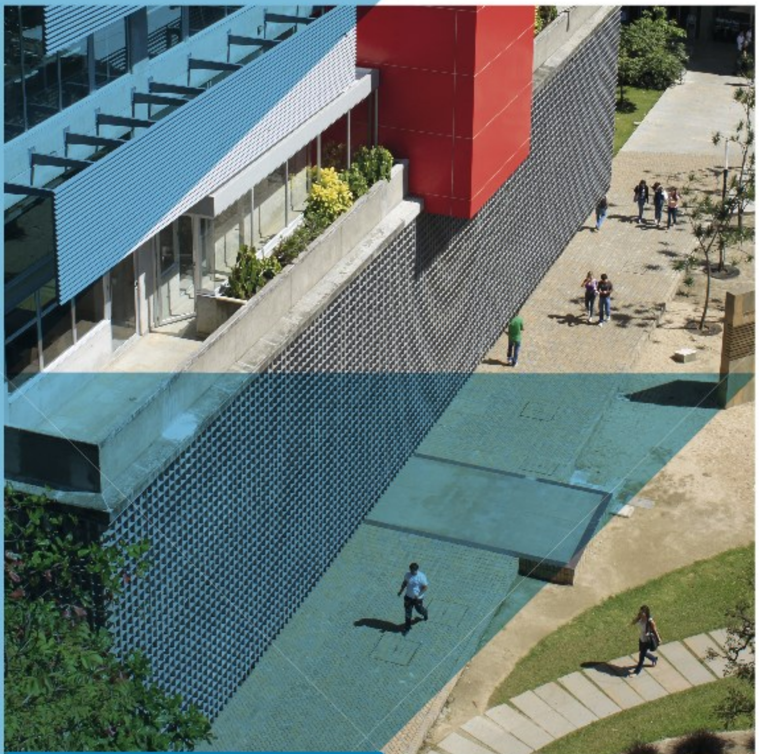

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Economía y Finanzas

Centro de Investigación Económicas y Financieras

No. 16-04
2016

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Congruence of higher education: determinants and effects of the allocation process in the labor market, applied case to Colombia

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Abstract

This paper provides new evidences to the literature of assignment in the labor market for the Colombian case. Specifically it focuses on the existing relationship between acquired human capital in higher education and its congruence in the labor market. Differing from previews studies, the misallocation analysis is not only based on the horizontal component and the educational mismatch, but it also includes the vertical mechanism (vertical mechanism is related to skills mismatch and horizontal mechanism is related to professional career mismatch). Another contribution is how we measure the abilities through an exploratory factor analysis. The data are taken from the Survey of Graduates of Higher Education Institutions 2014, provided by OLE. We employ a two-step treatment effect method proposed by Heckman (1974, 1979) and Lee (1978)), we found that generic abilities raise the probability of horizontal mismatch and diminish the probability of vertical mismatch. On the other hand, specific abilities lower the probability of both horizontal and vertical mismatch. In terms of wages, we found evidence that confirmed the results of the assignment models because it exists a wage penalty for the mismatched individuals (Sattinger, 1993).

JEL classification: C35; J24; J31

Keywords: Horizontal and vertical mismatch; assignment theory; generic and specific skills; congruence; productivity and wages

1. Introduction

Investment in education has been a recurrent policy to generate economic development[3]. These types of policies are based on the predictions of the classical theory of human capital, which arguments that the growth in educational levels produces a direct rise in individual productivity (Mincer, 1958). In

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[3] The World Conference on Education for All concluded that education is the safer and healthier path to reach a prosperous social, economic and cultural world.

(OECD, 2013) proposed investing in education as a main strategy to improve both economic growth and efficiency of the distribution of national income.

this model, the output per worker depends only of the individual´s quantity of human capital offered, and job characteristics don´t have any effect in the production. The latter suggests that increases in years of education should generate a direct impact in productivity, independent of the type of education and its relevance to the productive sector.

The growing interest in human capital has generated a significant increase in the investment in education which has led to greater access to education in almost all developing countries. For instance, according to World Bank data, in Latin America and the Caribbean the average rate of enrollment in primary and secondary school moved approximately from 69% in 1970 to 96% in 2013. Meanwhile, the percentage of enrollment to tertiary education rose from 7% to 60% in the same period.

Educational explosion comes with a body of literature that seeks to validate the efficacy of this approach. Efforts such those conducted by (Benhabib & Spiegel, 1994) and (Krueger & Lindahl, 2001) have concluded that there is not a positive relationship between education and worker productivity. For example, the percentage of enrollment in tertiary education in Colombia changed from 14% in 1990 to 48% in 2013, while the productivity index grew only 23% in the same period, far below the human capital investment.

Some studies have tried to identify the possible reasons why human capital investment does not directly increase individual productivity. (Easterly, 2002) argues that investment in education by itself is not enough; the incentives generated by the government through public policy should be aim towards congruence, creating educated people having both the required skills by the productive sector and the available technology to exploit those abilities. A better skills supply enhance workers' productivity, mainly because these workers would be performing tasks in which they have a comparative advantage, which should translate into a GDP growth (Eijs and Heijke, 2000). According to this, the educational policy should take into account the interaction between supply and demand of human capital, understanding how the match is generated between worker´s education and his or her job in the labor market. An appropriate match leads to an efficient use of the available resources, while a worker-job mismatch produces problems of productivity, unemployment and underemployment within the group with higher qualifications (Brown et al., 2011).

The accuracy of matching in the labor market has attracted the attention of researchers for some time. The main reason for this growing interest is the increasing acknowledgment of the influence of this variable in several labor market outcomes such as labor turnover, job satisfaction and wages (Badillo-Amador, García-Sánchez, & Vila, 2005). This interest has been focused mainly in the relationship with wages, with important theoretical background advances, which established the effects of worker-job mismatch on this outcome. Importantly, the interpretation of empirical results strongly depends on which theory is adopted for the researcher, and the focus and objective of the study realized.

The aim of this paper is to estimate the effect of congruence of higher education in the individual productivity, therefore in the individual´s earnings. The approach is based on the determinants of the allocation process in the labor market, defining congruence as the effect of area of education and acquiring skills on the chances of achieving an appropriate match, using an individual based approach. For this purpose, three important aspects will be taken into account: first, the theory under which the results are going to be considered; second, the types of mismatch and which of these will be used in the empirical analysis; and third, which forms of human capital and skills will be used as determinants of the assignment process and wage equation.

This article contributes to the literature of assignment in the labor market, specifically it is interested in the existing relationship between acquired human capital in higher education and its pertinence in the labor market. Differing from previews studies, the misallocation analysis is not only based on the horizontal component and the educational mismatch, but it also includes the vertical component (measuring the assignment skill process) and its interaction with the mentioned mechanisms. Another contribution is the way we used for quantifying the abilities in the model through exploratory factor analysis. The data are taken from the Survey of Graduates of Higher Education Institutions 2014 (Encuesta de Seguimiento a Graduados 2014 de Instituciones de Educación Superior) provided by the Labor Observatory for Education in Colombia (OLE, for its acronym in Spanish). Through the two-step treatment effect method we found that interpersonal competencies related to generic abilities, raise the probability of horizontal mismatch and diminish the probability of vertical mismatch. On the other hand, specific competencies related to technical abilities lower the probability of both horizontal and vertical mismatch. Regarding wages, it is confirmed the results of the assignment models because it exists a wage penalty for the mismatched individuals.

The remaining of this paper is divided as follows. Section 2 makes a literature review regarding wage determinants and their relationship with worker-job mismatch. Section 3 discusses the types of mismatch, the theories in which they can be framed and the determinants of the assignment process. Section 4 presents the data used. The empirical model is presented in section 5. Finally, section 6 contains the conclusion, discussion and possible further research.

2. Theoretical Perspectives

Economists have developed different models in an attempt to explain the behavior of wages, the differences between individual's incomes, and the differences in wage's growth in the agents' life-cycle. A part of the heterogeneity in individuals' wages is explained by the observed and unobserved characteristics of workers and firms, this is where the worker-job matching appears. This paper is going to describe the human capital, search and matching, assignment and heterogeneous skills theory and their relationship with assignment process.

2.1. Human capital theory

This line of economic thought was developed by Becker (1975); Mincer (1958, 1974) and Porat (1967) who assume a competitive and non-friction economy where workers receive a rental rate for its human capital stock which is equal among all firms. The model is based in homogeneous individuals with freedom to choose their educational level and occupations. The assumption of competitive economy implies that the present value of income life-cycle in different options should be the same; otherwise all individuals would take the option with the highest payout. The major constraint that emerges is that individual productivity is the same among all occupations (Rubinstein & Weiss, 2006).

