Scientific Annals of Economics and Business
63 (SI), 2016, 01-19
DOI: 10.1515/saeb-2016-0133

A MULTILEVEL ANALYSIS OF THE RETURNS TO EDUCATION IN ECUADOR. THE MULTIFACETED IMPACT OF HUMAN CAPITAL

Mercy Raquel ORELLANA BRAVO*, **Monica RĂILEANU SZELES****, **Dalia Maritza ARGUDO BARRERA*****

Abstract

This paper analyses the returns to education in Ecuador based on cross-sectional data collected by a National Survey at the individual- and canton-levels in 2005 and 2015. The multilevel analysis provides the methodological framework that allows capturing the regional peculiarities of data as well as addressing the high regional economic heterogeneity. The two level- random intercept and random slope models are used to examine the impact of individual-level and canton-level characteristics on the labour income. In subsidiary, the paper explains the proportion of variance in individual- level income that is explained by canton- level characteristics.

Keywords: regional heterogeneity, return to education, variance

JEL classification: I26, J31, I24

1. INTRODUCTION

Education is widely acknowledged as one of the most powerful drivers of economic growth and development in all countries. Stimulating the school attendance as well as encouraging young people to enter the higher education represent priority objectives in most education policies, as part of most national and international short term and long term growth strategies (Raileanu and Tache, 2016). Recently, education, alongside with the research and innovation activities, and the development of digital economy, have been considered as the main pillars of the "smart economic growth", which is a new type of economic growth mentioned into the European Union's 2020 Strategy (Palade and Bratucu, 2016). In the framework of this new approach, not any type of economic growth is desirable for an economy, but only that model which is inclusive and sustainable in the long term. For

* University of Cuenca; GIER research group in Ecuador, Ecuador; e-mail: *mercy.orellana@ucuenca.edu.ec*.
** Transilvania University of Brasov; and the Institute for Economic Forecasting within the National Institute for Economic Research, Romania; e-mail: *monica.szeles@unitbv.ro* (corresponding author).
*** University of Cuenca; GIER research group in Ecuador, Ecuador; e-mail: *dalia.argudob@ucuenca.ec*.

instance, formal education reinforces, does not reverse, the intergenerational reproduction of inequality (Hopenhayn, 2011).

The returns to education are particularly important because they reflect the influence of educational attainments on labour market earnings. They could therefore carry a strong impact on the performance of national education policies. In the literature, there is a broad strand of papers analysing the return to education, as well as the implications of education on economic growth and development. The topic of return to education has initially been addressed in the framework of the human capital theory by Becker (1964) and Mincer (1974), where the education has been seen as a measure of the human capital accumulation. In the years that have followed, the Mincer's econometric specification has continuously been improved and applied to the analysis of different related issues such as school quality and effectiveness, discrimination, screening hypothesis etc., *inter alia* by Griliches (1977), Wolpin (1977), Psacharopoulos (1979), Biddle and Hamermesh (1998), and Card (1999). These studies also found substantial dispersion in earnings across the industries and sectors. More recently, another strand of the literature introduces education as an endogenous variable, and by using a wider set of estimators and different non-linear effects of education over time, finds significant different results compared to previous studies (C. Harmon *et al.*, 2000).

Still using the Mincer's econometric specification, Sapelli (2003) separately calculates the returns to education for each level of educational attainment in Chile. He finds that for each additional year of schooling, the rate of return to primary education to an individual is 7.1% and the rate of return to tertiary education is 22.8%. By introducing interaction explanatory variables (gender and race), Heckman *et al.* (2003) find a rate of return to education of 12.2% for white men and 15.2% for black men in the US.

Among the econometric techniques used to capture the variation in returns to education across occupation, experience, industry etc. there is the use of dummy variables and fixed effects approaches (Goux and Maurin, 1999; Mincer and Higuchi, 1988; Preston, 1997; Zanchi, 1998). The broad methodological framework of measuring and analysing the returns to education also includes the multilevel analysis. Ignoring the hierarchical structure of data used in human capital analysis of earnings differentials may generate wrong results in testing of hypotheses and also in overlooking the importance of group effects (Goldstein, 1995). With the multilevel analysis, it is possible to introduce explanatory variables at each level of a hierarchy, and moreover, the variation in earnings of employees can be explained upon contextual variables linked to the characteristics of higher level units. When examining a set of manufacturing data, Naderi and Mace (2003) point out the advantages of using this methodology when dealing with hierarchical data, as well as the explanatory power of human capital variables.

All over the European Union, education in general, and the access to education in particular, represents a major concern for all governments. This is because more schooling years provide better opportunities on the labour market, as well as higher salaries, and ensure a better quality of life for a lifetime. But this is not necessarily the same in other countries and regions in the world. The education attainments as well as the access to education are sometimes conditioned upon local traditions and policy priorities. The gender and race discrimination as well as the poor regional economic structures and regional disparities hamper the process of economic development and the progress of education policies.

The Latin American economies are characterised in general by a high regional economic heterogeneity and large regional income inequalities. These regional patterns strongly influence the national education policies, as well as the access to education.

Remarkable progress in the education upgrading of the Latin America's population has continuously been done since 1990, and this positive dynamic has often been associated to the reduction in social inequality and poverty rates. Among all levels of education, the secondary education has been found to have the most impressive dynamic. The proportion of population with at least secondary education attainments increased from 40% in 1990 to almost 60% in 2010 (Barro and Lee, 2010). This dynamic has facilitated the development of skills that are generally acknowledged as stimulus for the increase of returns to education, greater equality of opportunity, economic growth and social inclusion.

According to the Human Development Reports of the United Nations Development Programme (2015), which uses data on educational attainment (1980-2013) from the UNESCO Institute for Statistics (2013) and the methodology from Barro and Lee (2013), Ecuador belongs to the category of medium human development from the point of view of the education indicator: mean years of schooling. In last years a very active policy in the field of education has been implemented by the Ecuadorian government which tries to raise up the national performances in terms of education, and also to use this policy as an instrument to alleviate poverty and reduce income inequalities.

This paper aims to analyse the returns to education in Ecuador based on a cross-sectional dataset that runs from 2005 to 2015, using the methodological framework of multilevel models. This methodology allows identifying the influence of both the individual level- and cantonal level- characteristics on the individual labour income. In subsidiary, the paper measures and analyses the impact of cantonal characteristics on the returns to education and therefore concludes over the importance of using multilevel models when dealing with regional data in the presence of high economic regional heterogeneity.

The paper is structured into four sections. In Background we present the aim and objectives, as well as a short literature review. The second section introduces the methodology, the third section is the empirical analysis, while the last section formulates the conclusions and policy recommendations. The empirical analysis is the most extensive section and includes a descriptive and a quantitative analysis.

2. METHODOLOGY AND DATA

This paper analyses the returns to education in Ecuador using cross-sectional data collected from ENEMDU 2000-2015 (National Survey on Employment, Unemployment and Underemployment) provided by the National Institute of Statistics and Census in Ecuador (INEC, 2015). Our working dataset includes individual level- and canton level- variables. At the individual level, the variables are on gender, race, education attainments, work experience and job characteristics (public/ private employment and economic sector). At the cantonal level, the data are on the average number of years of schooling and average income.

