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Cognitive and Non-Cognitive Skills for the Peruvian Labor Market

Addressing Measurement Error through Latent Skills Estimations

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Abstract

Evidence from developed country data suggests that cognitive and non-cognitive skills contribute to improved labor market outcomes. This paper tests this hypothesis in a developing country by using an individual-level data set from Peru that incorporates modules to measure cognitive and non-cognitive skills. The paper estimates a structural latent model with unobserved heterogeneity to capture full ability rather than just measured skill. It also applies standard ordinary least squares techniques for comparison. The analysis confirms that cognitive and non-cognitive skills are positively correlated with a range of labor market outcomes in Peru. In particular, cognitive skills positively correlate with wages and the probability of being a wage worker, white-collar, and formal worker, with verbal fluency and numeric ability playing particularly strong roles. The results are robust to methodology. The patterns are less uniform for non-cognitive skills. For instance, perseverance of effort (grit) emerges strongly for most outcomes regardless of methodology. However, plasticity—an aggregation of openness to experience and emotional stability—is only correlated with employment, and only when using the structural latent model. The ordinary least squares method also finds that the disaggregated non-cognitive skills of kindness, cooperation, emotional stability, and openness to experience emerge significantly, mostly for the wage estimates. The different results derived from the ordinary least squares and the structural model with latent skills suggest strong measurement bias in most non-cognitive skills measurement. These findings, although only correlational because of the use of a single cross-section, suggest that recent efforts by the Peruvian government to incorporate non-cognitive skill development into the school curriculum are justified.

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Cognitive and Non-Cognitive Skills for the Peruvian Labor Market: Addressing Measurement Error through Latent Skills Estimations*

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I. Introduction

In recent years, there has been a re-thinking of the concept of "skills" and how it relates to economic success. While hundreds of papers have estimated the returns to education using "years of schooling" as a proxy for understanding the impact of skills acquired on labor market success, more recent work (Hanushek and Woessmann 2008) argues that this previous research suffers from measurement error.[1] Instead, there is a growing effort to more accurately measure a range of skills and to correlate them with individual and aggregate economic success variables. In this strain of literature, economists have relied on works from behavioral and personality psychologists that refine the concept of "skills" to encompass "cognitive" skills and "non-cognitive" skills (see for example Almlund, 2011). The former refers to all forms of knowing and awareness such as perceiving, conceiving, remembering, reasoning, judging, imagining, and problem solving" (APA, 2006), while the latter is roughly defined as personality traits and socio-emotional behaviors that guide the way people feel, behave and react to different stimulate (Borgans et al., 2008).

The emerging literature confirms that higher measures of cognitive skills are associated with higher wages, even when holding constant years of education. For example, studies that use longitudinal data from the US to fit models of labor force variables of young adults and cognitive high school test scores, find that a one standard deviation increase in a mathematics test score in 12th grade increases annual earnings by 10-15 percent during their mid-twenties to early thirties (Mulligan 1999, Murnane et al. 2000, Lazear 2003). Similar results are found for the UK (McIntosh and Vignoles 2001) and Canada (Finnie and Meng 2001). Using literacy scores (to proxy cognitive skill measures) and labor force behaviors from the International Adult Literacy Survey (IALS), Hanushek and Zhang (2009) finds that a one standard deviation increase in literacy scores increases earnings by 9.3 percent in a 13 country sample. The impact of school attainment falls from 7.1 to 5.9 percent after controlling for literacy scores. A small set of papers find an impact of cognitive skills on wages in developing countries as diverse as Ghana (Glewwe 1996), Kenya (Knight and Sabot 1990), Pakistan (Alderman, Behrman, Ross and Sabot 1996), South Africa (Moll 1998), and Argentina (Tetaz and Cruces 2009).

Similar results are found for the effect of non-cognitive skills on wage earnings. Early work by Bowles and Gintis (1976) observes that a measurable part of the variance in earnings among observationally equal individuals with equal levels of education, are due to behavioral skills. Carneiro and Heckman (2003) report that participants in the Perry Pre-School program, who received intensive non-cognitive development interventions as children, have similar cognitive abilities but higher non-cognitive abilities than non-participants who were randomly selected out of the program; participants also have greater scholastic and labor market success as adults. Focusing on adults, Heckman, Stixrud and Urzúa (2006) find that both cognitive and non-cognitive skills are important in explaining higher wages, shorter job search periods, and occupational choice, and that non-cognitive skills are particularly important for those with lower levels of education, women, and youth.

[1] Hanushek and Woessman (2008) identify two sources of measurement error. First, there is a great deal of heterogeneity in the skills acquired at each level of schooling across countries, regions within countries, and schools within regions. Second, much skill acquisition occurs outside of the classroom (Hanusheck 1979).

Accounting for measures of cognition, specific facets of personality are correlated with higher wages, playing different roles in different countries or for specific facets of the population. Conscientiousness plays an essential role in determining wages in the United States (Kern et al 2013), especially for women (Mueller and Plug 2006). Swedish men who lack leadership abilities have lower annual earnings than men with higher leadership scores (Lindqvist and Vestman 2011);[2] similar results were found in Argentina (Tetaz and Cruces 2009). Traits related to emotional stability (locus of control and self-esteem) play an essential positive role in determining men's wages in the United States (Muller and Plug 2006) but have a strong negative impact on wages in Germany. Agreeableness has been found to be a trait that is rewarded by the US labor market for both men and women (Mueller and Plug 2006), but that harms German women's wages (Heineck and Anger 2010). Openness to experience is rewarded more among men in the United States than among women (Mueller and Plug 2006). Bassi et al. (2012), which bases their evidence on associations (correlations) rather than causal relationships, find that self-efficacy[3] positively correlates with wages in Argentina and Chile. Grit, defined as perseverance and passion for long-term goals, has great influence on professional success in the US (Duckworth et al. 2007).

A small literature finds that both cognitive abilities and personality traits have an important role in determining the participation of individuals in the labor market. Wichert and Pohlmeir (2010) and Glewwe, Huang and Park (2011) find that both cognitive and non-cognitive skills affect labor supply patterns. When considering specific skills, Conscientiousness and Extraversion have a large and positive effect on labor force participation in the United States and Germany (Barrick and Mount 1991, Wichert and Pohlmeier 2010). In contrast, Neuroticism and Openness have a negative effect in Germany (Wichert and Pohlmeier 2010) while Agreeableness plays a weaker role, only affecting labor force participation of married women. In Argentina and Chile, decision-making, leadership (cognitive), and self-efficacy (non-cognitive) skills are highly correlated with labor force participation in both countries (Bassi et al. 2012). As summarized by Wichert and Pohlmeier (2010), ignoring the effect of personality traits will overestimate the influence of education on labor participation, especially for women.

Few studies have also considered the role of different skills in the nature of work. 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 high self-esteem in adolescence are more likely to become successful incorporated entrepreneurs in the United States (Levine and Rubinstein 2013). In the Netherlands, lower-order cognitive skills (language and clerical abilities) predict wage employment, whereas mathematical and technical ability as well as extraversion in early childhood are more valuable for entrepreneurs (Hartog et al. 2010).

[2] The data used in this study are drawn from a psychological assessment for the military. The authors define "leadership" as 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).

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

Employers also highlight the demand for a range of skills. A review of 28 studies reveals remarkable consistency across the world in the skills demanded by employers. Although employers value all skill sets, there is a greater demand for socio-emotional and higher-order cognitive skills – the capacity to deal with complex information processing – than for basic cognitive or technical skills. These results are robust across economy size and level of development, sector, export-orientation, and occupations (Cunningham and Villaseñor 2014).

While most of the work correlating skills and labor market outcomes is based on US or European data, new data from developing countries permit the exploration of whether the skills important for success in developing country labor markets are the same as those identified in US and European labor markets. Both the OECD's PIAAC[4] and the World Bank's STEP[5] initiatives have begun to survey adults in countries as diverse as Bolivia, Colombia, Ghana, Sri Lanka, the Ukraine and Vietnam. These surveys collect data from adults on cognitive skills - primarily literacy and skills used on the job – and non-cognitive skills. The data analysis shows that both sets of skills affect wages and employment patterns. While these studies give the first insights into how these skills interact with labor markets, they suffer from a range of econometric issues that limit the robustness of their conclusions.

An early survey undertaken in Peru (ENHAB 2010) provides a richer set of variable that allow us to employ methodologies to overcome some of the econometric issues and perhaps present more robust results. Using these data, Diaz, Arias, and Vera-Tudela (2012) explore the impact of cognitive and non-cognitive skills on wages. The paper finds that an additional standard deviation in the overall non-cognitive skill measure increases earnings by 9 percent, similar in magnitude to the effects of individual cognitive skills. Specifically, emotional stability[6] and perseverance of effort are associated with 5 and 8 percent higher earnings respectively; while agreeableness is associated with 8 percent lower earnings. Lavado, Velarde, and Yamada (2014) complement the ENHAB with longitudinal data on national test scores and find that differences in non-cognitive skills explain gender gaps in returns to abilities, schooling, employment and occupation.

The case of Peru is interesting not only from a data, but also from a policy, point of view. The country is engaged in a debate about which skills are the key to labor market success, including a discussion about the role of non-cognitive skills. Since the beginning of the millennium, Peru has experienced impressive growth rates, rising from 2 percent in 2001 to more than 9 percent in 2008, returning to over 6 percent by 2013; largely due to a boom in export products in newly developed markets.[7] Drawing from evidence from the US and Europe, the Peruvian Ministry of Education designed and is pilot-testing a non-cognitive skills development program. Furthermore, since November 2013, the Ministry of Labor has been implementing a series of free short workshops that

[4] http://www.oecd.org/site/piaac/

[5] http://siteresources.worldbank.org/EXTHDOFFICE/Resources/5485726-1281723119684/TEP_Skills_Measurement_Brochure_Jan_2012.pdf

[6] The concept "emotional stability" captures the depth of reaction to emotions, particularly negative emotions. Those who have more moderated reactions are rated as having higher emotional stability. Those who are more reactive are rated as being less emotionally stable, or the (unfortunate) parlance of "neuroticism."

[7] World Development Indicators, accessed on June 13, 2014.

aim at improving youth's employability by strengthening their cognitive and non-cognitive skills as well as helping them identify and follow a life plan.[8]

This paper explores the role that cognitive and personality traits (a facet of non-cognitive skills) play in labor market outcomes in Peru. It contributes to the existing literature in two ways. First, it adds a new data point to the very limited evidence about whether non-cognitive skills are valued in developing economies. More importantly, though, it builds on the methodology presented in Heckman, Urzúa, and Stixraud (2006) to estimate of the effect of ability, as proxied by latent (rather than measured) skills, on wages and labor supply to more robustly measure both cognitive and non-cognitive skills, thereby permitting cleaner correlations than those estimated in the other developing country literature. Second, as a contribution to the more general skills literature, it explores the degree to which measurement error biases standard OLS estimates. The paper compares OLS estimates derived from measured skills and MLE estimates that employ latent skills measures, where the latter intends to correct for problems of measurement error emerging from written tests and multi-collinearity, which affect the precision of estimates derived from more standard methodologies.

II. Data and Definitions

This paper uses the National Skills and Labor Market Survey (*Encuesta Nacional de Habilidades*, ENHAB), collected in January through March 2010, which is based on the standard Peruvian household survey (ENAHO), augmented by modules measuring cognitive skills and personality traits. These cross-sectional data were gathered from a random sample of youth and adults in 11 cities (57 districts) in the three regions of Peru (coast, Andes and jungle).[9] The cognitive and non-cognitive test batteries were applied to a randomly selected adult at home, resulting in a sample of 1,394 individuals aged 18-50. Additional variables that provide early proxies for acquisition of abilities were also captured, including parental education and distance to primary school.

In Table 1, we present the descriptive statistics of the variables of interest. Females comprise 63% of the sample. Individuals are on average 32 years old and 10 percent report speaking an indigenous language as their mother tongue. One third of the individuals in the sample live in Lima, another third in the Coastal region, and the rest are equally distributed in the Andes and the Jungle regions.

The average individual has pursued about 12 years of education. About 60% of the sample has mothers with primary education or less. Another 20% have mothers who have completed secondary school while 8% have mothers who have pursued higher education. The distribution of individuals according to their father's education is similar; however, the proportion of individuals whose father has pursued higher education is 16% (13% completed) while the proportion of those with a father who has less than primary school is 8%.

[8] "*Fortalecimiento de Habilidades para el Empleo*".
[9] Cueto, Muñoz and Baertl (2010) page 8.

Turning to labor market indicators, approximately 62% of individuals in the sample are employed. Of the employed, 51% are wage workers, 60% are white-collar workers and 49% are formal workers. The standardized average log hourly wage is 1.25 soles, with a standard deviation of 0.88.[10]

A. Cognitive Skills

The American Psychological Association defines cognitive skills as the “ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought” (Neisser et al. 1996). This may include intelligence, reasoning, information-processing, perception, memory, literacy, numeracy, and learning. Measures of cognitive skills include IQ Tests, memory recollection, coding speed, and standardized achievement tests.[11]

Our data set measures four dimensions of cognitive skills.[12] First, the Peabody Picture Vocabulary test (PPVT-4) measures receptive vocabulary and the verbal ability of adult subjects, in other words, verbal ability and scholastic aptitude. The test taker is presented a page with four pictures; the examiner says a word and the test taker points to the picture on the page that corresponds to that word. The process is continued until the test taker cannot successively correctly identify the picture corresponding to the word presented by the examiner.[13] Second, a verbal fluency test developed by Cueto, Muñoz and Baertl (2010) assesses how quickly and easily individuals access words from memory. Individuals are asked to write as many words that begin with a specific letter (in our case “P”) in a given time. The test measures verbal fluency as it relies on word knowledge, strategic retrieval search and performance monitoring, and speed to process information. A third test was designed to test short term memory.[14] In the digit recollection test, respondents are asked to repeat numbers in the same sequence as read by the enumerator. The test begins with two to three numbers, increasing until the person commits errors. Finally, Cueto, Muñoz and Baertl (2010) developed a test of numeracy knowledge and problem solving[15] that requires basic operations such as addition, subtraction, multiplication, division and percentage.

Table 2 shows that the four cognitive measures are correlated with each other and with years of education. The correlation among the cognitive measures ranges from 0.32 (verbal fluency and working memory) to 0.57 (verbal and numerical abilities). All correlations are statistically significant at 10% level.

The kernel density plots of cognitive skills presented in Figure 1 show a varied distribution of skills. While numerical ability is normally distributed, verbal ability has a visible bimodal distribution

[10] In absolute terms, this is equivalent to 5.62 soles, with a standard deviation of 11.23.
[11] For a summary of tests to measure cognition, see Almlund et al. (2011).
[12] Cueto, Muñoz and Baertl (2010) provide a full explanation on the design and implementation of these tests.
[13] The PPVT was originally intended to measure literacy skills in children, but version 4 was developed to measure these skills in adults. Cueto, Muñoz and Baertl (2010) document that while there is a version of the PPVT test in Spanish it was targeted to adolescents rather than adults; they adapted the PPVT-4 test to Peruvian Spanish
[14] te Nijenhuis and van der Flier (2004); and te Nijenhuis, Resing, Tolboom and Bleichrodt, (2003) find that short term memory test such as forward digit span are a good predictor of working memory.
[15] Numeracy measures logic and reasoning, and is also a good predictor of fluid and crystallized intelligence.

with an underlying process that seems to be driven by the youngest and lowest educated group as discussed below. Verbal fluency has a longer right tail.

Women tend to have lower scores in cognitive tests than men, with the exception of verbal fluency. Men's distributions of numerical ability, working memory, and verbal ability are statistically different from and positioned to the right of the distributions for women (Figure 2).[16] The distributions of numerical ability and working memory exhibit smaller variance for women than for men. And in the case of verbal ability, the distribution for women has more values concentrated in the lower mode of the distribution than the male's distribution.

The distributions among age groups are similar in most cases with the exception of the younger groups (Figure 3). In particular, the distribution of numeric ability for the group of individuals aged 18 to 24 years old is significantly different than, and exhibits less variance than, that for the individuals aged 25-30. The distribution of working memory for individuals younger than 31 years old is significantly different than the distribution that for the older groups, and is slightly positioned towards the right reflecting higher working memory scores than the older groups. On the contrary, the distributions of verbal ability and verbal fluency for individuals younger than 25 are significantly positioned to the left of the distribution for the rest of the population. This implies that youth have fewer verbal abilities than adults.

Lastly, the distributions of numerical ability, working memory and verbal fluency are significantly different among individuals grouped by educational attainment with the exception of those for individuals with higher education. The distribution densities depicted in Figure 4 show that a higher degree of education is correlated with these higher cognitive skills. In the case of verbal ability, all distributions are significantly different among education levels. The distribution of scores for primary educated individuals is skewed to the left while for individuals with at least high-school it is skewed to the right. This fact explains the bimodal shape of the aggregated distribution observed in Figure 1.

B. Non-Cognitive Measures

Non-cognitive skills, often referred to as social-emotional skills by non-economists, can be defined as behavioral characteristics and personality traits.[17] The traits in which we focus are broad facets that are relatively stable over time (Borghans et al. 2008, Almlund et al. 2011).[18] A widely accepted taxonomy to measure personality traits is the Big Five Model (Goldberg 1993), where a

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[16] The Kolmogorov-Smirnov equality of distribution test was used to assess whether pairs of distributions were statistically different from one another.