According to the tradition of human capital theory (Almond & Currie, 2011) wages are determined solely by individual characteristics, such as education and experience level; theoretically, these features are independent to the demand. In a simple way the wage function assume equilibrium where all rental rates are equal through the market, which implies that the assignment process of workers to jobs would be irrelevant to the wages.

Based on human capital theory, educational mismatch cannot exist if the labor market is efficient; economists who support this theory propose two hypotheses to explain the apparent existence of suboptimal matches. The human capital compensation hypothesis says that the apparent mismatch is largely due to measurement errors that come from the unobservable heterogeneity, therefore when relevant abilities are taken into account; wage is independent of job characteristics. Career mobility hypothesis arguments that mismatch exist but only in the short run and disappear with the years of experience and training. Korpi & Tåhlin (2009) and the meta analysis conducted by Harmon & Walker (2003) tested and did not support neither of these two hypotheses; on the contrary they showed consistency in their results when they allowed for mismatch variables in the specifications. Because conclusions in human capital model are based on restrictive assumptions, other theories have emerged to explain the individual income.

2.2. Search and matching models

The theory developed by (Burdett, 1978; McCall, 1970; D. T. Mortensen & Pissarides, 1999; D. Mortensen, 1970) address the problem of asymmetric information and market rigidities in the labor market. In this limited information model the rate of return is heterogeneous among individuals with different levels of human capital. That is, firms paying low rental rate can coexist whit high-payment counterparts for employees with the same level of human capital.

In this model wage's growth is determined by the worker's option to accept or reject job offers, therefore wage's growth is marginally decreasing in time because more experience leads to more valuable works and higher occupational level. The latter explains the decreases in the likelihood to find better job matches (D. T. Mortensen & Pissarides, 1999). The search model explains how heterogeneous workers are being assigned to jobs with different characteristics suggesting a valuable implication: the better the match the higher their earnings. It is worth noting that this model does not involve explicitly interactions between demand and supply in the labor market, agents receive job offers randomly.

2.3. Assignment and heterogeneous skills theory

When supply and demand characteristics are taken into account to determine individual wages, assignment (Sattinger, 1993) and heterogeneous skills (Green & McIntosh, 2007) models come up. Both assignment theory and heterogeneous skills, postulate human capital investment and required level of education and skills for a job as main determinants of income. These models are based on the comparative advantage that emerges when two workers' outcomes are not the same in the same job task (Roy, 1951). If there were no comparative advantage, the election of human capital level by the firm would be completely arbitrary and the problem of assignment would disappear.

Following (Di Pietro & Urwin, 2003), the difference between the two theories lie on the interpretation of educational mismatch (under and overeducation) and skills mismatch (under and overcompetent). Assignment (Sattinger, 1993) theory establishes a really close relationship between these two concepts: employees that occupy positions with job requirements differing from his educational background –educational mismatch– is a consequence of the inappropriate match between their skills and the abilities needed to fulfill the job's necessities –skills mismatch–. Therefore, workers with educational and skills mismatch are less productive than their counterparts that work in the appropriate position.

On the other hand heterogeneous skills theory postulate a weaker relationship between educational and skills mismatch than the assignment theory. This model is based on the fact that even among individuals with the same educational background, the distribution of skills and knowledge is dissimilar due to the individual heterogeneity. Thus, it is possible to find workers apparently overeducated, because they are in the lowest tail of the skills distribution conditioned to individuals with similar qualifications, in terms of skills they may match better.

The differences between assignment and heterogeneous skills theories is relevant to conduct empirical evaluations, because of the difference in the construction of the educational mismatch and skills mismatch variables, also the effect of these variables on the labor market outcomes may differ too. Nevertheless, formalization and predictions of the two theories is the same. Then, we are going to specify the formal model and its main predictions according to the tradition of assignment models (Allen & Van Der Velden, 2001; Hartog, 1981, 1986a, 1986b, 2000; Roy, 1950, 1951; Sattinger & Hartog, 2013; Sattinger, 1975, 1993; Teulings, 1995; Willis & Rosen, 1979). These are going to serve as a basis for the development of this article. Empirically, after presentation of the data we are going to explain the creation process of the different variables to both types of mismatch and we will test if educational and skills mismatch are different process to the Colombian case.

2.3.1. Assignment model

We follow the theoretical model posed by (Hartog, 1986a) that is grounded on the model proposed by (Tinbergen, 1956) and (Sattinger, 1979) that focuses in a process of selection by workers and firms. First, firms are seeking for individuals with the indicate stock of human capital to each job that is characterized by labor requirements. For simplicity only one variable r_j is important to determine the labor requirements in a particular job j. In the short run firm´s characteristics are fixed and finding the correct worker can be difficult, thus the company may need to hire a worker whose skills differ from r_j.

Then, in the short run the problem is reduced to match the best worker to a given job. The capacity of the workers (we can include here skills and level of school) is defined as a, firms face a wage in function of labor requirement (r) and type of worker (a), where $w = w(a, r)$. Firms are maximizing profits when marginal product and marginal wage cost are equal: $\partial P(a, r_j)/\partial a = \partial w(a, r)/\partial a$. Where $P(a, r_j)$ indicates the marginal productivity of a worker a in a given job r_j.

In the second part of the model, workers have to choose a job given the level of capability a (in the short run capability levels are assumed as fixed). The assumption is that the worker decides on type of job, having into account the tradeoff between effort (r) and earnings (w). The individual's utility function is specified as $U = U(w, a, r)$ which captures the idea that some jobs (r) can be easier than others depending on the individual skills (a). The worker maximize his or her utility when marginal change in effort is identical to the marginal increase in earnings, it is $\partial w/\partial r = -\partial U/\partial r/\partial U/\partial w$. In terms of the empirical approach, it is important to note that employees also perform a maximization to choose the type of job they want, this optimization depends on the individual's abilities. Therefore type of labor is an endogenous variable and depends on observed and unobserved characteristics, this may produces two problems: selection bias because workers select themselves to the job they are going to apply; and double causality because workers optimize considering wage and at the same time wage is a function of the type of job and the type of worker.

The economy consists therefore in a numerous population of workers, for whom there is a distribution function of abilities (a) and a sufficiently large number of firms with distribution function of labor requirements (r). In this hypothetical world, companies look for the best worker given r and workers do the same thing for the companies given a. There is a wage function that guarantees the market equilibrium with the following theoretical implications: workers with the same level of skills (a) observed in different jobs are going to have different salaries in function of the job characteristics (r), the most suitable individuals for every job will receive a wage compensation. The slope with respect to a, represent the skills marginal productivity, to jobs with the same characteristics (r) are observed workers with different levels of abilities; the wage difference will reflect the differences in productivity.

3. Determinants of the assignment model and types of mismatch

From the assignment model we can detach the fact that individuals with a set of heterogeneous abilities are looking for positioning themselves in the best job given their characteristics. Individuals' competencies may have natural divisions, for instance, one job may seek a worker with knowledge in a specific discipline or field and at the same time, this individual should have ability to learn or solve generic problems. Furthermore employers do not only look at those kinds of skills, employees may have unobserved characteristics that help them to perform better in achieving employment like persistence or motivation. Then, skills can be separated into following dimensions: cognitive and noncognitive (Heckman, Stixrud, & Urzua, 2006) and within cognitive skills there is a sub set of generic and vocational skills (Heijke, Meng, & Ris, 2003).

Therefore we assume that the set of individual characteristics at time of graduation is a combination of noncognitive (NA_i), cognitive (CA_i), generic (G_i), and vocational (V_i) abilities, then the human capital of an individual (i) can be represented by $HC_i = f[NA_i, CA_i(G_i, V_i)]$. This paper will emphasize on the effect of these abilities on the assignment process, which reflects the pertinence of education, and at the same time we will measure the effect of this pertinence and different types of abilities on salaries.

To understand the assignment process we have to keep in mind the existence of two types of adjustment dimensions. On one side, the horizontal dimension involves the possibility that an individual is matched to an occupation close to their own professional carrier; on the other hand, the vertical dimension indicates whether workers have the required level of skills or they are under or overcompetent (Heijke et al., 2003). In this paper, we are going to represent vertical mismatch with skills mismatch (as stated in section 2.3), differing from (Heijke et al., 2003) whose representation is only based on vocational competences. Meanwhile, the effect of educational mismatch will be represented with the ORU model (Duncan & Hoffman, 1981) where attended education is discomposed into three parts: $AE = RE + OE - UE$, where AE denotes attained education, RE is the requirement amount of education, OE is the amount of years of attained education above the job requirements, and UE is the amount of years of attained education below job requirements.