To address the hierarchical structure of the dataset, the paper follows a multilevel approach and uses as econometric methods the random intercepts and random slopes/ coefficients models. The multilevel analysis is the appropriate methodology to be used whenever the data are clustered (i.e. nested data), as it is the case of our data. As in any linear regression model, in the multilevel framework as well, the dependent variable is explained through regression models upon a set of covariates. Specific to the multilevel analysis is that the dependent variable is usually considered at Level 1, whereas the explanatory variables could be at any level.

Several multilevel models were developed over time. The random-intercepts models are models in which intercepts are allowed to vary across groups, and slopes are fixed. Determining interclass correlations is particularly important when using this model. In contrast to them, the random slopes (coefficients) model assumes that both the intercepts and slopes vary across groups, being therefore considered to be the most complex and realist multilevel model.

When developing a multilevel model, one should always start by running the simplest model (e.g. the variance components model) and then to gradually add more parameters. The complex model must be always compared to the previous one in order to assess better model fit (e.g. using the likelihood-ratio test).

In this paper both the random intercept model and random slopes model are used. The linear random-intercept model with covariates is used in the empirical section to explain the returns to education upon a set of explanatory variables at the individual and cantonal levels, when individuals (at Level 1) are nested in cantons (at Level 2)[1]. With this model we presume that the impact of explanatory variables is constant across cantons. Even though this hypothesis might theoretically appear as unrealistic, we use this model for comparison purposes. This model, as presented in eq. (1), includes both fixed and random effects[2].

$$y_{ij} = (\beta_1 + \varsigma_j) + \beta_2 x_{2ij} + \ldots + \beta_p x_{pij} + \varepsilon_{ij} \tag{1}$$

Where, subscript i reflects the Level 1 and subscript j refers to Level 2, y_{ij} is the dependent variable (i.e. the labour hourly income of individual i located in canton j), x_{ijp} are the explanatory variables, and ε_{ij} and ς_j are error terms. The Level-2 error term ς_j is a canton-specific error component, which is constant across individual. In eq. (1), the term $\beta_1+\varsigma_j$ represents the canton-specific intercept. The Level-1 error term ε_{ij} is the individual-specific error component that varies between individuals i and also between cantons j. The two error components are independent of each other.

ς_j is the random parameter or canton-specific error component, whose variance Ψ is estimated together with the variance θ of the ε_{ij}. It represents the unobserved heterogeneity or the combined effects of omitted canton characteristics. As all individuals within each canton share the same ς_j , there is within-canton dependence among the total error terms ε_{ij}.

The total error terms, as well as the dependent variable y_{ij}, given the explanatory variables $x_{ij,}$ are homoscedastic, as shown in eq. (2) and (3).

$$Var(\xi_{ij}) = Var(\varsigma_j + \varepsilon_{ij}) = \psi + \vartheta \tag{2}$$

$$Var(y_{ij} \mid x_{ij}) = \psi + \vartheta \tag{3}$$

The conditional interclass correlation of y_{ij} and $y_{i'j}$ for canton j, given the set of explanatory variables, can be written as in eq. (4).

$$\rho \equiv Cor(y_{ij}, y_{i'j} \mid x_{ij}, x_{i'j}) = \frac{\psi}{\psi + \vartheta} \tag{4}$$

In the next step of our analysis we use the random-coefficient model, where random coefficients (also called random slopes) are introduced beside the random intercepts. The difference between the random intercept and the random-coefficient model is that the former specify a canton-specific random intercept, whereas the latter specifies not only a canton-specific random intercept, but also a canton-specific random slope, as in eq. (5).

$$y_{ij} = (\beta_1 + \varsigma_{1j}) + (\beta_2 + \varsigma_{2j})x_{ij} + \varepsilon_{ij} \tag{5}$$

where, ς_{1j} represents the deviation of canton j's intercept from the mean intercept β_1, and ς_{2j} represents the deviation of canton j's intercept from the mean intercept β_1. The intercepts ς_{1j} and slopes ς_{2j} are independent across cantons, and the Level-1 error terms are independent across cantons and individuals.

In eq. (5), given x_{ij}, the random intercept and random slope follow a bivariate normal distribution with zero mean and covariance matrix of the form:

$$\Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix} \equiv \begin{bmatrix} Var(\varsigma_{1j} \mid x_{ij}) & Cov(\varsigma_{1j}, \varsigma_{2j} \mid x_{ij}) \\ Cov(\varsigma_{2j}, \varsigma_{1j} \mid x_{ij}) & Var(\varsigma_{2j} \mid x_{ij}) \end{bmatrix} \tag{6}$$

The correlation between the random intercept and slope can be written as in eq. (7):

$$\rho_{21} = \frac{\psi_{21}}{\sqrt{\psi_{11}\psi_{22}}} \tag{7}$$

When particularly studying education and other social settings, the random-coefficient model is generally presented into the two-steps formulation, because this allows a better understanding of the model by separating the Level-1 and Level-2 covariates.

In the two-stage formulation, the model includes canton-specific coefficients at Level 1, as shown in eq. (8):

$$y_{ij} = \eta_{1j} + \eta_{2j}x_{ij} + \varepsilon_{ij} \tag{8}$$

where, η_{1j} is the canton-specific intercept, and η_{2j} is the canton-specific slope.

Further on, the canton-specific coefficients are modelled as in eq. (8):

$$\begin{aligned} \eta_{1j} &= \gamma_{11} + \varsigma_{1j} \\ \eta_{2j} &= \gamma_{21} + \varsigma_{2j} \end{aligned} \tag{9}$$

It is assumed that the error terms ς_{1j} and ς_{2j} in eq. (9) have a bivariate normal distribution, and covariance matrix of the form presented in eq. (6).

Although including random slopes generally allows enriching the empirical results, it could also generate a number of problems. First, including a random slope into the model (5) usually requires also including a random intercept for that covariate. Second, since there is a variance parameter for each random effect and a covariance parameter for each pair of random effects, the number of parameters in the random part of the model increases very fast with the number of random slope. Third, random-coefficient models are either not identified, or affected by convergence problems. Fourth, the covariate should exhibit a significant degree of variability at the lower level in order to justify the inclusion of random-coefficient.

By substituting eq. (9) in eq. (8) and rearranging the equations' terms, we get the reduced-form model:

$$y_{ij} = (\gamma_{11} + \gamma_{21} x_{ij}) + (\varsigma_{1j} + \varsigma_{2j} x_{ij} + \varepsilon_{ij}) \tag{10}$$

where, the term $(\gamma_{11}+\gamma_{21}x_{ij})$ represents the fixed part of the model, whereas the term $(\varsigma_{1j}+\varsigma_{2j}x_{ij}+\varepsilon_{ij})$ denotes the random part of the model.

Given that $\beta_1 \equiv \gamma_{11}$ and $\beta_2 \equiv \gamma_{21}$, the model specified in (10) is equivalent to the model in (5).

