A central concern is endogeneity as certain skills are very likely to determine schooling as well as being influenced by it. Cognitive skills and education are

[12] The General Educational Development (GED) program aims to provide a certification equivalent to high school diploma to high school dropout students.

[13] The low-dimensional vector captures latent cognitive and socio-emotional abilities that generate measured cognitive and non-cognitive test scores. This technique allows schooling to determine measured skills, occupational choice, and behavioral outcomes (Heckman et al. 2006).

[14] An additional concern is to pay attention to reverse causality when analyzing the impact of neuroticism on labor market outcomes. Indeed, evidence suggests that participation to the labor market affect this trait (Gottschalk, 2005). A way to palliate to this issue is to use measures of personality traits before individuals enter the labor market (Judge and Hurst 2007, Drago, 2008).

highly correlated so distinguishing their respective effect is technically challenging, at least; an issue unaddressed in the early 2000s' literature (Cawley et al. 2001). More advanced econometric models using instrumental variables (IVs) have not yet yield convincing results given the weak predictive power of available instruments. An alternative method was adapted to this context to bypass previous sources of error: a nonparametric estimation of latent cognitive and socio-emotional abilities (using a low-dimensional vector) (Heckman et al. 2006). It captures latent –unobservable - skills as opposed to measured skills. The former encompasses the effects measured skills (and schooling).

Similar findings have been found for Western Europe countries. Men with lack of leadership abilities in Sweden – as measured by psychological assessment for the military assessment[15] - are more have lower annual earnings (Lindqvist and Vestman 2011). External locus of control (opposite of strong feeling of self-determination) has a strong negative impact on wage in Germany; however neurotiscism has no robust effect on wages (Heineck and Anger 2010). Measures of behaviors and traits in childhood and adolescence also have important influence on adult earnings in West Germany and Great Britain (Carneiro et al. 2007, Borghans et al. 2008b).

The returns to higher levels of cognitive, socio-emotional abilities and personality traits are in some cases distinct across genders. Agreeableness and conscientiousness seem to be more rewarding for women whereas antagonism (the opposite of agreeableness), emotional stability (the opposite of neuroticism) and openness to experience were more rewarded among men in the United States (Mueller and Plug 2006). Similar results for Germany show extraversion and agreeableness negatively affect women's wages while the former has a positive effect on men's wage and the latter has no significant effect (Heineck and Anger 2010). Locus of control (self-motivation), persistence and self-esteem seem to play a predicting role too on labor market outcomes but with slightly variations across gender (Heckman et al. 2006). Locus of control has also been found to be with aggression and withdrawal strong predictor of wages for white women in the United States and the United Kingdom (Osborne-Groves 2005). However, difference 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). In Australia, women earn less on average not because they hold different occupations but they earn less than their men colleagues (Cobb-Clark and Tan 2011). As a consequence, the expected benefits of entering in different occupations may depend on one's abilities in ways that differ for men and women.

Due to their multidimensional nature, cognitive and non-cognitive skills are rewarded in the labor market according to their combinations (Carneiro et al. 2007, Maxwell 2007, Prada and

[15] In this study, leadership ability captures the ability to function in the very demanding environment of armed combat: willingness to assume responsibility; independence; outgoing character; persistence; emotional stability, teamwork and power of initiative (Lindqvist and Vestman 2011).

Urzúa forthcoming). For instance, the association of conscientiousness and agreeableness are associated with higher earnings in inner-cities in the United States (Kern et al. 2013).

Cognitive, socio-emotional abilities and personality traits are also rewarded differently across occupations. More complex jobs, i.e. more demanding in information processing, require high-order cognitive skills (fluid intelligence). This is the case for instance of professors, scientists and senior managers (Schmidt and Hunter 2004). Conversely, conscientiousness matters for a wider spectrum of job complexity (Barrick and Mount 1991). Higher levels of socio-emotional abilities are more important for some occupations requiring low-order cognitive skills, especially in the service sector (Bowles et al. 2001b). Occupational choices are driven by personality traits such as being a caring or a direct person in adolescence (Borghans et al. 2008b). Individuals partly select occupations that correspond to their orientations. The relative price for directness over caring determines wages. Finally, traits related to Grit (persistence and motivation for long-term goals) seems to be essential for success no matter the occupation through their effect on education achievements (Duckworth et al. 2007).

Another concern related to the analysis of the impact of skills on labor market outcome is that it is technically difficult to take in account the different reward of set of skills across occupational activities. Distinction has to be made for blue-collar and white-collar jobs with vocational education or college (Specific skills vs. broader set of skills). "Reward or punishment of the different personality characteristics is occupation-specific in that they are higher within specific occupations unaddressed by our general analyses" (Nyhus and Pons 2005).

The returns to skills differ across type of work as well, namely between salaried workers, incorporated self-employed and unincorporated self-employed. A mixture of traits seems to matter both for becoming and succeeding as an entrepreneur (Levine and Rubinstein 2013). Individuals with high-order cognitive skills (learning aptitudes and success as a salaried), tendency to "break-the-rules" (as measured by the degree to which the person engaged in illicit and risky activities before the age of 22) and high self-esteem in adolescence are more likely to become successful incorporated entrepreneurs in the United States (Levine and Rubinstein 2013). These abilities and traits more rewarding for incorporated entrepreneurs than for unincorporated ones and salaried workers. In the Netherlands, low-order cognitive skills and socio-emotional abilities tend to have a stronger impact on entrepreneurial incomes than on wages for salaried workers (Hartog et al. 2010). In particular, language and clerical abilities have a stronger impact on wages, whereas mathematical and technical ability as well as extraversion in early childhood are more valuable for entrepreneurs. Moreover, entrepreneurs with a balance in abilities across different fields, referred as the "Jacks-of-All-Trades", have a higher income vis-à-vis employees (Lazar 2005, Hartog et al. 2010).

Less attention has been paid by economists on the impact of technical skills on labor outcomes including wages. The role of these abilities is often associated with the impact of interventions like job trainings or vocational education rather than through the outcomes due to the acquisition of these skills (Cunningham and Villaseñor forthcoming). However, a couple of studies initiated the analysis of the impact of vocational abilities of teenagers on their labor outcomes after graduation using the same longitudinal data than analogous studies on cognitive and socio-emotional skills. They show that vocational abilities (mechanical abilities, psychomotor abilities, manual dexterity and eye-hand-foot coordination) have positive effects on labor income but with considerably lower returns than to cognitive and non-cognitive abilities in the United States. However, individuals with highest level of vocational ability but low levels of standard ability (cognitive and non-cognitive) benefit from not going to college: their set of skills is associated with the highest expected hourly wage (Prada and Urzúa forthcoming).

3.2 Evidence from Latin America on return to skills

There is much less evidence on the impact of cognitive and socio-emotional skills in Latin America. But the literature is growing. Adequate instruments, to measure them and observe their impact on given outcomes are being developed and expand the collection of existing evidence.

Initially, a range of studies addressed the impact of schooling and then cognitive skills – using achievement tests or IQ - on labor earnings at the individual level in Latin America. Their findings were challenge both by limited data (not allowing controlling for socio-emotional skills) or the methodological issues inherent to causal analysis of skills and education on labor outcomes. For instance, study examined how leadership traits, physical appearance, and intelligence affect labor market outcomes in Argentina (Tetaz and Cruces 2009). Results show that physical appearance (as judged by the interviewer) positively affect earnings for women but not when IQ levels are accounted for. On the other hand, IQ significantly influences earning even when controlling for education and tenure for both men and women. Leadership has a positive and significant effect on wages as well, even when controlling for IQ. However, following the argument to the endogeneity of education vis-à-vis measures of skills previously mentioned (Heckman et al. 2006), including education in all specification of the study suggests that the coefficients of the IQ, beauty, and leadership variables are likely to be biased.

Cross-sectional data with measures of cognitive and socio-emotional skills, job performance and education of individual between 25 and 30 year old in Argentina and Chile at the individual level have allowed drawing first evidence of that kind in the region (Bassi et al. 2012)[16]. Recognizing the risk of reverse causality between the measures of skills and labor outcomes of interest, the authors base their evidence on associations (correlations) rather than causal relationships[17]. The results show that self-efficacy[18] - a measure of high-level socio-emotional skills - is the ability that predominates in the association with higher wages in both countries. This association is

[16] The surveys - Skills and Trajectories Survey – were collected in 2008 in Chile and 2010 in Argentina.

[17] This methodological issue would arise for instance if some socio-emotional skills, say motivation, affects employment outcomes like wage and then in return higher wage affects motivation.

[18] Self-efficacy refers to how individuals perceive their capability to organize their work and achieve their goals (Bassi et al. 2012, p.93).

strong at the post-secondary level but weak for workers with secondary traditional[19] education. Other type of skills – low level socio-emotional skills, low- and high-order cognitive skills – do not show sizeable association. This could suggest that individuals in their late twenties with similar levels of education earn similar wages, despite their difference in cognitive abilities.

A 2010 survey of the working-age population in urban areas in Peru has provided material to explore the causal relationship between labor earnings, schooling, cognitive and socio-emotional skills (Díaz et al. 2012)[20]. Overall, the results confirm the importance of cognitive skills and personality traits as determinants of labor earnings, corroborating anterior findings in high-income countries. Cognitive skills and personality traits are equality valued in the Peruvian labor market[21]. Specifically, various traits and combinations of traits have distinct effects on earnings: perseverance (grit) has a high positive influence on earnings; emotional stability (opposite of neuroticism) has positive effects on earnings; agreeableness has negative effects. While employers report valuing interpersonal skills like teamwork, urban Peruvian labor market does not seem to reward cooperation. This may be due to the limitation of the Big-Five model as a proxy for personality traits. Alternatively, surveyed individuals might have reported more favorably the way they are than they actually behave. Data explorations suggest that it might be the case, with a relatively stronger bias for conscientiousness. If it is the case, it would explain the insignificant impact of this trait on earning in the analysis. Another notable feature of this study is that the earnings analysis correct for the potential endogeneity of measured skills and traits vis-à-vis schooling by using an instrumental variable (IV) method[22]. However, robustness tests suggest a weak instrument problem, altering the reliability of the findings.