Given the definitions of types of skills and mismatch is important to clarify the theoretical interpretation of the relationship between this two set of variables. From the assignment model all type of skills have a positive relationship with the probability to find a match in two assignment dimensions, because workers with higher levels of human capital are going to have better productivity given the job requirements, so they can easily find better jobs in terms of matching. However (Heijke et al., 2003) proposed other type of interpretation, they concluded that generic abilities have a negative effect in the probability of working inside a worker's educational domain (horizontal match), while vocational abilities have a positive relationship with this probability; this happens because a worker with higher level of generic competencies can deal with new problems in several fields, whereas higher vocational competencies are related to over-focusing in a particular field, making their knowledge and skills limited.

4. Data

The data used in this paper comes from the Survey of Graduates of Higher Education Institutions 2014 (*encuesta de seguimiento a graduados 2014 de instituciones de educación superior)* provided by the OLE. The survey was answered by 15,450 individuals graduated from higher education in technical, technological and university levels. Individuals are observed in three different cohorts: graduates one year before the survey, period between years 2012 and 2013. The second cohort consists of graduates three years before survey, period between 2010 and 2011. Finally, the third cohort contains graduates five years before the survey, between years 2008 and 2009. Furthermore, graduates are divided into three groups depending on their occupational sector: employees, self-employed and owners. We add the higher education graduates data base provided by the National Information System of Higher Education in Colombia (SNIES, by its acronym in Spanish) to include institutions and programs characteristics such as: code and name of the institution, sector and character, department and municipality of location of the institution, code and name of the program, level of education, methodology, area and basic core of knowledge, department and municipality where the program is offered.

The Survey of Graduates of Higher Education Institutions is divided in 6 parts. The part A contains information about personal and familiar situation of the graduates, including civil status, number of children and characteristics of housing payment. The part B contains information about graduate's skills. The part C, talk about the plan of life and future plans, there is information about academic activities, business creation and job search. The part D has information about internal and external mobility, if the graduate has lived or studied abroad and if he is in the same city where he finished his higher education studies. The part E is the employment situation of graduate, which as we mentioned before, is divided into employees, self-employed and owners of farms, businesses or companies. Each group is asked about employment situation, compliance with the activity they are performing at the time of the survey and the industry which they currently belongs. Finally, the part F consists of questions about the level of identity of the graduate with the educational institution he belongs to.

Since the objective of the research is to analyze the labor market and evaluate the congruence of education to meet the demand for workers, the sample is restricted to 9,615 graduates that are into the employees group, excluding of the study 3,266 graduates that are self-employed or owners.

Within the module of work activities we have questions that can be used to build mismatch variables. To construct the horizontal mismatch indicator, we used the answer to the question about the perception of the relevance of careers studied on the tasks doing in the workplace. Horizontal mismatch is a dummy variable where one is nothing related (mismatch) and cero is direct and indirect related (match), approximately 8% of graduates reported having a job outside their own educational domain.

The vertical mismatch variable (related to skills mismatch) is constructed using the answer to two question related with the possession of knowledge and skills. The first question asks about the job's usefulness of knowledge and skills learned in his or her career, and the second question asks whether graduates believe they should be in another job to further develop their professional skills. Workers responding negatively to the first question (little helpful or unhelpful) are classified as undercompetent, workers answering affirmatively to the first question (useful or very useful) and negatively to the second question are classified as match in competence, and workers answering affirmatively to both questions are classified as overcompetent (Badillo-Amador et al., 2005). Within the employees group approximately 60% of graduates consider themselves overcompetent, 8% undercompetent and 32% matched in competence.

In terms of educational mismatch, we use the question of level of study required in the actual job and compare it with the level of education attained by the graduate at the time of the survey; this way, we can get years of required education, years of overeducation and years of undereducation. Approximately 13% of the sample consider themself having years of overeducation, 34% having years of undereducation and 53% perceives themselves matched in education. In average, workers have 1.6 years of overeducation with a range between 1 and 7 years, meanwhile in terms of undereducation, workers have in average 2 years of undereducation with a range between 1 and 8 years.

It is important to take into account the types of measures of mismatch and the advantages and disadvantages of using one or the other. Hartog (2000) argues there are 3 classical ways to measure the mismatch: (1) Job analysis: systematic evaluation by professionals who specify the required level and type of education. For this process there is a lack of information in Colombia, precluding it´s use. (2) Worker self-assessment: workers responded a survey with mismatch information. This is a perception measure and can have problems related to the unobserved heterogeneity and inversed causality because salary could be affecting the perception. (3) Realized match: "required education is derived from what workers in the respondent's job or occupation usually have attained, e.g. the mean or the mode of that distribution" (Hartog, 2000). This measure is far from covering the technological requirements of a job and it is an endogenous process. Considering the options, job analysis is conceptually superior but the measurement is not available, worker self-assessment is therefore the best available alternative. Given the above and the characteristics of our survey this article is going to work with worker self-assessment measures, considering that it is the best method to which we can access and also accepting the problems we may face.

The part B of the survey contains questions related with the individual's skills, in the first part there is variables with the level of reading, writing and listening of 8 different languages[4]. In the second part there are 26 variables measuring the individual satisfaction with respect to a specific competence at the time of graduation. We use the multivariate technique of exploratory factor analysis to reduce the dimensionality of data regarding underlying structure caused by latent variables (See Appendix 1). We find 2 significant latent constructs that explain the 95% of the total variance. We used as a theoretical framework to lumping together the variables the articles by Ananiadou & Claro (2008) and Beneitone et al. (2007). The outcome of the latter show a first factor called "interpersonal dimension" explaining the information related to effective communication, solve problems and social impact, the second factors is called "information dimension" which explains how graduates analyze information and how they dominate the use of technological tools. Henceforth, interpersonal dimension will be understood as generic abilities and information dimension as specific abilities.

Much of the individual heterogeneity comes from unobservable characteristics as individuals abilities or intelligence (Heckman, Lochner, & Todd, 2006). To control the effect of these unobservable variables we take additional abilities information comes from the standardized test SABER-11[5] and SABER-PRO[6] with which we can approximate individuals' abilities, following Carneiro, Hansen, & Heckman (2003) and Neumann, Olitsky, & Robbins (2009). Data about test scores is reported by ICFES (*Instituto Colombiano para la Evaluación de la Educación*); with data available from year 2007 to year 2014. Using exploratory factor analysis to SABER-11 and SABER-PRO we find one factor to each test representing individual's abilities before and after higher education. Since the Survey of Graduates of Higher Education Institutions is anonymized[7] we cannot add directly the data base with the estimated individual abilities, thus using hierarchical models we impute the individual ability to the Survey of Graduates of Higher Education Institutions 2014 data base (See appendix 2). Table 2 shows descriptive statistics for all variables used in the empirical analysis.

[4] English, French, Italian, Portuguese, Mandarin, German, Japanese and Arabic

[5] This test is performed at the end of secondary education and is required to enter to tertiary education

[6] This test is performed at the end of higher education and is required to get the college degree

[7] The law 1581 of 2012 and the resolution MEN N. 326 of 2014 not allow us have the data with individual identification

Table 1

Variable	Mean	Std. Dev.	Min	Max
Horizontal Mismatch	0.07	0.26	0	1.0
Overcompetent	0.61	0.49	0	1.0
Undercompetent	0.08	0.26	0	1.0
Required education	15.29	1.76	9	21.0
Overeducated	2.49	1.39	1	7.0
Undereducated	2.03	1.02	1	8.0
Years of experience	2.63	1.74	0	5.0
Years of experience^2	9.95	9.59	0	25.0
Physical limitations	0.10	0.29	0	1.0
Number of languages	0.57	0.66	0	7.0
studied abroad	0.03	0.17	0	1.0
Individuals' abilities	5.66	0.26	5	7.1
Individuals' abilities after college	1.96	3.00	0	8.3
Interpersonal dimension	8.23	1.20	0	10.0
Information dimension	7.55	1.43	0	10.0
Rented housing	0.47	0.50	0	1.0
Single	0.67	0.47	0	1.0
Number of children	0.32	0.47	0	1.0
You used social networks to get the current job	0.54	0.50	0	1.0
IES accredited	0.22	0.41	0	1.0
Agronomy and related	0.04	0.19	0	1.0
Arts and humanities	0.09	0.29	0	1.0
Educational science	0.08	0.27	0	1.0
Health	0.13	0.34	0	1.0
Social sciences	0.11	0.32	0	1.0
Economy and business	0.21	0.41	0	1.0
Engineering	0.26	0.44	0	1.0
Mathematics and Natural Sciences	0.04	0.20	0	1.0
Cohort 1	0.36	0.48	0	1.0
Cohort 2	0.33	0.47	0	1.0
Cohort 3	0.31	0.46	0	1.0

Own elaboration with data from the OLE

Additionally, as mentioned before, we will test which model fit better to the Colombian situation, this paper uses a statistical approach used by Badillo-Amador et al. (2005) compares the marginal distribution of the two types of mismatch (education and skills) and estimates the degree of statistical association between them. To build up the empirical joint distribution function we assume that a worker can be simultaneously classified, for instance, as matched in skills and mismatch in education or mismatched in skills and matched in education, or any other possible combination. Table 2 shows the empirical joint distribution function (see the data section), marginally it is worth noting that educational and skills mismatch are quite different, for example, only 8% of the sample are classified as undercompetent whereas 34% are undereducated and at the same time barely 14% are overeducate while 60% are overcompetent. Apparently these measures are explaining phenomena of different nature; formal statistical tests of association strongly suggest that this suspicion is correct.