The covariates at Level 2 are included in the Level 2 models (eq. 9) either for the random intercept, or for the random slope. If we include a categorical variable v_{2j} for the random intercept, then eq. (9) and (10) takes the following form:

$$\eta_{1j} = \gamma_{11} + \gamma_{12} v_{2j} + \varsigma_{1j} \tag{11}$$

$$y_{ij} = (\gamma_{11} + \gamma_{12} v_{2j} + \gamma_{21} x_{ij}) + (\varsigma_{1j} + \varsigma_{2j} x_{ij} + \varepsilon_{ij}) \tag{12}$$

If we include the categorical variable v_{2j} in the model for the random slope, then eq. (9) and eq. (10) become:

$$\eta_{2j} = \gamma_{21} + \gamma_{22} v_{2j} + \varsigma_{2j} \tag{13}$$

$$y_{ij} = (\gamma_{11} + \gamma_{12} v_{2j} + \gamma_{21} x_{ij} + \gamma_{22} v_{2j} x_{ij}) + (\varsigma_{1j} + \varsigma_{2j} x_{ij} + \varepsilon_{ij}) \tag{14}$$

The model in eq. (14) reflects in fact the cross-level interactions in the reduced form.

3. EMPIRICAL ANALYSIS

The empirical analysis develops into two steps. In the first part, the descriptive analysis of data allows better understanding the cantonal pattern and the heterogeneity of our main variable of interest – number of years of schooling. In the second part, the quantitative analysis provides a more concrete and realistic picture of the impact of the cantonal level on the individual schooling performances.

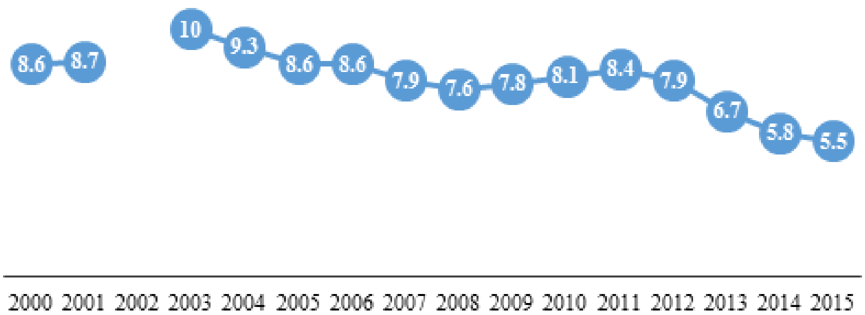
3.1 Descriptive analysis

This section presents a descriptive analysis of the most important indicators in the field of education (or indirectly related to education) in Ecuador, as to provide to the reader a more comprehensive overview over the performances in education, their dynamics over time and the returns to education. This section is also aimed to allow a better understanding of the findings presented into the quantitative section of the paper.

The Ecuador's economic bonanza in the last decades, which was mainly determined by the high prices of petroleum, has allowed the government to increase the public investment in the social sector, and particularly in education, from 2009 to 2013. According to the

Ministry of Finance, in 2015 the budget for education accounted for 4.5% of GDP, being therefore the most important "social" budgetary destination. That year the budget for education represented 52.8% into the total social sector budget, while the health and welfare had only 27.6% and 12.6% respectively.

As indicated by Figure no. 1, substantial progress has been done over time in continuously reducing the illiteracy in Ecuador, so that in 2015 the illiteracy rate was the lowest in the last 15 years (5.5%). However, according to the National Institute of Statistics and Census in Ecuador (INEC, 2015), there is a significant gender gap, as the female illiteracy rate is 6.7%, while the men illiteracy rate is 4.3%. Individuals aged 65 and over are the most exposed sub-group of population to illiteracy (24.5%).



Notes: The lack of information in 2002 is due to the fact that for this year only the urban illiteracy rate is available

Source: ENEMDU 2000-2015 (INEC, 2015)

Figure no. 1 – Illiteracy rate, 2000-2015

The average number of years of schooling, the young economically active population and the preference of highly educated people for certain economic sectors are among the most important characteristics of labour market in Ecuador.

The average number of years of schooling in Ecuador is 10 and includes only the primary education[3]. As regards the access to the tertiary education, in 2015, 21% of the population aged 24 or over graduated or was in train to graduate from a higher education institution. One of the most important peculiarities of the labour market in Ecuador is that the working age population is a very young one. For instance in 2015, 45.7% of the economically active population was aged 20-39.

In 2005 and 2015 most employees (60% of the total number of employees) were working in the following economic sectors: agriculture, trade, manufacturing and construction. In these sectors, the main educational background is given by the primary and secondary education (less than 13 years of schooling). But most employees with high educational attainments work in public administration and education (see Annex 1).

As shown in Table no. 1 the sector of manufacturing, construction and trade has the highest number of employees in 2005 and 2015, being then followed by the sector of agriculture, livestock, hunting, forestry and fishing whose weight is slightly decreasing over time.

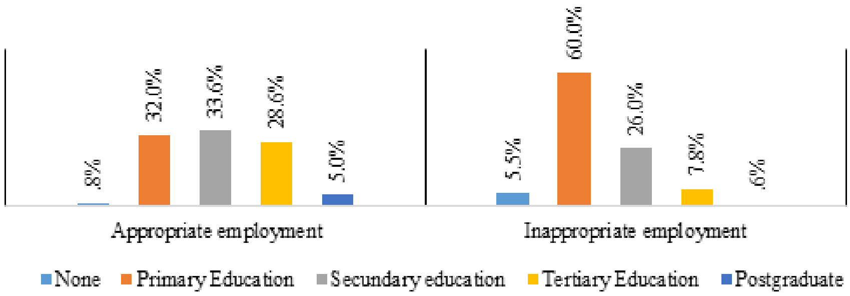
Tabel no. 1 – Distribution of employees upon economic sectors

Sectors of activity	2005	2015
Agriculture, livestock, hunting and forestry and fishing	26.3%	21.2%
Mining and quarrying	0.4%	0.8%
Manufacturing, Construction, Trade	38.8%	38.5%
Services, hotels, health, and other	24.4%	28.4%
Financial Intermediation	1.0	0.9%
Public administration and education	9.1%	10.2%

Source: Own elaboration based on ENEMDU data (2005-2015) provided by INEC (2015)

Upon the level of satisfaction with the working conditions, in Ecuador the employment is classified as *appropriate* and *inappropriate*. According to National Institute of Statistics and Census in Ecuador, the appropriate employment is defined as that type of employment accounting for more than 40 working hours per week and also a wage that is higher than the minimum wage in economy or than the wage corresponding to less than 40 working hours per week. All the other employments are defined as inappropriate. Among the latter category, the unemployment determined by insufficient salaries or insufficient number of working hours represents a major component. From 2005 to 2015, the number of appropriate employments has increased by 4% from 52% to 56%.