3.2. Impact of skills and personality traits on other labor outcomes

Abilities and personality traits have also an important role in determining the participation of individuals in the labor market. Ignoring the effect of personality traits on this matter tend to overestimate the influence of education on labor participation, especially for women (Wichert and Pohlmeier 2010).

Some of the Big-Five traits have distinct effect on labor participation in ways, with notable gender specificities. As on earnings, conscientiousness has a large a large and positive effect on

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[19] As opposed to technical.

[20] The Survey of Skills and the Labor Market in urban Peru (Encuesta Nacional de Habilidades, ENHAB 2010, in Spanish) measures cognitive and socio-emotional skills of the working-age urban population, data related to skill mismatches (including knowledge and capacity to acquire market-relevant skills), the information on available jobs, search techniques, the ability to signal competencies and credentials, together with a very rich dataset on employment and socio-economic conditions.

[21] Cognitive skills are measured by test scores (Peabody Picture Vocabulary, verbal fluency, working memory, and numeracy/problem-solving) and personality traits by the Big-Five model and Grit – the Duckworth Scale adapted to the Peru context (Díaz et al. 2012).

[22] The authors use instrumental variables such as scholastic achievement, effort exerted at school and time to get to school. These variables are directly related to schooling, but it is assumed that they are only indirectly related to post-schooling measured skills through schooling (Díaz et al. 2012).

labor participation in the United States and Germany; so does extraversion (Barrick and Mount 1991, Wichert and Pohlmeier 2010). In the contrary, neuroticism and openness have a negative effect in Germany, while agreeableness only has a negative effect on labor force participation decisions of married women and no effect for other population subgroups (Wichert and Pohlmeier 2010). Socio-emotional skills have a substantial effect on the probability of employment in many, though not all, occupations in ways that differ by gender (Cobb-Clark and Tan 2010). In the United States, a man who would move from the 25th to the 75th percentile of the distribution of socio-emotional skills (locus of control and self-esteem in this case) would increase his probability of being employed at age 30 by 15 percent (Heckman et al 2006). The effects on work experience are equally important. For the case of occupational outcomes, disagreeable, intelligent individuals, achieved higher occupational status, whereas disagreeable, low intelligent men were more likely to be unemployed or working at a lower status job (Kern et al. 2013).

Studies based on psychological assessments of Swedish enlistment data showed that men lower level of leadership skills have a higher probability of being unemployed than men with lower low-order cognitive abilities (Lindqvist and Vestman 2011). A concern about the validity of the methodology used in this study relies on the fact that education is not taken into account when assessing the impact of skills. This approach likely overestimates the net effect of skills as schooling probably affect skills in a substantial manner[23].

Behaviors of children in Great Britain affect significantly the probability of being in work as an adult. While hostility towards adults (at age 11) has a negative impact on the probability of being in employed at age 42, anxiety for acceptance by adults has a positive and significant impact on employment status (Carneiro et al. 2007). A potential explanation given by the study is that children who are maladjusted on this dimension are judged by their teachers to be over-zealous - which may be better rewarded in the labor market.

Technical skills developed by vocational education have a significant impact on employment and labor mobility. Specialized education through vocational curriculum in Poland and Estonia tends to results in greater employment for former students in the short-to-medium term but have more negative effects in the longer term. It reduces the mobility of workers and their capacity to cope with economic and technologic changes (Lamo et al. 2011).

For the case of Latin America, like for labor earnings, in Argentina and Chile a high-level socio-emotional skill (self-efficacy) seems to be the main determinant associated with labor force participation in both countries (Bassi et al. 2012). Patterns are almost entirely similar across the

[23] The authors argue that if cognitive and socio-emotional skills influence decisions to continue to secondary education and are not influenced significantly by the latter, the causal analysis should not control for educational attainment. A more practical argument is that controlling for education reduces little the estimated effect of skills on employment. However, they recognize the potential bias if schooling at that level influence skills.

two countries. Other skills do not show strong association with labor force participation[24] except that high-order cognitive skills are also associated with higher participation in the Argentine labor force. Regarding to probability of being employed, patterns of associations with skills are similar.

Research on labor supply decision and personality traits (Big-Five traits and grit) in urban Peru shows that a common set of personality traits that drive labor supply decisions; wide variation on different traits on labor force participation, sector and occupational choice (Cunningham and Calderón-Mejía forthcoming). Instrumental variables used in the study do not counter convincingly endogeneity of cognitive and socio-emotional skills so standard Ordinary Least Square estimation is preferred for the causal analysis[25].

3.4 Impact of skills and personality traits on schooling

While schools are privileged places to foster skills, measures of cognitive and socio-emotional abilities as well as personality traits influence schooling decisions and a range of educational outcomes (see an extensive review of the psychology and economic literature on that matter in Almlund et al. 2011, p.90-104). Quantitatively, estimations show that 12% of the variance in educational attainment is explained by personality measures and 16% accounted for by cognitive ability measures (Cunha et al. 2010).

Research using longitudinal datasets of children in the United Kingdom, the United States and Canada to evaluate school readiness shows that low-order cognitive skills – in this case, mathematics, reading and attention skills - were strong predictors of later academic achievement. By contrast, measures of socio-emotional skills at school entry had limited power in explaining educational success (Duncan et al. 2007)[26].

The Big-Five traits have distinct effects on schooling. Among these traits, conscientiousness is the main determinant of overall attainment and achievement, such as college grades (Almlund et al. 2011). Openness to experience affects also educational attainment but predict attendance and the difficulty of courses selected as well. Neuroticism – as captured by self-esteem and locus of control – influences also educational attainment like graduating from a four-year college (Heckman et al. 2006). It is to be noted that the relationship of neuroticism with schooling is no always monotonic. Broader measures of personality traits influence also students' performance in test scores (Heckman et al. 2006, Almlund et al. 2011, Borghans et al. 2011, Heckman and Kautz 2012).

[24] Skills analyzed in this study are low- and high-order cognitive skills, socio-emotional skills (such as communication and leadership) and high-order socio-emotional skills (self-efficacy) (Bassi et al. 2012).

[25] Instrumental variables used in the study include birth order, number of siblings and mother's and father's years of schooling (Cunningham and Calderón-Mejía forthcoming).

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

Misbehavior at young age, childhood or adolescent drives lower probabilities to stay longer at school in Great Britain and the United States (Carneiro et al. 2007, DiPrete and Jennings 2011, Segal 2012). 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 social-emotional skills but girls begin school with more advanced social and behavioral skills and their skill advantage grows over time DiPrete and Jennings 2011).

Psychology research shows that self disciple and grit are crucial determinant of adolescent academic success in the United States. Self-discipline (on several measures) outdoes IQ as a predictor of the academic performance of adolescents: self-discipline measured in the autumn accounts for twice as much variance as IQ in explaining final grades, in final grades, high school selection, school attendance, hours spent doing homework, hours spent watching television (inversely), and the time of day students began their homework (Duckworth and Seligman 2005). Grit has recently been found to be correlated with a range of schooling success such as educational attainment, grades and retention (Duckworth et al. 2007).

Technical skills at young age influence the probability of going to college. By contrast to cognitive and socio-emotional skills levels, higher level of vocational ability in the United States is associated with lower probability to attend 4 year college (Prada forthcoming, Prada and Urzúa forthcoming)[27]. This may not be surprising given that individuals with high vocational abilities are likely to be good at performing manual tasks (Autor et al. 2003); and thus they are likely to enter in vocational programs rather than to college. In fact, it may not be only an orientation toward adequate with an individual's skills set but also an expectation for higher labor earnings. Given that individuals in the top 10% of vocational skills have higher hourly wages than those in the 10 % of cognitive and socio-emotional abilities, not going to college is indeed associated with higher expected earnings.

The validity of existing evidence from empirical studies is challenged in several ways. First, data limitations prevent to measure adequately skills. Second, methodologies of causal analyses in economic studies are challenging to apply to the effect of skills on education and labor as they are interrelated.

Not only are the results from empirical studies conditional to their methodology but also of their context. Specifically the context includes the time period and population covered by the datasets but also the countries and its particularities.

[27] Measures of vocational abilities are constructed from three sections of the Armed Service Vocational Aptitude Battery (ASVAB): auto and shop information, mechanical comprehension and electronics information. The dataset used is the National Longitudinal Survey of Youth (NLSY79).

Box 2. A quest for accuracy: measures of skills and traits in empirical studies

The evolution of the metrics used in the studies of human capital, education and labor market have radically changed the approach and the conclusions on the impact of skills at the individual level.

Initially, standard measures of education, such as years of schooling or diplomas, were commonly used in the human capital literature to capture the effect of skills and assess their impact on labor outcomes. Later on, such indicators were consensually regarded as too limited to be used as proxy for abilities when contrasted with the results of international achievement test for students such as OECD's PISA[28]. These tests, comparable across countries, showed that student performances in reading, writing and mathematics could remain poor despite substantive improvements in school attendance[29]. This evidence drove a lot attention and led to a shift in the literature from educational level as a simple proxy to skills toward more accurate measures of students' academic performances.

Although they appear to reflect cognitive skills through academic abilities, these tests are also influenced by personality traits, like perseverance for work, and incentive systems (Heckman et al. 2006, Almlund et al. 2011, Borghans et al. 2011, Heckman and Kautz 2012). Skills measured by tests and exams are likely to be affected by schooling as opposed to latent skills that might not (Díaz et al. 2012). This is also corroborated with the psychology literature (Borghans et al. 2008a).