[17] The economics literature refers interchangeably to skills using the terms "behavioral skills", "life skills", "non-cognitive skills" and "soft skills". However, they are distinct categories. 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, Modecki, Cunningham 2014). 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).

[18] Personality traits are rank order consistent across the adult life-cycle (Roberts and DelVecchio 2000), meaning that while they can change with experience and education over time, a person with a rank of x in the distribution at age y will still have a rank of x in the distribution at age y+1.

standard battery of 35 questions are grouped into five traits using factor analysis methodologies. Each of the five personality factors - openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (opposite of emotional stability)[19] - summarizes a large number of distinct, more specific personality traits, behaviors, and beliefs.[20] More recently, the conscientiousness trait, which has been regularly correlated with labor market success, has been further explored through a set of sub-factors, capturing the Grit personality traits of perseverance and the motivation to strive for long term goals (Duckworth et al. 2007).

Recent literature, based on correlation estimates among the Big Five, proposes that these can actually be grouped into two higher order personality traits.[21] Digman (1997) names one trait Alpha, which encompasses Agreeableness, Conscientiousness, and Neuroticism (Emotional Stability) and can be understood as elements of social development. More recent studies have defined the Alpha factor as "stability", meaning that the individual is consistent in motivation, mood, and social interactions (Van der Linden, te Nijenhuis, and Baker 2010). The other trait, named the Beta factor, encompasses Extraversion and Openness to Experience, and is interpreted by Digman (1997) as "striving toward personal growth", or "plasticity", meaning the extent to which a person actively searches for new and rewarding intellectual and social experiences.[22]

Our survey instrument includes the standard battery of 35 questions defined by the Goldberg Big Five model as well as 17 additional questions to capture Grit personality facets. Rather than forcing the Goldberg Big Five categories on the 35 questions, we use factor analysis to group the questions into personality traits.[23] This allows the factors to endogenously emerge from the data rather than placing an exogenous structure on them. The data returned six factors parallel to the Goldberg Big Five, which we name Conscientiousness, Extraversion, Openness to Experience,

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[19] "Conscientiousness" is the capacity for self-regulation; the facets for this trait include orderliness, dutifulness, achievement striving, self-discipline, self-efficacy and cautiousness. "Agreeableness" measures involvement in congenial relationships with others; the facets of this trait are trust, morality, cooperation, modesty, and sympathy. "Emotional Stability" measures susceptibility to negative emotions or neuroticism; the facets are anxiety, anger, depression, self-consciousness, immoderation, and vulnerability. "Openness to Experience" refers to the decision making skills, as it measures the seeking of intellectual stimulation and novelty; the facets include imagination, artistic interest, emotionality, adventurousness, intellect and liberalism. Finally, "Extraversion" measures the positive emotionality and active involvement in a social world or pro-social connectedness; the facets for this trait include friendliness, gregariousness, assertiveness, activity level, excitement seeking and cheerfulness.

[20] 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 employer skill demand literature (Cunningham and Villaseñor 2014).

[21] As discussed in Borghans et al (2008) and Almlund et al (2011), while it is possible to measure cognitive ability in a single (though imperfect) IQ score, for example variables, "even the most parsimonious personality models incorporate more than one factor" (p 982, p 48). The most aggregated score that appears in the literature is Digman (1997) alpha-beta, which we utilize in this paper.

[22] Since the Big Five Factor Loadings are all very high in *alpha*, the eigenvalue for *beta* barely makes the cut-off, and the factors are correlated, some suggest that only the *alpha* factor should be maintained. However, Anusic et al. (2009) argues that the correlations are spurious due to single rater bias and that when data are derived from various raters, the factors are orthogonal.

[23] Specifically, we recoded the items previously inverted in the questionnaires so that all of them have the same direction. Later we applied iterative principal factor analysis to each set of items corresponding to the Big Five model and the Grit personality traits. At first we did not apply any restrictions to the number of factors and used all items. Then, based on the estimated model statistics, including eigen values, Kaiser-Meyer-Olkin and those related to the rotated factors, in addition to the Scree test, we discarded all trivial factors. Also, we discarded some items that either had no significant loadings or were considered complex (loaded significantly in more than two factors). Applying this recursive method we arrived to the model solutions described below. In all cases we used the oblique promax rotation after the proper tests of orthogonality were conducted.

Emotional Stability, Kindness, and Cooperation.[24] The latter two emerge from the "Agreeableness" factor that is common to the Big Five model. Applying the same methodology to the Grit scale, two factors emerge: perseverance of effort and consistency of interest.[25]

In Table 3 we present the correlation matrix among the eight personality traits and their correlation with years of schooling. The correlations among personality traits are much lower than those observed among cognitive skills. While most correlations are significant at the 10% level, the correlations range from 0.01 to 0.4 in absolute value. Consistency of interest, a measure of grit, is negatively correlated with the other personality traits, except with the other grit measure (perseverance of effort), and with low correlation coefficients (absolute value). Cooperation also has lower correlation with some other personality traits. Years of schooling is barely correlated with most personality traits (conscientiousness, kindness, emotional stability, cooperation, and consistency of interest) but has a correlation coefficient around 0.24 with extraversion, openness to experience, and perseverance of effort.

In Figure 5 we present the Kernel density functions of each of the non-cognitive measures. Many of the traits have long left tails, and Conscientiousness, Extraversion, and Consistency of Interest appear to have multiple underlying distributions. We look at the distribution by groups in order to further investigate this. The distribution of scores for all but Conscientiousness, Kindness and Consistency of Interest are significantly different among women and men. Women tend to attain lower scores than men in factors denoting Extraversion, Emotional Stability and Perseverance of Effort, with higher scores than men in the Cooperation factor Figure 6.

In Figure 7 one can observe different patterns among younger and older age groups, in which the former tend to obtain lower scores than the latter groups. In particular, the distribution of Conscientiousness for individuals aged 18-25 years old is significantly different than the for rest as well as the distribution for individuals aged 25-30 years old compared to that for individuals older than 40 years old. The distribution of Kindness for individuals older than 40 years old is significantly different than for the rest. In the case of Openness to Experience, only the distribution for people between 25 and 30 years old is significantly different than the distribution for people older than 40 years old while the distribution of Consistency of Interest for the former group is significantly different than the distribution for older (than 30 years old) individuals. The distributions of Extraversion, Emotional Stability and Perseverance of effort for the younger group of individuals are significantly different than for the rest of age groups. There are no significant differences among age groups in the density distributions of cooperation. These findings are consistent with research on stability of personality traits; namely, personality traits tend to shift with age, though the distributions are rank-order consistent over time (Roberts and DelVecchio, 2000).

According to Figure 8, density functions of non-cognitive measures differ by educational attainment in the sense that, in most cases, the densities for individuals with lower educational attainment are to the left of those for individuals with higher educational attainment. For instance, individuals with primary or secondary education tend to have lower scores in emotional stability

[24] Using the same original dataset, Yamada et al. (2013), Díaz et al. (2012) and Cueto et al. (2010) also find six instead of five factors.
[25] The factor analysis of the Grit scale returned both two and three grit factors. We selected the model with two grit factors since the results were more robust in the regression estimates, although both were qualitative similar.

and consistency of interest than individuals with higher education. The exception being once again the cooperation factor whose density functions show no significant difference among education groups except for individuals with complete secondary education compared to individuals with complete higher education.

C. Aggregated Factors of Skills

As we explain in detail below, the structural latent variable methodology used in part of this paper requires additional aggregation of several scores measured in the survey. In fact, identification of each factor requires the existence of at least three measures per factor (Carneiro et al., 2003). Therefore, we need twelve measured scores to identify four aggregated factors: cognitive, Alpha (Big 5), Beta (Big 5) and grit. In what follows we explain this data generating method as well as present a statistical analysis parallel to that presented above for the disaggregated skills.[26]

In order to generate the three cognitive-related variables measures needed for the identification of the cognitive skills factor, we a use a normalized measure of verbal fluency (P-test), a normalized measure of verbal ability based on the PPVT, and a measure that aggregates a normalized score of working memory ability and a normalized score of numeric ability.

In the case of the Big Five personality traits, we follow the Alpha-Beta model (Digman 1997; Anusic et al. 2009) and estimate the Alpha (stability) and Beta (plasticity) factors. First, we used the items from the Big Five instrument associated with Alpha, namely those related to emotional stability, agreeableness, and conscientiousness, and generated three components using factor analysis. Second, we followed the same methodology on the items of the Big Five instrument that are associated with Beta, that is, those related to extraversion and openness to experience.[27] For Grit, we apply factor analysis to the Grit scale and obtained three factors according to their association to perseverance of effort, persistence of goals and consistency of interest.

In Table 4, we present the correlation matrix among the aggregated cognitive and non-cognitive measures. Alpha and beta are highly correlated, as are years of schooling and cognitive skills. On the contrary, alpha and grit have a low correlation with years of schooling and cognitive skills.

In Figure 9, we present the Kernel density functions of the two cognitive and two non-cognitive measures. As observed, these functions are smoother than the individual measures. However, most of the results comparing across groups are maintained as show in Figure 10 (by gender), Figure 11 (by age groups) and Figure 12 (by educational attainment).

[26] For some reduced-form estimations we also aggregated the three measures that are used to identify each of the four skills into four scores.

[27] In particular, we used the principal component method and rotation with promax oblique rotation and obtained three factors as required in order to retrieve the latent heterogeneity variables.

III. Methodology

One of the methodological challenges in correlating skills to labor force outcomes is that it is not possible to precisely measure a person's ability. Standard tests are a proxy for actual abilities, but a range of factors, from environment where the test is being taken to intrinsic motivation will affect test scores leading to measurement error. Thus, the measured test scores are biased information and may result in an over- or under-estimation of the importance of various skills in determining the outcomes of interest.

To overcome issues of measurement error in test scores, we can estimate an individual's latent cognitive and non-cognitive abilities. In other words, we can use information on the observed outcomes and on skills and other characteristics to "back-out" a distribution of true skills, or ability, using a structural latent variable technique. A comparison of results from the OLS (using directly measured skills) and structural latent variable techniques (using MLE and a range of observed and unmeasured information) allows us to identify the direction of bias (if any) in OLS estimates resulting from measurement error.

In this paper we estimate the effect of skills on five labor market outcomes: log of hourly wages and the probability of being employed, being wage worker, being white-collar worker and being formal worker. We first estimate OLS regressions of the form

$$Y = \alpha + S\beta^{S} + T\beta^{S} + X_{y}\beta^{y} + \varepsilon^{y} \qquad (1)$$

Where Y refers to one of the outcomes of interest listed above, X_y are observable controls, S is either the individual's years of schooling or a set of parental education dummies, T are observed measures of cognitive and non-cognitive skills, and ε^{y} is the error term. We estimate (1) for a vector of cognitive skills (numerical skills, working memory, verbal ability, and verbal fluency) and a vector of non-cognitive skills, consisting of the eight factors derived from the factor analysis. We also estimate (1) for Alpha, Beta, Grit and the cognitive aggregated factor, thus allowing comparability with the structural latent variable model. A shortcoming of the model is the correlation between T and ε^{y}, due to measurement error in skills. This leads to biased estimates of β^{S} (Hansen, Heckman, and Mullen 2004). To address this issue, we turn to a methodology that allows us to indirectly proxy a truer measure of *T* that can then be correlated with our outcome of interest.

Now, if we want to treat skills (T) as consequences of unobserved heterogeneity instead of true manifestations of the scores, we need to turn to the following structural specification:[28]

$$Y = X_{Y}\beta^{Y} + \alpha_{A}^{Y}\theta_{A} + \alpha_{B}^{Y}\theta_{B} + \alpha_{C}^{Y}\theta_{C} + \alpha_{D}^{Y}\theta_{D} + e^{Y} \qquad (2)$$

[28] For a more detailed explanation of this type of models see Sarzosa and Urzúa (2013).

Where Y is the outcome of interest (e.g., wage), X_Y are observable controls (e.g., gender, age, parental education level, region, among others). The θ_A, $\theta_B, \theta_C, \theta_D$ are the latent skill factors or dimensions of unobserved heterogeneity, which provide a broader proxy of ability than did the vector *T*. The $\beta^Y, \alpha_A^Y, \alpha_B^T, \alpha_C^T$ and α_D^Y are coefficients of interest, and e^Y is a vector of independently distributed error terms orthogonal to X_Y, θ_A, θ_B, θ_C and θ_D.

The need for a structural estimation relies on the assumption that θ_A, θ_B, θ_C and θ_D are unobservable. That is, the measures or scores available in our dataset are only proxies of the true latent variables that we want to use for the estimation (Bartholomew et al., 2011). They are treated as realizations of a score-production function, presented in (3), whose inputs are observable and unobservable characteristics.

$$T = X_T\beta^T + \alpha_A^T\theta_A + \alpha_B^T\theta_B + \alpha_C^T\theta_C + \alpha_D^T\theta_D + e^T \tag{3}$$

Where T is a $L \times 1$ the vector of scores (e.g., measures of verbal ability, digit recollection, agreeableness or conscientiousness), X_T is a matrix of observable controls and e^T is a vector of independently distributed error terms orthogonal to X_Y, θ_A, $\theta_B, \theta_C, \theta_D$ and e^Y. In this sense, the model comprises a measurement system (i.e., outcomes, test scores, observable controls and error terms) that is linked by latent factors or unobserved heterogeneity (i.e., θ_A, θ_B, θ_C and θ_D). This is the type of model considered by Keane and Wolpin (1997), Cameron and Heckman (2001), Heckman et al. (2006), Urzúa (2008), Sarzosa and Urzúa (2013, 2014).

Carneiro et al. (2003), based on the findings of Kotlaski (1967), showed that we can use the system of test scores (3) to non-parametrically identify the distributions of the latent endowments $f_{\theta_A}(\cdot), f_{\theta_B}(\cdot), f_{\theta_C}(\cdot)$ and $f_{\theta_D}(\cdot)$, their coefficients $\alpha_A, \alpha_B, \alpha_C$ and α_D (up to one normalization),[29] and the diagonal matrix of their variance Σ_θ with the help of two restrictions.[30] First, $\theta_A, \theta_B, \theta_C$ and θ_D need to be orthogonal to each other and independent of each other. Second, we need to have at least three test scores per factor (the latent θ that proxies a skill) since one of the coefficients will be normalized and at least two others are required to solve the system.[31] That is, if we have four factors, we need 12 measured skills in our data set, three each that are sufficiently similar to describe a factor.[32] In practice, the test scores measurement system allows us to identify the distributions that are followed by the unobserved heterogeneity, in order to be able to integrate it away in a Maximum Likelihood procedure.[33] The likelihood function is then

[29] that is, we need to set one coefficient per latent factor equal to one and the rest will be interpreted relative to them

[30] It should be noted that the estimated distributions $f_{\theta_S}(\cdot)$ for $S = \{A, B, C, D\}$ are not assumed to follow any particular distribution. The procedure uses a mixture of normals, which are known to be able to recreate a wide range of distributions (Frühwirth-Schnatter, 2006).

[31] Carneiro et al. (2003) actually propose a slightly milder condition: $L > 2k + 1$, where k is the number of latent factors in the system.

[32] The three (or more) measured skills (T) underlying each factor will define the skill that the latent skill is measuring. Thus, the three (or more) skills should hang together in a conceptually meaningful way. Further, there needs to be a correlation among these measured skills for the model to converge; using measured T that measure quite different skills limit this convergence process.

[33] Integrals are calculated using the Gauss-Hermite quadrature (Judd, 1998)

$$\mathcal{L} = \prod_{i=1}^{N} \int\int\int\int f_{e^{Y}}(X_Y, Y, \varrho_A, \varrho_B, \varrho_C, \varrho_D) \times f_{e^{T_1}}(X_{T_1}, T_1, \varrho_A, \varrho_B, \varrho_C, \varrho_D) \cdots \times f_{e^{T_{12}}}(X_{T_{12}}, T_{12}, \varrho_A, \varrho_B, \varrho_C, \varrho_D) dF_{\theta_A}(\varrho_A)\, dF_{\theta_B}(\varrho_B)\, dF_{\theta_C}(\varrho_C) dF_{\theta_D}(\varrho_D) \quad (4)$$

Maximizing (4) we can retrieve all the parameters of interest: β_Y, β_{T_τ}, α_A^Y, $\alpha_B^Y, \alpha_C^Y, \alpha_C^Y$, $\alpha_A^{T_\tau}$, $\alpha_B^{T_\tau}, \alpha_C^{T_\tau}$, $\alpha_D^{T_\tau}$ for $\tau = \{1,2,\dots,12\}$, and the parameters (i.e., the means, standard deviations and mixing probabilities) that describe the distributions $f_{\theta_S}(\cdot)$ for $S = \{A, B, C, D\}$.

We estimate the unobserved heterogeneity[34, 35] using the scores that comprise four dimensions: Alpha, Beta, grit and cognitive skills. That is, we use a version of (3) for each dimension and we assume that only one factor affects each group of tests.

