First impressions matter for life: the contribution of skills for the first job

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First impressions matter for life: the contribution of skills for the first job

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Abstract

This paper develops a model which provides a characterization of the joint distribution of the duration of search, accepted wages and skills with unobserved heterogeneity based on Eckstein and Wolpin (1995). We aim to estimate the effect of cognitive and socio-emotional skills on first job wages and duration of job search. Observed and unobserved heterogeneity are exploited as sources of identification. The data is drawn from the 2010 ENHAB which has not been used for this purpose before and which contains full retrospective information on first job outcomes and children. The model is estimated through a maximization of the joint Likelihood. Preliminary results regarding wages show that socio-emotional skills are the most valued among high skilled individuals, whereas cognitive skills are the most valued among low skilled individuals. Predicted wages for type I individuals are always above the observed wage, for every schooling level. Regarding duration of first job search, results show that the socio-emotional high skilled individual receives more job offers than the cognitive high skilled with the same schooling level.

JEL CODES: J13, J21

KEYWORDS: Cognitive skills, socioemotional skills, first job, wages, job search.

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1 Introduction

It is a known fact that skills affect your employment outcomes. For decades the literature focus has been on cognitive skills. Cawley, Heckman, and Vytlacil (2001) summarize some of these findings. Basically, studies establish that measured cognitive ability is a strong predictor of schooling attainment and wages. To name two examples, Murnane, Willet and Levy (1995) assess the role of mathematics skills of graduating high school students on their wages at age 24. They found a positive and increasing effect of cognitive skills on wages. In a more recent study, Cunha et. al. (2005) state that cognitive ability increases the likelihood of acquiring higher levels of education and advanced training as well as the economic returns to these activities.

During the last decade, attention has been directed towards socioemotional skills. Early work by Marxist economists and researchers from other social sciences have stated the obvious: personality, persistence and motivation matter at work. Bowles and Gintis (1976) and Edwards (1976) found that employers in low skill labor markets value docility, dependability, and persistence more than cognitive ability or independent thought. Sociologists have written extensively about the role of noncognitive skills in predicting occupational attainment and wages (see Peter Mueser (1979)). Also, psychology literature have shown the important role of noncognitive skills on the schooling performance of children and adolescents (Wolfe and Johnson, 1995; Duckworth and Seligman, 2005). Recent economic studies (see Heckman, Stixrud and Urzua (2006); Cunha and Heckman 2007; Hanushek and Woessmann 2008) also support this fact with evidence of a positive relation between results in non-cognitive test scores and labor market outcomes.

In the region, Latin America, there are also some studies about the incidence of cognitive and socioemotional skills in several areas: their relation with health and parental care in Ecuador (Paxson and Schady, 2007), with conditional transfers in Nicaragua (Macorus, Schady, and Vakis, 2012), and with a preschool program in Bolivia (Behrman, Cheng, and Todd, 2004). Specifically in Peru, studies show the importance of these skills on accessing to a college education (Castro and Yamada, 2011), on the gender wage gap (Yamada, Lavado, and Velarde, 2013) and their return on income (Díaz, Arias, and Vera Tudela, 2011).

Why are skills so important? Because firms are demanding them. Some jobs require more cognitive skills and other more socioemotional ones. For example, the latter can be more important in certain low skill occupations, in particular in the service sector (Bowles, Gintis, and Osborne, 2001). An average Latin American worker is twice as likely to be employed in the service sector than in manufacturing (World Bank Group, 2014). Gradually, the economy is shifting towards a non-cognitive skill oriented job creation.

A World Bank survey indicates that Peruvian employees claim that workers generally lack the required skills for the job, though it is not yet clear which are the skills that are absent (Jaramillo and Silva-Jáuregui, 2011). Kuhn and Weinberger report that employers five most highly valued personal qualities, in order, were: communication skills, motivation/initiative, teamwork skills, leadership skills, and academic achievement/GPA (Kuhn and Weinberger, 2002). The majority reflects socio-emotional or soft skills that are best developed from preschool through high school education. While some of these socio-emotional skills can be developed on the job, firms are less likely to train on these foundational skills since there is a higher risk the investment is captured by other employers (Arias 2014). Policy interventions in education matters are most successful when they happen at early stages of the student formation (Brunello and Schlotter 2011). Disadvantages found at an early age will result in the intergenerational transmission of poverty and inequalities if not addressed by policymakers before children reach adulthood (Lopez 2014).