Meanwhile, a cluster of empirical studies intended to evaluate more directly the abilities of students and workers and their influences on decisions and outcomes by using longitudinal national surveys including batteries of tests measuring cognitive skills and personality traits. For a while, this segment of the literature has focused on the role of intelligence quotients (IQ) as primary determinants of wages. The complete spectrum of an individual's skills stock, encompassing lower- and higher-order cognitive skills, behaviors and personality traits as well as technical skills, was overlooked. Thus, considering only the influence of cognitive skills left a significant unexplained factor that predicts differences in labor earnings among observationally equal individuals (Bowles et al. 2001b). Since the mid-2000s, part of this unobserved predictor of labor earnings has been found to be personality traits and socio-emotional skills. These facets have since then been put at the center of this literature and studied expansively, simultaneously with cognitive skills, both by economists and psychologists.

[28] The Program for International Student Assessment (PISA) developed by the Organisation for Economic Co-operation and Development (OECD) assesses the capabilities of 15-year old individuals in reading, mathematics and science literacy in 70 countries. Data are collected every three years.

[29] This contradiction relies on the fact that much of the skills and personality traits that shape an individual's success are acquired outside the classroom. In addition to that, students acquire skills at each level of schooling very differently across schools and countries (Hanushek 1979, Hanushek and Woessman 2008).

However, self-reported questionnaires used to compute socio-emotional skills and personality traits have some limitations (Paulhus, 1991, Lucas and Baird 2006). Despite the confidentiality of the studies, measurement of factors may be corrupted by "faking", that is to say surveyed individuals who would deliberately report more favorable states of their strengths and weaknesses (Duckworth et al. 2007, Borghans et al. 2008b, Almund et al. 2011). It is of particular concern for surveys with relatively transparent scale for traits even if their results have no direct serious consequences on the people surveyed; for instance the Grit Scale (Duckworth et al. 2007). Most of existing studies are based on this kind of questionnaires. Notable exceptions include psychological assessment of the Swedish military enlistment (Lindqvist and Vestman 2011) and teacher's evaluations of eighth-graders' behaviors in the United States (Segal 2012) and 11 year-old children in Great Britain (Carneiro et al. 2007).

Technical skills have been studied relatively marginally besides their impact on employment outcomes of beneficiaries of vocational trainings. Still, research using batteries of tests to determine workers' abilities in teenage is increasingly analyzing this aspect, using analog methods to studies of the impact of cognitive and socio-emotional skills.

In parallel, recent works have investigated across countries and time the skills content of occupations based on the skills required to perform tasks associated with these jobs (Autor et al. 2003, Acemoglu and Autor 2010, Aedo et al. 2013). Such work has some limitations for the time being given that they dispose only of information on the skill content per occupation from the United States and consider them for lower income countries the same.

A new generation of skill measurement is currently being pioneered through the collection by the World Bank and other international organizations of original data combining information on job, education, skills levels and as well as environment and family background. These recent sources of critical information include the Inter-American Development Bank's (IADB) STS[30], the OECD's PIAAC[31] and the World Bank's STEP Skill Measurement Study. The last two surveys have comparable components. PIIAC and STEP Skill Measurement Study collect information on the levels and distributions of cognitive, technical and non-cognitive skills among adults; along with a range of additional information on activities, family and job background, perceptions, etc. For a given year, the World Bank's STEP Skill Measurement Study allows to quantify the mismatch between the skills of the adult population and employers' needs, when the complementary employers' survey is available; and assess how skills of individuals affect labor

[30] The Skills and Trajectory Survey (STS) were conducted in Argentina and Chile in 2008 and 2010. It provides information on individuals, aged 25 to 35, about their job performance, educational experiences and levels of low-order cognitive skills (fluid intelligence detected using a series of eight figural analogies), high-order cognitive skills (task-planning), socio-emotional skills (such as communication and leadership) and high-order socio-emotional skills (self-efficacy) (Bassi et al. 2012).

[31] The Survey of Adult Skills (Programme for the International Assessment of Adult Competencies, PIAAC) assesses the proficiency of adults aged 16-65 in literacy, numeracy and problem solving in technology-rich environments (OECD 2013b). The first round, collected in 2011-2012 has covered 24 high-income countries. More information and country results can be found at: www.oecd.org/site/piaac/

market outcomes using current or backward information on labor experience, education and family background. STEP skill measurement instruments collect information from participant countries through harmonized individual and employer surveys and by using comparable implementation protocols and technical standards. The STEP Skill Measurement Study has covered 14 countries for wave 1 and 2 (2011-2013).

Contextualizing the evidence

A central concern is to know to which extent existing evidence could be applied to developing country contexts and specifically to Latin American countries. Data are mainly available for the United States[32] or Western Europe so the conclusions emerging from the studies may not apply in the same way to Latin American countries. This region differs for its labor markets and institutions as well as more disadvantaged schooling and familial environments. For example, interventions aiming to foster socio-emotional learning in marginalized areas in Peru would face different factors, that would challenge improvement of children's outcomes, such as high levels of violence in marginal districts, children with greater socio-emotional challenges, generally weaker teachers' training and capacity to promote socio-emotional skills, lower teaching quality, student and teacher attendance (World Bank and IPA forthcoming).

In addition, most of studies used data for relatively old period of time (1980s, 1990s), for which the set of skills rewarded on labor markets at that time may be outdated as technologic changes and globalization may have called for different set of skills. Traits that are important for individuals from the United States who were in their fifties a decade ago are not necessarily relevant for current generations in the labor market (Mueller and Plug 2006).

External factors are not always taken into account too and might explain bias in the estimation of this impact of skills. For instance, wages in Sweden are determined by union bargaining so personality traits have been found to be little impact on it (Nyhus and Pons 2005). Labor regulations and labor market characteristics matter as well for the design of skills policies. High job turnover in Brazil leads to skill gaps because it creates a disincentive for firms' and workers' to invest in training (Corseuil et al. 2012). More generally, the way schools and labor markets work in a given country can reward different type of skills. Indeed, European labor markets are generally more occupational – abilities produced during vocational schools are associated to those demanded by specific occupations - whereas multiple capacities are a cornerstone of the labor market in the United States (Urzúa 2013).

[32] The dataset most frequently used by studies on the United States is the National Longitudinal Survey of Youth (NLSY79), a panel of individuals, born in the years 1957-64, young adults in the 1980s and re-interviewed at regular period of time since then. Datasets and more information can be found at: www.bls.gov/nls/

4. Data

The Skills Toward Employment and Productivity (STEP) household survey is a multi-country study led by the World Bank assessing skills that matter and their links to the labor market.

The STEP household survey elicits a wide range of information on personal background, education, employment and compensation, household wealth, and household size and composition, similar to a standard household survey. Additionally, a randomly-selected individual in each household is further survey on information related to reading proficiency, personality, personal health, and technical skills used on the-job. The measures of skills include:

Cognitive skills measures: Survey respondents take a reading proficiency test developed by the Educational Testing Service (ETS) for the project, drawing on ETS' work for the Program for the International Assessment of Adult Competencies (PIAAC). The test consists of several sub-tests: Reading Components that assesses "foundational reading skills", namely word meaning, sentence processing and reading comprehension; core literacy, and, for those who "pass" the first two tests, four advanced reading tests. Rather than generating a literacy test value based on each participant's measured scores, the ETC calculates a "plausible value" of literacy for each respondent. We use the posterior mean of these plausible values in our analysis. Additionally, survey respondents are asked about the amount of reading, writing, and the type of numerical calculations performed both on the job and outside work.

Non-cognitive skills measure: The non-cognitive battery is composed of: the short Big Five Inventory, consisting of fifteen items; a seven-item risk and time preference scale; and three items to capture grit, two to capture hostile attribution bias, and four to capture decision making skills.

Technical skills measure: The STEP items are drawn from the survey of Skills, Technology, and Management Practices (STAMP), a two-wave, nationally representative panel survey of U.S. wage and salary workers (for details see Handel 2008).

The STEP household survey of Colombia is representative of the country's thirteen main cities and their metropolitan areas. This covers the large majority of Colombia's urban population and is the area widely used by labor market household surveys in Colombia. This survey, however, actually included only 9 cities, but the cities are deemed to still be roughly representative of the 13 cities. The sample size is approximately 2,617 individuals. The distribution in age, gender and education is similar than national household surveys for the same urban areas.

5. Empirical strategy[33]

We would like to estimate the following relationship between labor market outcomes and skills:

$$Y_i = \alpha + \beta_1 A_i + \beta_2 X_i + \varepsilon_i \qquad (1)$$

where Y_i is a labor market outcome, A_i represents all ability (skills) that affects the labor market outcome, X_i is a set of factors (other than ability) that affect Y_i. Since ability is unobserved, the measure commonly used for A_i is years of schooling. Assuming that highest year of schooling completed S_i captures all A_i, we can substitute out A_i for S_i which, if Y_i is wages, gives us the typical Mincerian wage equation:

$$Y_i = \alpha + \beta_1 S_i + \beta_2 X_i + \varepsilon_i \qquad (2)$$

If the decision-maker for our outcomes of interest – wages, employment, occupation – is the employer, S_i may be a perfect measure for the ability information that the employer has at the time of hiring. Employers receive curricula vitae that list educational attainment and little else. Thus, that employer is making hiring and/or wage decisions based on the same information that the researcher has. The estimated β_1 will be an unbiased estimate of the impact of ability on labor market outcomes.

However, employers are likely to have more information than schooling attainment, such as that obtained through an interview, where the employer assesses communications skills, professional behavior, and other non-cognitive skills. In other words, S_i is unlikely to capture all ability measurement[34]. Thus, S_i is correlated with ε_i, which results in biased estimates of the returns to schooling (β_1). Suppose that T_i measures all skills that are captured in S_i and ε_i in equation (2). We can rewrite equation (2) as

$$Y_i = \alpha + \beta_1 T_i + \beta_2 X_i + \upsilon_i \qquad (3)$$

Under the assumption that our set of T_i perfectly measures all A_i,[35] we can estimate equation (3) using OLS without any ability bias and β_1 will give us the return to each skill captured by vector T_i. Returning to our employer's information, if she only has information about school test scores - a proxy for cognitive skills – and behavioral information from an interview, the T_i in equation 3 may be adequate to estimate β_1 without error.