IV. Results

A. Linear Probability Estimates: A First Approximation

Table 5 presents results from OLS estimations of equation (1) using aggregated measures in which S corresponds to a set of dummy variables measuring the education level of the individual's mother and father separately. Table 6 presents equivalent results but using disaggregated cognitive and non-cognitive measures.[36]

Cognitive skills play a significant role across a range of labor force outcomes. A one standard deviation increase in cognitive skills is correlated with a 24% increase in mean log hourly wages (Table 5). Cognitive skills are also positively correlated with being employed (3.5% probability increase), being an employee rather than self-employed (11%), being a white collar worker (13%), and holding a formal sector job (9%). The specific skills behind such correlations differ for each outcome. Verbal ability helps explain four of the five labor market outcomes; it relates positively with higher wages, being an employee (rather than self-employed), and holding a white-collar job or being in the formal sector. Verbal ability does not play a role in the likelihood of begin employed. Instead, verbal fluency increases the likelihood of being employed, being an employee and a white-collar worker (Table 6). Numeric skills are strongly correlated with higher wages and also with

[34] All the estimations presented in this chapter were implemented using the heterofactor command in Stata developed by Miguel Sarzosa and Sergio Urzúa (see Sarzosa and Urzúa, 2013)

[35] The reader should note that, as described in Section II, this paper uses a cross-sectional data set. Hence, we measure the latent traits at the same time we measure the outcome variables. Therefore, there is a concern regarding reverse causality, as some of the scores we retrieve the latent traits from might be affected by employment or education choices. The model presented here does not solve this issue so we cannot claim causality between the traits and the outcomes. Nonetheless, we have observed that the skills measures are stable in age, which can be an approximation of the consistency of the scores. Annex 2 presents a selection of personality traits measures by age and finds that a regression line fit through the plot has a 0 slope, suggesting that the challenge of reverse causality, and therefore a causal relationship between personality traits and labor market outcomes, is not obviously problematic in our data. The full set of plots is available from the authors.

[36] Annex I presents results from two similar specifications. First, it presents estimations that do not include S in the specification; this is intended to allow for all information about cognitive and non-cognitive skills to be captured in the skills T variables. Second, we present estimates that use years of schooling for the S variable, rather than parental education. The results are very similar to those presented in Tables 5 and 6 so they are not discussed in the text but only included as a reference.

holding a white-collar job. Lastly, working memory does not exhibit any significant correlation with labor market outcomes.

Non-cognitive skills play a significant, though lesser, role in predicting labor outcomes. Grit is the strongest predictor of labor market outcomes; as shown in Table 5, those with more grit earn higher wages (8%), are 4% more likely to be employed and to be wage workers (rather than self-employed) and tend to be in white collar jobs (5.5% more likely). When looking at specific skills Table 6, it is clear that perseverance of effort, rather than consistency of interest, is behind the correlations with the labor supply patterns. More perseverant individuals are 3% more likely to be employed and 5% more likely to be a white-collar worker or an employee (instead of self-employed). Note, however, that neither perseverance of effort nor consistency of interest individually affect hourly wages. It seems it is the joint role of these personality traits that increase the probability of earning higher wages.

The personality traits that are part of the Big Five scale play a lesser role in labor market outcomes. On the one hand, stability characteristics (measured by the Alpha factor) are only correlated with wage outcomes. A one standard deviation increase in stability is weakly correlated with a 12% decrease in wages Table 5. This can be attributed to the strong negative correlation between wages and the traits associated with agreeableness (kindness and cooperation) that dominates the strong positive correlation between wages and emotional stability (Table 6). On the other hand, plasticity (measured by the Beta factor) is not correlated with any labor outcome (Table 5). Looking at Table 6, the only significant relation between an underlying beta factor and a labor supply outcome is that of openness to experience and being wage-workers. Individuals that are more open to experience are more likely to be self-employed (they are less likely to be wage-workers).

The above is a first approximation to exploring the relationships between cognitive and non-cognitive skills and labor market outcomes. As discussed earlier, these estimations suffer from potential measurement error. Next, we present results that attempt to circumvent this problem.

B. Structural Latent Skills model: Skills as Unobserved Heterogeneity

Table 7 and Figures 13 to 17 present the results of the structural latent skill model. The figures result from simulation exercises that incorporate the distribution of each skill.[37] The simulations allow us to see how people with different skill levels obtain different outcomes. As noted by Carneiro et al (2007), Maxwell (2007), Prada and Urzúa (forthcoming), and others, skills are rewarded in the labor market according to their combinations, so it is useful to simultaneously explore the returns to different combinations of latent skills. Figures 13 to 17 show simulated labor market impacts of different combinations of skills types by decile of each skill measured.

Estimates based on the structural latent model confirm that cognitive skills correlate with most of the labor market outcomes we explore in this paper (Table 7). Higher cognitive abilities are positively and significantly correlated with being a white collar worker, being a wage-worker rather

[37] Such distributions, estimated from the scores presented in the Data and Definitions section, are presented in Figure 9.

than self-employed and holding a formal sector job, similar to the OLS estimations. Figures 16A, 17C and 15A show that people in the 10^{th} decile of the cognitive skill distribution are twice as likely to be white collar workers, wage-workers and hold a formal sector job than those in the 1st decile. The correlation between cognitive skills and employment estimated by OLS is not observed in the structural latent model. Also, Figure 13A shows that workers at the top of the cognitive abilities distribution earn around one third more per hour than those in the first decile.

Non-cognitive skills correlate with some of the outcomes of interest, but these correlations are quite different than those estimated using the OLS technique. Stability is positively correlated with wages; a one standard deviation increase in the Alpha factor is correlated with a 11.25% increase in mean log wages. This results contrasts with the one obtained from the OLS estimations, where a one standard deviation in wages was correlated with a 24% *decrease* in mean log wages. The very different results suggest that the stability variable suffers from severe measurement error.

Using the structural latent model, plasticity only emerges as a positive predictor of employment. Using Figure 14A to compare people in the tenth decile to those in the first decile of the plasticity distribution, the former are 35 percentage points more likely to be employed than the latter. This, again, contrasts with the OLS estimates, where plasticity did not emerge as a significant predictor of employment. In fact, openness to experience was the only trait underlying plasticity that came out significant in any of the OLS estimates (salaried workers). Thus, again we can conclude that the use of the measured plasticity score as a proxy of the underlying trait, incorporates substantial measurement error.

Grit is positively associated with characteristics of "better" jobs. Specifically, according to Figure 17A, an individual in the 10^{th} decile of grit is up to 45 percentage points more likely to be a wage-worker than those in the first decile. Also the former are around 20 percentage points more likely to hold a white-collar job than the latter (Figure 16C). These findings go in the same direction as those found in the OLS estimates. Wages and being employed are not correlated with grit in the structural latent variable estimates, in contrast to the findings with the OLS model; this suggests that mismeasurement of grit leads to erroneous correlations with these labor market outcomes.

Figure 13 clearly shows that the greatest wages are earned by those in the 10^{th} decile of alpha and cognitive skills. The log wage gradient for alpha is steeper than that for cognitive skills (Panel A), suggesting that incremental gains in Alpha have a much larger earnings gain than equal size gains in cognitive skills. For example, the graph shows that wages increase slowly in cognitive skills for those with very low alpha, but those with very low cognitive experience rapid wage gains with increasing Alpha. But for any combination of Alpha and cognitive skills, as alpha increases, the cognitive gradient increases and vice versa. A similar pattern is observed in Panel B, where higher deciles of Alpha increase log wage earnings but the wage gradient for grit is nearly flat. This reflects the significant relation of wages with Alpha and the inexistent correlation with grit in the structural model estimates.

The wage gradient for cognitive skills is quite steep while that of beta is very flat in Panel C in Figure 13. Here again, the steeper slope of the cognitive measure reflects the important relation of wages with cognitive skills.

The three graphs in Figure 14 showing the joint contribution of skills to labor force participation closely reflect the regression results: only plasticity – openness and extroversion – affect employment probabilities. The employment probability gradients are quite steep for Beta in each graph while the gradients for Alpha, grit, and cognitive skills are nearly flat. Unlike the wage graphs, the combination of skills sets does not lead to higher employment probabilities than are generated with only one dimension (Beta).

In contrast, only the formal probability gradients in Figure 15 and the white-collar probability gradients in Figure 16 are both quite steep for cognitive skills but nearly flat for non-cognitive skills. Although the formal probability gradients for Beta shows a slight positive gradient, the correlation is not strong enough to make very much of an impact, as reflected in the regression results. Similarly, the white collar probability gradients for grit, Beta, and Alpha increase with decile, but these increases are not very strong. However, a combination of cognitive skills with grit, for those with higher levels of cognition, leads to higher probabilities of formal sector work and of white collar work than if we hold grit constant. The same is observed for cognitive skills and Beta.

The gradients for wage worker (rather than self-employed) show very steep gradients for grit and cognitive skills, reflecting the regression results (Figure 17). Panel C shows that as one, the other, or both skills increase, the probability of being an employee increases rapidly. Panels A and B show a slight increase in the probability of self-employment as Alpha or Beta increase, holding constant grit. Thus, while being an employee increases in grit, it declines in Alpha and Beta, leading to greatest employee probabilities for those with high grit and low Alpha (Beta).

V. Concluding Remarks

Recent evidence from the United States and Western Europe has suggested that both cognitive and non-cognitive skills matter to improve labor market outcomes. This paper establishes the relationship between cognitive and non-cognitive skills with wages, employment and type of employment (wage worker, white-collar and formal) in urban Peru, utilizing a unique data set that measures a range of skills and a methodology to account for latent skills. We find that both cognitive and non-cognitive skills are important determinants of labor outcomes. In particular, we find that cognitive skills positively correlate with wages and the probability of being a wage worker, white-collar and formal worker, regardless of whether the estimation method employed was OLS or the structural latent skills model. Verbal fluency is the cognitive skill most associated with labor supply outcomes, positively related with being employed and with being white-collar or wage worker. Higher numeric ability is strongly positively correlated with wages and being white-collar.

The patterns are less uniform or strong for non-cognitive skills. Within the non-cognitive skills, kindness, cooperation, emotional stability, openness to experience emerge significantly for one outcome each, mostly for the wage estimates. Perseverance of effort emerges significant for three of the four labor supply outcomes. However, the other personality traits did not enter significantly. When using the structural latent model approach, the stability aggregated measure (Alpha, a composite of agreeableness, conscientiousness, and emotional stability) positively and significantly affects hourly wages while plasticity (beta, a composite of openness to experience and extroversion) affects the probability of employment. Grit increases the likelihood of being wage worker or white-collar.

The difference in the results derived from the OLS and a structural model with latent skills suggest measurement bias in the non-cognitive skills used in this analysis. While plasticity was not correlated with any labor force outcomes estimated through OLS, the results from the structural latent variable model shows that plasticity is positively correlated (at the 5% level) with being employed, suggesting that the OLS methodology underestimates the role of plasticity in employment outcomes. In contrast, OLS predicts a correlation between grit and four of our five outcomes while the structural latent skills model only finds a correlation between grit and two job-quality outcomes (wage worker and white collar). This suggests that OLS overestimates the role of grit in wage and employment outcomes. Finally, while stability is only correlated with wages in both methodologies, the estimated coefficient emerging from the OLS is negative while a positive coefficient estimate emerges from the structural latent variable model. This suggests that OLS severely underestimates the role of stability (kindness, cooperation, emotional stability, conscientiousness) on wages.

The different results emerging from the OLS and the structural latent variable estimation points to the need for better data to determine which non-cognitive skills are appropriate for developing country economies. The data used in this paper provide the minimum number of variables necessary to construct latent variables to proxy non-cognitive skills that are generally accepted by the profession (aggregating non-cognitive to just three measures). But these skills – stability, plasticity, and grit – are too aggregated to be policy relevant. Future work will require the survey teams to define *ex ante* the skills that they wish to correlate with labor market outcomes and design surveys such that a minimum of three measures can be used to construct the latent variables in the structural methodology. Further, since non-cognitive skills develop over time, and current labor status is a result of choices and actions taken in the past, panel data are needed to provide more robust results.

While Peruvian schools already teach cognitive skills, these findings suggest that the Peruvian government is well justified in incorporating non-cognitive skill development into the school curriculum. Although the non-cognitive skills explored in this paper only encompass personality traits, which are commonly assumed to not be malleable to interventions, emerging research is finding that, indeed, interventions do have short-run effects on personality (Magidson et al. 2014; Jackson et al. 2012). However, there is a significant body of research that quantifies the positive impact of program interventions on specific behaviors that can be linked to the personality traits explored in this paper.[38]

[38] These program designs are varied and too numerous to present here, but Guerra, Modecki, and Cunningham (2014) provides such a mapping and links to the mapping a list of programs with empirical evidence that show a positive impact of these behaviors in various countries throughout the world.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	S.D.	Min.	Max.
Explanatory					
Female	1,394	0.63	0.48	0.00	1.00
Age	1,394	31.77	8.80	18.00	50.00
Speaks indigenous as mother tongue	1,394	0.10	0.30	0.00	1.00
Lima region	1,394	0.29	0.45	0.00	1.00
Coastal region	1,394	0.28	0.45	0.00	1.00
Andes region	1,394	0.22	0.41	0.00	1.00
Jungle region	1,394	0.22	0.41	0.00	1.00
Years of schooling	1,394	11.40	3.18	1.00	19.00
Mother has less than primary education level	1,331	0.18	0.38	0.00	1.00
Mother has incomplete or complete primary education level	1,331	0.43	0.49	0.00	1.00
Mother has incomplete secondary education	1,331	0.09	0.29	0.00	1.00
Mother has complete secondary education	1,331	0.20	0.40	0.00	1.00
Mother has incomplete higher education	1,331	0.02	0.16	0.00	1.00
Mother has complete higher education	1,331	0.08	0.27	0.00	1.00
Father has less than primary education	1,307	0.08	0.27	0.00	1.00
Father has incomplete or complete primary education	1,307	0.41	0.49	0.00	1.00
Father has incomplete secondary education	1,307	0.10	0.31	0.00	1.00
Father has complete secondary education	1,307	0.25	0.43	0.00	1.00
Father has incomplete higher education	1,307	0.03	0.16	0.00	1.00
Father has complete higher education	1,307	0.13	0.34	0.00	1.00
Dummy for taking less than 1/2 hour to go to school	1,391	0.88	0.32	0.00	1.00
Skills					
Z-Score of cognitive measure- numeric skills	1,394	-0.06	1.02	-3.37	2.34
Z-Score of cognitive measure - working memory	1,394	-0.06	1.00	-2.96	3.58
Z-Score of cognitive measure - verbal ability (PPVT)	1,394	0.07	1.00	-4.19	2.76
Z-Score of cognitive measure - verbal fluency	1,394	0.04	1.01	-2.51	4.62
Z-Score of Big 5 - Conscientiousness	1,394	0.12	0.95	-4.02	1.71
Z-Score of Big 5 – Kindness	1,394	0.04	1.01	-5.65	2.09
Z-Score of Big 5 – Extraversion	1,394	0.02	1.00	-3.10	1.96
Z-Score of Big 5 - Openness to experience	1,394	-0.02	1.01	-3.37	1.83
Z-Score of Big 5 - Emotional stability	1,394	0.02	1.01	-3.41	1.75
Z-Score of Big 5 – Cooperation	1,394	0.01	0.98	-5.01	2.96
Z-Score of Grit - Perseverance of effort	1,394	0.06	1.00	-3.77	1.72
Z-Score of Grit - Consistency of interest	1,394	0.01	1.00	-1.92	2.98
Z-Score of Big 5 - Stability (alpha)	1,369	0.05	0.74	-3.56	1.28
Z-Score of Big 5 - Plasticity (beta)	1,392	0.02	0.72	-2.38	1.42
Z-Score of Grit	1,394	0.04	0.75	-2.86	2.12
Z-Score of Cognitive measure	1,394	0.00	0.76	-2.24	2.43
Outcomes					
Log of hourly wage	824	1.25	0.88	-3.26	5.15
Employed	1,394	0.62	0.48	0.00	1.00
Wage worker	869	0.51	0.50	0.00	1.00
White-collar worker	868	0.60	0.49	0.00	1.00
Formal worker	869	0.49	0.50	0.00	1.00

Table 2: Correlation among cognitive measures and schooling

	Numerical ability	Working memory	PPVT	Verbal fluency	Years of schooling
Numerical ability	1				
Working memory	0.4117*	1			
Verbal ability (PPVT)	0.5677*	0.3816*	1		
Verbal fluency	0.4501*	0.3152*	0.4561*	1	
Years of schooling	0.5287*	0.3487*	0.5773*	0.4373*	1

* Significant at 10% level

Table 3: Correlation among non-cognitive measures and schooling

	Conscien-Tiousness	Kindness	Extraver-sion	Openness to experience	Emotional Stability	Coopera-tion	Persever-ance of effort	Consis-tency of interest	Years of schooling
Conscientious-ness	1								
Kindness	0.3694*	1							
Extraversion	0.2761*	0.3163*	1						
Openness to Experience	0.3168*	0.3844*	0.3690*	1					
Emotional stability	0.2607*	0.3097*	0.2623*	0.3479*	1				
Cooperation	0.3292*	0.0109	0.1394*	0.0790*	0.1401*	1			
Perseverance of effort	0.3614*	0.2182*	0.3304*	0.3990*	0.2298*	0.1825*	1		
Consistency of interest	-0.1345*	-0.0944*	-0.1150*	-0.1083*	-0.1693*	-0.0488*	0.0319	1	
Years of schooling	0.0668*	0.0841*	0.2288*	0.2565*	0.1340*	0.0154	0.2386*	-0.0900*	1

* Significant at 10% level

Table 4: Correlation among aggregated cognitive, non-cognitive factors and schooling

	Stability (alpha)	Plasticity (beta)	Grit	Cognitive	Years of schooling
Stability (alpha)	1				
Plasticity (beta)	0.6418*	1			
Grit	0.2580*	0.3493*	1		
Cognitive	0.1467*	0.3340*	0.1609*	1	
Years of schooling	0.1348*	0.2881*	0.1692*	0.6250*	1

* Significant at 10% level

Table 5: OLS Estimations using aggregated factors, total sample.

