



# Education and income distribution. An unconditional quantile approach Ecuador: 2007-2016

Nicolás Mateo Larrea Ávila

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Nicolás Mateo Larrea Ávila. Education and income distribution. An unconditional quantile approach Ecuador: 2007-2016. Humanities and Social Sciences. 2021. dumas-03868471

**HAL Id: dumas-03868471**

**<https://dumas.ccsd.cnrs.fr/dumas-03868471>**

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# Education and Income Distribution

An Unconditional Quantile Approach  
Ecuador: 2007-2016

Présenté par **Nicolás Mateo Larrea Ávila**

Sous la direction de **Vera Chiodi**

Mémoire de **Master 2** mention **Sciences Sociales, Coopération et Développement en Amérique Latine/Latinamerican Studies**.

Parcours-type **Master Erasmus Mundus Latin America and Europe in a Global World (LAGLOBE)**, avec les universités de **Salamanque** et **Stockholm**.

Mémoire présenté le **21 juin 2021** à l'université **Sorbonne Nouvelle**.



## **ACKNOWLEDGMENTS**

I want to thank all the people that were around this research throughout its construction. No work can be accomplished exclusively by one person, on the contrary, it is the result of a continuous interaction among multiple actors that departs from a solid ground of accumulated knowledge, which is simultaneously both social and material.

In this sense, I am pretty thankful I could count on the technical and pedagogical support of Vera Chiodi, the director of my Master Thesis. She was always receptive and open to any question or doubt that might arose.

Likewise, neither this research nor the Master could have come true without the tireless support of my parents and my brother. My family is to whom I owe my personal and professional objectives achieved so far.

From the bottom of my heart, thank you.

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## 1. INTRODUCTION

Since the 1960s the subject of inequality, despite not only national but also international levels, has gradually received unprecedented importance (Atkinson, 2015). Contrary to what most economists as well as academics consider, the debate itself goes beyond pure social justice considerations. In fact, this can only be based on strictly economic efficiency grounds (Amarante et al., 2016; Atkinson, 2015). Among all the possible transmission channels that could effectively worsen income distribution, education has specifically provoked a significant interest in academia insofar as its distributive impact still remains ambiguous (Bourguignon et al., 2005).

Particularly, the Ecuadorian case rises exceptional attention for the period 2007-2016. During this cycle, the country experienced a schooling upgrading never seen before in its history (Legarda, 2016). In this sense, the accrued education public budget compared to the GDP soared considerably from 2.7% to 4.3%. Moreover, the gross fixed capital formation concerning education equaled USD 13.900 million, which meant a 2% of the 2016 GDP (Rueda et al., 2019).

Hence, the main thrust of this master thesis is to analyze the distributive effects of education on labor income as well as the impact of educational levels (basic, primary, secondary, university, etc.) on the different quantiles of the aggregate distribution for Ecuador throughout the decade under analysis.

In other words, whether the educational expansion abovementioned has exacerbated short term inequalities – particularly, benefiting the upper layers of the distribution – or has been decisive in improving the schooling attainment – and therefore, narrowing income revenue gaps – for the poorer.

In the same vein, we will attempt to trespass national boundaries when it comes to describe the peculiar performance of two ethnicities: Indigenous and Afro-American communities. In accordance with the regional context, these subgroups systematically have been subject to higher poverty rates and lower incomes (Aranda & Ratzlaff, 2018). Hence, although they account for small demographic shares, their participation in the lower quantiles of the income distribution largely outweighs their population percentage.

Nevertheless, according to the research previously carried out in this work, the distributive impact of education in the Andean country within this period remains still unraveled. Works like Atuesta et al. (2016) has limited their analysis to the conditional quantiles of income and the way they interact with several occupational categories. In spite of the fact that this research has brought to the table striking results, its scope remains restricted since it does not account for the entire – marginal – distribution. Overall, the current literature on the interaction between schooling and inequality has focused mostly on other countries in the region, namely Argentina and Brazil (Ferreira et al., 2017; Alejo et al., 2014). In the light of this absence of comprehensive studies for Ecuador this research intends to make a contribution to the scientific and academic debate.

Neither the order of magnitude nor the sign of the impact of education on income distribution have been unquestionably accepted in empirical and theoretical grounds. As a matter of fact, despite of what the common sense suggests, an educational enhancement – at least initially – could potentially produce unequalizing effects. In specialized literature, this phenomenon has received the name of “Paradox of Progress” (Bourguignon et al., 2005). Even a homogenously distributed schooling upgrading among the different educational levels could cause a divergence of income gaps between the quantiles of the distribution.