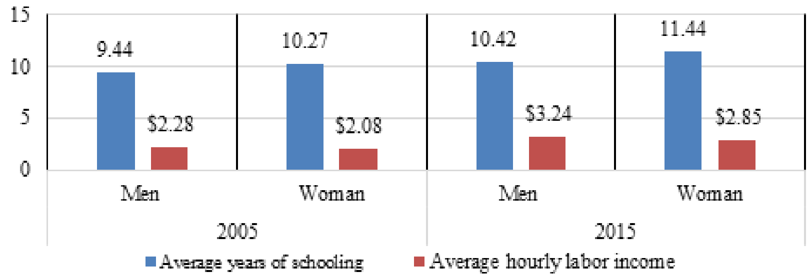
In 2015, a percentage of 28.6% individuals working in appropriate employments had tertiary education attainments, compared to only 7.8% who were working in inappropriate employments. This suggests the existence of a category of highly educated individuals (having more than 13 years of education), who still get wages that are below the minimum wage in Ecuador. This further indicates a very low return to education for this category of employees.



Source: Own elaboration based on ENEMDU data (2005-2015) provided by INEC (2015)
Figure no. 2 – Appropriate and inappropriate employment by levels of education, in 2015

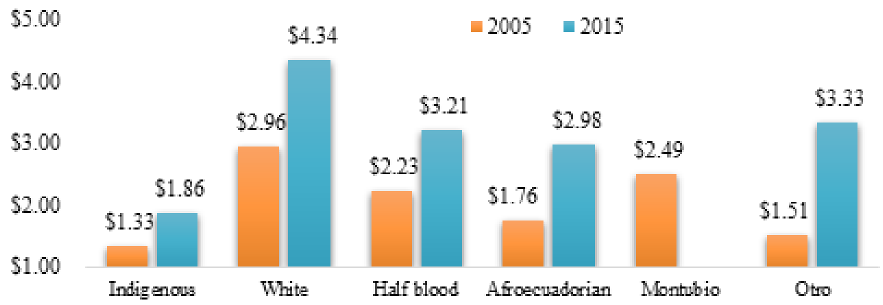
It is interesting to note that the number of individuals with primary education attainments working in inappropriate employments is almost double than those working in appropriate employments (see Figure no. 2). The level of educational attainments therefore becomes very important in acquiring good working conditions, so it is likely that educated people have in general more access to much better working conditions.

Figure no. 3 shows that women have in general lower hourly average wages in comparison with men, although the former have higher average number of schooling years. These statistically significant differences indicate the existence of the gender wage gap in Ecuador. Moreover, the returns to education are significantly different between women and men.



Note: The values are expressed in USD in constant prices with base year 2004 (Inflation-adjusted values)
Source: Own elaboration based on ENEMDU data (2005-2015) provided by INEC (2015)
Figure no. 3 – Average hourly labour income by years of schooling and gender (2005 and 2015)

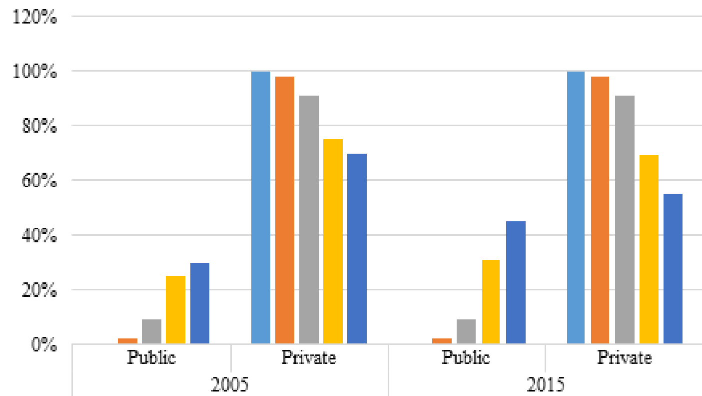
Figure no. 4 indicates the racial pay gaps in Ecuador which seems to become even larger over time. In 2015, as well as in 2005, the indigenous population gets less than 50% of the average hourly wage received by the white population. In comparison with all other races, the white workers receive the highest average hourly labour income in Ecuador. The indigenous population represents the most affected ethnic group by the racial pay gaps in Ecuador.



Note: Inflation-adjusted values (Base: 2004=100)
Source: Own elaboration based on ENEMDU data (2005-2015) provided by INEC (2015)
Figure no. 4 – Average hourly labour income by race (2005 and 2015)

The private sector is widely acknowledged as being the engine of any economy. The state sector is equally important because the state ensures the free access to public services such as health, infrastructure and health. In Ecuador, 9 out of 10 employees work in the private sector, so that this sector includes most labour force in 2005, and in 2015 as well (see Figure no. 5).

A large proportion of individuals with tertiary education and postgraduate attainments work in the public sector, and this proportion increases over time. While in 2005 a number of 3 out of 10 postgraduates from higher education institutions (e.g. Ph.D. holders) were working in the public sector, in 2015 almost half of them are employed in the public sector (4.5 out of 10). The percentage of graduates is also increasing from 2005 to 2015 (from 25% in 2005 to 31% in 2015). It is important to notice at this point that in Ecuador 50% of the highly educated employees work in education.



	2005 Public	2005 Private	2015 Public	2015 Private
None	0%	100%	0%	100%
Primary Education	2%	98%	2%	98%
Secundary education	9%	91%	9%	91%
Tertiary Education	25%	75%	31%	69%
Postgraduate	30%	70%	45%	55%

Note: The private employment includes the employee / private worker, employee / outsourced worker, labourer or farmhand, employer, self-employment, domestic employment, and other unpaid employment, as main activities.

Source: Own elaboration based on ENEMDU data (2005-2015) provided by INEC (2015)

Figure no. 5 – Structure of employed population by education and public/private sector job

The return to education increases along with the educational attainments, so that an individual with postgraduate attainments has an average hourly income that is around 6 time higher than the income of an individual without education (see Table no. 2). The wage gaps are increasing from 2005 to 2015 for graduates and postgraduates.

Table no. 2 – Average hourly wage upon education attainments (2005 and 2015)

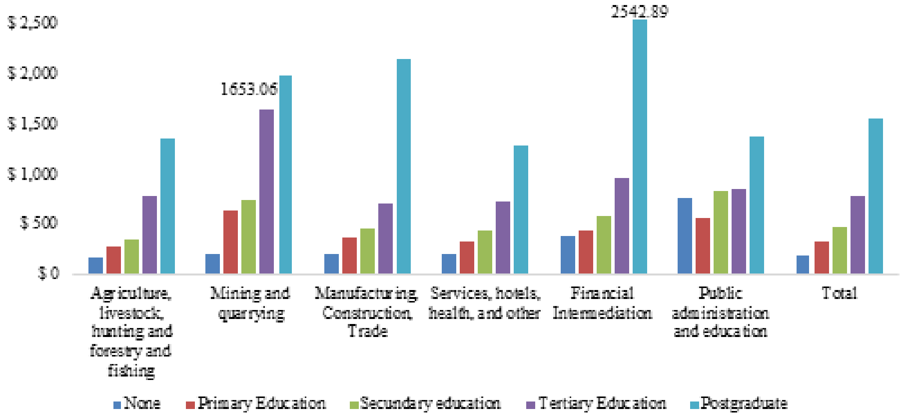
	Average hourly labour income	
	2005	**2015**
None	1.17	1.47
Primary education	1.52	2.16
Secondary education	2.22	2.89
Tertiary education	3.58	4.79
Postgraduates	5.96	9.37