	Log of hourly wage	Employed	Wage worker	White-collar worker	Formal worker
Stability (alpha)	-0.118*	-0.023	-0.016	-0.014	0.007
	(0.064)	(0.021)	(0.027)	(0.025)	(0.031)
Plasticity (beta)	0.067	0.033	-0.013	-0.008	-0.005
	(0.061)	(0.024)	(0.031)	(0.029)	(0.034)
Grit	0.083*	0.038**	0.042*	0.055**	0.006
	(0.046)	(0.018)	(0.023)	(0.022)	(0.025)
Cognitive	0.240***	0.035*	0.108***	0.129***	0.086***
	(0.043)	(0.018)	(0.024)	(0.021)	(0.025)
Female	-0.143**	-0.339***	-0.070**	0.094***	0.042
	(0.064)	(0.024)	(0.035)	(0.032)	(0.037)
Age	0.090***	0.054***	-0.036**	0.003	0.015
	(0.028)	(0.011)	(0.014)	(0.014)	(0.016)
Age squared	-0.001***	-0.001***	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indigenous mother tongue	0.127	-0.027	0.005	0.027	-0.116*
	(0.118)	(0.046)	(0.061)	(0.053)	(0.062)
Firstborn	-0.155**	0.037	-0.006	0.009	-0.073*
	(0.064)	(0.027)	(0.035)	(0.032)	(0.038)
Lima region	0.064	-0.090***	0.144***	-0.029	-0.173***
	(0.084)	(0.035)	(0.045)	(0.041)	(0.050)
Coastal region	0.011	-0.061*	0.080*	-0.062	-0.241***
	(0.087)	(0.035)	(0.047)	(0.041)	(0.048)
Andes region	0.014	-0.042	0.036	-0.032	-0.123**
	(0.098)	(0.039)	(0.049)	(0.043)	(0.053)
Agriculture, fishing and mining	0.160		0.030	-0.450***	-0.128
	(0.191)		(0.084)	(0.076)	(0.096)
Manufacturing	-0.294***		-0.192***	-0.589***	-0.238***
	(0.094)		(0.062)	(0.050)	(0.063)
Commercial	-0.442***		-0.402***	-0.046	-0.116***
	(0.080)		(0.039)	(0.039)	(0.044)
Utilities, transport, storage, communications	-0.234***		-0.270***	-0.458***	-0.149***
	(0.076)		(0.049)	(0.044)	(0.051)
Mother has complete secondary education	0.305***	-0.030	0.094*	0.120***	0.043
	(0.088)	(0.036)	(0.050)	(0.045)	(0.053)
Mother has incomplete higher education	0.024	0.057	-0.040	0.264***	0.199*
	(0.238)	(0.078)	(0.131)	(0.082)	(0.102)
Mother has complete higher education	0.238**	0.110**	0.107	0.102	0.060
	(0.116)	(0.055)	(0.069)	(0.064)	(0.076)
Father has complete secondary education	0.036	-0.014	-0.011	0.007	0.046
	(0.086)	(0.034)	(0.045)	(0.040)	(0.048)
Father has incomplete higher education	0.494**	0.108	0.014	-0.027	-0.016
	(0.233)	(0.079)	(0.099)	(0.090)	(0.113)
Father has complete higher education	0.144	-0.058	0.046	0.003	0.084
	(0.105)	(0.045)	(0.064)	(0.056)	(0.068)
Dummy for taking less than 1/2 hour to go to school	0.053	-0.047	0.006	-0.019	-0.045
	(0.083)	(0.040)	(0.050)	(0.046)	(0.055)
Constant	-0.321	-0.112	1.359***	0.655***	0.387
	(0.451)	(0.189)	(0.242)	(0.240)	(0.279)
Observations	752	1,267	789	789	789
R-squared	0.233	0.231	0.251	0.347	0.125

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: OLS Estimations, total sample.

	Log of hourly wage	Employed	Wage worker	White-collar worker	Formal worker
Numeric skills	0.107***	0.016	0.016	0.047**	-0.007
	(0.036)	(0.015)	(0.020)	(0.019)	(0.022)
Working memory	0.031	0.010	0.005	0.015	0.021
	(0.032)	(0.014)	(0.018)	(0.015)	(0.020)
Verbal ability (PPVT)	0.064*	-0.014	0.053**	0.033*	0.045**
	(0.038)	(0.016)	(0.023)	(0.020)	(0.022)
Verbal fluency	0.039	0.025*	0.031*	0.028*	0.020
	(0.035)	(0.014)	(0.018)	(0.015)	(0.019)
Conscientiousness	-0.036	-0.006	-0.012	0.005	-0.006
	(0.036)	(0.015)	(0.020)	(0.018)	(0.022)
Kindness	-0.087**	-0.014	0.008	-0.005	-0.003
	(0.036)	(0.014)	(0.019)	(0.016)	(0.020)
Cooperation	-0.067**	0.002	-0.025	-0.018	0.018
	(0.033)	(0.013)	(0.018)	(0.016)	(0.019)
Emotional stability	0.078**	-0.001	-0.015	-0.007	-0.012
	(0.033)	(0.014)	(0.019)	(0.019)	(0.020)
Extraversion	0.028	0.013	-0.007	0.012	-0.007
	(0.035)	(0.014)	(0.019)	(0.017)	(0.020)
Openness to experience	-0.002	0.011	-0.014	-0.031*	0.002
	(0.033)	(0.015)	(0.020)	(0.018)	(0.020)
Perseverance of effort	0.049	0.032**	0.048***	0.046***	0.024
	(0.038)	(0.015)	(0.018)	(0.017)	(0.020)
Consistency of interest	0.013	0.010	-0.010	0.003	-0.024
	(0.032)	(0.013)	(0.016)	(0.016)	(0.019)
Female	-0.113*	-0.341***	-0.073**	0.090***	0.036
	(0.065)	(0.024)	(0.036)	(0.032)	(0.038)
Age	0.082***	0.053***	-0.039***	0.003	0.015
	(0.028)	(0.011)	(0.014)	(0.014)	(0.016)
Age squared	-0.001**	-0.001***	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speaks indigenous as mother tongue	0.147	-0.024	0.014	0.018	-0.110*
	(0.115)	(0.046)	(0.062)	(0.052)	(0.063)
Firstborn	-0.153**	0.034	-0.015	0.007	-0.080**
	(0.062)	(0.027)	(0.034)	(0.032)	(0.038)
Lima region	0.078	-0.087**	0.145***	-0.025	-0.163***
	(0.086)	(0.035)	(0.046)	(0.043)	(0.051)
Coastal region	0.039	-0.049	0.095**	-0.042	-0.212***
	(0.090)	(0.035)	(0.048)	(0.042)	(0.050)
Andes region	0.045	-0.031	0.041	-0.035	-0.106**
	(0.097)	(0.039)	(0.051)	(0.043)	(0.053)
Agriculture, fishing and mining	0.131		0.025	-0.453***	-0.128
	(0.190)		(0.086)	(0.077)	(0.099)
Manufacturing	-0.288***		-0.184***	-0.583***	-0.226***
	(0.093)		(0.062)	(0.051)	(0.064)
Commercial	-0.441***		-0.398***	-0.043	-0.120***
	(0.079)		(0.039)	(0.039)	(0.044)
Utilities, transport, storage, communications	-0.236***		-0.272***	-0.481***	-0.140***
	(0.077)		(0.050)	(0.044)	(0.052)
Mother has complete secondary education	0.283***	-0.030	0.083*	0.115**	0.033
	(0.089)	(0.036)	(0.050)	(0.045)	(0.053)
Mother has incomplete higher education	0.034	0.067	-0.054	0.238***	0.160
	(0.227)	(0.076)	(0.124)	(0.081)	(0.102)
Mother has complete higher education	0.198*	0.114**	0.078	0.085	0.033
	(0.118)	(0.055)	(0.069)	(0.063)	(0.077)
Father has complete secondary education	0.057	-0.016	0.002	0.016	0.050

	Log of hourly wage	Employed	Wage worker	White-collar worker	Formal worker
	(0.085)	(0.034)	(0.045)	(0.040)	(0.048)
Father has incomplete higher education	0.524**	0.099	0.033	0.002	-0.005
	(0.234)	(0.079)	(0.097)	(0.091)	(0.114)
Father has complete higher education	0.135	-0.060	0.048	0.005	0.093
	(0.105)	(0.045)	(0.063)	(0.056)	(0.068)
Dummy for taking less than 1/2 hour to go to school	0.038	-0.047	-0.002	-0.021	-0.046
	(0.083)	(0.040)	(0.050)	(0.046)	(0.055)
Constant	-0.209	-0.111	1.430***	0.662***	0.390
	(0.450)	(0.189)	(0.244)	(0.244)	(0.279)
Observations	770	1,293	809	809	809
R-squared	0.245	0.235	0.255	0.354	0.123

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

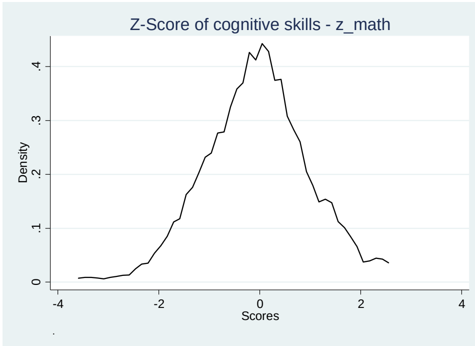
Table 7: Latent Estimations, total sample.

	Log of hourly wage	Employed	Wage worker	White-collar worker	Formal worker
Stability (alpha)	0.3986*	-0.0993	-0.3769	0.0633	-0.0261
	(0.227)	(0.291)	(0.383)	(0.457)	(0.332)
Plasticity (beta)	-0.0752	0.6729**	-0.3735	-0.3733	-0.2337
	(0.196)	(0.275)	(0.327)	(0.380)	(0.329)
Grit	0.0532	0.0600	0.1510**	0.1535**	0.0667
	(0.038)	(0.053)	(0.068)	(0.070)	(0.063)
Cognitive	0.1344***	-0.0019	0.2693***	0.3087***	0.2223***
	(0.037)	(0.054)	(0.069)	(0.072)	(0.065)
Female	-0.1908***	-1.1939***	-0.3333***	0.2103*	0.0680
	(0.062)	(0.097)	(0.109)	(0.113)	(0.102)
Age	0.1012***	0.1868***	-0.1136**	0.0226	0.0481
	(0.028)	(0.036)	(0.050)	(0.050)	(0.045)
Age squared	-0.0013***	-0.0022***	0.0012*	-0.0003	-0.0005
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Indigenous mother tongue	0.0732	-0.1290	-0.0456	-0.0281	-0.3976**
	(0.107)	(0.154)	(0.194)	(0.204)	(0.188)
Firstborn	-0.1183*	0.1306	0.0154	0.0686	-0.2022**
	(0.062)	(0.090)	(0.110)	(0.115)	(0.102)
Lima region	0.1397*	-0.2223*	0.5520***	0.0385	-0.4501***
	(0.082)	(0.117)	(0.145)	(0.151)	(0.135)
Coastal region	0.0375	-0.1725	0.2740*	-0.1718	-0.6696***
	(0.082)	(0.120)	(0.144)	(0.152)	(0.138)
Andes region	0.0646	-0.0888	0.1690	-0.0524	-0.3349**
	(0.088)	(0.133)	(0.156)	(0.167)	(0.147)
Agriculture, fishing and mining	0.0584		0.0453	-1.5182***	-0.3650
	(0.155)		(0.274)	(0.289)	(0.250)
Manufacturing	-0.3301***		-0.6199***	-1.9291***	-0.7021***
	(0.106)		(0.185)	(0.218)	(0.182)
Commercial	-0.4454***		-1.2702***	-0.2856**	-0.3331***
	(0.072)		(0.135)	(0.131)	(0.118)
Utilities, transport, storage, communications	-0.2333***		-0.8320***	-1.4530***	-0.4325***
	(0.084)		(0.146)	(0.159)	(0.139)
Mother has complete secondary education	0.2985***	-0.0940	0.2873*	0.4486***	0.1337
	(0.088)	(0.121)	(0.154)	(0.164)	(0.144)
Mother has incomplete higher education	-0.1348	0.1871	-0.1179	1.4512***	0.6539*
	(0.207)	(0.283)	(0.315)	(0.521)	(0.340)
Mother has complete higher education	0.2544**	0.4207**	0.4173*	0.4326*	0.2118
	(0.129)	(0.195)	(0.228)	(0.244)	(0.208)
Father has complete secondary education	0.0852	0.0055	0.0408	0.1135	0.1687
	(0.080)	(0.113)	(0.138)	(0.146)	(0.131)
Father has incomplete higher education	0.7440***	0.4959*	0.2694	0.2740	0.0687
	(0.182)	(0.291)	(0.321)	(0.357)	(0.288)
Father has complete higher education	0.2944***	-0.1108	0.2696	0.1648	0.3065*
	(0.112)	(0.159)	(0.196)	(0.212)	(0.184)
Dummy for taking less than 1/2 hour to go to school		-0.1293	0.0341	-0.0154	-0.1482
		(0.129)	(0.161)	(0.170)	(0.152)
Constant	-0.4588	-2.2127***	2.7002***	0.2131	-0.3759
	(0.455)	(0.589)	(0.847)	(0.840)	(0.762)
Observations	748	1,265	789	789	789

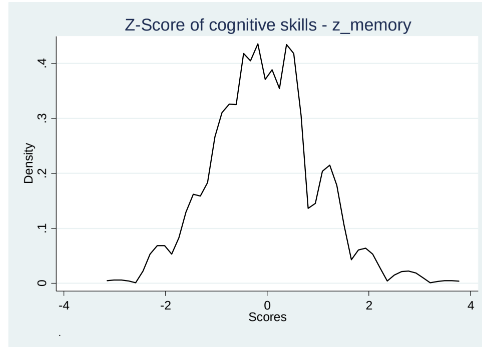
Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1: Kernel densities of cognitive measures

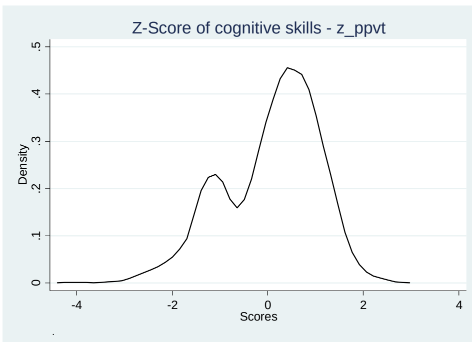
A. Numeric ability



B. Working memory



C. Verbal ability (PPVT)



D. Verbal fluency

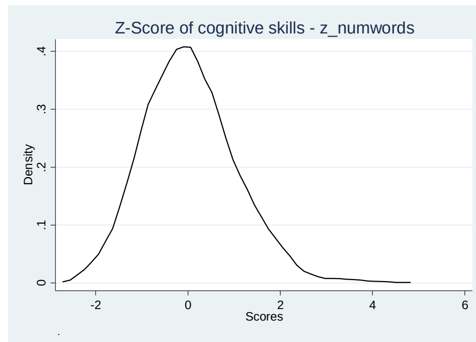
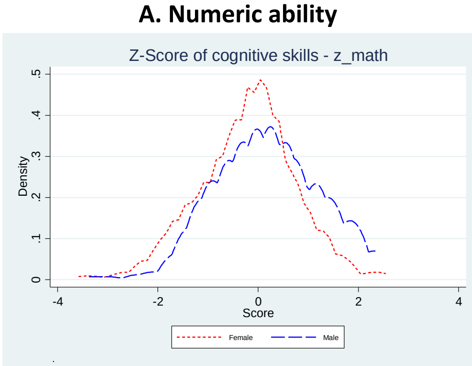
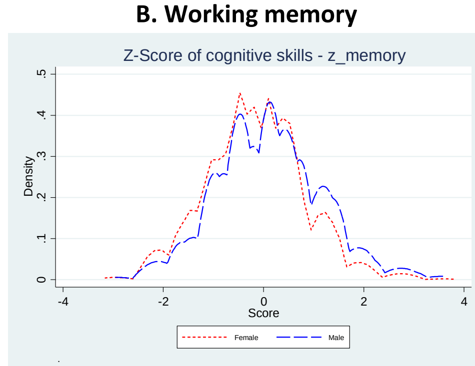


Figure 2: Kernel densities of cognitive measures by gender

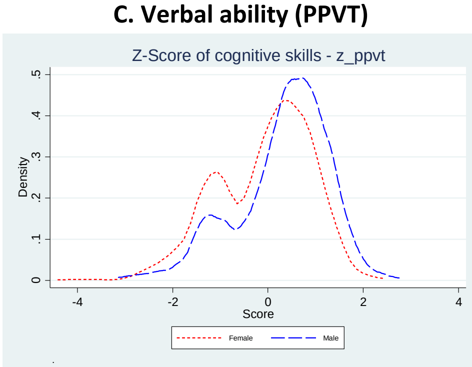
A. Numeric ability



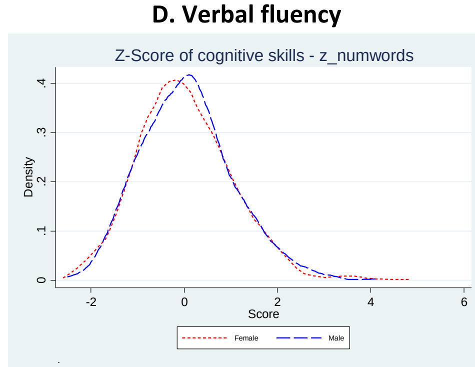
B. Working memory



C. Verbal ability (PPVT)



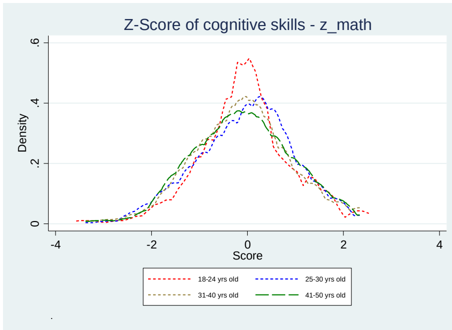
D. Verbal fluency



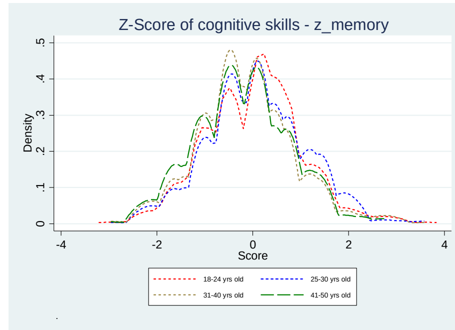
Note: All density distributions are significantly different among groups except in the case of verbal fluency.