In this respect, a vast literature has been devoted to understand this apparently contradictory issue of heterogenous effects of education. Bourguignon et al. (2005) point out two underlying mechanisms whereby it might occur. On the one hand, the convexification process of the wage profile that ultimately means that labor income is a convex function of years of schooling. An increase of one year of education will rise the wage proportionally more in the upper educational levels than those in the bottom. According to many empirical studies (Battistón et al., 2014; Binelli, 2008, 2015), this dynamic particularly fits the Latin American context whose labor market structure and socioeconomic characteristics are similar across countries.

On the other, labor supply might be negatively affected within a short-term period due to a schooling expansion. The inclusion of a non-negligeable mass of people in the educational system – mostly children and young – causes their temporary departure from the working active life. Thus, households’ income might suffer a considerable reduction since

part of their members is not contributing economically anymore. Needless to say, the poorer are more likely to undergo this monetary shortage. As a consequence, income differentials among households across the entire distribution could widen. Given its features, educational investments would yield higher returns for oncoming generations.

However, taking into account the complexity of the subject due to its social character, the work estimates that this relationship varies mainly according to the previous distribution of education and the way the market rewards individuals' socioeconomic attributes. In fact, we believe that the former – educational endowments allocation – is the key factor that ultimately models the labor market reward structure. In other words, *a priori* there is not necessarily an unequal schooling impact on the distribution. Moreover, we believe the government could account for an enormous role within the dynamic abovementioned.

Furthermore, inasmuch as this dynamic involves, to a large extent, an unresolved problem, a significant number of works have attempted to measure not only the correlation but also de causation between these two variables. Since the seminal article of Firpo *et al.* (2009) a novel methodology was implemented in the distributive field of economy. The Recentered Influence Function (RIF) enables to isolate the distributive impact of a particular covariate on a statistic of interest. Building upon this methodological framework the research will gauge the influence of education – measured both by years of schooling and educational level attained – on two statistical of interest: the unconditional quantiles of the distribution and the Gini coefficient. The idea is to disentangle the distributive impact across the quantiles in order to capture the heterogeneous effects of this variable on the entire (marginal) distribution of labor income. A comparative analysis will ease a better understanding of the changes in educational returns during the period under analysis given the complexities of the Ecuadorian labor market.

The estimations carried out in this work suggest that education played an important role when determining the income distribution in the Andean country. The variable “Years of Schooling” has a heterogeneous and increasing effect on monetary returns along the quantiles. This implies that, considering a marginal shift of education to the right, it will be the upper layers of the distribution who would benefit the most. Notwithstanding, throughout the period, this effect has considerably weakened showing a reconfiguration of the labor



market rewards in favor of the poorest. This movement was even more profound for the two ethnic groups considered in this work.

When taking into account educational levels, in line with previous works (Gasparini *et al.*, 2013), primary education showed a pro-poor bias widening its magnitude along the period. On the other hand, unlike what is commonly stated in literature, we find that although higher education had a regressive effect at the beginning of the decade, its impact was reverted, or at least substantially reduced, for the last year under analysis. In a way, this might be indicating that the effect of education is far from being unchangeable and homogeneous. It depends mostly on the context and the policies envisaged, their scope, target, and length.

Finally, it is worth to point out that this research was inspired by a previous project undertaken in 2017<sup>1</sup>, within the framework of a research fellowship at University of Buenos Aires<sup>2</sup>. We analyzed the educational impact on income distribution for the Argentinean case in the past three decades (1992-2015). Through the use of RIF methodology we studied the unconditional quantiles leading to enriching results. By and large, given its distributive effects, an educational expansion proved to be a desirable policy for social welfare alleviating inequalities.

In the same vein, it is worth to mention that the current research will be presented during the XXIX Annual Conference of the International Association for Feminist Economics (IAFFE) “Sustaining Life: Challenges of Multidimensional Crises”<sup>3</sup>.

The rest of the thesis is organized following the next structure. Chapter 2 addresses the debate between education expenditure and economic development from a theoretical point of view. This in turn allows us to introduce the stylized facts of the Ecuadorian case throughout the period in what concerns public intervention, and therefore the educational expansion. Accordingly, Chapter 3 presents the discussion of the underlying forces behind the heterogeneous effects of education upon income distribution. We depart from the cornerstone conception of the Economics of Education, Human Capital theory, and then move forward towards the vast group of empirical works that built upon this framework.

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<sup>1</sup> Larrea & Fabris (2017).

<sup>2</sup> UBACyT 2017 scholarship.

<sup>3</sup> The event will be held virtually on June the 22<sup>nd</sup> -25<sup>th</sup> 2021.