[33] This section is extracted from Acosta and Cunningham (2013), Skills for the LAC Labor Market - Methodology Note, Internal document, World Bank, Washington, DC.
[34] Educational attainment is a poor measurement of actual scholastic ability, as shown by the high variance in grade-specific achievement tests that are administered in various countries.
[35] We are careful to define T_i as "measured skills" and not as skills. Heckman et al. (2006) posit a latent variable that affects measured skills (and schooling); we adopt that assumption, as well, as recommended by the psychology literature (Borghans et al. 2008).

However, a growing literature shows that T_i does not fully capture A_i so $Corr(T_{i,}\ \upsilon_i) \neq 0$. In that case, we again have a biased estimate of β_1.[36] The literature has addressed this problem through various means. One approach is to use an instrumental variable, Z_i that is correlated with T_i but not correlated with υ_i. The weaknesses of this approach are multiple, including difficulty in selecting a good IV for T_i, the need to select an IV for each T_i (many of which are produced through similar processes), and the inability of IV to solve measurement error. For a discussion of these challenges, see Heckman et al. (2006) and the sources cited therein.
The above discussion produces an estimate of the net effect of abilities on wages. However, schooling may contribute differently to wages than do measured skills, for instance if there are complementarities between schooling and specific measured skills, which would argue for including a schooling variable in the estimates to reduce missing variable bias.

Thus, one could estimate the equation[37]:

$$Y_i = \alpha + \beta_1 S_i + \beta_2 T_i + \beta_3 X_i + \varepsilon_i \tag{4}$$

This estimate takes care of one econometric issue but introduces a new problem – endogeneity between the schooling and the skills measurement variables. For example, Bowles and Gintis (1976) find that schooling creates non-cognitive skills that are valued in the marketplace. And, one could imagine that youth that possess greater discipline and persistence (non-cognitive skills) would perform better on standardized tests than cognitively equal but non-cognitively less skilled peers. This suggests that estimating labor market outcomes on schooling, cognitive, and non-cognitive skills will deliver biased and inconsistent estimates.

Since our object of interest is the effect of T_i on Y_i, a potential solution is to extract cognitive and non-cognitive skills measures from schooling, and use an estimated schooling residual in the OLS estimate.[38] This two-stage process first estimates

$$S_i = \boldsymbol{\delta_0} + \boldsymbol{\delta_1}\ T_i + \boldsymbol{\delta_2}\ \boldsymbol{X_i} + \boldsymbol{\mu} \tag{5}$$

The $\widehat{\boldsymbol{S}}_{\boldsymbol{i}}$ is estimated in the standard way and then $\widehat{\boldsymbol{\mu}}_{\boldsymbol{i}} = S_i - \widehat{\boldsymbol{S}}_{\boldsymbol{i}}$, which is orthogonal, by construction, to T_i and is used to estimate the second stage:

[36] Test scores are sensitive to the amount of schooling completed at the time of the test and family background. Further, the measures of ability are known to be very noisy. Thus, using test scores as an independent variable in regression model analysis will lead to measurement error bias.
[37] In the country papers, equation 4 will be the starting point. Equations 1-3 were only presented in this Methodology Note to guide the reader from the common starting point – regressing Y on S – to our new starting point which is regressing Y on S and T.
[38] This is similar to Diaz et al. (2012), but in that paper, the variable of interest is the impact of S_i on Y_i. Thus, in the first step, the authors regress each measured T on S and estimate a vector of residuals of T that has been cleansed of S.

$$Y_i = \alpha + \beta_1 \hat{\boldsymbol{\mu}}_i + \beta_2 T_i + \beta_3 X_i + \varepsilon_i \qquad (6)$$

Equation 5 also gives us our estimate of the correlation between skills and schooling outcomes.

Under this specification, another problem arises. Namely, parents affect the production of cognitive, non-cognitive, and schooling variables.[39] This latent variable is responsible for endogeneity between S_i and T_i in equation (5) and between $\hat{\boldsymbol{\mu}}_i$ and T_i in equation 6.

To eliminate the endogeneity due to reverse causality between S and T in equation (5), Diaz et al. (2012) use an IV method. Applying their methodology to our model, we would first instrument each element in the T vector, based on variables that affect T but not level of schooling S. We would then estimate the production function of S, regressing S on a vector of X and on the instrumented T measures. The residual of S would then be used in equation (6). The data demands of this methodology are quite high since latent factors that uniquely affect the formation of each measured skills also likely affect the schooling variable.

6. Results (WORK IN PROGRESS)

6.1. Distribution of skills across cities, gender, age groups, highest educational levels completed and labor market status

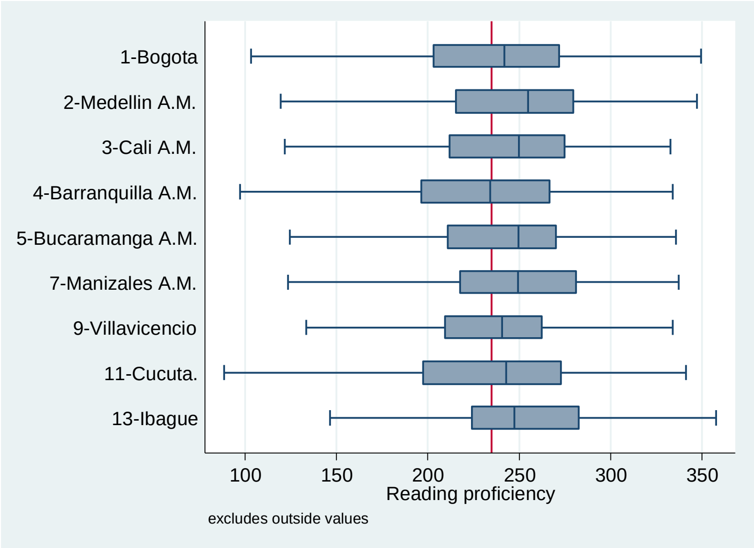
Cognitive skills

- Our measure of cognitive skills is a score of reading proficiency (posterior mean of plausible values).
- Reading proficiency performances are relatively homogeneous *between* main cities and their metropolitan areas but highly heterogeneous *within* them (Figure 1).
- No significant difference across gender.
- Younger generations perform substantially better than older one (Figure 2).
- Individuals with highest education perform better than lowest one but the relationship between highest educational level completed and reading proficiency scores does not seem to be linear (Figure 3). It is noteworthy that individuals at the top of the distribution of their educational level (last decile) perform better than 75% of individual with the best performing educational level – tertiary education.
- Students have generally outstanding scores compared to unemployed, employed and other inactive. It is expected that students perform better at this kind of assessment given that they are dealing frequently with them. Interestingly, the unemployed show higher

[39] Heckman et al. (2006), Carneiro et al. (2003), Carneiro and Heckman (2003), Cunha et al. (2005) Heckman et al. (2006b) find that parents and family background play an important part in producing cognitive and non-cognitive skills.

bell curve than employed. It confirms in a way the idea that the unemployed in Colombia may have better labor market prospects than low-paid workers in the sense that they can "afford" to take time to look for a job and can pretend to jobs requiring higher lower-order cognitive ability (Figure 4).

Figure 1. Distribution of reading proficiency across main cities and their metropolitan areas



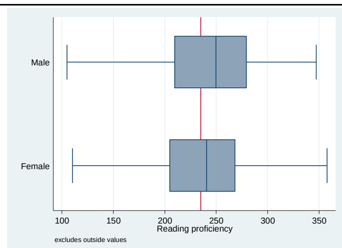
Note: the red line indicates the total average score (235).
Source: Authors' elaboration based on Colombia STEP Household Survey (2012).