Note: Inflation-adjusted values (Base: 2004=100)

Source: ENEMDU data (2005-2015) provided by INEC (2015)

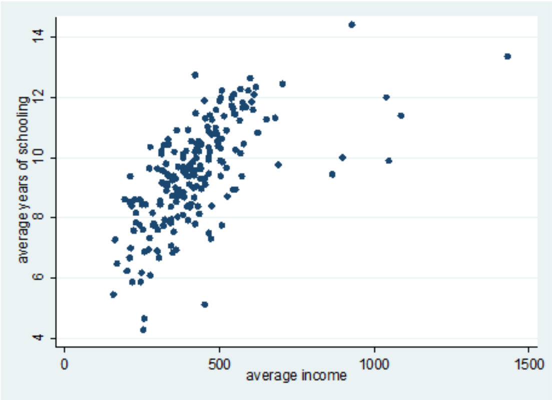
The economic sectors providing the highest average hourly wages in 2015 were: (1) Financial activities; (2) Public administration and education; (3) Mining and quarrying. The average hourly wage in these sectors are approximately three times higher than in agriculture, fishery and forestry where most people work (see Annex 2). This indicates once again the large income inequality that persist in the Ecuadorian economy.

In general, the average monthly wage increases with the level of education, but also depends upon the economic sector. An individual with postgraduate educational attainments could get the highest monthly salary in Ecuador for his education category when being employed in constructions. In contrast individuals with no education get the lowest wages in agriculture. Individuals with tertiary education attainments can get the maximum salary corresponding to their level of education when working in mining and quarrying. Figure no. 6 indicates once again the very large discrepancies in wages across the economic sectors and educational attainments, which suggests once again the broad range of returns to education in Ecuador.



Note: Inflation-adjusted values (Base: 2004=100)
Source: ENEMDU *data (2005-2015) provided by INEC (2015)*
Figure no. 6 – Average monthly labor income by sector and level of education in 2015

The large differences in the levels of returns to education in Ecuador is a main determinant of social inequality and relative poverty. Moreover, the large concentration of highly educated employees in the state sector is likely to induce important income inequalities and large differences in the returns to education, aggravating therefore even more the social problems in Ecuador.

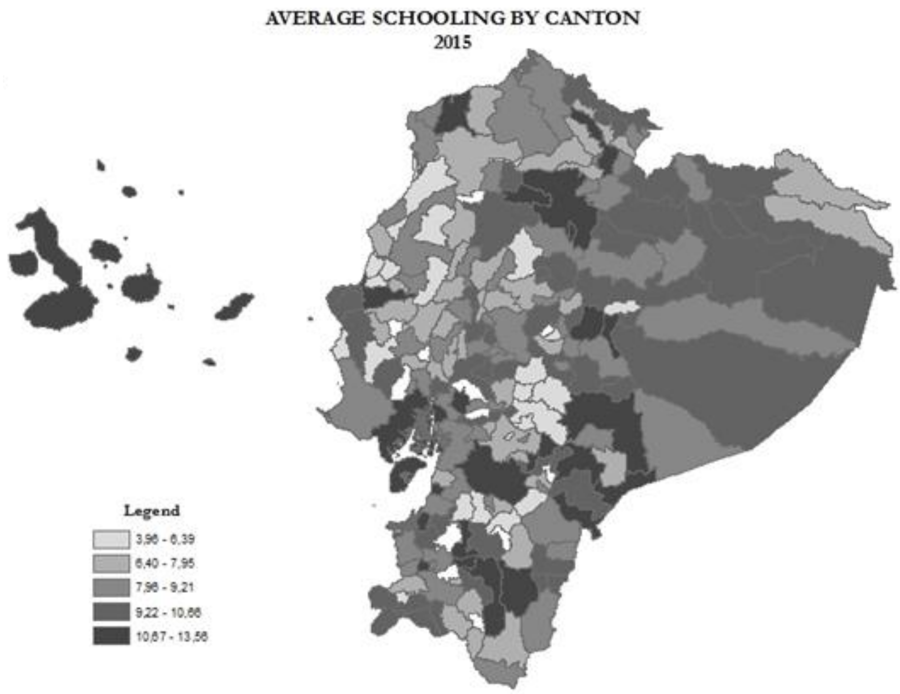


Note: The average income refers at cantonal average wage per month; 206 cantons in 2015
Source: Data are taken from ENEMDU data provided by INEC (2015)
Figure no. 7 – The relationship between the average cantonal income and the cantonal average years of schooling in 2015

In Figure no. 7 the relationship between the average cantonal income and the average cantonal years of schooling seems to be a direct one, in the sense that individuals have on average more years of schooling in the rich cantons, in comparison with the poor cantons. From another point of view, the data exhibit a large dispersion thus indicating a large regional heterogeneity at the cantonal level. The analysis also indicates the presence of a small group of outliers, but this aspect is widely explained in the literature on regional convergence in Ecuador (e.g. Mendieta Munoz, 2015).

In Figure no. 8 below, the spatial representation of schooling performance across the Ecuadorian cantons suggests, once again, the high heterogeneity with the education attainments within Ecuador. Only few cantons have higher average rates of schooling performance, while the majority have rather lower rates. However, the most important finding that can be derived from Figure no. 8 is that there is also a large spatial heterogeneity, in the sense that neighbouring cantons do not share the same patterns with regard to the average number of schooling years. This suggests that the spatial econometric techniques are not appropriate to allow capturing the regional peculiarities of the Ecuadorian economy.

It is interesting to note that the Amazonian cantons have relative higher levels of average education attainments than expected. This is because the petroleum sector is mostly concentrated into the Amazon area, so that a lot of engineers are located here.



Note: 206 cantons in 2015
Source: Data are taken from the ENEMDU data provided by INEC (2015)
Figure no. 8 – The map of performance in terms of number of schooling years across cantons

The output from a number of four random intercept- and random slope models are examined in comparison with the output provided by the OLS estimator, when a set of variables are used to explain the labour income. The working dataset is composed of individual level data and cantonal level data. Given the hierarchical structure of our dataset, as explained in the previous section, the multilevel models represent the econometric techniques applied here, and whose results are reported in Table no. 3.

3.2 Quantitative analysis and discussion

The random intercept model (RI) is applied on two different sets on data (models 2 and 3), while the random slope model (RS) is used with and without cantonal level variables (models 4 and 5 respectively). The OLS model (model 1) is only used here for comparative purposes. The individual level variables in the field of education are: number of years of education (*years education*) and three interaction variables about the educational achievements (i.e. *Prim. ed. * y. educ., Sec. Ed. * y. educ., and Tert. ed. * y. educ.*). The continuous variable about the work experience (Work exp.) and the dummy variable named “Emp. in priv sector” give insights to the participation on the labour market. A number of 8 dummy variables are used here to examine the impact of gender and race on the labour income (*Men, Black, Afro-Ecu, Mulatto, Montubio, Mestizo, White* and *Other race*). Other dummy variables identify the individuals’ employment into different economic sectors: the primary sector including mining and quarries (Primary: *Mining*), the secondary sector including the industry, manufacturing, construction and trade (Secondary: *Industry*), and the tertiary sector which is formed of three different components. The first component includes the activities specific to services, health and hotels (Tertiary: *Services*); the second component delimitates the financial intermediation activities (Tertiary: *Fin.interm.*), and the third component groups together public administration and education (Tertiary: *Pub.adm.-educ.*).