Moreover, Chapter 4 summarizes the empirical strategy used in the research as well as the most meaningful characteristics of the methodological tools specifically employed in the estimations. Chapter 5 presents the main results of the model assessment for both the national average and the ethnic groups. Chapter 6 exposes the limitation of the empirical approach highlighting possible research paths that open up from this work. Finally, Chapter 7 concludes with the most relevant facts attempting to contribute to a more comprehensive knowledge of this complex socioeconomic phenomenon.

## **2. BACKGROUND**

The main interest of this chapter is to briefly discuss in theoretical terms the impact of education on economic development and the channels whereby the former affects the latter. In order to carry out this analysis, we will focus on public spending in education as a proxy of the process of Human Capital accumulation and educational attainment. Beyond a fiscal approach, which is outside the scope of the study, we seek to understand the potential effects of these instrumental policies as well as the different empirical perspectives that support or cast doubt on it.

Thereafter, we will analyze and illustrate the performance of public spending on education in one country within the Latin American region: Ecuador. In this respect, the period under analysis (2007-2016) is of utmost relevance because it meant a turning point in terms of social spending and investment compared to the previous decades.

### **2.1. Education Expenditure and Economic Development**

The impact of public expenditure on economic growth and development has been a controversial point in specialized literature. Over time, rather than a widespread consensus we have witnessed a divergence of approaches essentially due to the variety of both results and conclusions (Nyasha & Odhiambo, 2019). Likewise, although less cumbersome, education expenditure has given rise to a somewhat large debate concerning the extent, the focalization, and the length of schooling programs, scholarships, and infrastructure investment. In the same vein, whether or not these policies could effectively cause a positive impact on the micro and macro levels has inspired an intense discussion as well.

In this sense, the theoretical departure point that gave birth a blooming of works centered on the causal relation between education and economic development emerged during 1960 with a new field of study. The Economics of Education<sup>4</sup> drew on Human Capital theory, first dubbed by Shultz in his seminal work “Investment in Human Capital”, to elucidate a plausible explanation about the channels through which education could

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<sup>4</sup> Probably a comprehensive definition of this field of economics is the one coined out by a classical book of Cohen & Geske (1990): “The economics of education is the study of how men and society choose, with or without necessity use of money, use scarce productive resources to produce various types of training, the development of knowledge, skills, character, etc. – especially through formal education – over time to be distributed among the different people and groups in the society”.

positively affect several sets of economic indicators. The focus shifted hereinafter to the conception of individuals as capital, and education as a particular sort of investment (Sevilla, 2004) because it involves a sacrifice of current earnings towards a higher profile afterwards (Bils & Klenow, 2000).

The first channel, more years of schooling will be associated with higher returns of individual earnings (Hanushek & Woessmann, 2008) since education increases productivity of the labor factor. This microeconomic dynamic concerning the internal rate of return (Becker, 1964) can be easily scaled up to a bigger dimension insofar as economic growth depends on the total productivity of economic agents. In other words, labor productivity enhancement will be traduced in greater levels of output.

A second channel by which education fosters economic growth is an improvement in the innovative capacity of the economy (Hanushek & Woessmann, 2008). In general terms, counting on more skilled workers will be a suitable scenario where new technologies and knowledge are likely to emerge and diffuse<sup>5</sup>. This virtuous circle is needed in order to properly link the new technologies coming from the innovation system to the productive process in the economy.

Supporting these theoretical explanations, a non negligible group of empirical works have demonstrated a positive relation between schooling and economic growth across different countries (Barro, 1991; Mankiw *et al.*, 1992; Barro and Lee, 1993). In an in-depth study Barro and Sala Martin (2004) find that places with higher real per capita GDP are associated with greater ratios of educational attainment to physical capital.

Notwithstanding, other studies have argued a contradictory or ambiguous effect of Human Capital accumulation on economic growth, such as Hendricks (1999), Brauning and Vidal (1999) or Bouzazah *et al.* (2002) showing that the issue is far from being straightforward. Moreover, the order of causality<sup>6</sup> – whether education impacts on economic growth or vice versa (Bils & Klenow, 2000) –, has given intense discussion among authors. For instance, Chang (2009) and Bils and Klenow (2000) argue that contrary to what is usually stated in the common sense, economic development will enhance education improvement in

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<sup>5</sup> See the endogenous model introduced by Lucas (1988).

<sup>6</sup> See also Morduchowicz (2004).

a country and not the other way around. Despite of these results, by and large, literature has agreed on a positive relation between education and growth (Mallick et al., 2016).