Figure 2. Distribution of reading proficiency across groups of interest

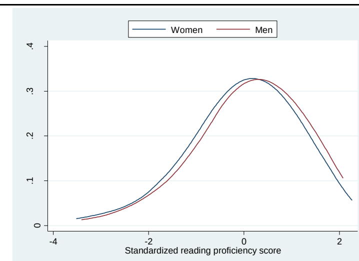
Kernel density

Gender

A. Box plot

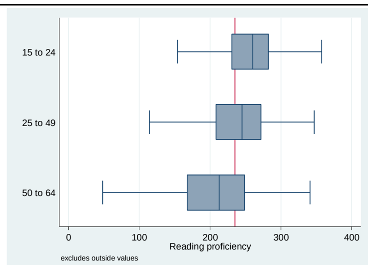


B. Kernel density of z-score

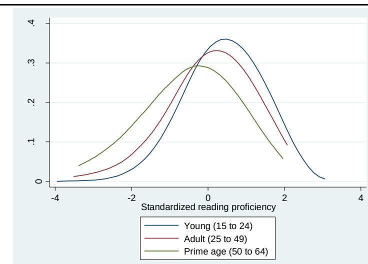


Age group

C. Box plot

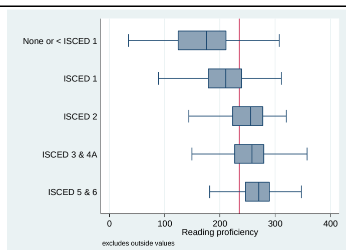


D. Kernel density of z-score

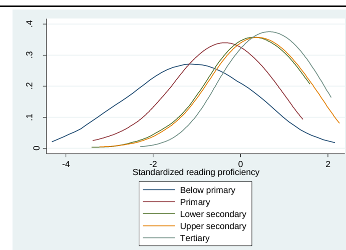


Highest educational level completed

E. Box plot

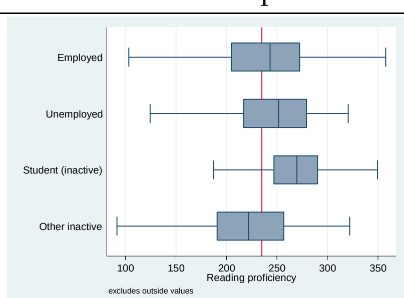


F. Kernel density of z-score

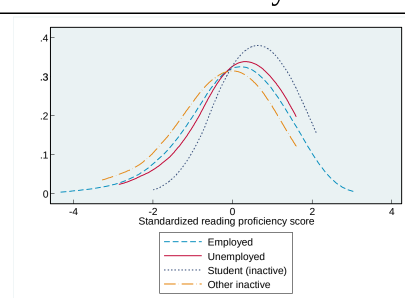


Labor force status

G. Box plot



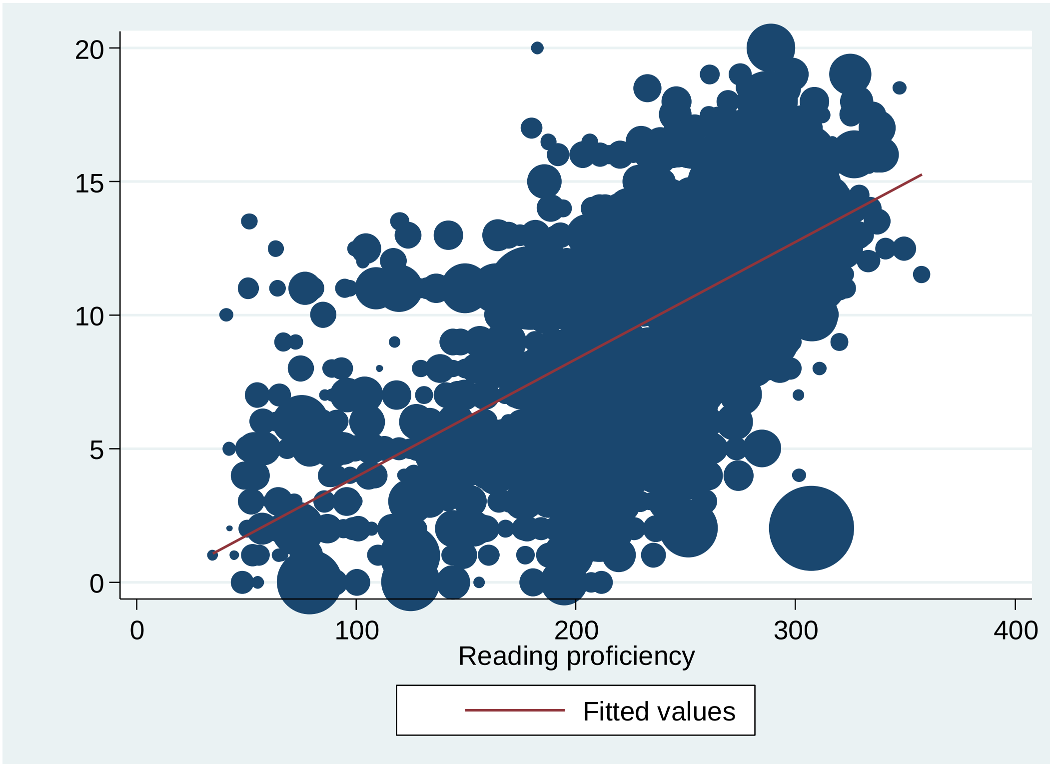
H. Kernel density of z-score



Note: the red line indicates the total average score (235).

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

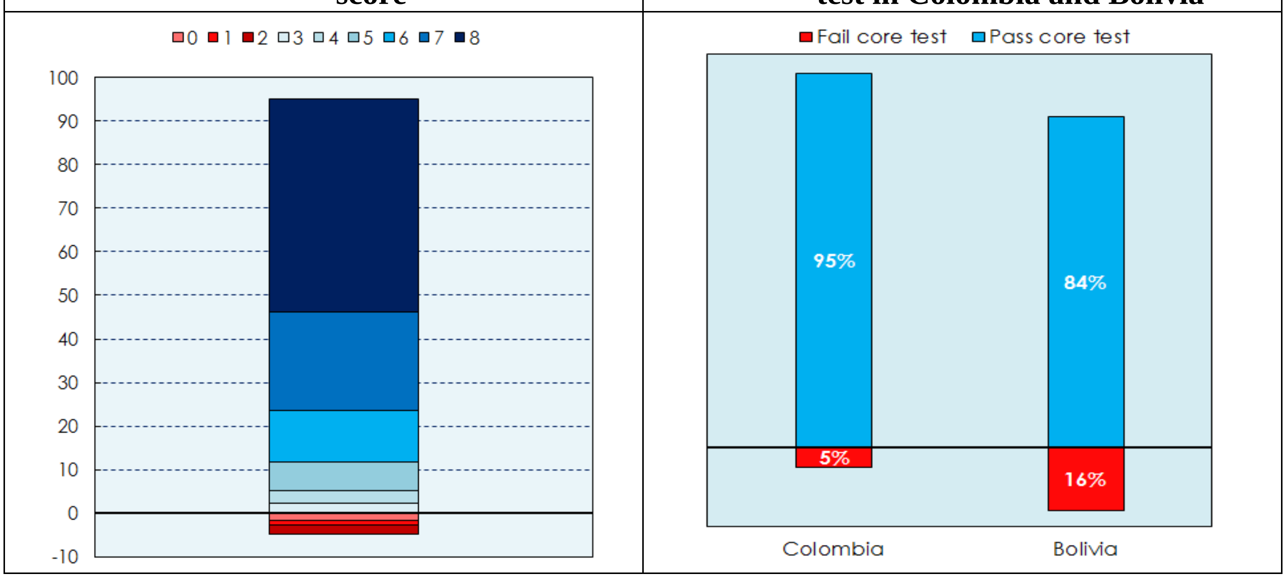
Figure 3. Unconditional correlation between years of education and reading proficiency



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

Figure 4. Percentage of working-age individuals in urban areas by reading core test score

A. Detail of Colombia reading core test score	B. Share of individuals who passed the test in Colombia and Bolivia



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

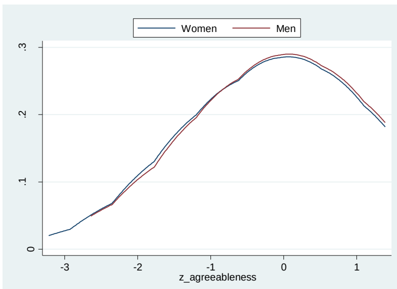
Personality traits

- Our measure of personality traits are: the short Big Five Inventory, consisting of fifteen items; and three items to capture grit, two to capture hostile attribution bias, and four to capture decision-making skill.
- No substantial difference across gender to the notable exception of emotional stability (Figure 5).
- Young (15-24) tend to be less agreeable, conscious, more hostile and have less grit (Figure 6).
- Individuals with none to very low education (below primary) are generally less extroverted, opened and more hostile than their peers (Figure 7).
- Personality traits seem to be fairly equally distributed between employed, unemployed and inactive (excluding students). Students seem to be differ in the way they differ due to their younger age (Figure 8).

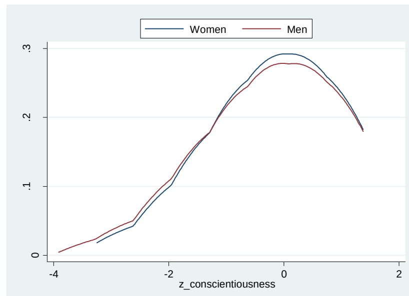
Figure 5. Distribution of personality traits across gender

Kernel density

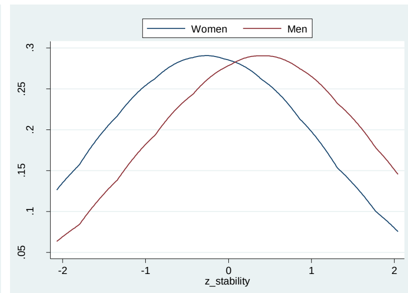
A. Agreeableness



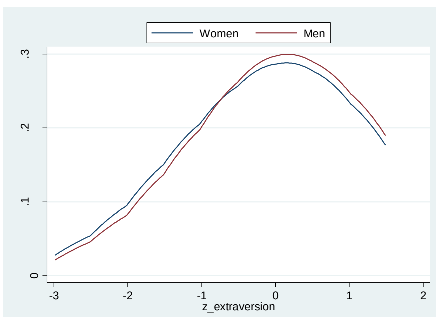
B. Conscientiousness



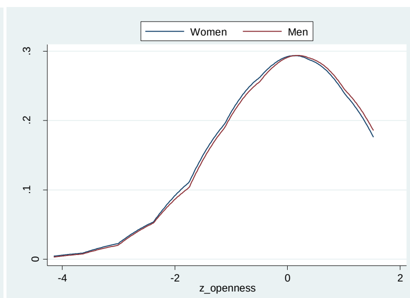
C. Emotional Stability



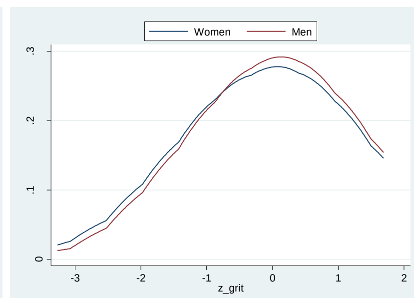
D. Extraversion



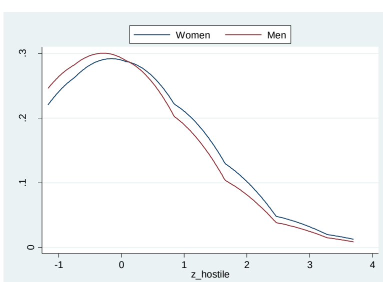
E. Openness



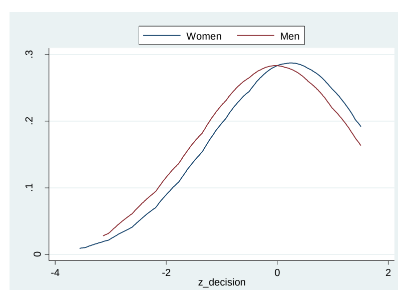
F. Grit



G. Hostile bias



H. Decision-making

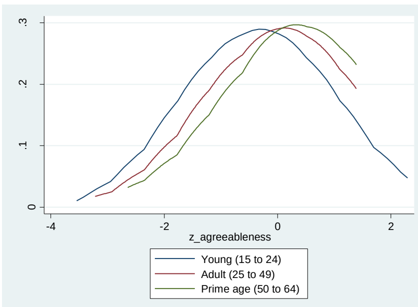


Source: Authors’ elaboration based on Colombia STEP Household Survey (2012).