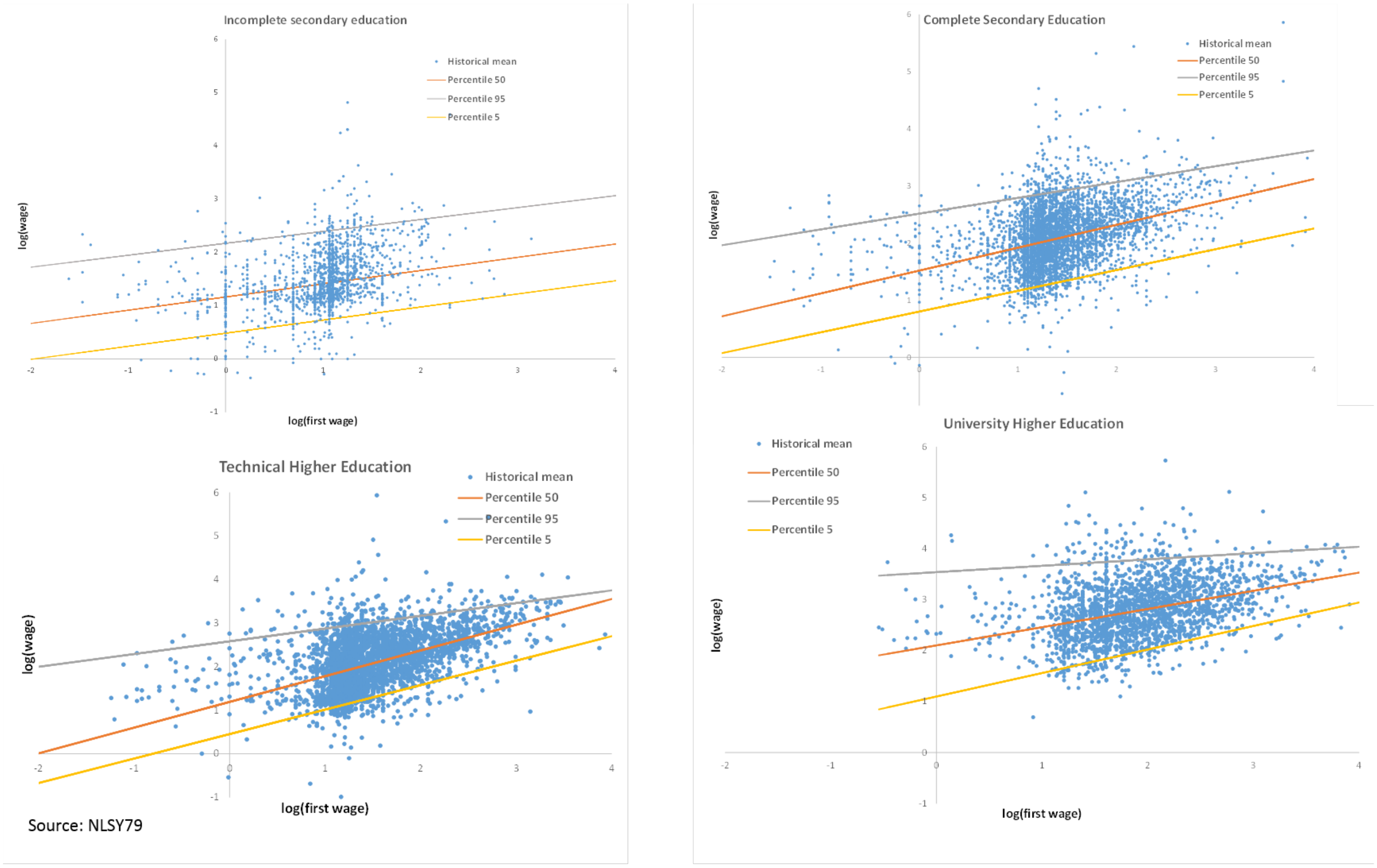
An increasing demand for skills and, thus, a positive relationship between skills and labor outcomes seems to be a fact. However, literature is mainly showing contemporaneous correlation between abilities and wages or employability. They do not take into account dynamic aspects in abilities formation and wages. Regarding the dynamic aspects in wages, relationship between skills and first wage has not been addressed. If skills are that important for labor market outcomes, will they not be as important for employment outcomes for the first job? The question arises due to the importance of first job.

First job can be a strong predictor of the subsequent career when it is used in conjunction with other determining factors such as education and parent's occupation. Lillard and Willis (1979) found that 73% of the variance in earnings is explained by permanent unobserved differences (controlling for schooling, experience, race and gender) identified by the variance of wages at first job. Lipset and Malm (1955) found that even when the American occupational structure encourages and helps those beginning in a disadvantaged labor state to rise, these opportunity would never as good as being fortunate at the beginning of their work careers.

Using American and Peruvian data, we obtained some empirical evidence supporting the literature regarding first job. Looking at the National Longitudinal Survey of Youth 1979 (NLSY79), we observed a strong positive correlation between the current wages (50 years old on average) and the first wages for all education levels (incomplete high school, complete high school, technical higher education and college graduates) and by percentiles of the distribution of wages (see Figure 1). The correlation coefficient is between 0.28 to 0.42.

There is also a correlation in the dispersion. The variance of wages at first job is approximately 50 to 67% of the variance of wages at around 50 years old (see Figure 2). In Peru, using the National Household Survey, the dispersion in wages at first job is almost equal to the dispersion in wages at 50 years old (see Figure 3). Therefore, what we are taking with us just before the school to work transition is significantly important in order to get a good first job and subsequently to have a successful labor market history. These things are schooling and skills and there is no literature on the relationship between cognitive and socioemotional abilities and the first wage.

Figure 1: US: mean of current wages and first wages by age



Moreover, research related to skills does not usually take into account the skill formation process. Vast amount of literature exists on the formation of cognitive and non-cognitive abilities (Cunha et. al. 2005; Cunha and Heckman 2007). Some research acknowledges this abilities' process and their results in the labor market (Heckman, Stixrud and Urzua 2006). However, to the best of our knowledge, none asseses the relationship between cognitive and non-cognitive skills with the probability of being hired at a quality level first job.

Finally, to be as precise as possible, we recognize that test scores may be fallible. We also recognize that a person's schooling and family background at the time tests are taken affect test scores. Building on the analysis of Cunha and Heckman (2007), we will use the latent cognitive and socioemotional abilities. As proposed by the mentioned authors, we will use correlation between four cognitive skills and six socioemotional skills to obtain the latent ones.