Moreover, a third channel, a broader effect of education – not only on the economic realm but also on the social side and general well-being of society – are the positive externalities generated through schooling gain. Overall, a better educated citizenry means lower crime rate, improvements in children health, a more active civic participation, more informed political decisions, etc. In developing countries, education is associated with lower women fertility rates and higher infants' health (Krueger & Lindahl, 2001). These social spillovers in exchange will strengthen not only the life quality of society as a whole but also democratic institutions.

As a result, supported by the mechanisms abovementioned, governments both in developing and developed countries have a solid justification to endorse public education expenditure<sup>7</sup> (Fagerlind & Saha, 1997). Nevertheless, the policies enacted in the former have lacked both impact and extent in the productive realm and in the economy as a whole. On the one hand, due to structural shortcomings in the science and innovation systems that hamper and dismantle a proper interaction between the production of knowledge and the implementation of new technologies. On the other, because of insufficient developed institutions that hinder the correct implementation of education policies.

Paradoxically, in general terms, during the 1990's, public spending in Latin America underwent a reversal with a sharp decline in its share compared to the GDP (Almeida et al., 2012). More particularly, education spending in the region dropped drastically representing in the beginning of 1990 barely a 1.9% of the GDP (Cetrángolo et al., 2018).

Ecuador was not the exception. Throughout this period the Andean country implemented a set of economic and political reforms known as the structural adjustment whose primary objective was the reduction of social spending, more particularly, the one related to education (Almeida et al., 2012). The limited role of the State, already deteriorated since the 80s mainly due to the debt crisis, deepened as a result of privatizations, fiscal

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<sup>7</sup> “The main public policy implication that arises one of these theoretical approaches is that countries should invest in the development of Human Capital. Policies are recommended that promote broad access to skills and, especially, the ability to learn” (Morduchowicz, 2004).

adjustments (through tax reforms but also spending austerity) and financial and monetary deregulations. Consequently, the period 1982-2006 is called by many authors as the “neoliberal historic cycle”<sup>8</sup>.

## **2.2. Public Intervention on Economy: Ecuador (2007-2016)**

The year 2007 meant a breaking point in terms of policies, institutions, and conceptions about what was the role of the public apparatus. The latter gained in relevance as a crucial economic actor. A brand-new political party seized power in this year. Thus, the new elected authority, led by the economist Rafael Correa, sought to recover the policy instruments and institutions that were defunded during the previous period. This realignment of the structures of the State pursued three main urgent goals: poverty eradication, fighting against inequality and environment protection (Benito Gil, 2017). Furthermore, the institutional framework that shaped the design and enforcement of public policies, and more particularly, the way through which these elements should influence the qualitative conditions of the citizens, was the “Sumak Kawsay”<sup>9</sup>; a complex, thorough, and ancient concept, whose origins are related to the Andean indigenous<sup>10</sup>. Good Living, thus, emphasizes values such as reciprocity, solidarity, and harmony with nature, which in turn rejects consumption and material accumulation. In the same vein, to a large extent, what really matters is the community as a whole. This philosophy does not rely on the individual as the ultimately social unit. Consequently, since the community is the relevant level of mediation in society, it is crucial to acknowledge and describe how this unit models the experiences of everyone. This shift, albeit apparently subtle, dramatically changes the conception of how a society behaves and, moreover, the way in which its members interact with each other.

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<sup>8</sup> One of the main characteristics anchored in this term is the aim to reduce the political action through delegitimizing the public realm (Minteguaga, 2014).

<sup>9</sup> In Spanish: “el Buen Vivir” (Good living). “It is an ancestral Andean conception of life that has remained in force in many indigenous communities until today. Sumak means the ideal, the beautiful, the good, the realization; and kawsay is life, referring to a dignified life, in harmony and balance with the universe and the human being, in synthesis the sumak kawsay means the fullness of life” (Briones, 2012).

<sup>10</sup> It is worth noticing that similar categories can be appreciated throughout almost all the pre-Hispanic cultures in Latin America as the “suma qumaña” of the Aymara, the “ñandareko” of the Guaraní, the “shiir waras” of the Shuar, and the “kume mongen” of the Mapuche, among others” (Kucic-Riker, 2015).

The new Constitution of 2008 embodied these principles in the legal body of the country, which in turn meant to a certain extent the deepening of the cleavage with the previous period.