When comparing the OLS simple regression model and the random intercept model (models 1 and 2) we get close results. As expected, the OLS overestimates the regression coefficients, which is very obvious in the case of variables “Years education” and “Work exp”. Ignoring the interclass correlations (i.e. between individuals which belong to the same canton) therefore lead to wrong overestimated random effects. Each additional year of schooling determines for every level of education a different return to education. The RS Models (4-5) provide in general lower estimates than the RI models (2-3) because the variance of data is explained by more variables.

In 2015 each additional year of education is found to increase the returns to education by almost 6% in the most complex specifications (models 3-5). This finding is in line with other empirical results in the literature, such as Devereux Devereux and Hart (2010) and Grenet (2009). However we notice that from 2005 to 2015 there was a decrease of 1.5 pp. in the returns to each year of additional schooling (see Annex 3), that may suggests the effect of saturation sent by the labour market.

When interacting the number of years of schooling with the level of education, we get that in 2005, as well as in 2015, the returns to education increase with each level of education. According to our results, in 2015 the hourly incomes of postgraduates were 1.2% higher than the returns to tertiary education, 2.6% higher than the returns to secondary education, and 3% higher than the returns to primary education. In comparison with 2005, in 2015 the premium income earned by postgraduates in comparison with graduates has slightly increased by 2pp, maybe because of the overall need for highly qualified employees (e.g. Ph.D. holders).

Table no. 3 – Multilevel models explaining the determinants of labour income

Variables	2015				
	Models 1 (OLS)	Model 2 (RI)	Model 3 (RI)	Model 4 (RS)	Model 5 (RS)
Fixed effects					
Years education	0.0922***	0.0863***	0.0564***	0.0563***	0.0511***
Prim. ed. * y educ.	-0.0380***	-0.0384***	-0.0300***	-0.0298***	-0.0284***
Sec. ed. * y educ.	-0.0327***	-0.0327***	-0.0266***	-0.0265***	-0.0255***
Tert. ed. * y educ.	-0.0136***	-0.0138***	-0.0124***	-0.0124***	-0.0123***
Work exp	0.0214***	0.0205***	0.0168***	0.0167***	0.0166***
Work exp^2	-0.00034***	-0.00033***	-0.00029***	-0.00029***	-0.00028***
Men			0.271***	0.271***	0.268***
Primary: Mining			0.617***	0.606***	0.605***
Secondary: Industry			0.245***	0.240***	0.248***
Tertiary: Services			0.305***	0.299***	0.304***
Tertiary: Fin.interm			0.701***	0.695***	0.691***
Tertiary: Pub. adm.-educ.			0.312***	0.306***	0.311***
Emp. in priv sector			-0.572***	-0.570***	-0.567***
Afro-Ecu.			0.159***	0.156***	0.144***
Black			0.187***	0.184***	0.171***
Mulatto			0.172***	0.170***	0.156***
Montubio			0.228***	0.233***	0.211***
Mestizo			0.226***	0.225***	0.212***
White			0.288***	0.286***	0.271***
Other race			0.279	0.279	0.258
Av. cant. inc. (log)				0.678***	0.686***
Av. cant. years ed.				-0.0610***	-0.0529***
Constant	-0.154***	-0.132***	0.110***	-3.382***	-3.455***
Random effects					
var(Res)	0,60859	0,57811	0,50940	0,50946	0,50559
var(cons)		0,05622	0,04556	0,01476	0,07396
var(ed)					0,00029
Cov. (ed_cons)					-0,00448
VPC		**9,73%**	**8,94%**	**2,90%**	**12,81%**
Obs.	41180	41180	41180	41180	41180
Log lik.	-48206.6	-47392.0	-44779.5	-44692.5	-44598.8

*Notes. (1) Dependent variable: hourly labor income (logarithm); (2) * p<0.1, ** p<0.05, *** p<0.01, (3) Reference categories: postgraduate*years of education; women; agriculture, livestock and fishing, public employment, indigenous, (4) OLS – Ordinary Least Squares, RI – Random Intercept model, RS – Random Slope model. (5) The log likelihood tests indicate that it is worth introducing more parameters with each model, from model 1 to model 5.*

The work experience increases the returns to education, so that one additional year of work experience increases the hourly income by 1.66%-1.68% (models 3-5) in 2015, which is lower than in 2005, when it ranges between 2.13%-2.16%. When being raised to power two, the variable work experience gives insights into the marginal effects. Under all specifications and models the coefficient is negative, which indicates that the work experience has decreasing marginal effect.

The gender pay gap increases from 2005, when men had hourly incomes by 21%-21.5% higher than women, to 2015, when men' incomes were by 26.8%-27.1% higher than women' incomes. The results are in line with other empirical findings. Rivera Vásquez (2015) finds that the gender pay gap was 12% and that it is decreasing over time. Cóndor Pumisacho (2010) finds that the gender pay gap is 21%.

The output from the multilevel regression analysis also suggests the existence of large racial pay gaps. The most disadvantaged ethnical group is represented by the indigenous people who get hourly incomes which are by 27%-28% lower than the white population incomes, 21%-22% lower than the Montubio and Mestizo population incomes, 17%-18% lower than the Black population incomes, 15%-17% lower than Mulatto incomes, and 14%-16% lower in comparison with the Afro-Ecuadorian population.

A very surprising empirical finding regards the returns to education for employees in the public *versus* private sector. In 2015 the returns to education in the public sector are with 56-57% higher than in the private sector. This represents a large increase from 2005, when the returns to education in the public sector were 37%-38% higher than in the private sector. In past years, the high remuneration of people working in the state sector is supported by the government revenue from petroleum export. However, the concentration of high returns to education in the state sector is not in line with the principles of a free market economy where they should go hand in hand with the work productivity and should therefore be specific to the private sector.

When analysing the returns to education upon economic sectors, we find that in 2005 and 2015 the highest returns were first in financial intermediaries (tertiary sector) and second in mining and quarries (primary sector), while the lowest returns were in agriculture, fishery and forestry, followed by the secondary sector (industry, manufacturing, construction and trade).

In the RS model, whose results are reported in models 4 and 5, a random slope is introduced for the variable "Years education". By this specification we assume that the effect of the number of schooling years on the hourly income is different across cantons. This assumption is required by the large regional economic heterogeneity and also by the heterogeneous returns to education indicated by the descriptive analysis conducted in the previous section. The estimates provided by models 3 (RI) and 4 (RS) are very similar. The supplementary empirical evidence brought by models (4) and (5) is that the returns to education are likely to be higher in cantons where the average income is higher and the average years of schooling is lower. This finding is in line with our expectations because (1) rich cantons provide better opportunities on the labour market, and (2) educated employees are generally better remunerated where the competition among employees on the labour market is rather low.