The main objective of this paper is to estimate the contribution of cognitive and socioemotional latent abilities on the quality of the first job. Salary is commonly presented as the measure of the quality of first job. However, other indicators reflect quality such as the nature of the job, the time spent searching for it, and its conditions (part time or full time) (Abel, Deitz, and Su, 2014). We will measure quality of the first job by the joint distribution of wages and time spent searching for the first job. For that purpose we develop a job search model which characterizes the joint

Figure 2: US: wage dispersion by age

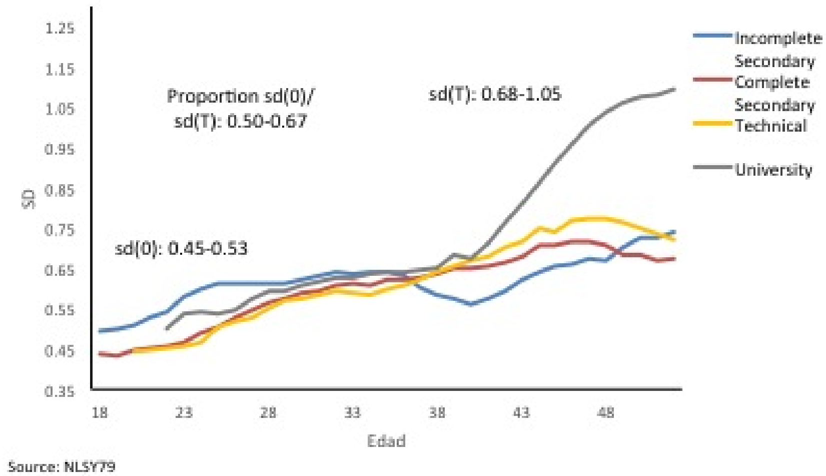
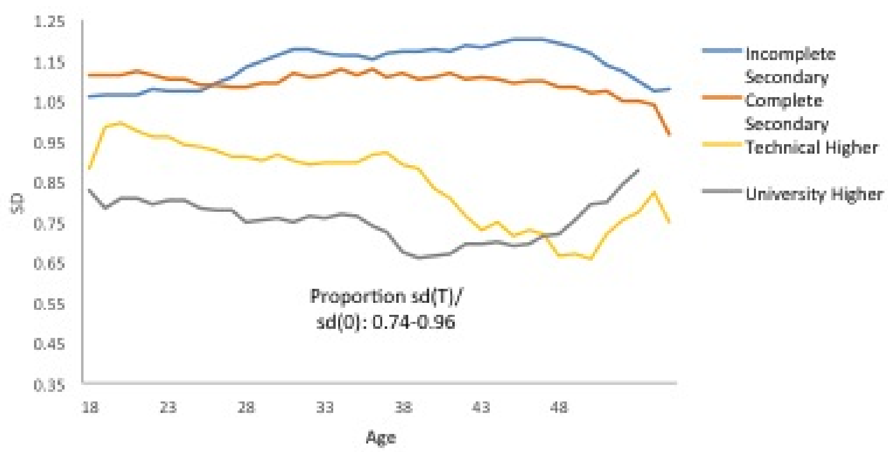


Figure 3: Peru: wage dispersion by age



distribution of wages and time spent searching for the first job as a function of abilities. Abilities affect the joint distributuion through the value of matching, the arrival rate of offers and the cost of search.

The paper is organized as follows. The following section presents the formal model. Section 3 and 4 present the econometric implementation – the construction of the likelihood function – and the identification of the model through unobserved heterogeneity. Section 5 describes the data and sample. Section 6 presents preliminary results and section 7 concludes.

2 The Model

We propose a model which provides a characterization of the joint distribution of the duration of search, accepted wages and skills with unobserved heterogeneity. The model is based on Eckstein and Wolpin (1995) incoporating a simple skill formation technology. The main objective of the model is to estimate the effect of skills on the duration of job search and on accepted wages for first job.

Consider a simple job search model where a worker (w), who lives forever, meets a firm (π) with probability P. Once a firm and a worker meet they sample a value of their match that is equal to $m \in [0, M]$. The value of m is a random draw from the distribution function F(m). Let w(m) be the wage and $\pi(m)$ be the profits of the firm from a match of value m. Then, it is required that, w(m)+$\pi(m)$ $\leq$ m.

Each worker can meet at most one firm in each period. If the firm and the worker arrive at an agreement about w(m) and $\pi(m)$, search finishes. If they do not agree, then they can search again during the next period. Time is assumed to be disrete.

Each party will maximize their search function on each period. The division of the surplus m is determined by the static Nash Axiomatic solution relative to the disagreement outcome of continued search. Given increasing functions w(m) and $\pi(m)$, let V^j denote the steady state expected value of search by party j, (j=w,π); it is given by the equation:

$$V^j(m_j) = PEmaxj(m), \delta^j V^j(.) + (1-P)\delta^j V^j(.) \tag{1}$$

The search policy is characterized by a constant reservation value m_j, that is, search until the match value m is above m_j. j=w,π. Now, the steady state expected value of search can be written as follows:

$$\begin{aligned} V^j(s^j, m_j; s^i) =& PE(j(m)|m > m_j)Pr(m > m_j) \\ &+ P\delta^j V^j(s^j, m_j; s^i)Pr(m < m_j) + (1-P)\delta^j V^j(s^j, m_j; s^i) \end{aligned} \tag{2}$$

The optimal search strategy of party j is to maximize $V^j(m_j)$ with respect to m_j. Let $\bar{V}^j$, j=w,π, denote the maximized value of V^j with respect to m_j. At each date the disagreement values for the worker and the firm are the one period discounted value of continued search, that is, $\delta^j \bar{V}^j$.

The Nash Axiomatic bargaining solution is efficient, which implies that equation holds as an equality and in equiilibrium is required that only for match values m $\geq$ δ^w $\bar{V}^w$+δ^π $\bar{V}^\pi$ will the worker and the firm arrive at an agreement. Hence, the solution is characterized by worker and firm reservation match values such that m_w=m_π=$m*$, where $m*$ is the reservation match value satisfying: $m* = \delta^w \bar{V}^w + \delta^\pi \bar{V}^\pi$.

The Axiomatic Nash bargaining solution for a non-symmetric case with a weight α for workers implies that the wage schedule satisfies:

$$w(m) = \delta^w \bar{V}^w + \alpha(m - m*) \tag{3}$$

and the profit schedules satisfies:

$$\pi(m) = \delta^{\pi}\bar{V}^{\pi} + \alpha(m - m*) \quad (4)$$

The solution for V^j, j=w, π, must satisfy:

$$\bar{V}^w = max_{m*}[P\alpha E(m - m*)|m > m*)Pr(m > m*]/(1 - \delta^w) \quad (5)$$

and

$$\bar{V}^{\pi} = max_{m*}[P(1 - \alpha)E(m - m*)|m > m*)Pr(m > m*]/(1 - \delta^{\pi}) \quad (6)$$

Solving for $m*$ we have: $\delta^j\bar{V}^j$, j=w, π. The model provides a complete characterization of the joint distribution of the duration of search and accepted rents for both parties, workers and firms.