Simultaneously, the relevance of planification in a long-term framework, taking into account strategic sectors intended to develop the country, took enormous importance. In effect, two tools were constructed in order to align economically and socially the common interest of the country in the medium and long term. On the one hand, the National Plan for Development (2007-2010), and the Well-being National Plan both in its first (2009-2013) and second version (2013-2017), on the other. Both Plans encompassed the strategies and goals set regarding the socioeconomic transformation of Ecuador that met with the standards and principles mentioned in the Constitution. Following Kucic-Riker (2015), the objectives tied to Good Living and their consequent implications could be synthesized in these basic guidelines: political inclusivity, society-nature relations, and economic pluralism. Finally, it is worth noticing that during this period the three emblematic sectors concerning public expenditure were education, health, and infrastructure (Benito Gil, 2017).

For the government, education would be a key pillar with a two-side virtuous effect. First, enhancing schooling – throughout all its educational levels; the first stage in the learning process with the “Wawas Centros”, the basic education in school and high school with the “Escuelas del Milenio”, and the higher education with the construction of four emblematic public universities<sup>11</sup>–, would ease the country the transition from a primary extractivist economy based essentially on oil exports to a knowledge-based one whose motor would be Human Capital accumulation and the increasing production of more value-added. The so-called change in the energy matrix, one of the flagships of the administration, was underpinned by the transition above-mentioned. Second, education policies were conceived as instrumental vehicles for the achievement of a cultural break aligned with the principles of Sumak Kawsay. Consequently, improving the life quality conditions of society.

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<sup>11</sup> Yachay (scientific and technological university placed in Imbabura), Ikiam (university focused on research on biodiversity placed in Tena) Universidad de las Artes (artistic university situated in Guayaquil) and Universidad Nacional de Educación – UNAE (teaching training university placed in Azogues).

The implementation and assignment of public investment was backed up by a massive amount of economic resources coming from a reframing of public income (tax and oil revenues) which originally were preassigned and financed inflexible spending (mostly external debt).

According to Almeida et al. (2012), within the fiscal sector, there were two meaningful sources. On the one hand, a tax reform<sup>12</sup> that ultimately shifted a non negligible amount of money to the central government budget. On the other, a more profitable distribution of oil income thanks to the approval of a law reform<sup>13</sup> intended to guarantee public property rights over this commodity and facilitate the renegotiation of oil contracts. This in fact overturned the percentage received from the government and the oil companies. For instance, due to a successful process, the Ecuadorian government gained USD 4.153 million between 2011-2014 (SENPLADES, 2017).

Likewise, concerning the external sector, the economic relief in the Balance of Payments as a result of the renegotiation of the external debt<sup>14</sup> allowed a reallocation of resources towards social spending. Thus, the balance of external public debt between 2007 and 2011 was reduced by 8.12% (Almeida et al., 2012). It is worth pointing out, however, that from 2008, the public expenditure underwent a compositional change; the accounts and interest payments of the external debt reduced their share to 22% and 3%, respectively (Carrillo, 2017).

On the other hand, thanks to a rather favorable international context – the so-called commodities boom –, and a set of political decisions that spurred these external resources into the domestic economy, the country experienced a significant growth in the period 2007-2014 showing a 4.4% increase in real terms of GDP followed, however, by a drop in economic activity in 2015 (García-Álvarez, 2019). Then, there was a weak recovery during 2016 which subsequently allowed a new economic take-off in 2017 (García-Álvarez, 2019).

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<sup>12</sup> “Ley de Equidad Tributaria” (December 29th, 2007) and “Ley de Recuperación del Uso Público de los Recursos Petroleros y Racionalización Administrativa de los Procesos de Endeudamiento” (April 2<sup>nd</sup>, 2008).

<sup>13</sup> “Ley de Hidrocarburos y Renegociación de Contratos Petroleros” (2010).

<sup>14</sup> The strategy applied by the Ecuadorian government was completed with an offer to purchase these bonds at 30% of their nominal value, made in April 2009 using the modified Dutch auction methodology (BCE, 2010).