The random effects reported in the second part of Table no. 3 allow determining the variance partition coefficient (VPC), which is the percentage variance explained by the higher level (canton). In 2005 as well as in 2015, a percentage of 8-12% of the variance in individuals' hourly incomes can be attributed to differences between cantons. The between-canton (Level 2) variance in hourly income is estimated as 5%-8%, and the within-cantons between-individuals (Level 1) variance is estimated as 50%-60%.

4. CONCLUSIONS

This paper was aimed to examine the returns to education in Ecuador using the multilevel analysis, which allows here capturing the regional economic heterogeneity through a two level- approach: individuals at Level 1, and cantons at Level 2.

The descriptive analysis, as well as the quantitative approach, has revealed a series of conclusions that will be summarized as follows. First, the higher the level of education, the higher the rate of return to education. In 2015 each additional year of education is found to increase the returns to education by almost 6% and more specifically, the hourly incomes of postgraduates are 1.2% higher than the returns to tertiary education, 2.6% higher than the returns to secondary education, and 3% higher than the returns to primary education. In general, the returns to education are found to be higher for each additional year of schooling, so that education could be seen as one of the most effective policy measures against poverty and income inequality.

A number of control variables are included in most econometric models, such as ethnical groups, gender, economic sectors and type of employment (public *versus* private). When controlling for a larger number of control variables, the rates of return to education are found to be in line with the literature (e.g. C. Harmon *et al.*, 2000, C. P. Harmon *et al.*, 2003).

The highest remunerations are in financial intermediation and in activities specific to the primary sector (mining and quarrying), while the lowest are in agriculture, livestock, fishing and hunting. The gender pay gap and race pay gap are important forms of discrimination on the Ecuadorian labour market. The highest incomes (especially for graduates and postgraduates) are provided by the state sector, which could be seen as surprising and in contrast to experiences of advanced economies.

The introduction of canton-level explanatory variables allows finding that higher individual hourly incomes are more likely to be obtained in richer cantons and also in cantons where the average number of schooling years is rather low.

According to the random effects output and following the most complex specification, a percentage of 12% of the variance in individuals' hourly incomes is found to be determined by differences between cantons.

In conclusion, the multilevel approach allows determining and also analysing the returns to education when they are strongly influenced by regional specific characteristics. With multilevel models, one can also examine the impact of cantonal characteristics on the individual level- dependent variable, as well as including both the individual level- and cantonal level – explanatory variables. Moreover, the multilevel analysis allows dealing with the interclass correlations (i.e. the between-individuals within-cantons correlations) which could be important when the regional peculiarities are also important, as it is the Ecuador's case.

The implications of empirical results for policy makers are threefold. First, the national authorities must continue implementing effective education policies to ensure the free access to education and to also encourage people staying more years in education. Second, anti-discrimination policies must be designed by governments as to eliminate the gender and race pay gaps, and to therefore ensure equal conditions on the labour market for all citizens. Third, the process of regional economic convergence must continue and to finally determine the elimination of the regional economic heterogeneity that carries a negative impact on the regional dispersion of the returns to education as well.

References

Barro, R. J., and Lee, J.-W., 2010. A New Data Set of Educational Attainment in the World, 1950-2010. *National Bureau of Economic Research Working Paper Series, 15902*(april), 1-47. doi: http://dx.doi.org/10.3386/w15902

Barro, R. J., and Lee, J. W., 2013. A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics, 104*, 184-198. doi: http://dx.doi.org/10.1016/j.jdeveco.2012.10.001

Becker, G., 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. New York: Columbia University Press.

Biddle, J. E., and Hamermesh, D. S., 1998. Beauty, Productivity and Discrimination: Lawyers' Looks and Lucre. *Journal of Labor Economics, 16*(1), 172-201. doi: http://dx.doi.org/10.1086/209886

Card, D., 1999. The causal effect of education on earnings. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3 (A), pp. 1801-1863): Elsevier.

Cóndor Pumisacho, J. E., 2010. *Discriminacion salarial en el mercado laboral por etnia.* (Maestría), FLACSO Ecuador, FLACSO Sede Ecuador. Retrieved from http://hdl.handle.net/10469/3248

Devereux, P. J., and Hart, R. A., 2010. Forced to be rich? Returns to compulsory schooling in Britain. *Economic Journal, 120*(549), 1345-1364. doi: http://dx.doi.org/10.1111/j.1468-0297.2010.02365.x

Goldstein, H., 1995. *Multilevel statistical models*. London: Edward Arnold.

Goux, D., and Maurin, E., 1999. Persistence of interindustry wage differentials: A reexamination on matched worker-firm panel data. *Journal of Labor Economics, 17*(3), 492-533. doi: http://dx.doi.org/10.1086/209929

Grenet, J., 2009. *Is It Enough to Increase Compulsory Education to Raise Earnings? Evidence from French and British Compulsory Schooling Laws. Mimeo*. London: Centre for Economic Performance, London School of Economics.

Griliches, Z., 1977. Estimating the Returns to Schooling: Some Econometric Problems. *Econometrica, 45*(1), 1-22. doi: http://dx.doi.org/10.2307/1913285

Harmon, C., Oosterbeek, H., and Walker, I., 2000. The Returns to Education. A Review of Evidence, Issues and Deficiencies in the Literature *LSE Centre for the Economics of Education, Discussion Paper no. 0005*, 51. http://cee.lse.ac.uk/ceedps/ceedp05.pdf

Harmon, C. P., Hogan, V., and Walker, I., 2003. Dispersion in the economic return to schooling. *Labour Economics, 10*(2), 205-214. doi: http://dx.doi.org/10.1016/S0927-5371(03)00003-4

Heckman, J. J., Lochner, L., and Todd, P., 2003. Fifty Years of Mincer Earnings Regressions. *National Bureau of Economic Research Working Paper Series, 9732*(may), 71. doi: http://dx.doi.org/10.3386/w9732

Hopenhayn, M., 2011. *Education, life-cycle and mobility: A Latin American perspective*. Paper presented at the Expert Group Meeting on Adolescents, Youth and Development on 21st and 22nd July, 2011, New York.

INEC, 2015. Encuesta Nacional de Empleo, Desempleo y Subempleo Urbano (ENEMDU) 2000-2015. from http://www.ecuadorencifras.gob.ec/

Mendieta Munoz, R., 2015. La hipotesis de la convergencia condicional en Ecuador. Un analisis a nivel cantonal. *Revista Retos, 9*(1), 13-25.

Mincer, J., 1974. *Schooling, Experience and Earnings*. New York: Columbia University Press.

Mincer, J., and Higuchi, Y., 1988. Wage structures and labor turnover in the United States and Japan. *Journal of the Japanese and International Economies, 2*(2), 97-133. doi: http://dx.doi.org/10.1016/0889-1583(88)90017-2

Naderi, A., and Mace, J., 2003. Education and earnings: A multilevel analysis. A case study of the manufacturing sector in Iran. *Economics of Education Review, 22*(2), 143-156. doi: http://dx.doi.org/10.1016/S0272-7757(02)00026-2

Palade, A., and Bratucu, G., 2016. Considerations on the European higher education area. *Journal of Smart Economic Growth, 1*(1), 97-105.