2.1 Worker Heterogeneity

Workers with different levels of observed levels of schooling are assumed to have different fundamental parameters and this observed heterogeneity is fully observed by firms.[1] Furthermore, heterogeneity in characteristics also exists within schooling groups, i.e. differences in cognitive and socioemotional abilities.The latter are unobserved by the econometrician.

The unobserved heterogeneity provide a potential explanation for the observed differences between schooling groups: low schooling groups have lower mean accepted wages and longer durations of unemployment. Suppose that within each shooling level there are two types of individuals. One type has a low match productivity mean and the other a high mean. Because workers with a low mean will search intensively, they will also have a lower offer probability and a lower reservation wage than the high-mean type. The resulting hazard rate of the low mean type may be lower than that of the high mena type, leading to a longer mean duration of unemployment. If some group are disproportionately of the low mean type, beacuse they have less cognitive and socioemotional abilities, then they will have lower mean accepted wages and longer durations.

3 Econometric Implementation

We estimate the model at the steady−state equilibrium characterization using the above data. In order to estimate the model, let us assume the match value m comes from a log-normal distribution with density function:

$$f(m) = \frac{1}{m\sigma_m(2\pi)^{1/2}}exp(-\frac{1}{2}(\frac{ln\ m - \mu}{\sigma_m})^2) \quad (7)$$

As explained in the model, two situations can be described:

[1] We should relax this assumption.

- Successful match: An offer arrives with probability P and the accepted wage derived from the match is higher than its reservation value.
- Unsuccessful match: The search will continue on the next period subject to a discount value because of two possible reasons.
  - An offer does not arrive with probability 1-P
  - An offer arrives with probability P and the accepted wage derived from the match is lower than its reservation value

Using the properties for the mean of the log normal distribution, it can be shown that:

$$E(m|m > m^*)Pr(m > m^*) = exp(\frac{1}{2}\sigma_m^2 + \mu)[1 - \Phi(\frac{ln\ m^* - (\sigma_m^2 + \mu)}{\sigma_m})] \tag{8}$$

where Φ is the normal cdf and note that σ_m affect the mean of the match distritbution.The probability of accepting a job conditional on search, the hazard rate (h), is given by:

$$h(m^*) = P(1 - F(m^*)) \tag{9}$$

where P is the offer probability.

The wage distribution parameters are μ, σ_m and α. If we assume that firms and workers in the model are symmetric, that is, that all of the fundamental parameters of the model are the same for workers and firms, the α woulde be 0.5. Given the simplification that results in the likelihood specification, we restrict out attention to the symmetric case where $w = 0.5m$.

We extend the model by assuming that the population of workers in a given schooling level consists of K different type of individuals where each type may have a different value of the mean of the distribution of the match. We also assume that the observed wage is measured without error. Hence, w(m) is the observed and true wage. Then, the joint probability that the wage exceeds the reservation wage (w^*) $-$ succesful match $-$ and that w is realized is:

$$Pr(w(m) > w^*(m), w) = Pr(w(m) > w^*(m)|w)Pr(w) \tag{10}$$

$$= [1 - \Phi(\frac{ln\ w^* - (ln0.5 + \mu)}{\sigma})]\frac{1}{w}\frac{1}{\sigma}\phi(\frac{lnw - (ln0.5 + \mu)}{\sigma}) \tag{11}$$

where $\sigma^2 = \sigma_m^2$ and ϕ is the normal pdf.

This is a version of the search$-$matching model in which probability of arrival of an offer and wages only change between schooling levels. However, we want to identify the unobserved heterogeneity within schooling levels using the cognitive and socioemotional abilities. Thus, we parametrize mean wages and the job offer probability using the latent abilities:

$$\mu = \gamma_0 + \gamma_1\theta_C + \gamma_2\theta_S + \gamma_3 T + \gamma_4 X + \gamma_5 T^2 + \gamma_6 A + \epsilon \tag{12}$$

$$P = \frac{exp(\beta_0 + \beta_1\theta_C + \beta_2\theta_S)}{1 + exp(\beta_0 + \beta_1\theta_C + \beta_2\theta_S)} \tag{13}$$

where θ is the latent ability, X is the number of previous jobs, T is the number of months in the current job and ϵ is a measurement error. In order to get the latent abilities, we follow the model proposed by Cunha et. al. (2010). Abilities today depend on latent abilities (unobserved heterogeneity) and on all activities related to skill formation (e.g. schooling, experience and on the job training). Thus prediction of abilities before the first job is possible just by knowing the motion law of abilities and schooling trajectories, assuming that experience on the job training are only accumulated after the first job.

We use several mesaures of cognitive and socioemotional abilities to identify unobserved heterogeneity in contrast to Cunha et. al (2007) who proposed the identification of a latent dynamic factor model using panel data information on measured tests. The main assumption here is that the we are assuming a latent model identified by the correlation between measured tests. In other words, the correlation between measured tests is only explained by a latent common factor (unobserved heterogeneity). In particular, we have 4 cognitive tests and 6 socioemocional tests. Let Z_r^j be the rth test for j=C,S. We establish the following system based on Heckman et. al. (2007):

$$Z_r^j = \mu_r^j + \alpha_r^j\theta^j + u_r \tag{14}$$

where θ is the latent ability and u are independent measurement errors. We assume that $E(\theta) = 0$ and $\alpha_1^j = 1$. Under these assumptions, we identify μ, α and θ:

$$\theta^j = \frac{1}{R^j}\sum_{r=1}^{R^j}\frac{Z_r^j - \mu_r^j}{\alpha_r^j} \tag{15}$$

where R is the total number of tests.