Table 2

Competence vs. Education mismatch				
	Overcompetent	Undercompetent	Match in competence	Educational Match
Overeducated	9.59	2.92	1.53	14.04
Undereducated	18.82	2.21	13.08	34.1
Match in education	31.15	2.82	17.89	51.86
Competence Match	59.56	7.95	32.49	100

Own elaboration with data from the OLE

It is also important to note that a relatively high proportion of people are simultaneously classified as undereducated and overcompetent (19%) and as undereducated having the competences required for their job (13%). We might be tempting to say that firms in the Colombian labor market have higher job requirements than they should have (in terms of level of education), because workers with less education than required have skills and knowledge enough (or even more) to perform adequately their tasks.

From the above we can conclude that for our sample, heterogeneous skills theory has a greater explanatory power since statistically, education and skills mismatch are independent processes so we cannot use education match as a proxy for competence match in the labor market as also found Di Pietro & Urwin (2003), Badillo-Amador et al. (2005) and Green & McIntosh (2007), it is important to the empirical approach and conclusions.

5. Empirical Model

The objective of the empirical approach is to evaluate the theoretical hypothesis provided by the assignment model which postulates that the most suitable individuals for every job will receive a wage compensation and the wage differentials will reflect differences in productivity. We try to measure the impact of horizontal and vertical mismatch in wages, if we use a simple OLS regression controlling for individuals characteristics we cannot deal with the selection and inverse causality problems (as mentioned before). The problem is that the fact of belonging to the group of workers matched is a process determined by both graduates' observed and unobserved abilities (Goux & Maurin, 2000) additionally the perception of mismatch can be influenced by salary.

Since the exogeneity of the assignment process cannot be guaranteed (even controlling for observables) we propose the method developed by (Heckman, 1974, 1979) and (Lee, 1978) based on two basic assumptions. First, it acknowledges the existence of latent variables underlying the decision making process and allowing us to model individual choices. Second, it assumes that the choices are function of a vector of co-variables that affect the fact that the individual is matched but not his salary.

We suggest the following model based on (Heijke et al., 2003). Let HM_{ij} a Dummy variable which represents the horizontal mismatch: the individual i is assigned to a work j not related to his field of studies. The vertical mismatch will be measured with two Dummy variables representing the individual misallocation of abilities, one for overcompetent and one for undercompetent. VO_{ij} is a variable that indicates the graduate i is overqualified for the job j and VU_{ij} indicates the individual i is underqualified for the job j. It also defines $\ln w_{ij}$ as the wage logarithm of individual i for the job j. We consider the following model of simultaneous equations:

$$VO_{ij}^{*} = \tau_1 Z_{ij} + \varepsilon_{1ij}$$

$$VO_{ij} = 1 \;\; if \;\; VO_{ij}^{*} > 0 \;\; and \;\; VO_{ij}^{*} = 0 \;\; otherwise$$

$$VU_{ij}^{*} = \gamma_1 J_{ij} + \varepsilon_{2ij}$$

$$VU_{ij} = 1 \;\; if \;\; VU_{ij}^{*} > 0 \;\; and \;\; VU_{ij}^{*} = 0 \;\; otherwise$$

$$HM_{ij}^{*} = \delta_1 W_{ij} + \delta_1 VO_{ij} + \delta_1 VU_{ij} + \varepsilon_{3ij}$$

$$HM_{ij} = 1 \;\; if \;\; HM_{ij}^{*} > 0 \;\; and \;\; HM_{ij}^{*} = 0 \;\; otherwise$$

$$\ln w_{ij} = \beta_1 X_{ij} + \beta_2 HM_{ij} + \beta_3 VU_{ij} + \beta_4 VO_{ij} + \mu_{ij}$$

Where Z_{ij}, J_{ij} and W_{ij} are independent variable vectors that affect the vertical and horizontal mismatches respectively do not necessarily have to be different. It is important to note that the correlation between the two types of mismatch is allowed, since it is possible to think that the fact that a person has skills different to those required for his job would affect his probability of being outside of his vocational domain. β_2, β_3 and β_4 identify the impact of the misallocation in the wages, and are the parameters of interest.

The model is called the two-step treatment effect method; it starts by estimating the process of mismatch using the multivariate probit model. Then, the inverse Mills ratio are built using the results of the probit models for each estimation (λ_{1ij} referred to the model for horizontal mismatch model, λ_2 referred to overcompetent and λ_3 referred to undercompetent) and they are used as independent variables to control for selection. If the coefficient of any inverse Mills ratio is equal to zero there are no bias issues in the estimation of the effect of the variable that generates it, whereas if the effect is positive and significant, there are non-observable factors that positively influence the probability of the occurrence of the event (Hamilton & Nickerson, 2003).

The second assumption mentioned, which guarantees the identification of parameters, is that there are variables that are supposed to be correlated with the assignment process but not with the non-observable determinants of the wage. We used the same exogenous variable vector for the estimation of the three processes of misallocations. First, we took into account the personal situation of the individual as a proxy for his financial urgency to find a job. The number of children, rent housing, and being married can be a pressure for the graduate to find a job quickly making it possible that he gets a job not suitable for his characteristics. Second, following the argument used by (Heijke et al., 2003) we used the interpersonal abilities (interpersonal dimension) related with the generic skills and the abilities of the information related with technical or specific skills, reported by the individuals at the moment of their graduation. The assumption to use these variables is that the level of skills of the graduates increases with experience and training during their years in labor market, besides it is expected that this raise differs between graduates, which means there is no expectation of correlation between this latent constructs and non-observables variables of wage. It's important to note that the differences between the increments of skills among individuals can happen because of their initial skills; therefore the general intelligence would mostly explain the changes of the wages. This variable is included as control in the wage equation (the variable is measured by the Saber 11 and Saber Pro tests). According to the latter, the interpersonal and information dimensions in their initial levels affect only the assignment process.

The table 3 shows the results of the trivariate probit. First, by analyzing the horizontal mismatch, we can see the importance of all the other mismatch measures by explaining the probability of an individual being outside his educational domain. The vertical mismatch variables and the education mismatch have a positive effects in the probability of the field of studies not being related with the individual work field, it is interesting to note that not only the undercompetent and undereducated increase the probability of vertical mismatch, but also the overcompetent and overeducated, which indicates that the direction of the mismatch is not what is important, but the mismatch in itself. The interpersonal and information skills dimensions also have a significant effect in this part of the assignment process. The latent construct referred to the generic skills such as effective communication, problem solving and social impact raises the probability of having a horizontal mismatch; the construct referred to technical skills or specific abilities such as technological tools decreases the probability of being outside the educational domain. These results confirm the hypothesis that the specific knowledge focuses the skills in a particular field, making it more likely to find a job in that area, while a more general knowledge allows the individual to deal with problems in different fields, making him more likely to find jobs in different areas outside of his vocational domain.