Figure 3: Kernel densities of cognitive measures by age group

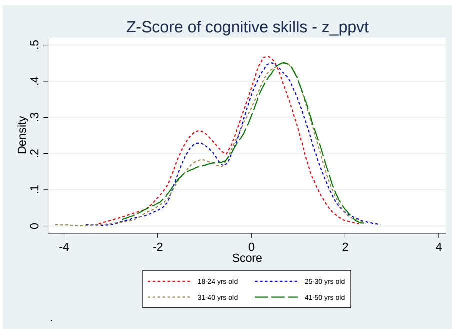
A. Numeric ability



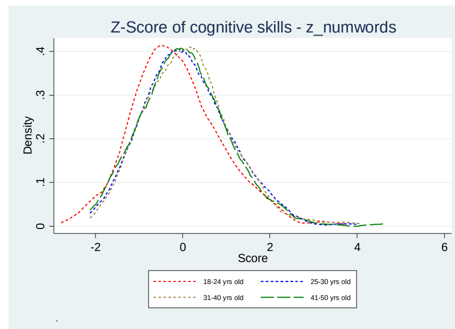
B. Working memory



C. Verbal ability (PPVT)



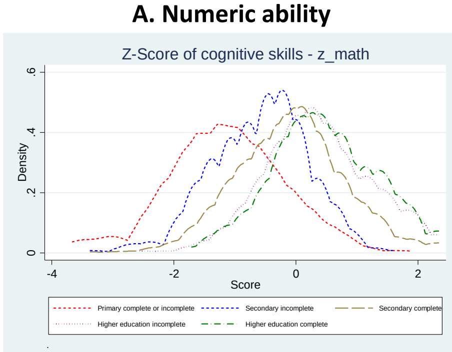
D. Verbal fluency



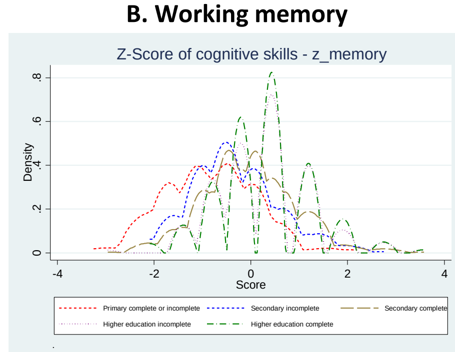
Note: The only densities that are significantly different are those of numeric skills between individuals in the age range of 18-24 and of 25-30 years old; those of working memory for the groups of individuals in the age range 18-24 and 25-30 compared to individuals older than 31 years old; and those of verbal fluency and verbal ability between the group of individuals younger than 25 years old and older groups.

Figure 4: Kernel densities of cognitive measures by educational attainment

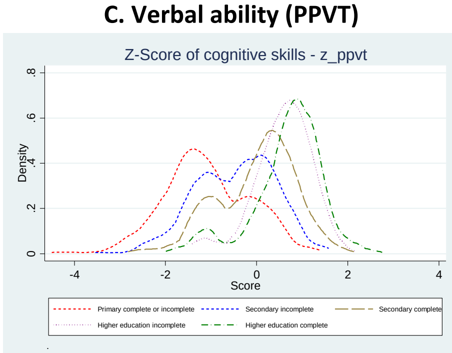
A. Numeric ability



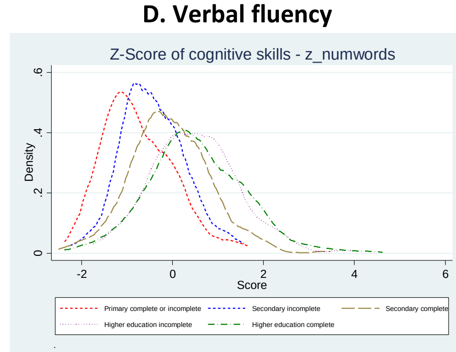
B. Working memory



C. Verbal ability (PPVT)



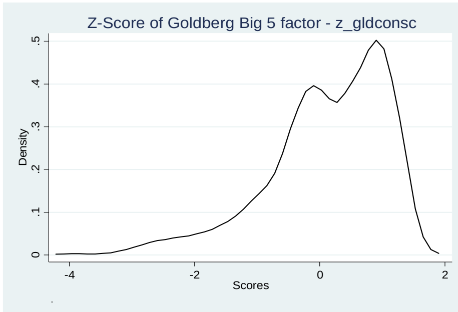
D. Verbal fluency



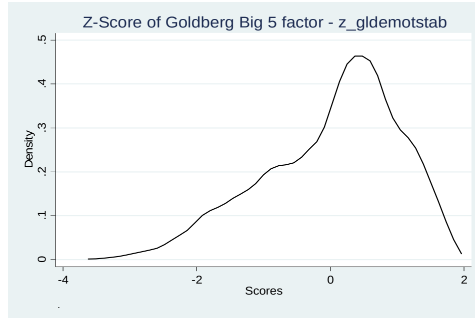
Note: All densities are significantly different form others except those for individuals with higher incomplete education and higher complete education in the case of numeric skills, working memory and verbal fluency between.

Figure 5: Kernel densities of non-cognitive measures

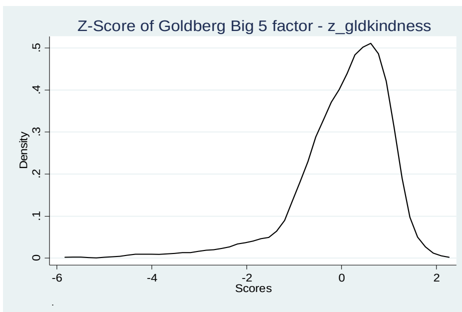
A. Conscientiousness



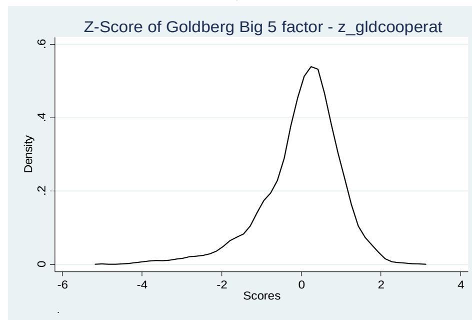
B. Emotional stability



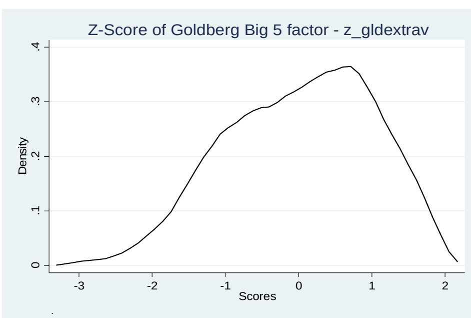
C. Kindness



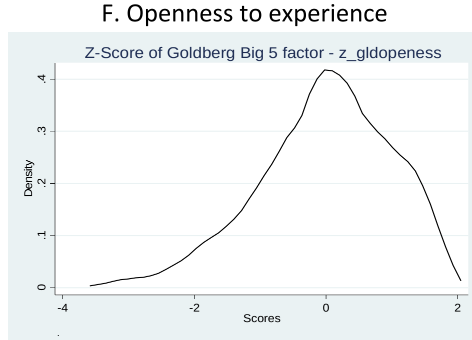
D. Cooperation



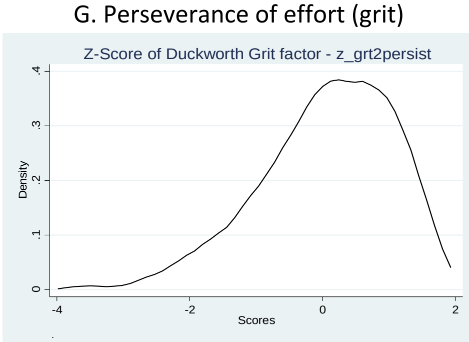
E. Extraversion



F. Openness to experience



G. Perseverance of effort (grit)



H. Consistency of interest (grit)

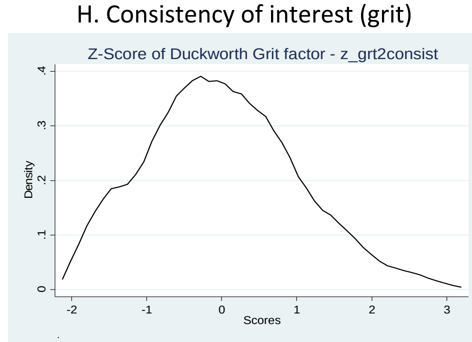
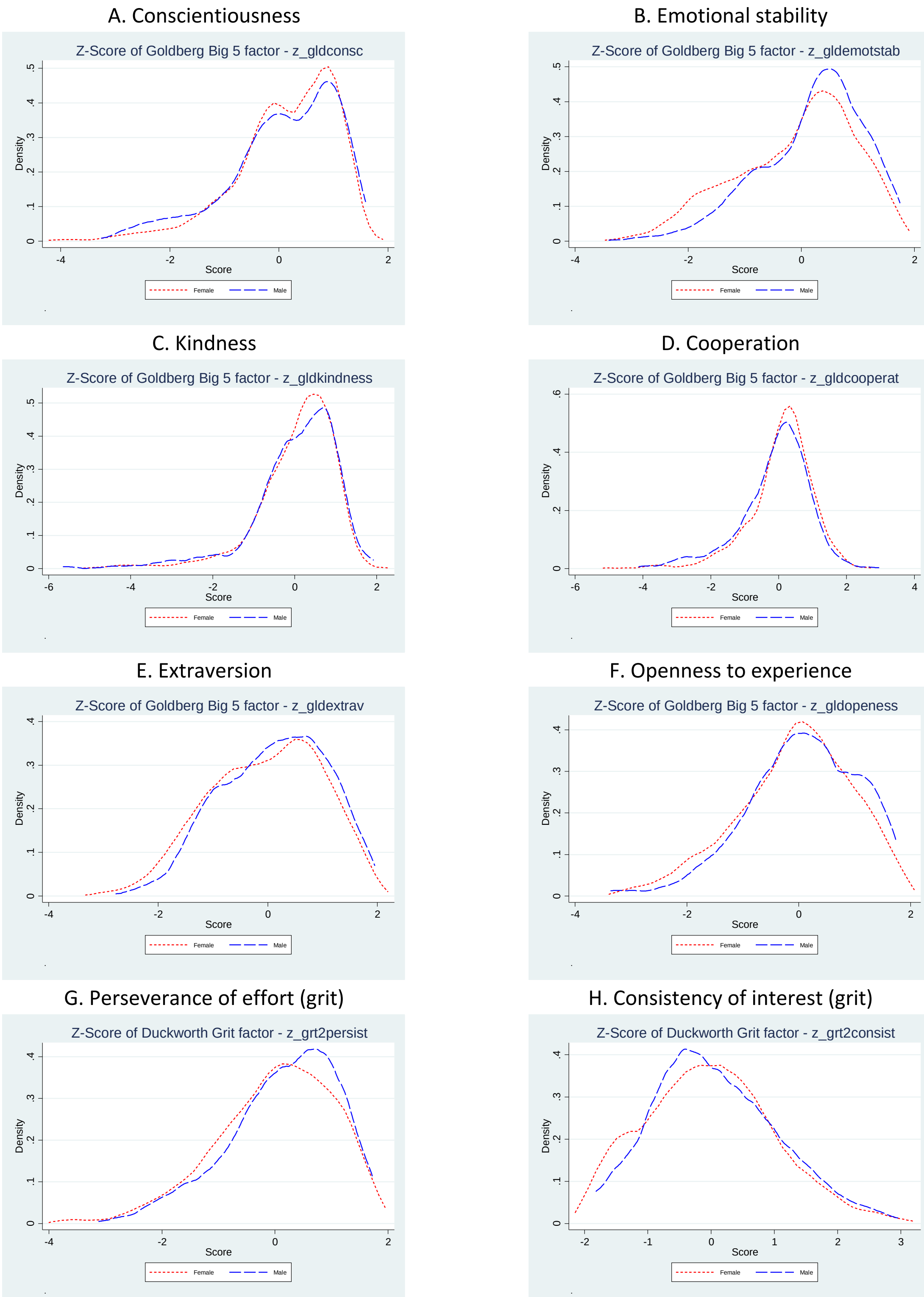


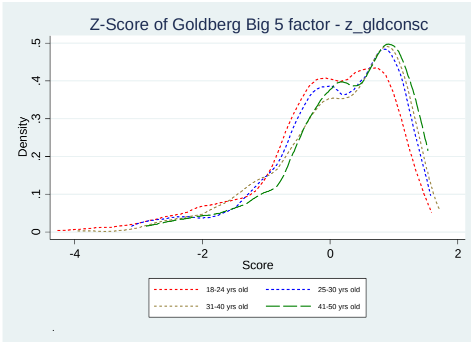
Figure 6: Kernel densities of non-cognitive measures by gender



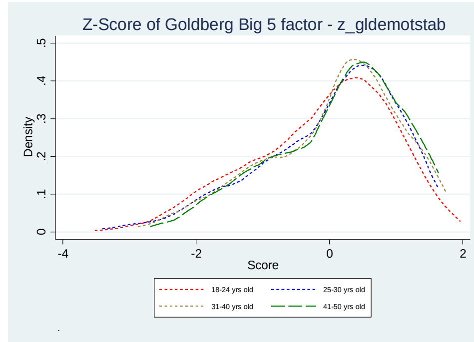
Note: All densities are significantly different except for those of conscientiousness, kindness, and consistency of interest.