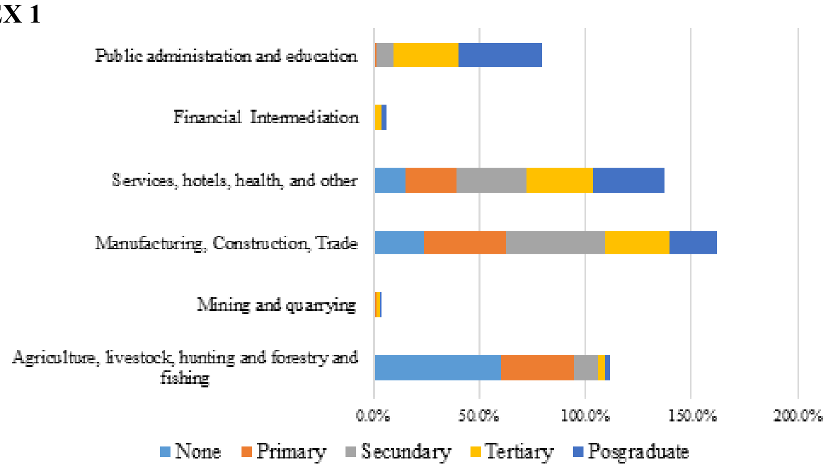
Preston, A., 1997. Where are we now with human capital in Australia? *The Economic Record, 73*(220), 51-78. doi: http://dx.doi.org/10.1111/j.1475-4932.1997.tb00979.x

Psacharopoulos, G., 1979. On the weak versus the strong version of the screening hypothesis. *Economics Letters, 4*(2), 181-185. doi: http://dx.doi.org/10.1016/0165-1765(79)90232-5

Rabe-Hesketh, S., and Skrondal, A., 2008. *Multilevel and longitudinal modeling using Stata*. Texas: USA: Stata Press.

Raileanu, M., and Tache, I., 2016. Discussing the role of migration and education in fighting economic vulnerability in South-Eastern Europe. *1*(1), 73-85.
Rivera Vásquez, J. I., 2015. Retornos a la educación en Ecuador: entre brechas salariales y mercados especializados. *Proyectos de Investigación-Informes del Fondo de Investigación*, 1-38. http://hdl.handle.net/10644/4295
Sapelli, C., 2003. Ecuaciones de Mincer y las tasas de retorno a la educación en Chile: 1990-1998. *Documentos de Trabajo Instituto de Economía, 254*. https://repositorio.uc.cl/handle/11534/4836
UNESCO Institute for Statistics, 2013. International Literacy Data 2013. Retrieved 15 March 2015, from www.uis.unesco.org/literacy/Pages/data-release-map-2013.aspx
United Nations Development Programme, 2015. Human Development Report 2015. In United Nations Development Programme (UNDP) (Ed.), *Global Human Development Reports* (pp. 273). New York, USA: UNDP.
Wolpin, K. I., 1977. Education and screening. *The American Economic Review, 67*(5), 949-958.
Zanchi, L., 1998. Interindustry wage differentials in dummy variable models. *Economics Letters, 60*(3), 297-301. doi: http://dx.doi.org/10.1016/S0165-1765(98)00120-7

ANNEX 1



Note: The percentages correspond to the total number of workers
Source: ENEMDU 2015 provided by INEC (2015)
Figure no. A1 – Activity sector of workers by level of education. 2015

ANNEX 2

Table no. A1 – Average hourly labor income by sectors of activity

Sectors of activity	Average hourly labor income
Agriculture, livestock, hunting and forestry and fishing	2.05 $
Mining and quarrying	5.36 $
Manufacturing, Construction, Trade	2.92 $
Services, hotels, health, and other	3.11 $
Financial Intermediation	6.09 $
Public administration and education	5.43 $
Total	3.09 $

Note: Inflation-adjusted values (Base: 2004=100)
Source: ENEMDU 2005-2015 provided by INEC (2015)

ANNEX 3

Table no. A2 – Multilevel models explaining the determinants of labour income

Variables	2005				
	Models 1 (OLS)	Model 2 (RI)	Model 3 (RI)	Model 4 (RS)	Model 5 (RS)
Fixed effects					
Years education	0.0937***	0.0877***	0.0706***	0.0704***	0.0602***
Prim. ed. * y educ.	-0.0319***	-0.0313***	-0.0307***	-0.0305***	-0.0252***
Sec. ed. * y educ.	-0.0235***	-0.0231***	-0.0224***	-0.0223***	-0.0185***
Tert. ed. * y educ.	-0.0118***	-0.0105***	-0.0108***	-0.0109***	-0.00908***
Work exp	0.0255***	0.0253***	0.0216***	0.0215***	0.0213***
Work exp^2	-0.000315***	-0.000304***	-0.000264***	-0.000263***	-0.000259***
Men			0.215***	0.216***	0.210***
Primary: Mining			0.449***	0.439***	0.451***
Secondary: Industry			0.160***	0.155***	0.166***
Tertiary: Services			0.213***	0.208***	0.217***
Tertiary: Fin.interm			0.488***	0.481***	0.465***
Tertiary: Pub. adm.-educ.			0.154***	0.152***	0.171***
Emp. in priv sector			-0.380***	-0.376***	-0.371***
White			0.187***	0.196***	0.163***
Mestizo			0.167***	0.178***	0.145***
Black			0.120**	0.131***	0.108**
Mulato			0.0911*	0.0986*	0.0745
Other race			0.0961	0.110	0.0626
Av. cant. inc. (log)				0.620***	0.658***
Av. cant. years ed.				-0.0694***	-0.0567***
Constant	-1.147***	-1.151***	-1.000***	-3.638***	-3.860***
Random effects					
var(Res)	0,70225	0,66348	0,63766	0,63753	0,63009
var(cons)		0,05726	0,05097	0,02119	0,08430
var(ed)					0,00039
Cov. (ed_cons)					-0,00552
VPC		**8,630%**	**7,994%**	**3,323%**	**11,849%**
Obs.	28675	28675	28675	28675	28675
Log lik.	-35620.2	-35006.0	-34430.8	-34364.0	-34246.5

*Notes. (1) Dependent variable: hourly labor income (logarithm); (2) * p<0.1, **p<0.05, *** p<0.01, (3) Reference categories: postgraduate*years of education; women; agriculture, livestock and fishing, public employment, indigenous, (4) OLS – Ordinary Least Squares, RI – Random Intercept model, RS – Random Slope model. (5) The log likelihood tests indicate that it is worth introducing more parameters with each model, from model 1 to model 5.*

Notes

[1] All multilevel models can be written using two different formulations: (1) by separately writing the Level 1 and level 2 equations, and (2) by integrating both the Level 1 and Level 2 equations into a single equation. In this paper, the presentation of methodology uses the formulation (2) only for the random intercepts and slopes model.

[2] The random-intercept and random-coefficient models are presented into this section following Rabe-Hesketh and Skrondal (2008).

[3] In Ecuador, the primary education includes 10 years of schooling, secondary education is completed within 13 years, while the tertiary education accounts for 18 years of study, and postgraduate studies for 19 years.