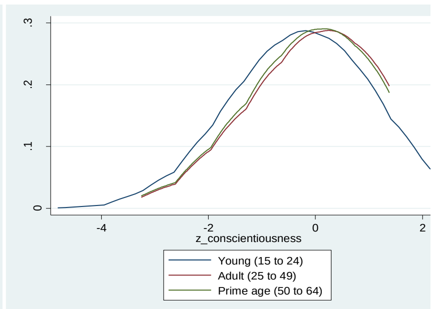
Figure 6. Distribution of personality traits across age groups

Kernel density

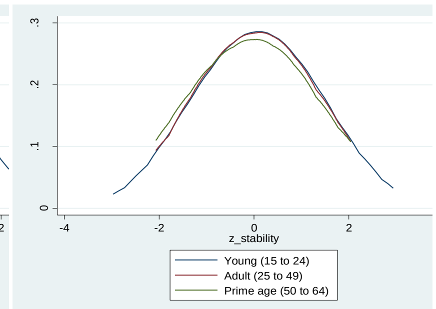
A. Agreeableness



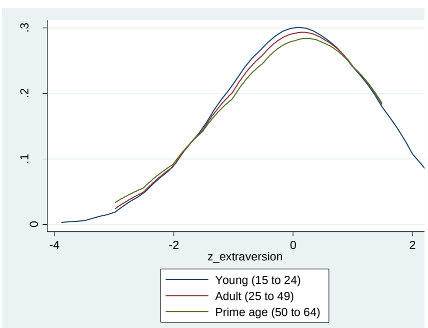
B. Conscientiousness



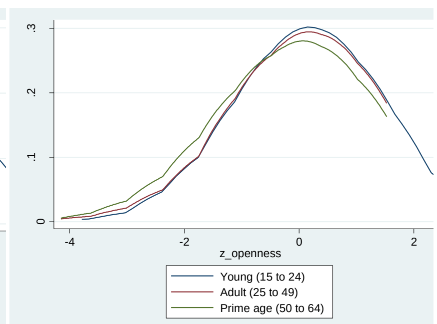
C. Emotional Stability



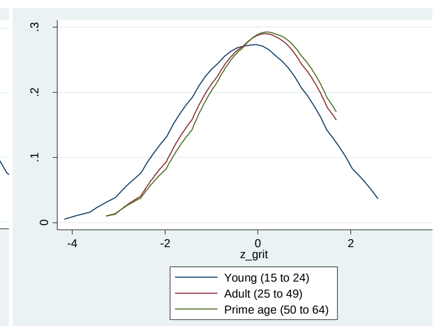
D. Extraversion



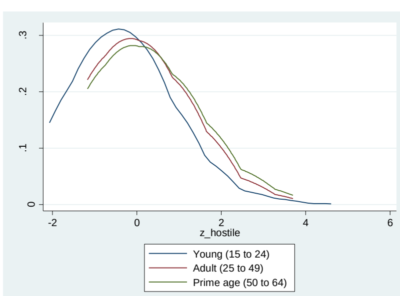
E. Openness



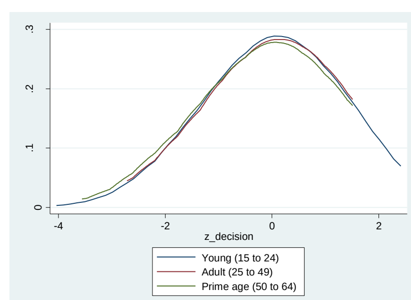
F. Grit



G. Hostile bias



H. Decision-making

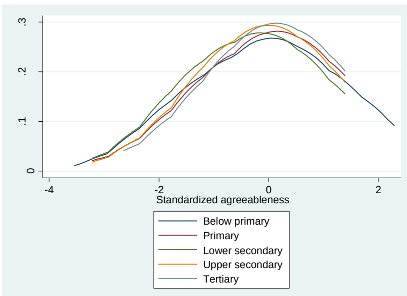


Source: Authors' elaboration based on Colombia STEP Household Survey (2012).

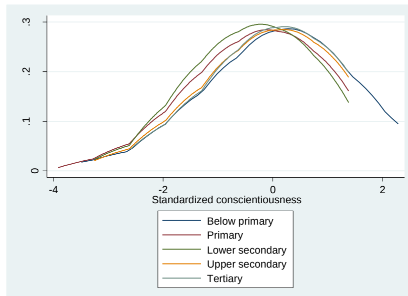
Figure 7. Distribution of personality traits across highest educational level completed

Kernel density

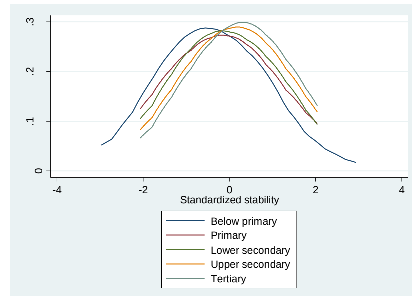
A. Agreeableness



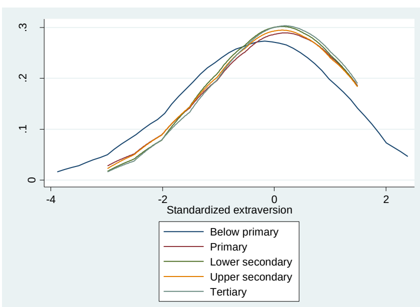
B. Conscientiousness



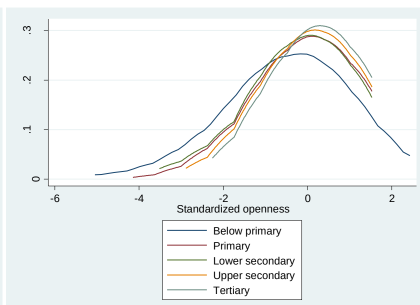
C. Emotional Stability



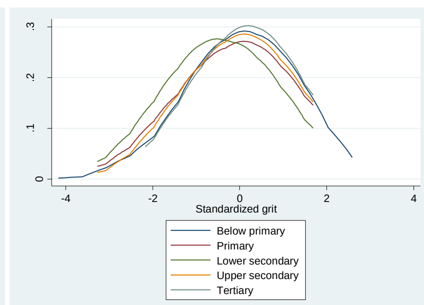
D. Extraversion



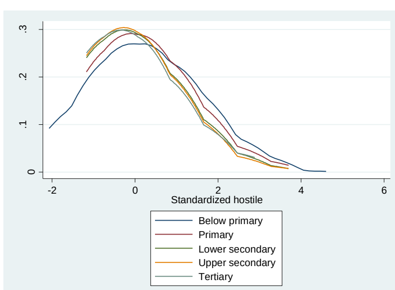
E. Openness



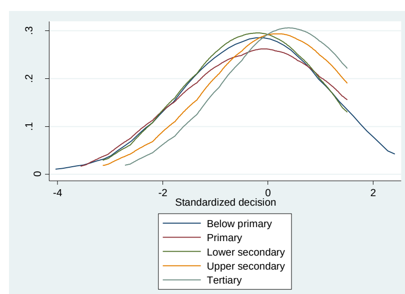
F. Grit



G. Hostile bias



H. Decision-making

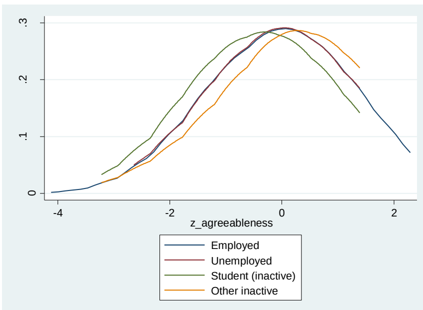


Source: Authors' elaboration based on Colombia STEP Household Survey (2012).