Table 3

Trivariate Probit Analysis			
Independent Variables	Coefficient		S.E.
Dependent Variable: Horizontal Mismatch			
Vertical Mismatch			
Overcompetent	0.173	**	0.067
Undercompetent	1.239	***	0.113
Competencies			
Interpersonal Dimension	0.114	**	0.056
information Dimension	-0.181	***	0.049
Single	-0.064		0.051
Number of Children	-0.058		0.052
Rent Housing	-0.085	**	0.042
Required Education	-0.217	***	0.020
Overeducation	0.027		0.023
Undereducation	0.126	***	0.024
Years of Experience	-0.158	***	0.043
Years of Experience^2	0.017	**	0.008
Number of Languages	0.024		0.033
Lived Abroad	0.044		0.131
studied abroad	-0.020		0.183
Individuals' abilities	-0.122	***	0.034
Individuals' abilities after college	0.076		0.057
Accredited University	0.000		0.124
Intercept	2.068	***	0.366
Dependent Variable: Overcompetent			
Interpersonal Dimension	-0.004		0.034
information Dimension	0.078	***	0.029
Single	0.048	*	0.030
Number of Children	0.029		0.031
Rent Housing	-0.011		0.024
Required Education	-0.040	***	0.013
Overeducation	-0.008		0.017
Undereducation	-0.044	***	0.013
Years of Experience	0.001		0.027
Years of Experience^2	-0.003		0.005
Number of Languages	-0.030		0.019
Lived Abroad	-0.079		0.075
studied abroad	0.017		0.098
Individuals' abilities	-0.012		0.018
Individuals' abilities after college	-0.093	***	0.027
Accredited University	0.002		0.058
Intercept	0.727	**	0.230

Table 3 (*continued*)

Independent Variables	Coefficient		S.E.
Dependent Variable: Undercompetent			
Interpersonal Dimension	-0.176	***	0.046
information Dimension	-0.196	***	0.041
Single	0.004		0.045
Number of Children	-0.091	**	0.045
Rent Housing	-0.032		0.035
Required Education	-0.097	***	0.018
Overeducation	0.070	***	0.022
Undereducation	0.069	***	0.020
Years of Experience	-0.080	**	0.038
Years of Experience^2	0.010		0.007
Number of Languages	0.081	**	0.027
Lived Abroad	0.118		0.105
studied abroad	0.021		0.135
Individuals' abilities	0.008		0.027
Individuals' abilities after college	0.026		0.042
Accredited University	-0.161	*	0.091
Intercept	1.693	***	0.314
Correlation (missalocation and overcompetent)	0.017		0.031
Correlation (missalocation and undercompetent)	-0.035		0.051
Correlation (overcompetent and undercompetent)	-0.800	***	0.009

The estimation also include dummies for employees own account, owners and academic areas.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Noting the initial individual skills (measured as a general intelligence latent construct), it seems we can confirm the result of the assignment model according to which the more competent individuals have better opportunities to have a successful match, since that variable reduces the probability of an individual being horizontally mismatched. It is to be expected, according to the results of the searching model, that the years of experience decrease (seemingly exponentially during the first few years in the labor market) the probability of being vertically mismatched. The graduates from Health sciences, mathematics and natural sciences have, respectively, a bigger probability of finding an occupation in those areas.

The skills involved in being overcompetent show similar results to the horizontal mismatch, individuals with higher generic skills increase the probability of being overcompetent for their job. Meanwhile, both, generic and specific skills significantly reduce the probability of being undercompetent for the job. Having the required education for a job reduces both, the probability of being overcompetent and undercompetent. The undereducation affects the probability of being overcompetent in a negative way, which has a practical sense because it's presumable that people with fewer studies than those required will not declare that their skills are above those required. The overeducartion, on the other hand, has no effect, which still suggests the success of using the heterogeneous skills theory to understand the results. Any form of educational misallocation increases the probability of an individual being undercompetent for a job, the relationship between undereducation and being undercompetent is evident; the relationship between overeducation and being undercompetent, not so much. This might have something to do with what we mention before when we talked about the difference between assignment models and heterogeneous skills models. That is: an individual who is apparently overeducated can appear to be so because he is in the lower tail of the skills distribution in a specific academic level, which would increase the probability to have fewer skills than those required for a job. As in the case of horizontal mismatch, in both over and undercompetences, the years of experience reduce (in this case, linearly) the probability of having a vertical mismatch. In the knowledge areas, Health sciences and Arts and humanities are the ones that mostly decrease the probability of being overcompetent. Both, Health and Education sciences are also involved in the decrease of the probability of being undercompetent.

5.1. Mismatches' effects on wages

After the estimation of the selection process for the mismatch variables we proceed with the consistent estimation of the wage equation. The results can be seen in table 4. These results include the effect treatment procedure in two stages, which guarantees the identification of coefficients. The results of this regression show that the effects of the horizontal and vertical mismatches are negative and significant; this validates the prediction of the assignment model in which, for the wage function that ensures the market equilibrium, the more competent individuals for each job (those well matched) receive a wage premium due to the existence of comparative advantages. There's evidence in favor of the assignment models (Hartog, 1981, 1986a, 1986b, 2000; Heijke et al., 2003; Neumann et al., 2009; Sattinger, 1975, 1993) regarding that the wage is determined not only by individual characteristics but also by job characteristics.

About the educational mismatch, when using OLS (see table 5), we came up with the usual results that can also be found in the literature (Dolton & Vignoles, 2000; Duncan & Hoffman, 1981; Hartog, 2000; Korpi & Tåhlin, 2009), the coefficients related to the required education and the overeducation are positive and the coefficient of the undereducation is negative. Also, the coefficient of the required education is higher than the overeducation coefficient, which means that a worker over educated earns more than a worker in that same position, but properly matched, but less than another worker properly matched with his same level of education. When using the two-step treatment effect method the coefficient of the required education decreases quantitatively, which means there are non-observable factors that affect that variable. This keeps the qualitative conclusions, but not the quantitative ones.

The comparison between OLS and the model that corrects endogeneity can be seen in table 5. It shows that there are no significant changes in the estimated coefficient in the case of the horizontal mismatch, which can be explained by the lack of statistical significance of the inverse Mills ratio that comes from the selection model of this variable. As mentioned before, this implies that the bias does not seem to be a problem in the estimation of the effect of this variable.

Table 4

The wage equation			
Independent variables	Coefficient		S.E.
Horizontal Mismatch	-0.095	***	0.024
Overcompetent	-0.118	***	0.018
Undercompetent	-0.011		0.084
Required Education	0.077	***	0.022
Overeducation	0.110	***	0.008
Undereducation	-0.085	***	0.009
Years of Experience	0.052	***	0.016
Years of Experience^2	0.000		0.002
Number of Languages	0.005		0.009
Lived Abroad	0.003		0.040
studied abroad	0.070		0.050
Individuals' abilities	0.048	***	0.012
Individuals' abilities after college	-0.027		0.020
Accredited University	-0.071	**	0.028
$\lambda 1$ (Horizontal Mismatch)	0.097		0.083
$\lambda 2$ (Overcompetent)	1.355	***	0.320
$\lambda 3$ (Undercompetent)	0.333	***	0.052
Intercept	11.364	***	0.123

The estimation also include dummies for employees own account, owners and academic areas.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Table 5

Comparison Between Methods				
Variable	OLS		Two-step treatment effect	
Horizontal Mismatch	-0.092	***	-0.095	***
	(0.024)		(0.024)	
Overcompetent	-0.137	***	-0.118	***
	(0.012)		(0.018)	
Undercompetent	-0.121	***	-0.011	
	(0.024)		(0.084)	

On the contrary, the vertical mismatch coefficients had significant reductions (the undercompetent mismatch became non-significant), which can be explained by the positive and significant value of the inverse Mills ratio estimated by these two selection processes. These variables have a positive bias and the estimated values for the two-stage correction method have to be lower in absolute values, as the results are showing. Though it seems that the estimation method is solving the bias in the estimation of the parameters, this methodology still has two issues. First, it assumes that the terms of error of the equations are jointly distributed; and second (and more important) the validity of the instruments (Z_{ij}, J_{ij} y W_{ij}), because if they were not correct, the estimations would be unstable and the parameters unreliable.

6. Conclusions

The pertinence in education understood as the mismatch between individual skills and job characteristics, to the Colombian case confirms the economic theory postulated by the assignment model (Roy, 1951; Sattinger, 1975, 1993) where there is a wage penalty for mismatched individuals. Then we can think this is a relevant topic for public policy within the country because it has real effects on social welfare such as better wages, better productivity and better life quality due to working in a job that matches his career. The results of this article are important because they allow establishing knowledge fields and institutions for higher education that are doing things better in terms of pertinence.

We included three types of abilities: first, the competences extracted from saber 11 that are important in the empirical model to control for initial abilities. Differences in initial abilities may generate unobserved heterogeneity. Second, competences taken from Saber Pro used to measure the specific abilities and finally the Survey of Graduates of Higher Education Institutions 2014 to measure generic abilities. Abilities variables created using these data sets, allowed us a better understanding of the assignment process and it made easier to establish relationships between human capital and the probability of being matched in the labor market. Mainly, we found that generic abilities raise the probability of horizontal mismatch and diminish the probability of vertical mismatch, while information competencies lower the probability of both horizontal and vertical mismatch.

Although this methodology has certain important advantages dealing with the endogenity problem, the results found should be look cautiously due to two disadvantages: the assumption of the normality of the errors and the validity of the instruments. New data sets are is planned to be included in the analysis to measure the mismatch variables trying to create a more objective indicator, whit the objective to use systematic evaluation by professionals who specify the required level and type of education. It is important to have into account these issues for further research.