We have current information on skills. Skills are affected by events during working lifetime: tenure in the current job, number of jobs unemployment spells. In addition to tenure and the number of previous jobs, we exploit the fact that we have duration of job search before first job for all individuals. We assume that duration of job search before first job is the most important unemployment spell (or equivalently, once an individual gets her first job, she is permanently employed). We assume the following law of motion of skills:

$$\theta^j = \alpha_0^j + \alpha_1^j d_2 + \alpha_2^j d_3 + \alpha_3^j X + \alpha_4^j T + \epsilon^j \quad j = C, S \tag{16}$$

where θ is the latent ability, d_2 is a dichotomous variable which takes the value of 1 if duration of first job search lasted more than 1 month and less than 3 months, d_3 is a dichotomous variable which takes the value of 1 if duration of first job search lasted more than three months, X is the number of previous jobs, T is the number of months in the current job and ϵ is a measurement error.

Thus, the likelihood function for I individuals of K types, each with a completed spell length of d_i and an observed wage of w_i^o, is:

$$\begin{aligned} L(\Psi) =& \Pi_{i \in I} \Sigma_{k=1,2}^{K} Prob_k [1 - P_k(1 - \Phi(\frac{lnw_k^* - (ln0.5 + \mu_k)}{\sigma}))]_i^d P_k \\ & [1 - \Phi(\frac{lnw_k^* - (ln0.5 + \mu_k)}{\sigma})] \\ & \frac{1}{w_i}\frac{1}{\sigma}\phi(\frac{lnw_i - (ln0.5 + \mu_k)}{\sigma}) \\ & \frac{1}{\sigma_C}\phi(\frac{\theta^C - \alpha_0^C - \alpha_1^C d_2 - \alpha_2^C d_3 - \alpha_3^C X - \alpha_0^C T}{\sigma_C}) \\ & \frac{1}{\sigma_S}\phi(\frac{\theta^S - \alpha_0^S - \alpha_1^S d_2 - \alpha_2^S d_3 - \alpha_3^S X - \alpha_0^S T}{\sigma_S}) \end{aligned} \tag{17}$$

where $Prob_k$ is the proportion of type k individuals in the population and ψ is the vector of parameters. The first part of the equation represents the number of times an unsuccessful match occurs. The exponent d is the number of periods the individual remains in unemployment.

However, consistency of this estimator is not achieved due to the small number of measured tests by individuals. Hence, a grouped fixed effect estimator is proposed. Consistency is achieved as long the number of groups is known or a functional form is assumed.

Regarding sources of heterogeneity (unobserved to the econometrician): from latent abilities which drives decisions on first job choices behaviors. This heterogeneity allows matching serial and contemporaneous correlation in measured tests. This heterogeneity is observationally equivalent as if it were considered in first job choices. This economy has 2 types of individuals: high-skilled and low-skilled.[2] The probability of being high-skilled follows a logistic function conditioned on Ω_0, discrete measurements of cognitive and socio-emotional skills:

$$Prob(type1|\Omega_0) = \frac{(\gamma_0 + \gamma_1 D_C + \gamma_2 D_S)}{1 + exp(\gamma_0 + \gamma_1 D_C + \gamma_2 D_S)} \tag{18}$$

where D_C is a dummy variable that takes the value of 1 if the individual's cognitive skill exceeds the sample's mean and D_S is a dummy variable that takes the value of 1 if his/her socio-emotional skill exceeds the sample's mean. This probability affects the two measures of quality of the first job: wages (μ_k) and job offer probability (P_k). Thus, we will obtain different parameters within those functions for high and low skilled individuals:

$$\mu_k = \gamma_{0k} + \gamma_{1k}\theta_C + \gamma_{2k}\theta_S + \gamma_3 T + \gamma_4 X + \gamma_5 T^2 + \gamma_6 A + \epsilon \quad k = 1, 2 \tag{19}$$

[2]Future exercises will increase the number of types.

$$P_k = \frac{exp(\beta_{0k} + \beta_{1k}\theta_C + \beta_{2k}\theta_S)}{1 + exp(\beta_{0k} + \beta_{1k}\theta_C + \beta_{2k}\theta_S)} \quad k = 1, 2 \tag{20}$$

4 Identification

There are two sources of heterogeneity. Observed heterogeneity between schooling groups and unobserved heterogeneity within schooling groups in the mean of wages and in the arrival rate of offers.

The variance of unobserved heterogeneity in the mean wages is identified by the correlation of observed wages and (latent) abilities. Heterogeneity in the arrival rate of offer is identified by the correlation between the time spent searching and abilities. Unobserved types are identified by the correlation between different measures of cognitive and socioemotional abilities. Parameters of the mean of wages are identified by the correlation of tenure, experience and age with wages. Parameters of the law of motion of abilities are identified by the correlation between experience, tenure with cognitive and socioemotional abilities. Parameters related to the evolution of abilities conditional on time spent searching are identified by the mean of abilities conditional on time spent searching.

5 Data

To address labor supply characteristics we use Peruvian's database ENHAB 2010 (Survey of Skills and the Labor Market), a World Bank project developed with collaboration of Peruvian research institutes. ENHAB is a nationally representative household survey that comprises information on urban areas of 11235 randomly selected individuals from 2600 cities. This unique labor force survey -first of its kind in Latin America-, includes measures of cognitive (PPVT-4, verbal ability, working memory and mathematics problem-solving) and socio-emotional skills (Big-Five Personality Factors and Grit) of a random sample from the population age 14-50. It also contains information on household living conditions, demographic information, academic achievement, current employment/earnings and early labor market participation.