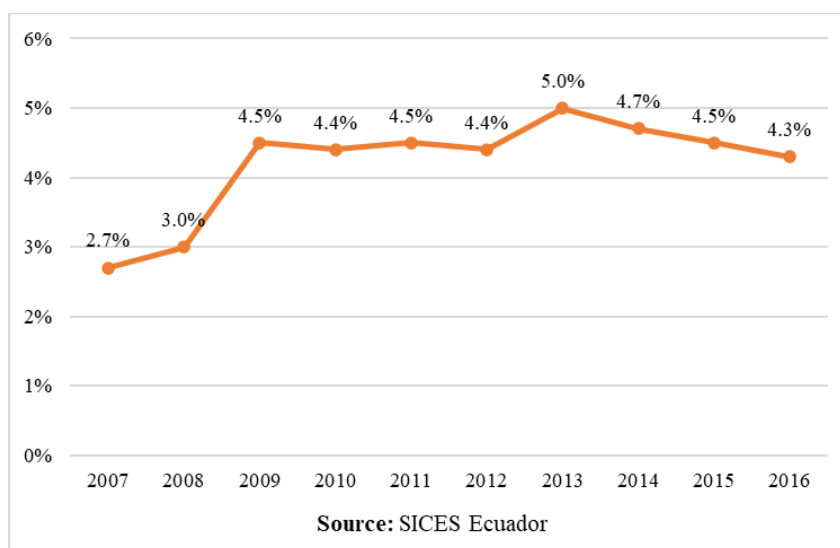


### 2.2.1. Schooling and Inequalities

All the factors above-mentioned advocated for a more visible presence of the State as an economic actor which triggered a widening of social spending, in particular those of health, education, and social inclusion (Legarda, 2016). Thus, social spending per capita increased between 2007 and 2010 by around 20% rising from USD 261 to USD 314 (CEPAL, 2012). Likewise, with regard to social investment in the period 2006-2012, within the institutional framework of the Presupuesto General del Estado (General State Budget), the sectors of health, education and social welfare were those that have experienced a major increase with a growth rate of 6% (Legarda, 2016).

More specifically, the accrued education public budget compared to the GDP soared considerably from 2.7% in 2007 to 4.3% in 2016. Nonetheless, this rising curve is representative of the average in the Latin American region whose percentage reached 4.35% of the GDP in 2015 (Cetrángolo *et al.*, 2018).

**Figure 1 - Accrued education public budget (%GDP)**

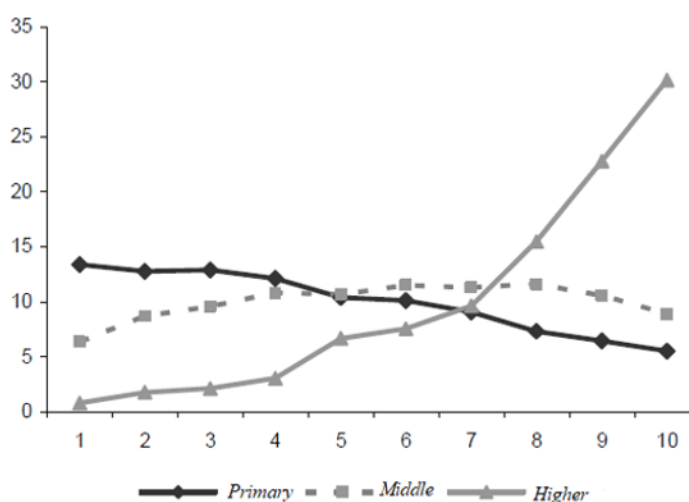


Consequently, the State took hold on its role as major economic actor within the educational boundaries. The economic activities related to teaching were funded mostly by public sources. The percentage moved from 63.09% in 2007 to 68.13% in 2017. On the other hand, the gross fixed capital formation in education (essentially infrastructure; schools, universities, etc.) compared to the GDP showed a stagnation from tail to tail during the period

2007-2016 (0.5%). However, in global terms this allocation of resources during the period under analysis equaled USD 13.900 million or 2% of the 2016 GDP (Rueda et al., 2019). In the same vein, when evaluating the compositional change, that is, the relation between the public and private sectors, it is worth mentioning that the share of central government witnessed an increase of 80% moving from USD 163 million to USD 292 million (INEC, 2019).

Before disentangling the expenditure by educational level, it is worthy to analyze the distribution of public-school attendance by deciles of per capita income at the beginning of the period in question (2006). This clearly shows the picture of the uneven educational endowment distribution witnessed by the Andean country. Thus, highlighting the potential impact of each educational level according to the different deciles of the distribution.

**Figure 2 - Distribution of Public-School Attendance by deciles of per capita income - Ecuador 2006**



Source: Gasparini, Cicowiez, & Sosa Escudero (2013)

As for the whole Latin American region, primary education in Ecuador is pro-poor (Gasparini et al., 2013) with a higher weight in lower income households. Moreover, whereas middle education stands for an inverted “U-shape”<sup>15</sup> concentrating middle income households – therefore, bearing an ambiguous effect on the income distribution –, higher education is pro-rich given the considerable absence of young people from low and middle