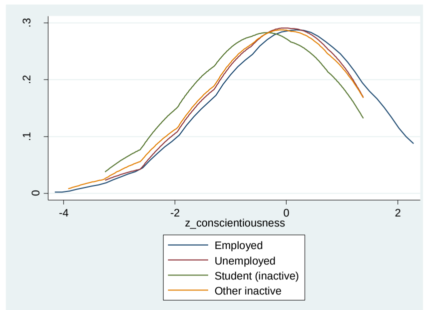
Figure 8. Distribution of personality traits across labor market status

Kernel density

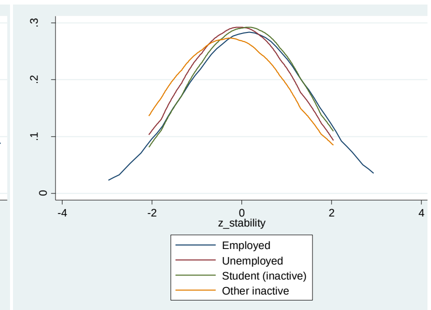
A. Agreeableness



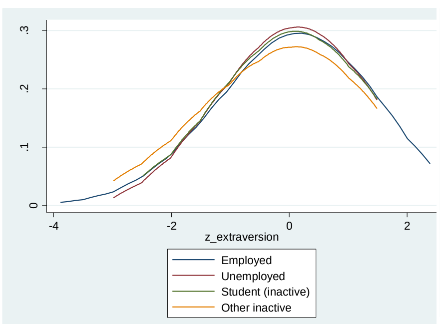
B. Conscientiousness



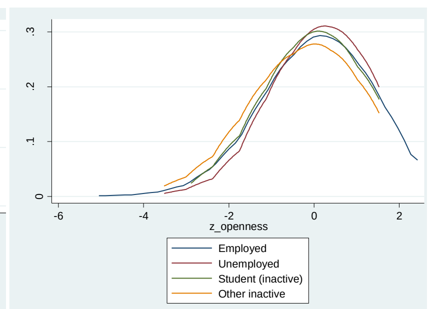
C. Emotional Stability



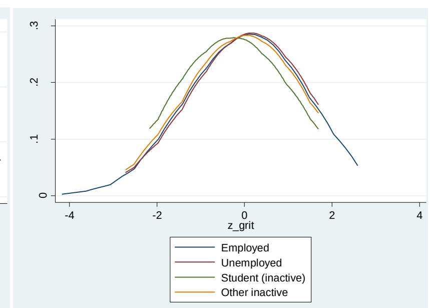
D. Extraversion



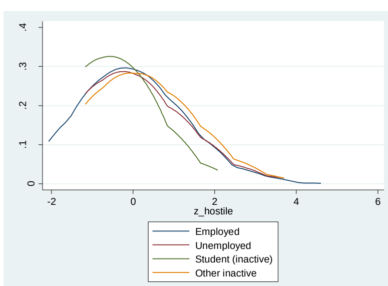
E. Openness



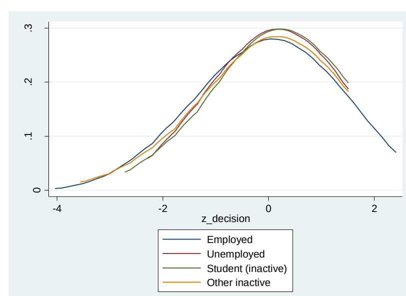
F. Grit



G. Hostile bias



H. Decision-making



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

6.2. Exploring the returns to skills and traits on wages using Mincer regressions (WORK IN PROGRESS)

- At this stage, we use conventional approach to observe the conditional correlations between log hourly labor earnings (wage for wage workers or net profit for self-employed) using Ordinary Least Squares (OLS).
- We eliminate the bottom and the bottom and top 1 % of the distribution of labor income.
- We use the following covariates (control variables):
  - Age
  - Age^2
  - Education (highest level completed, primary complete is the reference, or years of education)
  - Industry (dummies; "other services than commerce" is the reference category)
  - Main cities and their metropolitan areas (dummies; Bogota is the reference)

Results for the whole population

- Standard Mincer equation in our sample yields similar results than for national surveys representative of the same main cities (Table 1).
- Not controlling for schooling, basic cognitive skills (reading proficiency) is strongly associated with higher wages. Conditional to our set of covariates, openness and agreeableness are positively but more weakly associated with higher earnings (Table 2).
- When controlling for schooling, the predictive power of reading proficiency no longer hold. Openness remains weakly associated with higher earnings. However it does not take into account the endogeneity of schooling (Table 3). The higher educated an individual is the greater his (her) earnings.

Results for men and women

- Not controlling for schooling, basic cognitive skills (reading proficiency) are both strongly associated with higher wages both for men and women. However, while openness and agreeableness to a less extend, are good predictors of men's earnings, this is not the case for women. Emotional stability is positively but weakly associated to higher earnings (at 10% level) but is no longer significant when controlling for reading proficiency.
- When controlling for schooling, reading proficiency is no longer significant for both sex. Upper secondary and tertiary educations are highly significant for both sex. Somewhat surprisingly, lower secondary education is also positive and significant for men and yields larger returns than upper secondary. Openness is still significant for men.

Results for wage workers and self-employed

- Not controlling for schooling, basic cognitive skills (reading proficiency) are even more strongly associated with higher wages for wage workers. Agreeableness is also positively significant (at the 1% level). Emotional stability is also positively but weakly associated with higher wages (at the 10% level). Experience, as proxied by age, is positive and significant. For self-employed reading proficiency is also positively associated with earnings of the same magnitude but in a weaker way (5% level confidence). Openness is the trait associated with higher earnings for the self-employed (positively associated at the 5% level).
- When controlling for schooling, the predictive power of reading proficiency is significantly lower for wage workers and weakly significant) at the 10% level). Agreeableness is strongly significant and positive for this category. Surprisingly, grit is negatively associated with higher wages and significant at the 5% level. Openness remains weakly associated with higher earnings. The higher educated an individual is the greater his (her) earnings.

Table 1. Standard Mincer regression – regression of log hourly wage on age, education and covariates

	(1)	(2)	(3)
age	-0.010	-0.011	-0.011
	(0.02)	(0.02)	(0.02)
age2	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
Woman	-0.177**	-0.183**	-0.177***
	(0.07)	(0.07)	(0.06)
Years of education	0.072***		
	(0.01)		
Below primary		-0.040	-0.068
		(0.10)	(0.10)
Lower secondary		0.313**	0.318***
		(0.12)	(0.12)
Upper secondary		0.385***	0.385***
		(0.10)	(0.10)
Tertiary		0.667***	0.669***
		(0.10)	(0.10)
Agriculture, fishery, mining			-0.065
			(0.26)
Manufacturing, construction			0.015
			(0.10)
Commerce			-0.110
			(0.07)
Medellin			0.037
			(0.11)
Cali			-0.046
			(0.09)
Barranquilla			-0.109
			(0.10)
Bucaramanga			0.171
			(0.11)
Manizales			0.128
			(0.15)
Villavicencio			0.214
			(0.15)
Cucuta			0.292**
			(0.12)
Ibague			-0.017
			(0.16)
Constant	7.563***	8.009***	7.980***
	(0.31)	(0.33)	(0.32)
Observations	1,505	1,499	1,499
R-squared	0.11	0.10	0.12

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

Table 2. OLS regressions of log hourly wage on cognitive skills and personality traits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Reading proficiency	0.198***											0.157***	0.180***
	(0.04)											(0.04)	(0.04)
Extraversion		0.015								-0.003	-0.006	-0.015	-0.010
		(0.03)								(0.03)	(0.03)	(0.03)	(0.03)
Conscientiousness			-0.029							-0.045	-0.052	-0.046	-0.046
			(0.04)							(0.04)	(0.04)	(0.04)	(0.04)
Openness				0.084**						0.081**	0.070**	0.043	0.050*
				(0.03)						(0.03)	(0.03)	(0.03)	(0.03)
Emotional stability					0.021					0.017	0.019	0.027	0.008
					(0.04)					(0.04)	(0.04)	(0.04)	(0.04)
Agreeableness						0.071**				0.066*	0.059*	0.081**	0.062*
						(0.03)				(0.03)	(0.03)	(0.03)	(0.03)
Grit							-0.008			-0.022	-0.027	-0.002	-0.023
							(0.04)			(0.04)	(0.04)	(0.05)	(0.04)
Hostile bias								-0.025			-0.028	-0.013	-0.019
								(0.03)			(0.03)	(0.03)	(0.03)
Decision making									0.066*		0.050	-0.003	0.014
									(0.04)		(0.04)	(0.04)	(0.03)
age	-0.003	0.002	0.003	0.003	0.002	0.000	0.002	0.002	0.001	0.006	0.006		0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
age2	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000		0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Woman	-0.181***	-0.199***	-0.200***	-0.201***	-0.189***	-0.199***	-0.200***	-0.198***	-0.218***	-0.193***	-0.203***		-0.182***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
Agriculture, fishery, mining	0.018	-0.112	-0.101	-0.118	-0.109	-0.056	-0.113	-0.119	-0.084	-0.060	-0.053		0.056
	(0.27)	(0.32)	(0.32)	(0.31)	(0.31)	(0.31)	(0.32)	(0.31)	(0.32)	(0.31)	(0.31)		(0.27)
Manufacturing, construction	-0.025	-0.038	-0.039	-0.032	-0.035	-0.039	-0.039	-0.037	-0.026	-0.030	-0.020		-0.018
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)		(0.09)

Commerce	-0.136*	-0.140*	-0.140*	-0.127*	-0.136*	-0.138*	-0.141**	-0.136*	-0.125*	-0.128*	-0.116*		-0.125*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
Medellin	0.077	0.110	0.100	0.122	0.113	0.098	0.114	0.103	0.103	0.115	0.103		0.073
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.11)		(0.11)
Cali	0.021	0.061	0.066	0.078	0.064	0.055	0.058	0.053	0.073	0.087	0.090		0.041
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)		(0.09)
Barranquilla	-0.014	-0.039	-0.038	-0.019	-0.036	-0.054	-0.037	-0.034	-0.032	-0.032	-0.024		-0.012
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)		(0.09)
Bucaramanga	0.201*	0.253**	0.252**	0.276**	0.257**	0.253**	0.250**	0.250**	0.273**	0.272**	0.280**		0.213*
	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)		(0.11)
Manizales	0.120	0.179	0.189	0.172	0.179	0.147	0.183	0.177	0.200	0.155	0.172		0.108
	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)	(0.15)		(0.15)
Villavicencio	0.255*	0.240	0.232	0.258*	0.242	0.234	0.239	0.238	0.240*	0.254*	0.254*		0.261*
	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)		(0.14)
Cucuta	0.256**	0.243**	0.234*	0.266**	0.244**	0.250**	0.238*	0.244**	0.262**	0.267**	0.282**		0.275**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)		(0.12)
Ibague	0.045	0.116	0.126	0.103	0.118	0.096	0.122	0.118	0.103	0.092	0.084		0.029
	(0.17)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.18)		(0.17)
Constant	8.169***	8.199***	8.167***	8.159***	8.189***	8.247***	8.187***	8.181***	8.211***	8.117***	8.091***	8.202***	8.094***
	(0.34)	(0.36)	(0.37)	(0.36)	(0.36)	(0.36)	(0.38)	(0.36)	(0.38)	(0.38)	(0.39)	(0.04)	(0.37)
Observations	1,505	1,504	1,504	1,504	1,504	1,504	1,504	1,504	1,504	1,504	1,504	1,504	1,504
R-squared	0.07	0.03	0.03	0.04	0.03	0.04	0.03	0.03	0.04	0.05	0.06	0.05	0.09