Our main module for the analysis on first job is the labor insertion segment. Detailed questions about age at first job, methods for job search, duration of first job search, credentials of workers, reservation wages, perceptions on factors affecting employability and factors affecting willingness to move for a better job are available. This database will enable us to relate non-cognitive and cognitive abilities with the quality of first job, as well as the importance of the first job in their current employment status. Concretely, relevant variables for this research are monthly earnings, duration of first job search, tenure on current job, schooling level, age and cognitive and socioemotional abilities. In order to maximize the proposed likelihood, we should clean the database.

Originally, ENHAB has 11 235 individuals. Out of the 11235, 2501 have information on wages and 2656 have information on cognitive and socioemotinal skills. However, only 620 have both information on wages and skills. Therefore, our sample consists on 620 individuals.

Specifically, we we consider four schooling groups: (i) individuals with incomplete secondary education, (ii) individuals with complete secondary education, (iii) individuals with complete non-university higher education and (iv) individuals with complete university higher education. We define the duration to the first job to be the number of months before the individual began working at a full-time job. A full-time job is defined to be a job in which the individual worked at least 30 hours per week in the entire month.

Table 1 reports relevant descriptive statistics for all four subsamples. Wages are higher for individuals with higher levels of schooling. Also, duration of first job search is longer for individuals with higher levels of schooling. This suggests that more educated individuals are being employed slower, but once employed their mean wage is higher. The return to schooling as measured by the percentage wage difference between adjacent schooling groups is between 27% and 39%. On the side of the skills, cognitive skills are higher for subsamples with higher educational levels. Such relationship is not observed in the socioemotional skills. Thus, a positive correlation between skills and wages/duration of first job search is not clear.

6 Results

Using the estimated parameters (see table 2), we predicted the labor outcomes of interest. Table 3 presents these results. On the side of wages, these are higher for more educated individuals. This also holds for the high skilled individuals (type I) within every schooling level. Wage is always higher for type I. For example, wage is S/. 1126 for a type I individual with complete secondary education, whereas it is S/. 799 for a type II individual with the same schooling level.

The probability of receiving an offer is between 0.3 and 0.5 for almost all individuals. The higher the education level, the lower the probability. However, once employed, their wage is higher. Regarding unobserved heterogeneity, this holds for both types of individuals and the probability is similar for both types of individuals within schooling levels. The only exception is incomplete secondary where type I are more likely to receive an offer than type II. In lower attainment levels, skills are more valued.

Another interesting result is that groups with lower schooling level have lower proportion of type I individuals. For example, among individuals with incomplete secondary education, 49% are high skilled. Whereas, among individuals with complete university education, 78% are high skilled.

Table 1
Descriptive Statistics for the ENHAB sample

	All	Incomplete Secondary Education	Complete Secondary Education	Complete Non-university Higher Education	Complete University Higher Education
Cognitive Abilities					
PPVT	184.76	165.20	184.09	192.29	200.35
	(0.844)	(1.732)	(1.136)	(1.567)	(1.338)
Mathematics/Problem solving	11.02	8.34	10.94	11.68	13.51
	(0.152)	(0.321)	(0.217)	(0.326)	(0.263)
Language proficiency	21.45	15.80	21.16	23.54	26.30
	(0.346)	(0.622)	(0.478)	(0.786)	(0.825)
Working memory	7.44	6.59	7.51	7.78	7.86
	(0.061)	(0.143)	(0.087)	(0.128)	(0.139)
Non-cognitive Abilities					
Grit	30.46	28.25	30.27	31.31	31.50
	(0.249)	(0.635)	(0.366)	(0.557)	(0.476)
Extraversion	26.04	23.54	26.30	27.48	26.65
	(0.214)	(0.506)	(0.312)	(0.467)	(0.462)
Cooperation	16.65	16.16	16.63	16.96	16.95
	(0.118)	(0.284)	(0.176)	(0.287)	(0.252)
Consciousness	29.62	28.52	29.80	30.34	29.64
	(0.185)	(0.432)	(0.265)	(0.440)	(0.449)
Emotional stability	18.810	17.754	18.704	19.642	19.422
	(0.168)	(0.411)	(0.254)	(0.379)	(0.344)
Openness	24.65	23.46	24.73	25.48	24.89
	(0.154)	(0.363)	(0.231)	(0.333)	(0.345)
Labor Market Variables					
Monthly Earnings	919.83	603.32	843.91	1047.60	1334.86
(S/.)	(39.075)	(89.713)	(50.334)	(105.771)	(96.065)
Duration of first job search	1.52	1.23	1.07	2.22	2.36
(months)	(0.117)	(0.237)	(0.106)	(0.347)	(0.418)
Tenure on current job	4.61	3.69	3.35	6.76	6.83
(months)	(0.246)	(0.464)	(0.302)	(0.694)	(0.704)
Minimum observed earnings	100.00	100.00	120.00	120.00	100.00
(S/.)					
Other Variables					
Age	30.08	27.47	28.42	33.00	34.42
(years)	(0.371)	(0.924)	(0.520)	(0.827)	(0.748)
N	620	118	287	106	109

Note: Standard deviations in parenthesis.