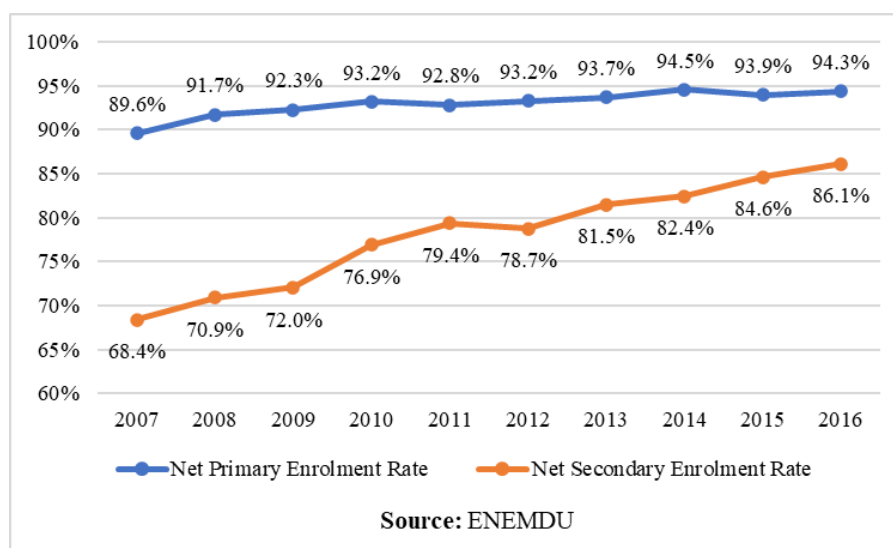
<sup>15</sup> Since students of lower income households tend not to attend to secondary school and those of upper income households assist mostly to private system.

socioeconomic strata at that level. Such contextualization emphasizes the relevance of the schooling expenditure composition by level of education when it comes to assess the focalization and impact of public intervention.

In this respect, in Ecuador, the final public expenditure per student<sup>16</sup> in the primary level more than doubled from USD 406 in 2007 to USD 940 in 2016. Unlike the latter, within the secondary, the amount remained approximately the same moving from USD 493 per student to USD 501. Notwithstanding, higher education stood for the best performance where the public expenditure passed from USD 1.402 to USD 3.045 (INEC, 2019). Thus, the ratio private/public expenditure in this level decreased from 1.6 to 1.2 endorsing the increasing role of the government in this particular subsector.

Furthermore, we can witness a somewhat similar performance from the demand side within the public education system. In this respect, it is handy to analyze the enrolment rate across educational levels. First of all, the net enrolment rate in the primary school<sup>17</sup> increased from 89.6% in 2007 to 94.3% in 2016. Concerning secondary school, the change was relatively higher from 68.4% to 86.1% respectively.

**Figure 3 - Net Enrolment Rate 2007-2016**

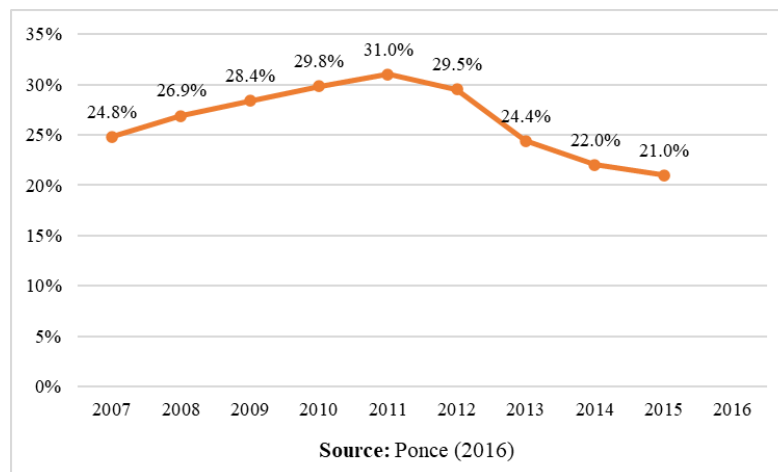


<sup>16</sup> Approximately the educational system, both private and public and in every level, accounted for 5.401.370 students (INEC, 2019).

<sup>17</sup> The ratio: (Population aged 6 to 11 years enrolled in primary school education / Total population aged 6 to 11) \*100. The same applies for the rest of educational levels.

University education describes a more complex performance. If we take the gross enrolment rate<sup>18</sup> for the period under analysis the variable shows a hump-like curve. More precisely, since the year 2008, the line increased progressively until it reached a maximum in 2011-2012. This coincides with the gratuity in the university public system established just two years after the take-over of the new government. However, after the turning point a downwards curve clearly appeared until the year 2016. According to Ponce (2016) this can be fully explained not only by the implementation of the national entrance exam<sup>19</sup> but also because in this moment a generalized depuration processed was carried out closing low level private universities along the country. In other words, at the same time that the entry requirements partially hampered the incorporation of new students, the supply side was reduced.