Figure 7: Kernel densities of non-cognitive measures by age

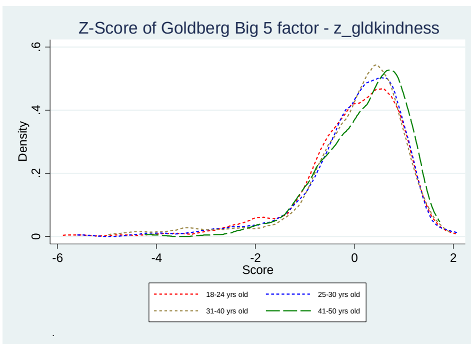
A. Conscientiousness



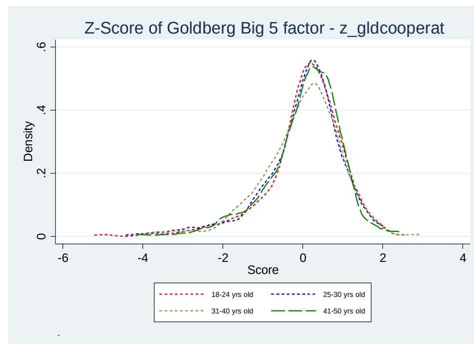
B. Emotional stability



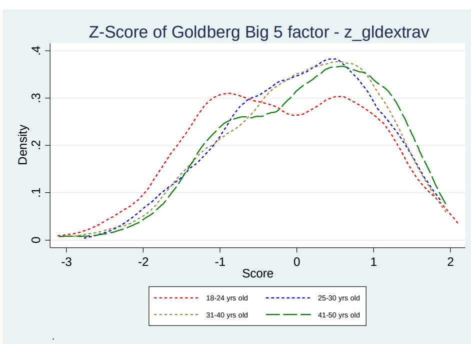
C. Kindness



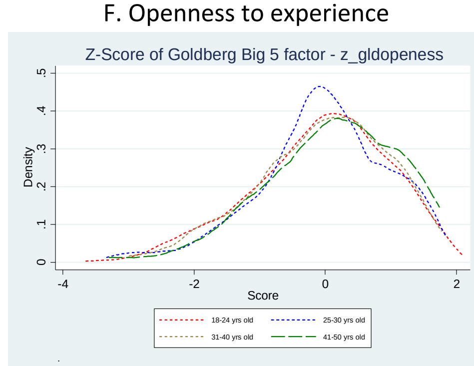
D. Cooperation



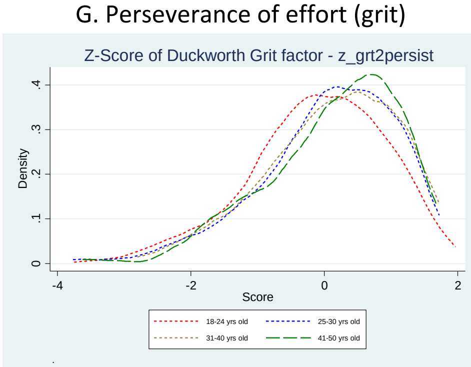
E. Extraversion



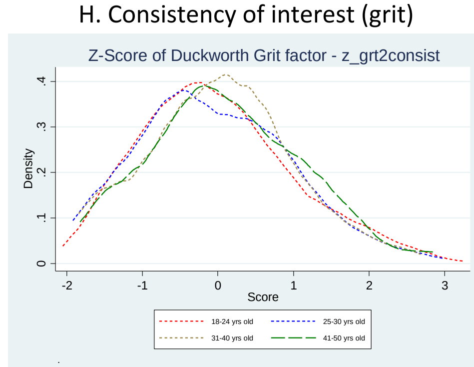
F. Openness to experience



G. Perseverance of effort (grit)

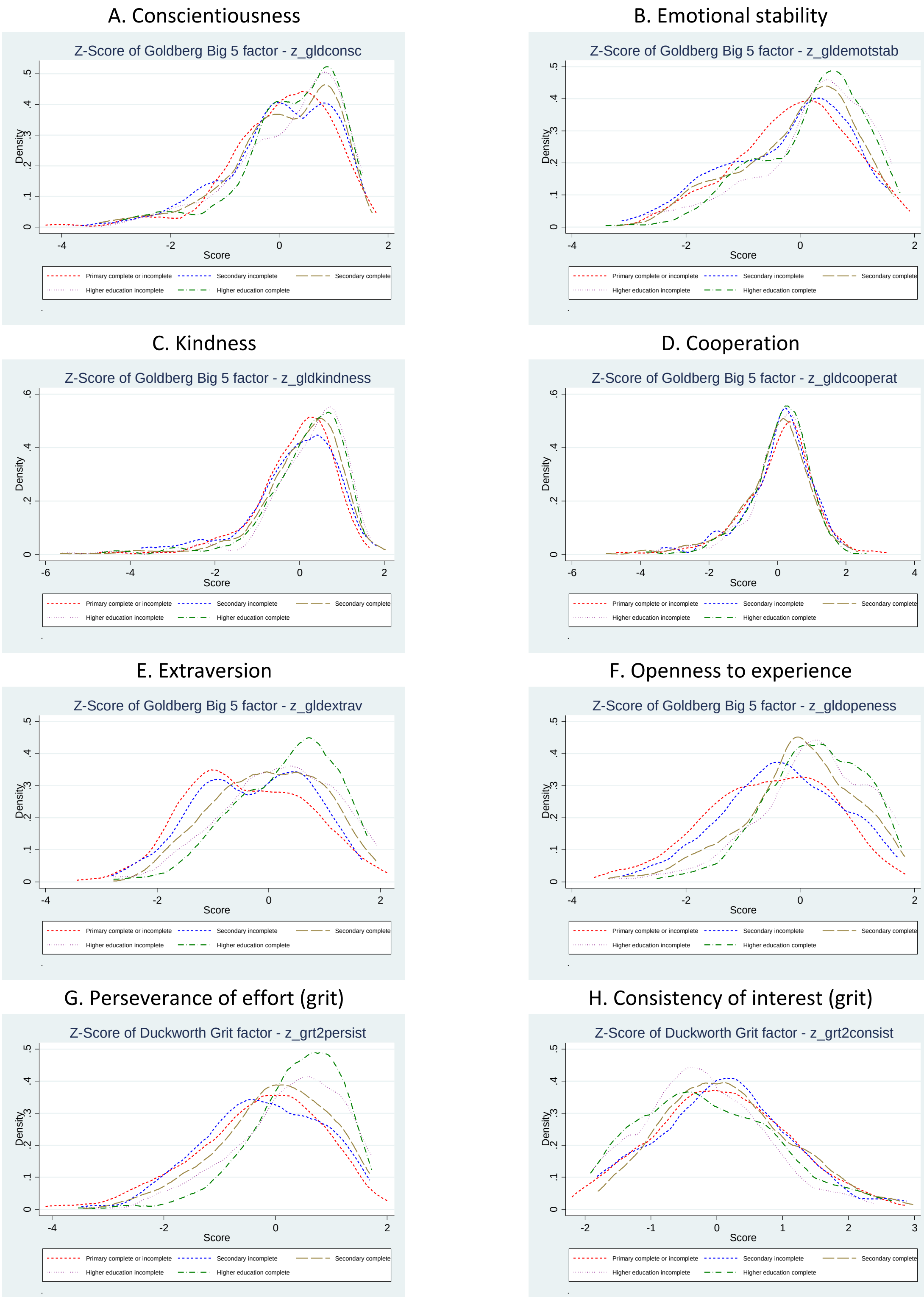


H. Consistency of interest (grit)



Note: The only densities that are significantly different from others are those of consciousness for individuals aged 18 to 25 years old compared to any older group and for individuals aged 25-30 years old compared to individuals older than 40 years old; those of kindness for all age groups when compared to individuals older than 40 years old; those of extraversion, emotional stability, and perseverance of effort for individuals aged 18-24 compared to any older groups; those of openness between individuals aged 25-30 years old and older than 40; and those of consistency of interest for individuals in the age range of 25-30 compared to older groups.

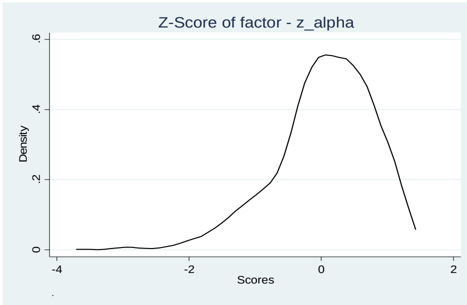
Figure 8: Kernel densities of non-cognitive measures by educational attainment



Note: In the cases of openness to experience and perseverance of effort all densities are significantly different from the others except those for individuals with primary school compared to those with secondary incomplete, and those for individuals with incomplete higher education compared with complete higher education. The densities for individuals with complete secondary education are significantly different than those for individuals with primary education in the case of kindness and extraversion and significantly different than that for individuals with incomplete higher education in the case of extraversion. The densities for individuals with either incomplete or complete higher education are significantly different than those for individuals with primary or incomplete secondary education in the case of conscientiousness, emotional stability, kindness, extraversion and consistency of interest. These densities are also significantly different than those for individuals with complete secondary education in the case of kindness, emotional stability, and consistency of interest. In addition, the density for individuals with complete higher education is significantly different than that for individuals with complete secondary education and incomplete higher education in the case of extraversion.

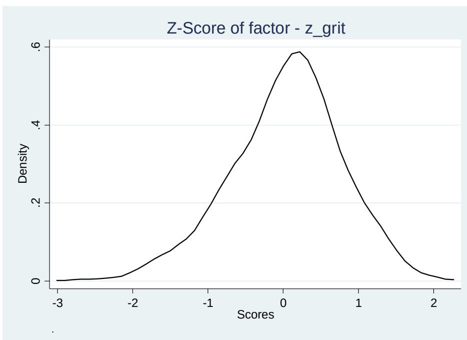
Figure 9: Kernel densities of cognitive and non-cognitive factors

A. Stability (Agreeableness + Conscientiousness+ Emotional Stability)



B. Plasticity (Openness to Experience + Extroversion)

C. Grit



A. Cognitive factor

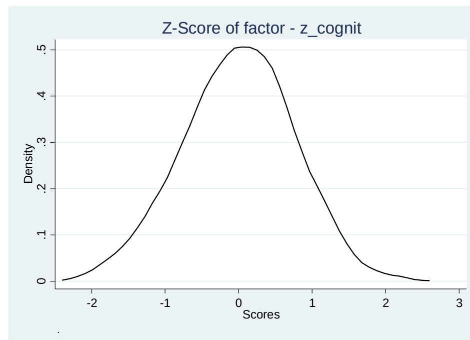
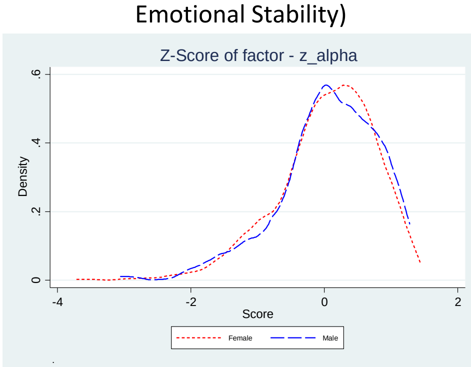
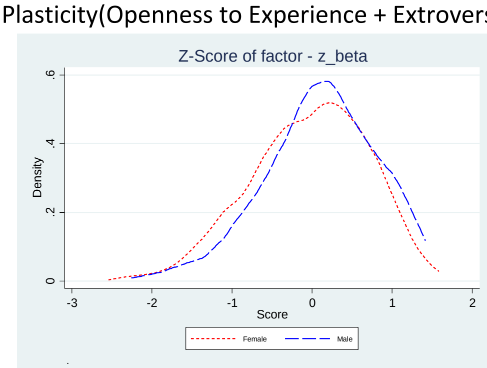


Figure 10: Kernel densities of cognitive and non-cognitive factors by gender

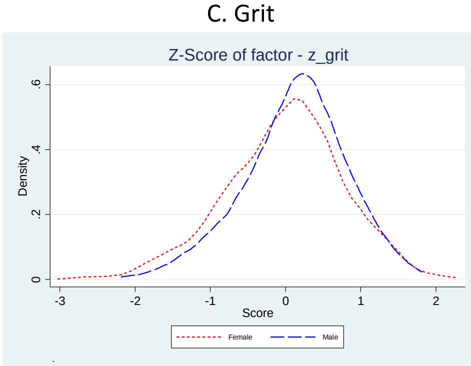
A. Stability (Agreeableness + Conscientiousness+ Emotional Stability)



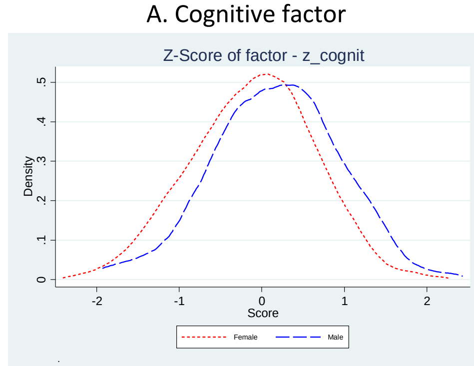
B. Plasticity(Openness to Experience + Extroversion)



C. Grit



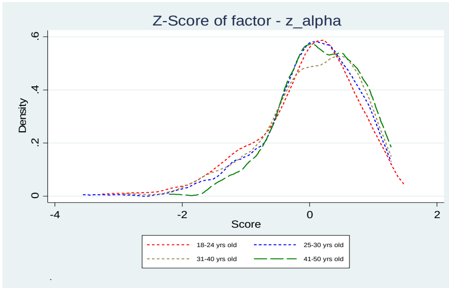
A. Cognitive factor



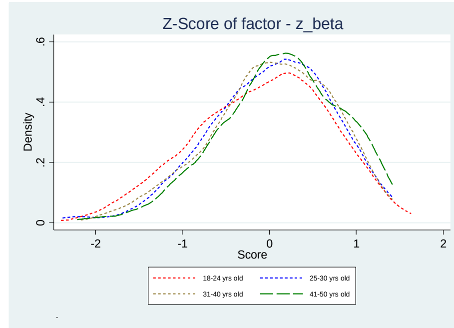
Note: All densities are significantly different except for those of stability.

Figure 11: Kernel densities of cognitive and non-cognitive factors by age

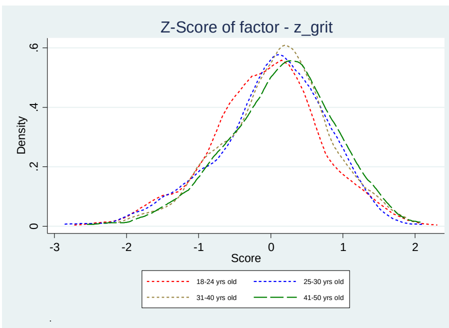
A. Stability (agreeableness + Conscientiousness + Emotional Stability)



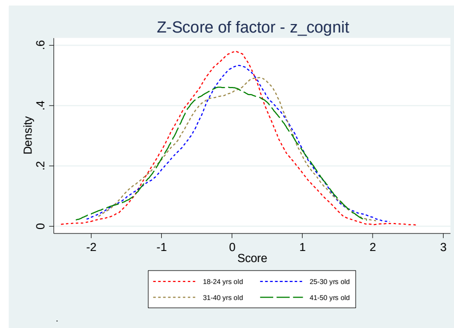
B. Plasticity(Openness to Experience + Extroversion)



C. Grit



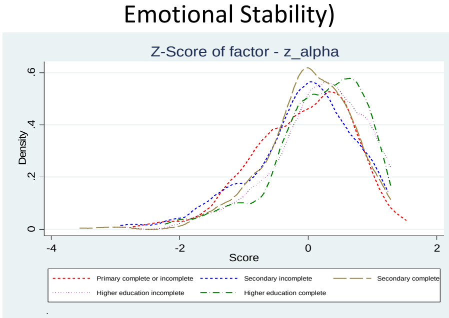
A. Cognitive factor



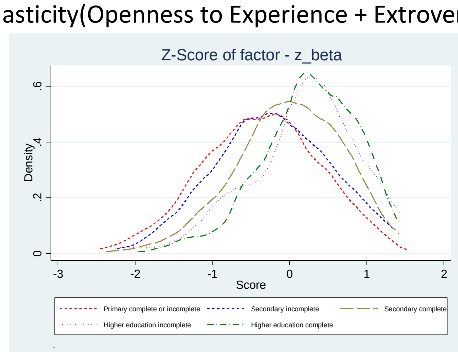
Note: The only densities that are significantly different from others are those of Stability for individuals in the age range 18-24 compared to those in the 41-50 age range, those of Plasticity and Grit for individuals aged 18-24 compared to those for older individuals, and those of the aggregate cognitive factor for individuals younger than 25 years old compared to those for individuals between 25 and 40 years old, and for individuals between 25 and 30 years old compared to those older than 40.

Figure 12: Kernel densities of cognitive and non-cognitive factors by educational attainment

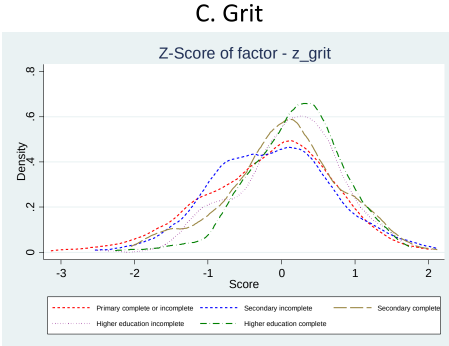
A. Stability (agreeableness + Conscientiousness + Emotional Stability)



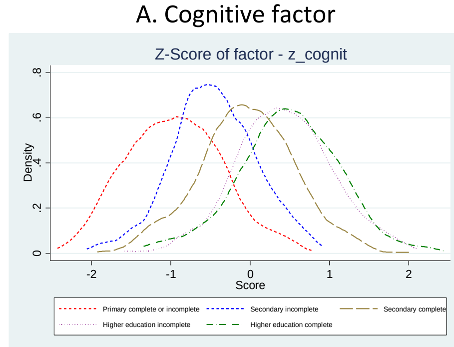
B. Plasticity(Openness to Experience + Extroversion)



C. Grit



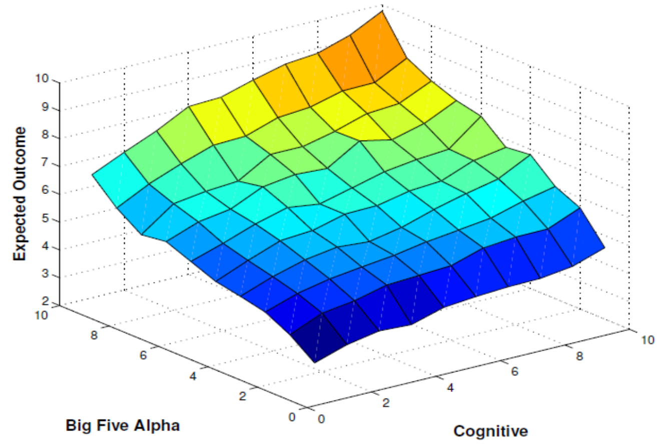
A. Cognitive factor



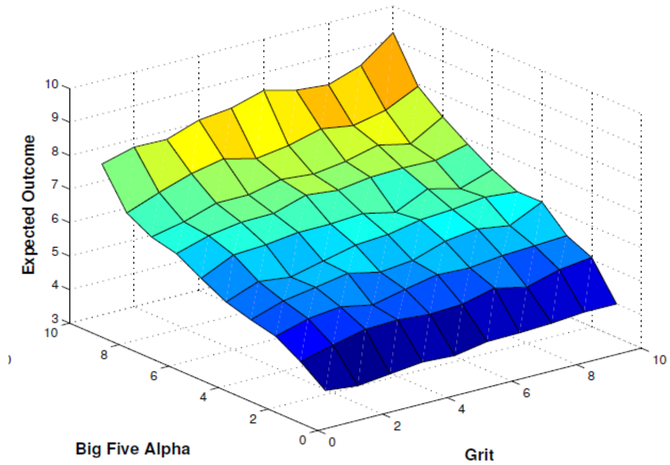
Note: All densities are significantly different from others except those for individuals with primary education compared to secondary incomplete in the case of the non-cognitive aggregated factors, those for individuals with incomplete secondary compared to secondary complete in the case of Stability, those for individuals with complete secondary education compared to incomplete higher education, and the densities of all aggregated factors for individuals with incomplete higher education compared to those for individuals with complete higher education.