Table 2
Estimated parameters of the model

	All	Incomplete Secondary Education	Complete Secondary Education	Complete Non-university Higher Education	Complete University Higher Education
Wages (type I)	$\mu_k = \gamma_{0k} + \gamma_{1k}\theta_C + \gamma_{2k}\theta_S + \gamma_3 T + \gamma_4 X + \gamma_5 T^2 + \gamma_6 A + \epsilon;\quad k = 1,2$				
Constant	6,968	6,590	6,953	6,885***	7,145
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Cognitive ability	0,008	-0,016	0,001	0,006	0,012
	(0,002)	(0,001)	(0,002)	(0,004)	(0,005)
Socioemotional ability	0,003	0,013	0,003	0,006	-0,009
	(0,003)	(0,001)	(0,002)	(0,004)	(0,005)
Wages (type II)					
Constant	5,935	5,602	5,999	5,856	5,446
	(0,003)	(0,001)	(0,002)	(0,004)	(0,005)
Cognitive ability	0,008	-0,009	-0,004	0,021	0,045
	(0,002)	(0,001)	(0,002)	(0,005)	(0,005)
Socioemotional ability	-0,002	0,010	-0,015	-0,031	-0,038
	(0,003)	(0,001)	(0,002)	(0,005)	(0,005)
Prob. of arrival of an offer (type I)	$P_k = \frac{exp(\beta_{0k}+\beta_{1k}\theta_C+\beta_{2k}\theta_S)}{1+exp(\beta_{0k}+\beta_{1k}\theta_C+\beta_{2k}\theta_S)};\quad k = 1,2$				
Constant	-0,464	0,024	-0,151	-0,321	-1,123
	(0,001)	(0,001)	(0,000)	(0,001)	(0,001)
Cognitive ability	-0,005	-0,002	0,019	0,013	0,009
	(0,001)	(0,000)	(0,001)	(0,001)	(0,001)
Socioemotional ability	0,015	-0,075	0,035	-0,138	0,089
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Prob. of arrival of an offer (type II)					
Constant	-0,273	-0,688	-0,007	-1,073	0,128
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Cognitive ability	-0,004	-0,025	-0,012	-0,023	-0,011
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Socioemotional ability	0,051	0,117	0,052	0,032	-0,104
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)
Cognitive Abilities	$\theta^j = \alpha_0^j + \alpha_1^j d_2 + \alpha_2^j d_3 + \alpha_3^j X + \alpha_4^j T + +\alpha_5^j X^2 + \epsilon^j;\quad j = C, S$				
Constant	-0,726	-17,212	-1,386	-6,468	2,275
	(0,002)	(0,001)	(0,002)	(0,005)	(0,005)
Duration of job search of 3-6 months	0,774	-0,017	-1,339	-1,179	-1,608
	(0,003)	(0,001)	(0,002)	(0,005)	(0,005)
Duration of job search of 6+ months	1,787	1,739	-3,372	-0,538	0,465
	(0,003)	(0,001)	(0,002)	(0,005)	(0,005)
Socioemotional Abilities					
Constant	-0,927	-3,483	-1,630	0,894	-0,841
	(0,004)	(0,002)	(0,005)	(0,006)	(0,006)
Duration of job search of 3-6 months	0,162	-0,318	-0,995	-0,984	0,206
	(0,004)	(0,002)	(0,005)	(0,006)	(0,006)
Duration of job search of 6+ months	0,187	0,108	0,770	-0,033	0,372
	(0,004)	(0,002)	(0,005)	(0,006)	(0,006)
N	620	118	287	106	109

NOTE: * indicates 10% significance level; ** indicates 5% significance level; and *** indicates 1% significance level of the mean test between males and females. Model controls for experience, tenure and age of the individual.

Table 3
Predicted labor outcomes

	Incomplete Secondary	Complete Secondary	Complete Technical	Complete University
Type I				
$Wage_1$	860.86	1126.38	1100.88	1471.32
$Probofarrivalofanoffer_1$	0.56	0.44	0.31	0.31
Proportion of type I	0.49	0.51	0.82	0.78
Type II				
$Wage_2$	286.97	799.26	963.68	1253.36
$Probofarrivalofanoffer_2$	0.38	0.46	0.32	0.34
Proportion of type II	0.51	0.49	0.18	0.22
Average				
Wage	567.04	799.26	963.68	1253.36
Prob of arrival of an offer	0.47	0.46	0.32	0.34
N	118	287	106	109

NOTE: * The expected offered wage for type $k = exp(\mu_k + 0.5\sigma^2 + ln(0.5))$. Wages are expresed in Peruvian Soles.

Table 4
Counterfactuals

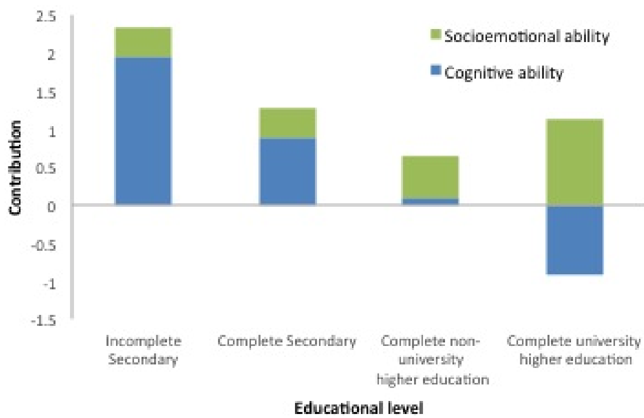
	Incomplete Secondary		Complete Secondary		Complete Technical		Complete University	
	Δ C	Δ S	Δ C	Δ S	Δ C	Δ S	Δ C	Δ S
Type I								
$Wage_1$	-26.2%	5.6%	2.6%	1.3%	12.0%	4.7%	27.5%	-2.5%
$Probofarrivalofanoffer_1$	-0.01	-0.08	-0.13	0.07	0.00	-0.04	0.02	0.11
Proportion of type I	0.31	0.06	0.11	0.04	0.03	0.03	-0.03	0.07
Type II								
$Wage_2$	-16.7%	4.4%	9.6%	3.0%	14.3%	6.3%	32.5%	2.5%
$Probofarrivalofanoffer_2$	-0.11	0.12	-0.13	0.07	-0.08	-0.02	-0.07	-0.08
Proportion of type II	-0.31	-0.06	-0.11	-0.04	-0.03	-0.03	0.03	-0.07
Average								
Wage	-3.2%	11.1%	9.6%	3.0%	14.3%	6.3%	32.5%	2.5%
Prob of arrival of an offer	0.03	0.02	0.01	0.05	-0.02	-0.04	0.00	0.07
N	118		287		106		109	

NOTE: * The expected offered wage for type $k = exp(\mu_k + 0.5\sigma^2 + ln(0.5))$. Wages are expresed in Peruvian Soles. Δ C and Δ S are variations in labor outcomes when cognitive and socioemotional skills, respectively, increase in one standard deviation.