Appendix 1: Factor analysis to abilities

In this section we seek to adapt the skills variables for the Survey of Graduates of Higher Education Institutions 2014 data base for a multivariate statistical analysis with the aim to regard underlying structure caused by latent variables which also allows us to reduce the dimensionality of the data. We use 26 variables measuring the individual satisfaction with respect to a specific competence at the time of graduation, skills measures are:

Competences measures
Present ideas for written media
Clearly communicate orally
Persuade and convince
Communication Symbols
Multicultural differences
Use basic computer tools
Learn and stay updated
Be creative and innovative
Search, analyze, manage and share information
Create, investigate and adopt technology
Design and implement solutions supported by technology
Identify, formulate and solve problems
Capacity for abstraction, analysis and synthesis
Understand the reality that surrounds it
Taking culture of coexistence
Take responsibility and make decisions
Plan and use time effectively to achieve the objectives
Using specialized computer tools
Develop and implement projects
Work together to achieve common goals
Work independently without constant supervision
Apply professional values and ethics in work performance
Adapt to changes
Working under pressure
Being able to take risks
Identify opportunities and resources in the environment

Own elaboration with data from the OLE

Individuals using a rating scale of 1-4, with 1 being very unsatisfied, 2 unsatisfied, 3 satisfied and 4 very satisfied. (Olsson, 1979a) argument that common approximation when ordinal scale variables are analyzed is assign an integer value to each category and proceed with the analysis as if the data were measured on an interval scale with desirable distributional properties, proceed with this assumption can lead to erroneous results statistically. Specifically (Olsson, 1979b) shows that when factor analysis are performed with discrete data the conclusion of number of factors is wrong and the estimation of factor loadings is imprecise, mostly due to biased estimates of correlation.

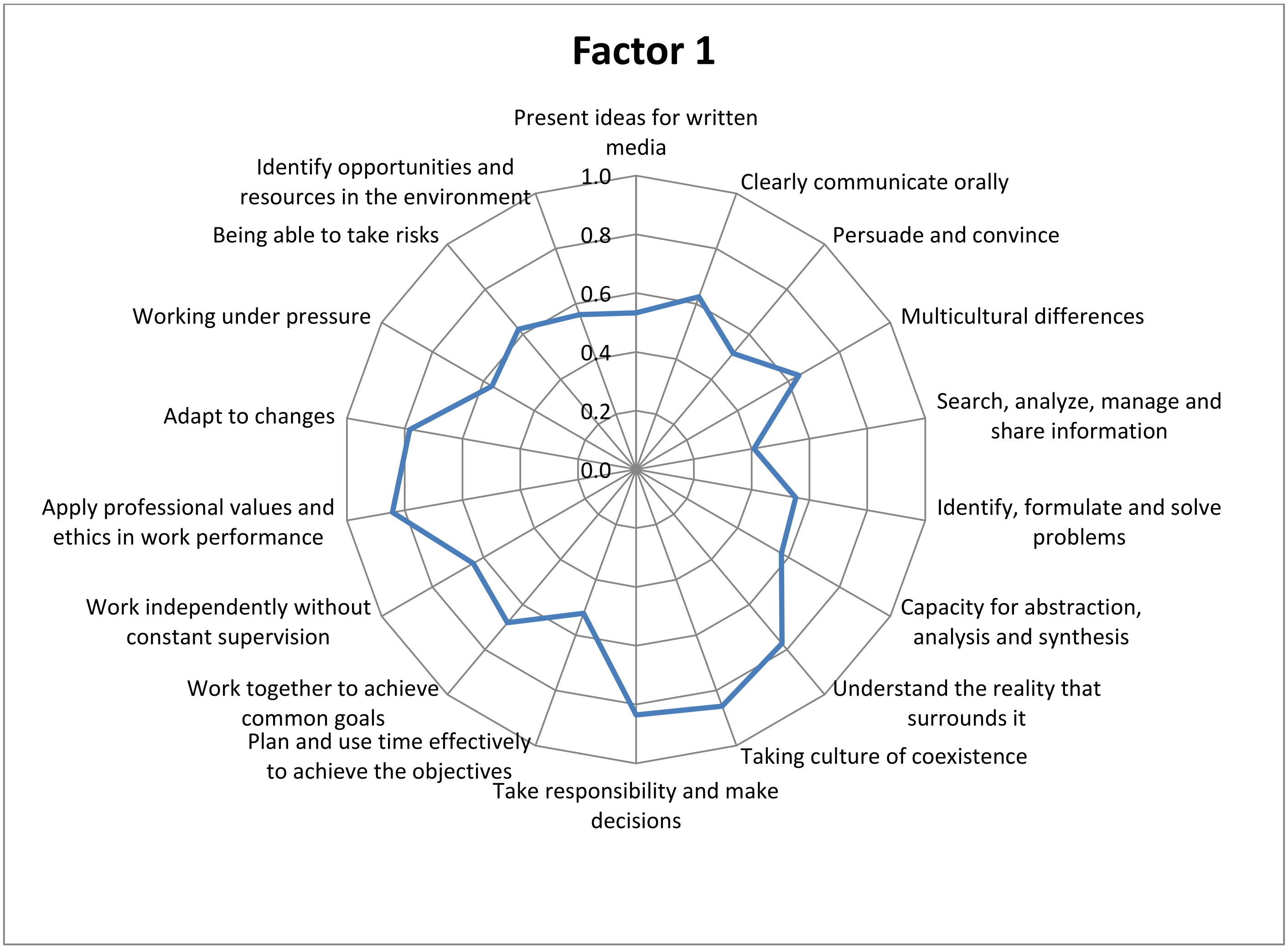
(Kolenikov & Angeles, 2004) argue that the most common way of dealing with discrete variables is to assume that come from a continuous variable underlying X_k^*. If observed variables are divided in $1, \dots, K$ categories, it is assumed to be obtained by dividing the continuous variable (X_k^*) according to a set of thresholds $\alpha_{k1}, \dots, \alpha_{k,K-1}$, where $X_k = r \ if \ \alpha_{k,r-1} < X_k^* < X_{k,r}$. To obtain unbiased estimates of correlation between two categorical variables X_1 and X_2 the correlation of the underlying continuous variables X_1^* and X_2^* should be found. This type of estimation is called polychorical correlation (Olsson, 1979a) and is a generalization of tetrachorical correlation to variables with more than two election options (Pearson, 1904).

We use the polychorical correlation matrix to perform the exploratory factor analysis. First we conduct tests to verify tests to verify the strength of the relationship and the existence of linear relationships in the correlation matrix; results are summarized in the following table. The determinant of the correlation matrix is very close to zero indicating that the matrix might not be full range. To assess whether the determinant of the matrix is statistically different from zero Bartlett test of sphericity is used, the null hypothesis is that the observed correlation matrix is equal to the identity matrix, suggesting that the observed matrix is factorable. There is statistical evidence to reject the null hypothesis confirming that there are linear combinations in the matrix. Proficiency Test sampling Kaiser-Meyer-Olkin is a measure of share variance, closer to one, there is more shared variance. The KMO value is 0.968 presents evidence of the high degree of common variance in the group of selected variables so it is appropriate to use multivariate factor analysis.