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. OLS regressions of log hourly wage on cognitive skills, personality traits and schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Reading proficiency	0.070											0.058
	(0.04)											(0.04)
Extraversion		0.009								-0.000	-0.001	-0.003
		(0.03)								(0.03)	(0.03)	(0.03)
Conscientiousness			-0.022							-0.028	-0.031	-0.031
			(0.04)							(0.04)	(0.04)	(0.04)
Openness				0.055*						0.058*	0.055*	0.050*
				(0.03)						(0.03)	(0.03)	(0.03)
Emotional stability					-0.023					-0.025	-0.024	-0.022
					(0.04)					(0.04)	(0.04)	(0.03)
Agreeableness						0.048				0.047	0.045	0.048
						(0.03)				(0.03)	(0.03)	(0.03)
Grit							-0.026			-0.037	-0.038	-0.036
							(0.04)			(0.04)	(0.04)	(0.04)
Hostile bias								-0.000			-0.009	-0.008
								(0.03)			(0.03)	(0.03)
Decision making									0.030		0.017	0.008
									(0.03)		(0.03)	(0.03)
Below primary	-0.029	-0.066	-0.062	-0.054	-0.076	-0.059	-0.064	-0.068	-0.064	-0.042	-0.040	-0.009
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Lower secondary	0.281**	0.318***	0.316***	0.320***	0.316***	0.316***	0.313***	0.318***	0.322***	0.306**	0.309**	0.277**
	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)
Upper secondary	0.339***	0.386***	0.387***	0.380***	0.390***	0.381***	0.390***	0.385***	0.381***	0.389***	0.385***	0.348***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
Tertiary	0.592***	0.669***	0.669***	0.654***	0.676***	0.660***	0.674***	0.669***	0.655***	0.659***	0.650***	0.589***
	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
age	-0.011	-0.011	-0.009	-0.010	-0.011	-0.011	-0.009	-0.011	-0.011	-0.007	-0.006	-0.006
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
age2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Woman	-0.173***	-0.176***	-0.176***	-0.179***	-0.189***	-0.177***	-0.178***	-0.177***	-0.186***	-0.194***	-0.198***	-0.191***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)

Agriculture, fishery, mining	-0.027	-0.067	-0.058	-0.074	-0.065	-0.030	-0.073	-0.065	-0.056	-0.041	-0.040	-0.007
	(0.25)	(0.25)	(0.26)	(0.26)	(0.26)	(0.25)	(0.25)	(0.26)	(0.26)	(0.26)	(0.26)	(0.25)
Manufacturing, construction	0.013	0.015	0.015	0.018	0.012	0.014	0.013	0.015	0.019	0.012	0.014	0.012
	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
Commerce	-0.111	-0.110	-0.110	-0.103	-0.114	-0.110	-0.114	-0.110	-0.105	-0.114*	-0.111	-0.113*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Medellin	0.035	0.038	0.030	0.048	0.032	0.031	0.052	0.037	0.037	0.051	0.048	0.044
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Cali	-0.048	-0.045	-0.041	-0.030	-0.052	-0.047	-0.050	-0.046	-0.037	-0.034	-0.031	-0.036
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Barranquilla	-0.091	-0.110	-0.109	-0.094	-0.111	-0.119	-0.107	-0.109	-0.104	-0.103	-0.099	-0.087
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
Bucaramanga	0.161	0.170	0.170	0.188*	0.165	0.172	0.163	0.170	0.182*	0.174*	0.178*	0.167
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)
Manizales	0.115	0.127	0.133	0.125	0.130	0.106	0.133	0.128	0.139	0.120	0.127	0.112
	(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Villavicencio	0.223	0.215	0.209	0.229	0.209	0.212	0.218	0.214	0.216	0.222	0.223	0.229
	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)
Cucuta	0.288**	0.293**	0.287**	0.308***	0.288**	0.298**	0.288**	0.292**	0.301**	0.300**	0.305**	0.298**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Ibague	-0.026	-0.019	-0.012	-0.024	-0.015	-0.030	-0.012	-0.017	-0.021	-0.024	-0.025	-0.031
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Constant	7.996***	7.980***	7.956***	7.958***	7.990***	8.015***	7.943***	7.980***	7.987***	7.917***	7.910***	7.927***
	(0.32)	(0.32)	(0.33)	(0.32)	(0.32)	(0.32)	(0.34)	(0.32)	(0.32)	(0.35)	(0.36)	(0.35)
Observations	1,499	1,498	1,498	1,498	1,498	1,498	1,498	1,498	1,498	1,498	1,498	1,498
R-squared	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13	0.13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.3.Exploring the returns to skills on labor supply outcomes (WORK IN PROGRESS)

Being employed vs. jobless

- When controlling for schooling, the predictive power of reading proficiency become significant but negative. Most of schooling level is not associated with the probability of being employed. This is coherent with the idea that being jobless or rather unemployed is a situation that higher educated or higher skilled individual can afford. Informal worker, most likely with low-qualifications and low-quality jobs are employed. As a consequence being employed or not does not capture the best the well-being of individuals in the labor market. Conscientiousness is however strongly associated with the probability of being employed.

Holding an informal job vs. a formal job

- An informal job is defined by the absence of social security benefit from a job.
- Not controlling for schooling, basic cognitive skills (reading proficiency) and age are strongly negatively associated with the probability of being an informal worker.
- When controlling for schooling, reading proficiency and traits are no longer significant. Upper secondary and tertiary educations are strongly negative and significant.

Being a wage worker vs. self-employed

- Not controlling for schooling, reading proficiency and emotional stability are positively associated with being a wage worker and extraversion has a negative effect. However these relationships do no hold when controlling for age, age squared, industry, main city and metropolitan area. Conditional to our set of covariates, openness and agreeableness are positively but more weakly associated with higher earnings (Table 2).
- When controlling for schooling, reading proficiency and traits are no longer significant. Upper secondary and tertiary educations are strongly positive and significant.

Working as white-collar worker vs. blue-collar worker

- Not controlling for schooling, basic cognitive skills (reading proficiency) is very strongly associated with being a white collar. Conditional to our set of covariates, agreeableness is negatively but more weakly associated with this outcome. Hostile bias is negative and decision making positive considered alone but do remain as such when controlling for cognitive skills.
- When controlling for schooling, reading proficiency is no longer significant. Agreeableness is still negative and significant. Extraversion is positive and significant at

the 10% level. Upper secondary and tertiary educations are highly positive and significant.

6.4.Robustness Check accounting for reverse causality (TBC)

7. Policy implications (TBC)

8. Conclusion and way forward (WORK IN PROGRESS)

The economic and psychology literatures have identified cognitive skills as a driver of higher wages as well as a range of other outcomes in high income countries. More recently, these professions have recognized the salient impact of socio-emotional skills and personality traits. Evidence suggests that both types of skills have overall strong positive effects on labor market outcomes, schooling performances and choices, and are associated with lower probability of engaging in risky behaviors or criminal activities. Technical skills developed through vocational education are associated with higher chances of employment in the short-to-medium term but a weaker capacity of adaptation in rapidly changing economies. Yet, abilities are multidimensional by nature. It is actually a set of cognitive and non-cognitive skills that is rewarded in the labor market. Distinct combinations of skills and facets can lead very different outcomes and influence them sometimes negatively.

Abilities and traits are typically rewarded differently occupations and type of work, and sometimes across gender. Above all, there is little understanding of the economic mechanisms behind the role of skills. With a few notable exceptions, most of studies suffer from methodological issues and use limited data, particularly on the effects of socio-emotional, personality traits and technical skills.

The literature is marked by methodological shortcomings and data limitation. Causal analysis of the impact of skills and traits on employment suffer from endogeneity bias with education. Indicators to measure skills often narrow the measurement of one's abilities and traits in most of empirical works (IQ test, literacy and numeracy for cognitive skills; Big-Five model for non-cognitive skills).

This evidence emerges mostly from high-income countries, for which more and better data were available. In this regard, transposing the existing evidence to the Latin American context should be taken with caution. The vast majority of evidence comes from the United States and Western Europe, and relate mostly to relatively well educated people at primary age in the 1980s and 1990s. Beyond more disadvantaged contexts that Latin American are likely to face in their countries, the set of skills valued by the labor market has probably changed dramatically. Globalization and technology upgrading have called for more cross-cutting and adaptive skills. Meanwhile, the structure of labor markets in the United States and Western Europe are quite different from those in Latin America (labor market regulations and enforcement, education systems, profile of the working-able population, among others).

More evidence is needed to inform policy making in Latin America. Existing studies of this field on Latin America confirm the importance of both cognitive and non-cognitive skills but causal analyses, if any, have a weak reliability. Particularly, further information is needed for disadvantaged groups (such as the young and the poor) to assess their potential deficit in skills and design solutions to reduce these carences. There is room for manoeuvre for interventions fostering cognitive or behavioral skills but better and more information would increase the collective limited knowledge about which skills should be taught at which phase of the lifecycle, how, when, and through which institutions (higher education, labor training institutions, etc.).

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