Figure 13: Wages and skills

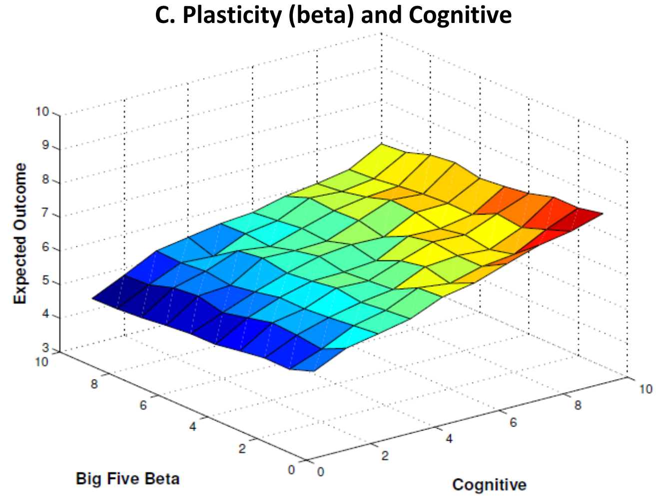
A. Stability (alpha) and Cognitive



B. Stability (alpha) and Grit



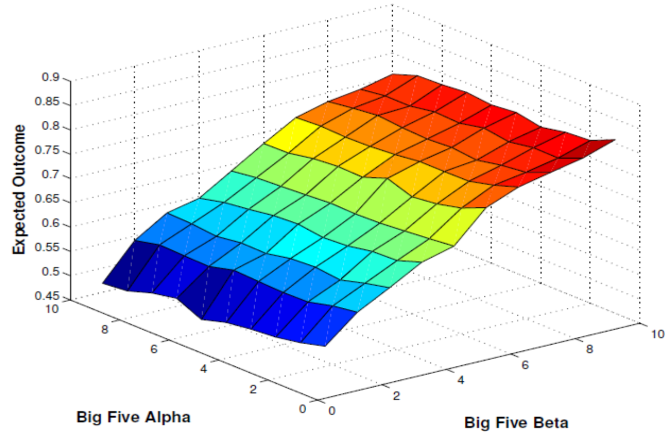
C. Plasticity (beta) and Cognitive



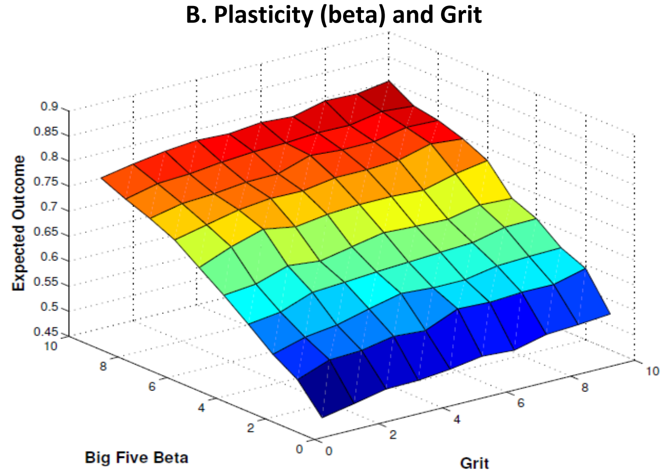
Note: "Stability" and "Big Five Alpha" are the composite of agreeableness, conscientiousness, and emotional stability Big Five traits. "Plasticity"and "Big Five Beta" are the composite of the openness to experience and extroversion Big Five traits. The x-axis are measured in deciles of the distribution associated with each skill.

Figure 14: Employment and skills

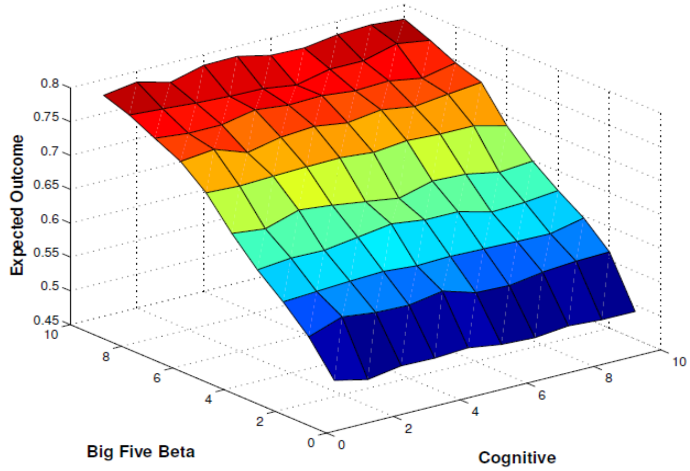
A. Stability (alpha) and Plasticity (beta)



B. Plasticity (beta) and Grit



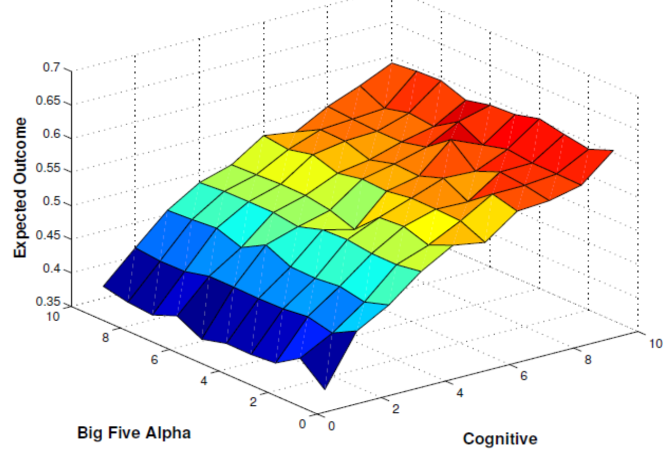
C. Plasticity (beta) and Cognitive



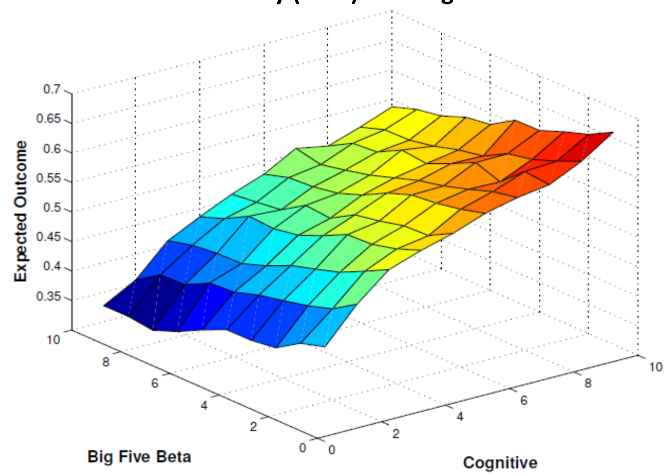
Note: "Stability" and "Big Five Alpha" are the composite of agreeableness, conscientiousness, and emotional stability Big Five traits. "Plasticity"and "Big Five Beta" are the composite of the openness to experience and extroversion Big Five traits. The x-axis are measured in deciles of the distribution associated with each skill.

Figure 15: Formal workers and skills

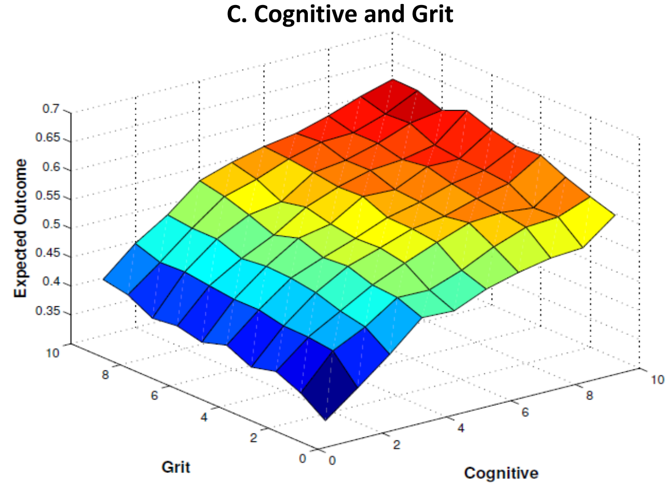
A. Stability (alpha) and Cognitive



B. Plasticity (beta) and Cognitive



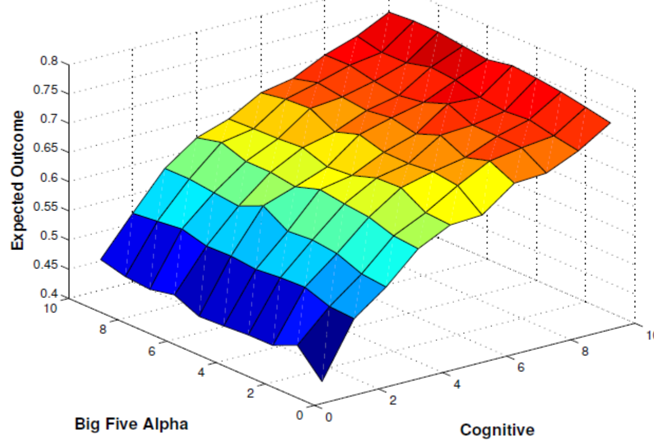
C. Cognitive and Grit



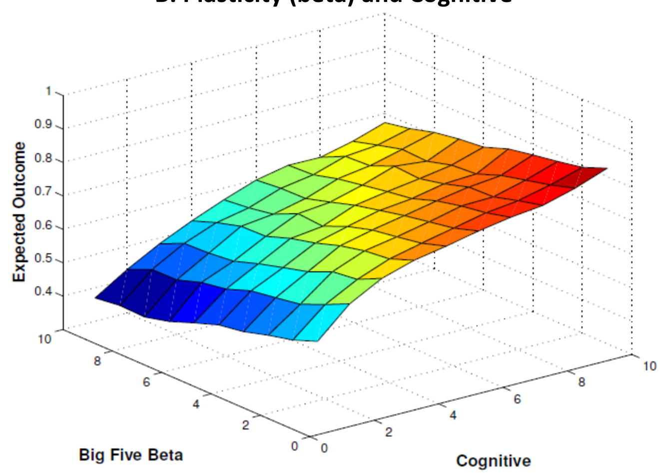
Note: "Stability" and "Big Five Alpha" are the composite of agreeableness, conscientiousness, and emotional stability Big Five traits. "Plasticity"and "Big Five Beta" are the composite of the openness to experience and extroversion Big Five traits. The x-axis are measured in deciles of the distribution associated with each skill.

Figure 16: White-collar workers and skills

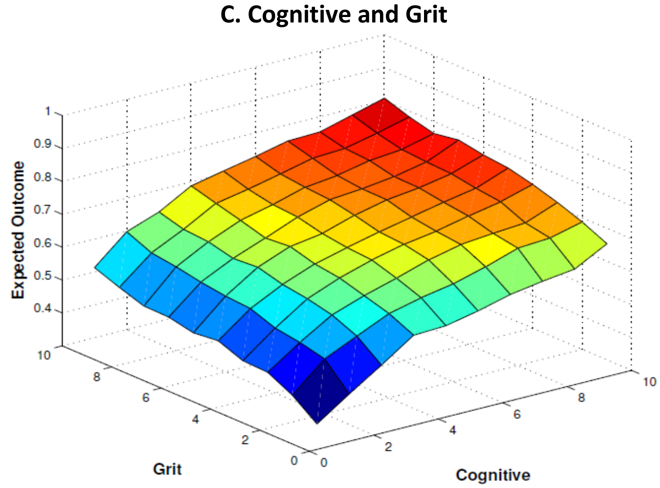
A. Stability (alpha) and Cognitive



B. Plasticity (beta) and Cognitive



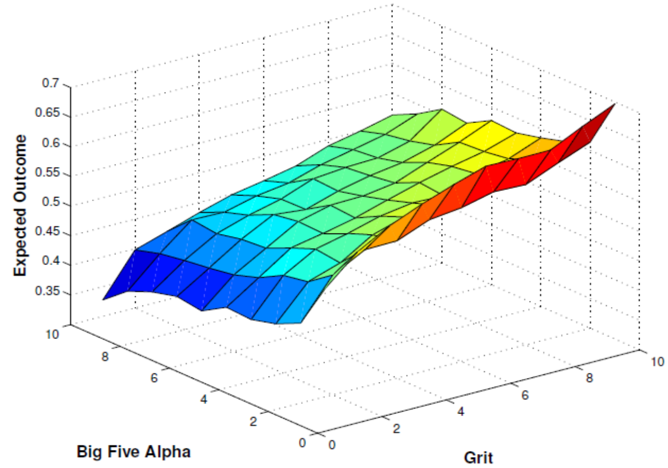
C. Cognitive and Grit



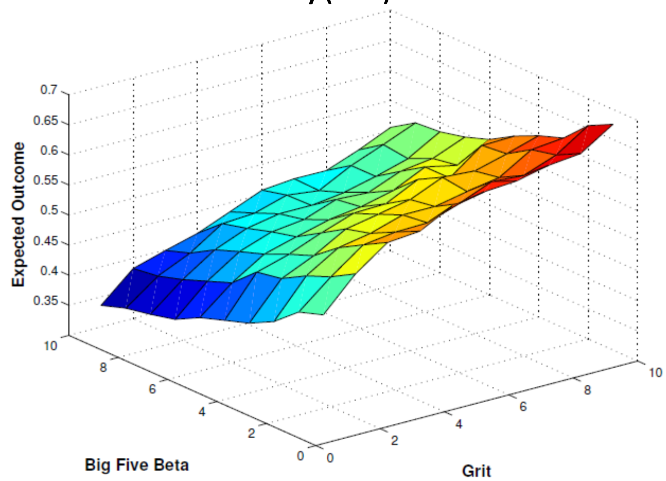
Note: "Stability" and "Big Five Alpha" are the composite of agreeableness, conscientiousness, and emotional stability Big Five traits. "Plasticity"and "Big Five Beta" are the composite of the openness to experience and extroversion Big Five traits. The x-axis are measured in deciles of the distribution associated with each skill.

Figure 17: Wage-workers and skills

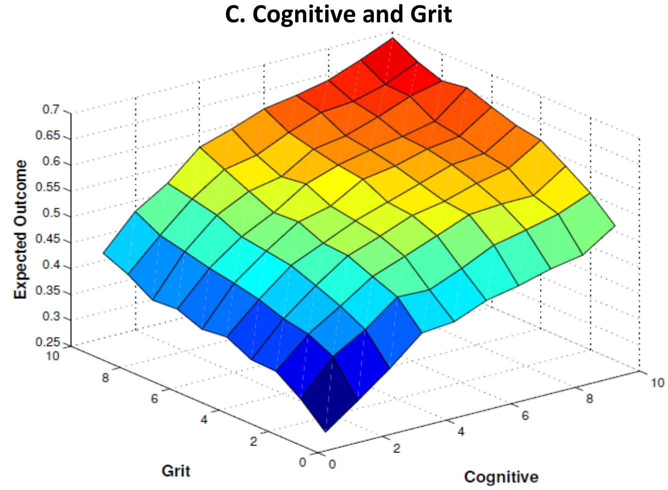
A. Stability (alpha) and Grit



B. Plasticity (beta) and Grit



C. Cognitive and Grit



Note: "Stability" and "Big Five Alpha" are the composite of agreeableness, conscientiousness, and emotional stability Big Five traits. "Plasticity"and "Big Five Beta" are the composite of the openness to experience and extroversion Big Five traits. The x-axis are measured in deciles of the distribution associated with each skill.