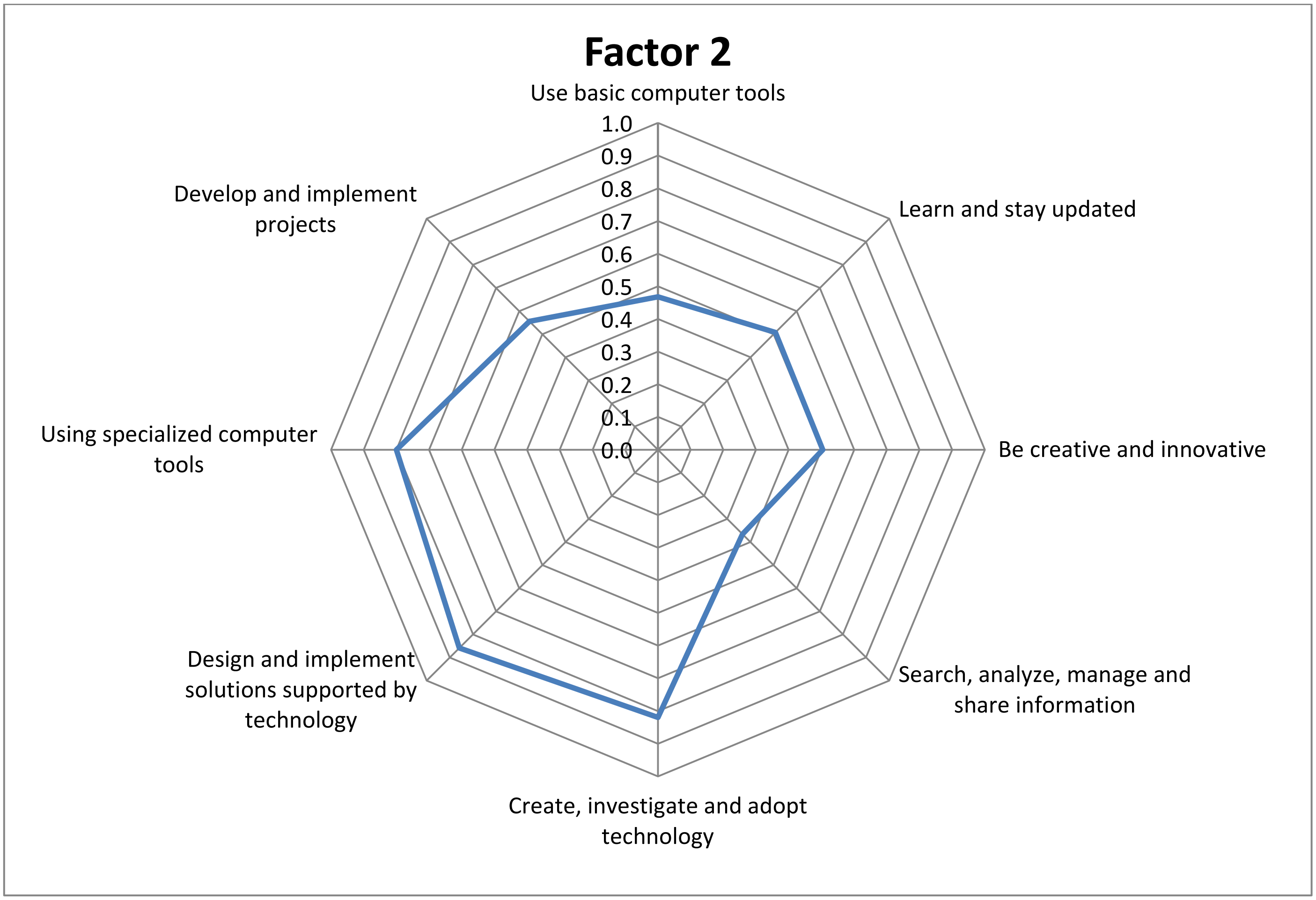
Measurement	Value
Determinant of the correlation matrix	0.000
Bartlett test of sphericity	0.000
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.968

Own elaboration with data from the OLE

We perform an exploratory factor analysis using the iterated principal factor method, following the rule of Kaiser we retain the first two components whose eigenvalues are above one and explain about 95% of the variance. The eigenvectors include the correlations of factors and original variables, and serve to interpret the dimension to which each factor belongs. Following (Beavers et al., 2013) and (Fabrigar et al., 1999) we use an oblique rotation to interpret the results and because in social sciences oblique rotation is indicated by allowing the correlation between factors. We present the results of the 2 factors selected, only correlation coefficients greater than 0.3 are included since these values are considered significant (Schönrock-Adema, Heijne-Penninga, Van Hell, & Cohen-Schotanus, 2009).



The first factor explains variables of communication, problem solving and social impact, taking latter dimension higher correlation levels. We interpret this factor based on (Beneitone et al., 2007) where the group of interpersonal skills possesses all the competences explained by the first latent construct (decision-making skills, interpersonal skills, ability to motivate and work towards common goals, capacity for teamwork, ability to organize and plan time, ability to act in new situations, creativity, ability to work autonomously, capacity for formulate and manage projects, commitment to quality). Meanwhile the second factor relates more clearly to the analysis of information and mastery of technological tools, based on (Ananiadou & Claro, 2008) the information dimension is related to information as a source (search, selection, evaluation and organization of information) and information as a product (Restructuring and modeling of information and the development of ideas).



The values of estimated factors may be positive or negative, which make difficult their interpretation (Krishnan, 2010). Thus, we re-scale the factors to be measured from 0 to 10. The values of the factors measure the graduate's perception regarding the interpersonal and information dimension relative to the perception of other graduates, it means, the factors only provide relative measures, we cannot extract absolute information of individual´s abilities.

Appendix 2: Estimating individuals' skills using "Saber 11" and "Saber Pro" test scores

With the aim to find a good prediction of individual abilities, we are going to use a hierarchical model of test performance as a function of student-level, program-level, college-level and municipality-level characteristics.

The hierarchical structure with a random-intercept is as follows:

(1)

First level (student): $y_{ijkl} = \beta_{0jkl} + \beta_3 NE_{ijkl} + \varepsilon_{ijkl}$

Second level (program): $\beta_{0jkl} = \gamma_{00kl} + \mu_{0jkl}$

Third level (institution) $\gamma_{00kl} = \alpha_{000l} + \alpha_{001l} S_k + \alpha_{002l} A_k + \omega_{00kl}$

Fourth level (municipality): $\alpha_{000l} = \delta_{0000} + \vartheta_{000l}$

Where y_{ijkl} is a measure of test performance for individual i nested in program j, in the institution k in the municipality l. β_{0jkl} is the average outcome, NE_{ijkl} is the individual educational level and ε_{ijkl} is an individual-level error. To the other levels the formulation is analogous. S_k and A_k are institutions characteristics, first is referred to the institution's sector: public or private, and second indicates weather the institution is high quality certified or not. The errors are not independent so is necessary to estimate a random model (Hofmann, 1985).

The objective of y_{ijkl} is to act as a measure of individual abilities before and after higher education. In that sense performed a factor analysis to find the latent variables that account for the patterns of the process. The analysis was based on mathematics, language, philosophy, biology, chemistry and physics tests in the case of SABER-11. In the case of SABER-PRO we included the results of written communication, English, quantitative reasoning, critical reading and citizenship skills. We found one factor in each case that explained the 97% and 98% of the total variance of the results of SABER-11 and SABER-PRO respectively. The factors in each case have positive correlation with the results of all components, whereby we can interpret the each factor as individual abilities measured by the tests. As in the previous case, the estimated factors were re-scaled in a measure from 0 to 10.

The results using both methods are in the following table. All variables using as a fixed effects to both measures of abilities are significant and have the expected correlation sign to the dependent variable in the four models. We estimate 4 models including and extracting random effects of program, institution and municipality. The model that includes only effects of program and municipality is the best fit following AIC and BIC criteria. The average test score for the population was 5.44 and 6.96 to SABER-11 and SABER-PRO respectably, reflected in the constant term. To the SABER-11 case, the result of random effects, program and municipality, was 0.86 and 1.53 respectably. The explained variance was attributable, approximately, in a 20% to the program effects, while 36% was attributable to the municipality effects. To the SABER-PRO case the values for program and municipality was 0.89 and 0.12 respectively and in terms of explained variance 25% was attributable to program effects and 3.6% to municipality effects.

Test	SABER-11		SABER-PRO	
Fixed effects				
Constant	5.444	***	6.961	***
	(0.017)		0.007	
Educational level	0.027	***		
	(0.010)			
Sector	0.036	**		
	(0.006)			
Acreditation	0.322	***	0.539	***
	(0.012)		(0.013)	
Random effects				
Program	0.865		0.890	
	(0.032)		(0.026)	
Institution	0.000			
	(0.000)			
Municipality	1.535		0.128	
	(0.014)		(0.006)	
Residual variation	1.797		2.515	
	(0.004)		0.008)	

standard deviation in parentheses

** significant at 5% level

*** significant at 1% level

The model fit well the data so we use previous estimations to predict latent abilities of individuals in the Survey of Graduates of Higher Education Institutions 2014 data base. We use the coefficients of the best model and predicted random intercept for each level. With of equations (1) we estimate the individual's abilities.

References

Allen, J., & Van Der Velden, R. (2001). Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, *3*, 434–452. http://doi.org/10.1093/oep/53.3.434

Almond, D., & Currie, J. (2011). *Human capital development before age five*. *Handbook of Labor Economics* (Vol. 4). Elsevier B.V. http://doi.org/10.1016/S0169-7218(11)02413-0

Ananiadou, K., & Claro, M. (2008). 21st Century Skills and Competencies for New Millenium Learners in OECD, (41).

Badillo-Amador, L., García-Sánchez, A., & Vila, L. E. (2005). Mismatches in the Spanish labor market: Education vs. competence match. *International Advances in Economic Research*, *11*(1), 93–109. http://doi.org/10.1007/s11294-004-7491-z

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical Considerations for Using Exploratory Factor Analysis in Educational Research. *Practical Assessment*, *Research & Evaluation*, *18*(6).