A type I individual does better in labor outcomes. Do skills help you being type I? Our model estimates the effects of skills on the probability of being type I. We parametrize this probability as a function of skills. Figure 1 presents the results. We find two interesting results. First, for incomplete secondary, complete secondary and technical education, the probability of being type I is higher when both skills are higher. Thus, type I is a high skilled individual. Furthermore, the importance of socioemotional skills is higher as the education level increases.

However, for university education, the probability of being type I is higher when socioemotional skills are higher and is lower when cognitive skills are higher. Therefore, type I is a high socioemotional skilled individual and type II is a high cognitive skilled individual.

Figure 4: Contribution of skills to probability of being type I



Skills increase the probability of being type I for every education level but university (where only the cognitive skill does). Skills also increase the labor outcomes. Thus, what is the net effect of skills? With the estimated parameters, we did two counterfactual experiments. First, we increase in one standard deviation cognitive skills (ΔC). Second, we increase in one standard deviation socioemotional skills (ΔS). We observe the effect of these variations on labor outcomes: wages and probability of receiving a job offer.

Table 4 presents the counterfactuals results. With respect to wages, both the increase in one standard deviation (SD) in cognitive and socioemotional skills increase wages. For the cognitive variation, the higher the education level, the higher the effect on wages. An increase of cognitive skills in one SD increase wages in 9.6% for individuals with complete secondary and 32.5% for individuals with university. Cognitive skills are more important if they are interacted with increases in education years. On the contrary, for the socioemotional variation, the effect is higher in lower education levels: wage increases in 11.1% for incomplete secondary and 2.5% for university level. Therefore, socioemotional skills are more important when schooling or cognitive skills are lower. Finally, the cognitive variation has a non-significant negative effect on wages for incomplete secondary education.

With respect to the probability of receiving a job offer, both variations increase the probability. For the cognitive variation, the higher the education level, the lower the effect. An increase of cognitive skill in one SD increases 0.03 percentage points (pp) the probability for individuals with incomplete secondary and 0.0001 pp for individuals with university. Why? Cognitive skills in lower education levels will increase the knowledge of sources and job vacancies and will not be important in higher education levels. For the socioemotional variation, the higher the education level, the higher the effect on the probability. The increase is 0.02 pp for individuals with incomplete secondary and 0.07 pp for individuals with university. This is in line with what firms are demanding and report as difficult to find. Thus, how the candidate develops during the interview and their first days at job will be important to show his/her attitude, responsibility and commitment.

6.1 Destruction of skills

The literature points the importance of the first job. Empirical evidence, using Peruvian and American data, suggest the importance of first wage: it is highly correlated with your future wages (both in mean and variance). If first job is important, how do we improve the quality of first job? Our results show that cognitive and socioemotional skills are crucial for improving its quality. However, skills are not fixed. We know they are formed over time. Is this formation somewhat affected for the duration of job search? Our model includes an equation that acknowledges the skill formation process.

Table 5 presents the skill formation parameters. Results show that skills are being destroyed when individuals are unemployed for more than three months. For the cognitive skills, the higher the education level, the lower the destruction of skills. Being unemployed for three months or more reduces your latent cognitive skill in more than 3 points for incomplete secondary and in 0.46 for university. For the socioemotional skills, the destruction is relatively constant between schooling levels. Being unemployed for more than three months reduces the latent socioemotional skill in 0.20 points for every schooling level. Thus, for every schooling level, destruction of skills is higher for cognitive skills. The accumulation of socioemotional skills is more cost-effective because these are more durable. These should be prioritized. However, continuous training will be necessary to slow down the destruction of cognitive during the searching for a new job, especially for those individuals who have low education levels.

7 Final Remarks

This paper addresses the estimation of the effect of cognitive and socio-emotional skills on two labor outcomes for the first job: (i) wages and (ii) duration of job search. We exploit skills and first job outcomes from the 2010 ENHAB which has not been used before for this purpose. We

Table 5
Destruction of skills

	Incomplete Secondary	Complete Secondary	Complete Technical	Complete University
Cognitive skills				
3+ months of search	1.72	-3.18	-1.53	-0.46
	(0.003)	(0.004)	(0.010)	(0.011)
Socioemotional skills				
3+ months of search	-0.21	-0.22	-0.18	1.36
	(0.005)	(0.010)	(0.013)	(0.011)
N	118	287	106	109

Note: * Model controls for age and job experience. Standard deviations in parenthesis.

develop a model which provides a characterization of the joint distribution of the duration of search, accepted wages and skills with unobserved heterogeneity based on Eckstein and Wolpin (1995). This model helps interpreting the estimated effect, exploiting differences in first job wages and duration of job search taking into account skill formation in contrast to cross-sectional work.

We found that, regarding wages, both the increase in one standard deviation (SD) in cognitive and socioemotional skills increase them. For the cognitive variation, the higher the education level, the higher the effect on wages. On the contrary, for the socioemotional variation, the effect is higher in lower education levels. As predicted, socioemotional skills are more important in certain low skill occupations, in particular in the service sector as predicted by Bowles et. al. (2011).

Regarding the probability of receiving a job offer, both increasements in skills increase the probability. For the cognitive variation, the higher the education level, the lower the effect on the probability. For the socioemotional variation, the higher the education level, the higher the effect on the probability. This latter result is in line with what firms are demanding and report as difficult to find.

Finally, we found that skills can be destroyed. Results show that skills are being diminished when the individual is unemployed for more than three months. We also found that socioemotional skills are more durable, whereas cognitive skills are destroyed faster. Then, cultivating socioemotional skills should be prioritized. However, continuous training will be necessary for the cognitive skills, especially for those individuals who have low education levels.

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