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Annex I: Additional estimations

Table A1: OLS Estimations based on aggregated factors - including schooling, total

	Log of hourly wage		Employed		Wage worker		White-collar worker		Formal worker	
Years of schooling		0.067***		0.005		0.031***		0.039***		0.018***
		(0.012)		(0.005)		(0.006)		(0.006)		(0.007)
Stability (alpha)	-0.129**	-0.131**	-0.016	-0.016	-0.014	-0.015	-0.010	-0.011	0.003	0.003
	(0.061)	(0.060)	(0.021)	(0.021)	(0.026)	(0.026)	(0.025)	(0.024)	(0.030)	(0.030)
Plasticity (beta)	0.097	0.078	0.037	0.036	-0.013	-0.021	-0.003	-0.013	-0.010	-0.014
	(0.060)	(0.059)	(0.023)	(0.023)	(0.030)	(0.029)	(0.028)	(0.028)	(0.033)	(0.033)
Grit	0.083*	0.075*	0.037**	0.036**	0.052**	0.046**	0.059***	0.051**	0.017	0.013
	(0.044)	(0.044)	(0.018)	(0.018)	(0.022)	(0.022)	(0.022)	(0.021)	(0.024)	(0.024)
Cognitive	0.306***	0.153***	0.035**	0.023	0.115***	0.043*	0.141***	0.052**	0.090***	0.049*
	(0.040)	(0.043)	(0.017)	(0.020)	(0.022)	(0.026)	(0.019)	(0.022)	(0.024)	(0.028)
Female	-0.156**	-0.168***	-0.352***	-0.353***	-0.082**	-0.087***	0.095***	0.089***	0.035	0.032
	(0.061)	(0.060)	(0.023)	(0.023)	(0.033)	(0.033)	(0.031)	(0.031)	(0.036)	(0.036)
Age	0.098***	0.087***	0.055***	0.054***	-0.030**	-0.035***	0.008	0.001	0.023	0.020
	(0.027)	(0.027)	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)	(0.013)	(0.016)	(0.015)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	0.000	0.000*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indigenous mother tongue	0.037	0.084	-0.013	-0.010	-0.010	0.011	0.006	0.033	-0.157***	-0.145***
	(0.102)	(0.103)	(0.042)	(0.042)	(0.054)	(0.054)	(0.047)	(0.046)	(0.056)	(0.056)
Firstborn	-0.151**	-0.166***	0.040	0.040	-0.016	-0.022	0.025	0.017	-0.054	-0.058
	(0.061)	(0.060)	(0.026)	(0.026)	(0.033)	(0.033)	(0.030)	(0.030)	(0.037)	(0.037)
Lima region	0.078	0.090	-0.074**	-0.073**	0.158***	0.164***	-0.022	-0.015	-0.154***	-0.151***
	(0.080)	(0.077)	(0.033)	(0.033)	(0.043)	(0.042)	(0.040)	(0.039)	(0.047)	(0.047)
Coastal region	0.029	0.008	-0.051	-0.052	0.111**	0.102**	-0.058	-0.069*	-0.217***	-0.222***
	(0.083)	(0.080)	(0.033)	(0.033)	(0.044)	(0.043)	(0.039)	(0.038)	(0.046)	(0.046)
Andes region	-0.004	-0.049	-0.011	-0.015	0.048	0.027	-0.028	-0.054	-0.097*	-0.109**
	(0.091)	(0.089)	(0.036)	(0.037)	(0.047)	(0.046)	(0.041)	(0.040)	(0.050)	(0.050)
Agriculture, fishing and mining	0.202	0.230			-0.028	-0.016	-0.452***	-0.437***	-0.142	-0.135
	(0.181)	(0.177)			(0.079)	(0.077)	(0.074)	(0.077)	(0.094)	(0.094)
Manufacturing	-0.342***	-0.246***			-0.222***	-0.172***	-0.632***	-0.570***	-0.262***	-0.234***
	(0.086)	(0.084)			(0.058)	(0.058)	(0.045)	(0.046)	(0.060)	(0.061)
Commercial	-0.434***	-0.361***			-0.417***	-0.378***	-0.065*	-0.018	-0.132***	-0.110**
	(0.077)	(0.079)			(0.037)	(0.037)	(0.038)	(0.039)	(0.042)	(0.043)
Utilities, transport, storage, communications	-0.255***	-0.182**			-0.310***	-0.272***	-0.490***	-0.443***	-0.190***	-0.168***
	(0.071)	(0.073)			(0.048)	(0.048)	(0.043)	(0.042)	(0.049)	(0.050)
Constant	-0.242	-0.844**	-0.183	-0.223	1.334***	1.045***	0.615***	0.258	0.261	0.098
	(0.433)	(0.409)	(0.174)	(0.178)	(0.228)	(0.228)	(0.230)	(0.234)	(0.259)	(0.265)
Observations	803	803	1,363	1,363	844	844	844	844	844	844
R-squared	0.201	0.234	0.230	0.231	0.248	0.271	0.343	0.379	0.110	0.117

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TableA2: OLS Estimations – including schooling, Total

	Log of hourly wage		Employed		Wage worker		White-collar worker		Formal worker	
Years of schooling		0.065***		0.006		0.032***		0.039***		0.018***
		(0.012)		(0.005)		(0.006)		(0.006)		(0.007)
Numeric skills	0.096***	0.047	0.012	0.008	0.013	-0.011	0.046**	0.016	-0.008	-0.022
	(0.035)	(0.035)	(0.014)	(0.014)	(0.020)	(0.020)	(0.018)	(0.018)	(0.021)	(0.022)
Working memory	0.053*	0.042	0.007	0.006	0.013	0.008	0.018	0.012	0.025	0.022
	(0.030)	(0.030)	(0.013)	(0.013)	(0.018)	(0.018)	(0.015)	(0.015)	(0.019)	(0.019)
Verbal ability (PPVT)	0.103***	0.039	-0.011	-0.017	0.061***	0.030	0.045**	0.008	0.050**	0.032
	(0.035)	(0.036)	(0.015)	(0.016)	(0.022)	(0.023)	(0.019)	(0.019)	(0.021)	(0.022)
Verbal fluency	0.049	0.028	0.027**	0.025*	0.025	0.014	0.026*	0.012	0.016	0.010
	(0.033)	(0.032)	(0.013)	(0.013)	(0.017)	(0.017)	(0.015)	(0.015)	(0.018)	(0.018)
Conscientiousness	-0.043	-0.044	-0.001	-0.001	-0.005	-0.005	0.002	0.002	-0.004	-0.004
	(0.036)	(0.035)	(0.015)	(0.015)	(0.019)	(0.019)	(0.018)	(0.018)	(0.021)	(0.021)
Kindness	-0.093***	-0.086**	-0.008	-0.008	0.006	0.009	-0.007	-0.004	0.000	0.002
	(0.035)	(0.034)	(0.013)	(0.013)	(0.019)	(0.018)	(0.016)	(0.015)	(0.019)	(0.019)
Cooperation	-0.058*	-0.056*	0.002	0.003	-0.026	-0.024	-0.011	-0.009	0.018	0.019
	(0.030)	(0.030)	(0.013)	(0.013)	(0.017)	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)
Emotional stability	0.074**	0.067**	-0.003	-0.003	-0.014	-0.017	0.001	-0.003	-0.021	-0.023
	(0.032)	(0.031)	(0.013)	(0.013)	(0.018)	(0.018)	(0.017)	(0.017)	(0.019)	(0.019)
Extraversion	0.025	0.021	0.010	0.010	-0.010	-0.012	0.013	0.011	-0.007	-0.008
	(0.034)	(0.033)	(0.014)	(0.014)	(0.018)	(0.018)	(0.016)	(0.016)	(0.019)	(0.019)
Openness to experience	0.015	0.009	0.015	0.014	-0.016	-0.019	-0.032*	-0.035**	-0.008	-0.009
	(0.032)	(0.031)	(0.014)	(0.014)	(0.019)	(0.018)	(0.017)	(0.016)	(0.020)	(0.020)
Perseverance of effort	0.058	0.044	0.033**	0.032**	0.054***	0.045***	0.050***	0.039**	0.035*	0.030
	(0.037)	(0.037)	(0.014)	(0.014)	(0.017)	(0.017)	(0.016)	(0.016)	(0.019)	(0.019)
Consistency of interest	0.004	0.011	0.005	0.005	-0.004	-0.001	0.002	0.005	-0.025	-0.024
	(0.031)	(0.030)	(0.012)	(0.012)	(0.016)	(0.016)	(0.016)	(0.015)	(0.018)	(0.018)
Female	-0.132**	-0.146**	-0.359***	-0.360***	-0.086**	-0.093***	0.091***	0.083***	0.024	0.020
	(0.062)	(0.062)	(0.023)	(0.023)	(0.034)	(0.034)	(0.032)	(0.031)	(0.036)	(0.036)
Age	0.090***	0.083***	0.054***	0.053***	-0.034**	-0.037***	0.007	0.004	0.023	0.021
	(0.027)	(0.027)	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	0.000	0.000*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Speaks indigenous as mother tongue	0.073	0.104	-0.011	-0.008	0.007	0.023	0.011	0.030	-0.142**	-0.133**
	(0.100)	(0.101)	(0.041)	(0.041)	(0.055)	(0.054)	(0.047)	(0.046)	(0.057)	(0.057)
Firstborn	-0.148**	-0.161***	0.036	0.036	-0.023	-0.028	0.024	0.019	-0.062*	-0.064*
	(0.059)	(0.059)	(0.026)	(0.026)	(0.033)	(0.033)	(0.031)	(0.030)	(0.037)	(0.037)
Lima region	0.098	0.117	-0.071**	-0.069**	0.162***	0.170***	-0.014	-0.003	-0.143***	-0.138***
	(0.081)	(0.078)	(0.033)	(0.033)	(0.044)	(0.043)	(0.040)	(0.040)	(0.048)	(0.048)
Coastal region	0.059	0.035	-0.038	-0.039	0.124***	0.114***	-0.037	-0.049	-0.192***	-0.198***
	(0.085)	(0.083)	(0.033)	(0.033)	(0.045)	(0.044)	(0.040)	(0.039)	(0.047)	(0.047)

	Log of hourly wage		Employed		Wage worker		White-collar worker		Formal worker	
Andes region	0.031	-0.005	-0.000	-0.004	0.049	0.031	-0.029	-0.051	-0.080	-0.091*
	(0.090)	(0.088)	(0.036)	(0.037)	(0.048)	(0.047)	(0.041)	(0.040)	(0.051)	(0.050)
Agriculture, fishing and mining	0.182	0.212			-0.029	-0.015	-0.450***	-0.434***	-0.145	-0.138
	(0.182)	(0.178)			(0.080)	(0.078)	(0.077)	(0.079)	(0.096)	(0.096)
Manufacturing	-0.336***	-0.240***			-0.221***	-0.168***	-0.626***	-0.563***	-0.250***	-0.221***
	(0.085)	(0.084)			(0.057)	(0.058)	(0.046)	(0.047)	(0.060)	(0.061)
Commercial	-0.426***	-0.353***			-0.412***	-0.372***	-0.060	-0.012	-0.137***	-0.115***
	(0.076)	(0.077)			(0.037)	(0.037)	(0.038)	(0.039)	(0.041)	(0.042)
Utilities, transport, storage, communicat.	-0.240***	-0.164**			-0.306***	-0.265***	-0.503***	-0.454***	-0.175***	-0.152***
	(0.071)	(0.072)			(0.047)	(0.048)	(0.042)	(0.042)	(0.049)	(0.050)
Constant	-0.131	-0.803*	-0.176	-0.232	1.408***	1.072***	0.631***	0.225	0.273	0.084
	(0.433)	(0.418)	(0.174)	(0.179)	(0.231)	(0.233)	(0.234)	(0.241)	(0.258)	(0.267)
Observations	822	822	1,390	1,390	865	865	865	865	865	865
R-squared	0.212	0.242	0.233	0.234	0.253	0.275	0.348	0.383	0.112	0.119

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Annex 2: Personality Traits across the Life-cycle, holding constant years of schooling and fitting a regression line

Stability (Alpha)

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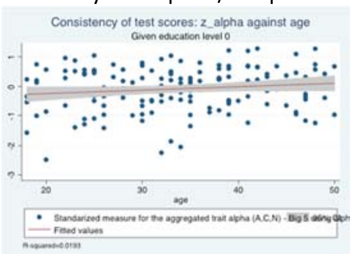

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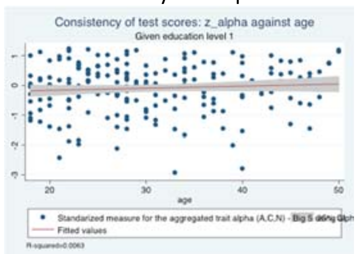

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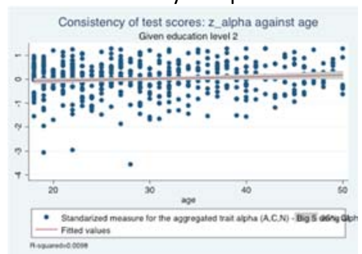
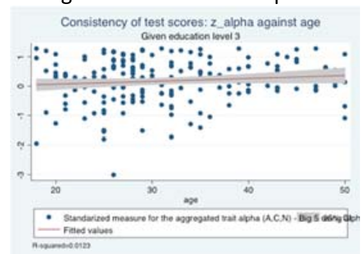


Higher education incomplete



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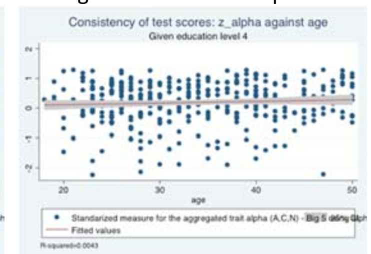

Plasticity (Beta)

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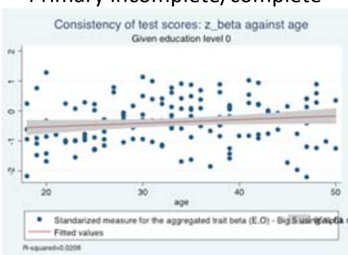

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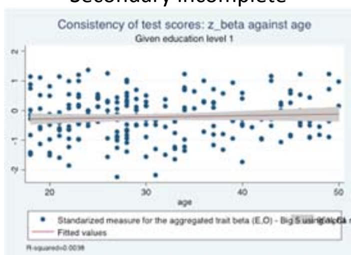

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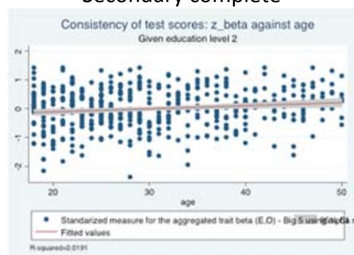

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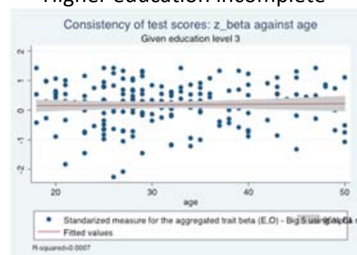

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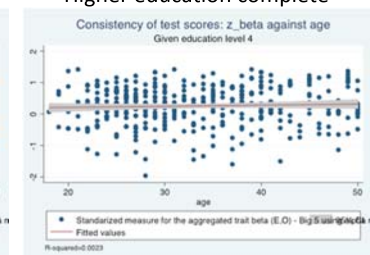
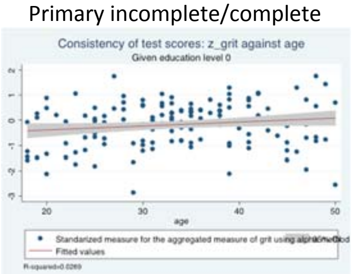


Grit

Primary incomplete/complete



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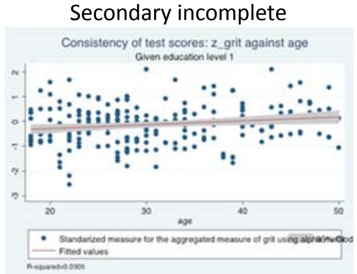
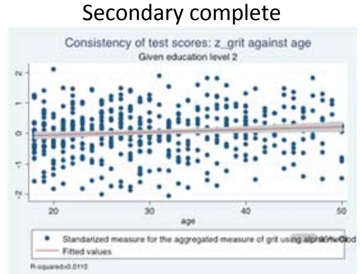
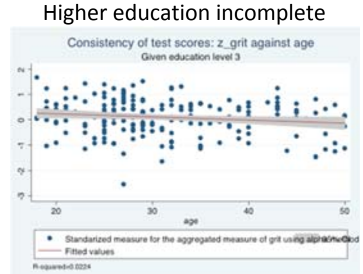


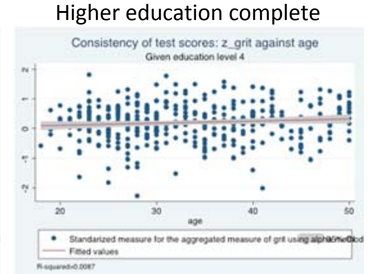
Secondary complete



Higher education incomplete



Higher education complete



*these results are robust to the disaggregated traits, namely to each of the Peru “Big Five” (conscientiousness, emotional stability, cooperation, kindness, extraversion, openness to experience) and grit (perserverance of effort, consistency of interest). The full set of graphs are available from the authors.