Becker, G. S. (1975). *Human capital: a theoretical and empirical analysis*, *with special reference*. *Columbia University Press.* Retrieved from http://books.google.com/books?id=nowHzq2QoYsC&pgis=1

Beneitone, P., Esquetini, C., González, J., Maletá, M. M., Siufi, G., & Wagenaar, R. (2007). Reflections on and outlook for higher education in Latin America. Final report - Tuning Latin America Project 2004-2007, 1–420. Retrieved from http://tuning.unideusto.org/tuningal/index.php?option=com_frontpage&Itemid=1

Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, *34*(2), 143–173. http://doi.org/10.1016/0304-3932(94)90047-7

Burdett, K. (1978). A theory of employee job search and quit rates. *American Economic Review*, *68*(1), p212. 9p.

Carneiro, P., Hansen, K. T., & Heckman, J. J. (2003). Estimating distributions of treatment effects with an application to the returns to schooling and measurement of the effects of uncertainty on college choice. *International Economic Review*, *44*(2), 361–422. http://doi.org/10.1111/1468-2354.t01-1-00074

Di Pietro, G., & Urwin, P. J. (2003). Education and skills mismatch in the Italian graduate labour market. *Applied Economics*, *38*, 79–93. http://doi.org/10.1080/00036840500215303

Dolton, P., & Vignoles, A. (2000). The incidence and effects of overeducation in the U . K . graduate labour market. *Economics of Education Review*, *19*, 179–198.

Duncan, G. J., & Hoffman, S. D. (1981). The incidence and wage effects of overeducation. *Economics of Education Review*. http://doi.org/10.1016/0272-7757(81)90028-5

Eijs and Heijke. (2000). *Mismatch between occupation and education and the cost and benefits of job-related training*.

Fabrigar, L. R., Fabrigar, L. R., Wegener, D. T., Wegener, D. T., MacCallum, R. C., MacCallum, R. C., … Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *PSYCHOLOGICAL METHODS*, *4*(3), 272–299. http://doi.org/10.1037/1082-989X.4.3.272

Goux, D., & Maurin, E. (2000). Returns to firm-provided training: evidence from French worker–firm matched data. *Labour Economics*, *7*(1), 1–19. http://doi.org/10.1016/S0927-5371(99)00023-8

Green, F., & McIntosh, S. (2007). Is there a genuine under-utilization of skills amongst the over-qualified? *Applied Economics*, 427–439. http://doi.org/10.1080/00036840500427700

Hamilton, B. H., & Nickerson, J. A. (2003). from the SAGE Social Science Collections . All Rights Reserved . *Strategic Organization*, *1*(1), 51–78. http://doi.org/0803973233

Harmon, C., & Walker, I. (2003). The returns to education: Microeconomics. *Journal of Economic Surveys*, *17*(2). http://doi.org/10.1111/1467-6419.00191

Hartog, J. (1981). WAGES AND ALLOCATION UNDER IMPERFECT INFORMATION. *DE ECONOMIST*, *129*(3).

Hartog, J. (1986a). Allocation and the earnings function. *Empirical Economics*, *11*(2), 97–110. http://doi.org/10.1007/BF01987507

Hartog, J. (1986b). Earnings functions: beyond human capital. *Applied Economics*. http://doi.org/10.1080/00036848600000004

Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, *19*(2), 131–147. http://doi.org/10.1016/S0272-7757(99)00050-3

Heckman, J. J. (1974). Shadow Prices, Market Wages, and Labor Supply. *Econometrica*, *42*(4), 679–694. http://doi.org/10.2307/1913937

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153–161. http://doi.org/10.2307/1912352

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2006). Chapter 7 Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond. *Handbook of the Economics of Education*, *1*(06), 307–458. http://doi.org/10.1016/S1574-0692(06)01007-5

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, *24*(3), 411–482. http://doi.org/10.1086/504455

Heijke, H., Meng, C., & Ris, C. (2003). Fitting to the job: The role of generic and vocational competencies in adjustment and performance. *Labour Economics*, *10*(2), 215–229. http://doi.org/10.1016/S0927-5371(03)00013-7

Hofmann, D. (1985). APPLICATIONS OF HIERARCHICAL LINEAR MODELS TO MULTI-LEVEL DATA. *Pennsylvania State University*, 327–332.

Kolenikov, S., & Angeles, G. (2004). The Use of Discrete Data in PCA: Theory , Simulations , and Applications to Socioeconomic Indices. *Chapel Hill: Carolina Population Center, University of North Carolina.*, 1–59.

Korpi, T., & Tåhlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974-2000. *Labour Economics*, *16*(2), 183–193. http://doi.org/10.1016/j.labeco.2008.08.004

Krishnan, V. (2010). Constructing an area-based socioeconomic status index: a principal components analysis approach. *Every Day in Every Way: Creating Learning Experiences for Every Child*, (May), 2–26. Retrieved from http://www.cup.ualberta.ca/wp-content/uploads/2013/04/SEICUPWebsite_10April13.pdf

Krueger, A. B., & Lindahl, M. (2001). Education for Growth: Why and for Whom? *Journal of Economic Literature*, *39*(4), 1101–1136. http://doi.org/10.1257/jel.39.4.1101

Lee, L.-F. (1978). Unionism and Wage Rates: A Simultaneous Equations Model with Qualitative and Limited Dependent Variables. *International Economic Review*. http://doi.org/10.2307/2526310

McCall, J. (1970). Economics of information and job search. *The Quarterly Journal of Economics*, *84*(1), 113–126. Retrieved from http://www.jstor.org/stable/1879403

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy*. http://doi.org/10.1086/258055

Mincer, J. (1974). *Schooling, Experience, and Earnings. Human Behavior & Social Institutions No. 2. NBER* (Vol. I). Retrieved from http://www.eric.ed.gov/ERICWebPortal/detail?accno=ED103621

Mortensen, D. (1970). Job search, the duration of unemployment, and the Phillips curve. *The American Economic Review*, *60*(5), 847–862. Retrieved from http://www.jstor.org/stable/1818285

Mortensen, D. T., & Pissarides, C. a. (1999). New Developments in Models of Search in the Labour Market. *Handbook of Labour Economics, Volume 3B, Chapter 39*, *3*, 2567–2627.

Neumann, G., Olitsky, N., & Robbins, S. (2009). Job congruence, academic achievement, and earnings. *Labour Economics*, *16*(5), 503–509. http://doi.org/10.1016/j.labeco.2009.03.004

Olsson, U. (1979a). Maximum likelihood estimation of the polychoric correlation coefficient. *Psychometrika*, *44*(4), 443–460. http://doi.org/10.1007/BF02296207

Olsson, U. (1979b). On the robustness of factor analysis against crude clasifications of the observations.pdf. *Multivariate Behavioral Research*, *13*(4), 485–500.

Pearson, K. (1904). Mathematical Contributions to the Theory of Evolution. XII. On a Generalised Theory of Alternative Inheritance, with Special Reference to Mendel's Laws. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. http://doi.org/10.1098/rsta.1904.0015

Porath, B. (1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy*, *75*(4).

Roy, A. (1950). The Distribution of Earnings and of Individual Output. *The Economic Journal*, *60*(239), 489–505. Retrieved from http://www.jstor.org/stable/10.2307/2226792

Roy, A. (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers*, *3*(2), 135–146.

Rubinstein, Y., & Weiss, Y. (2006). Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning. *Handbook of the Economics of Education*, *1*(06), 1–67. http://doi.org/10.1016/S1574-0692(06)01001-4

Sattinger, M. (1975). Comparative Advantage and the Distributions of Earnings and Abilities. *Econometrica*, *43*(3), 455–468. http://doi.org/10.2307/1914276

Sattinger, M. (1979). Differential Rents and the Distribution of Earnings. *Oxford Economic Papers*, *31*(1), 60–71.

Sattinger, M. (1993). Assignment Models of the Distribution of Earnings. *Journal of Economic Literature*, *31*(2), 831–880.

Sattinger, M., & Hartog, J. (2013). Nash bargaining and the wage consequences of educational mismatches. *Labour Economics*, *23*, 50–56. http://doi.org/10.1016/j.labeco.2013.03.002

Schönrock-Adema, J., Heijne-Penninga, M., Van Hell, E. A., & Cohen-Schotanus, J. (2009). Necessary steps in factor analysis: enhancing validation studies of educational instruments. The PHEEM applied to clerks as an example. *Medical Teacher*, *31*(6), e226–e232. http://doi.org/10.1080/01421590802516756

Teulings, C. N. (1995). The wage distribution in a model of the assingment of skills to jobs. *Journal of Political Economy*, *103*(2), 280–315.

Willis, R. J., & Rosen, S. (1979). Education and Self-Selection. *Journal of Political Economy*, *85*(S5), S7.