**Figure 4 - Gross University Enrolment Rate**



On the other hand, inequalities stand for a clear overall declining trend throughout the same period. In effect, after experiencing an increase in income distribution measured by the Gini coefficient over the years 1995 and 2007<sup>20</sup> (Moscoso, 2017), the country witnessed a gradual decrease in this coefficient, whose departure point in 2007 was 0.55, reaching the value of 0.46 in 2016 (ENEMDU, 2018). At the same time, national poverty in the country<sup>21</sup> fell sharply from 36.7% in 2007 to 22.9% in 2016 (INEC, 2017). Also, extreme poverty

<sup>18</sup> The ratio: (Population that enrolled in higher education classes / Total population between 18 and 24 years of age) \*100

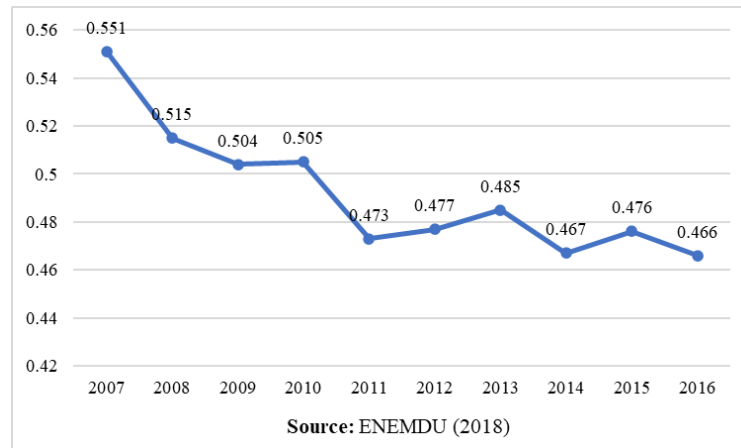
<sup>19</sup> “Examen Nacional de Educación Superior” (ENES).

<sup>20</sup> At that time, the country was one of the most unequal with a Gini coefficient of 0.54 (Moscoso, 2017).

<sup>21</sup> Composed by urban and rural ones.

showed an equally significant decrease in percentages from 16.5% to 8.7% in the same period.

**Figure 5 - Wage Gini Coefficient in Ecuador 2007-2016**



However, national averages usually hide particular dynamics within the figures. According to its relative economic position in society or its ethnic origin certain groups describe different patterns essentially because public policies affect them asymmetrically. This fact should be taken into account since Ecuador is composed by a variety of ethnic subgroups as a product of the historical syncretism witnessed with special emphasis from the Spanish conquest in the end of XV century. Unraveling these situations will enrich the research as well as provide a clearer vision of a complex phenomenon.

### **2.2.2. Afro-American and Indigenous Groups: a Disadvantaged Situation**

As most of Latin-American countries, the Andean nation has an ethnically diverse demographic matrix. Although the majority of the population is self-identified as mestizo, there are other communities that cohabit within the geographic boundaries. According to the last census carried out in 2010, Indigenous represented 7% while Afro-American accounted for the 7.2% of society. These communities have been historically excluded not only as a result of cultural and racial discriminations but also in what concerns the access to public services such as education (SENESCYT, 2018).

A clear illustrative panorama of the economic situation in the beginning of the period under analysis is the picture of the distribution of society according to their ethnical origins

across the quantiles of the income distribution<sup>22</sup>. Table 1<sup>23</sup> depicts this dynamic. In 2007, while Indigenous and Afro-American were mostly concentrated in the lower socioeconomic layers – with 38.4% and 23.9% in the poorest quantiles, respectively –, Mestizo and in particular White people are evenly distributed among them. The latter in fact tends to accumulate slightly more in the upper quantiles.

**Table 1 - Quintiles & Ethnic Origin**

Year 2007					Year 2016				
Quintiles	Indigenous (%)	Afro-American (%)	Mestizo (%)	White (%)	Quintiles	Indigenou s (%)	Afro-American (%)	Mestizo (%)	White (%)
q1	38.4	23.9	18.5	19.4	q1	40	20.3	18.4	19.4
q2	18.4	24.2	20.2	16.9	q2	20.1	24.9	19.9	14.2
q3	19.7	19.7	20.2	18.6	q3	15.2	19.8	20.4	17.7
q4	16.1	19.2	20.4	18.9	q4	15.1	19.2	20.3	26.2
q5	7.4	12.9	20.8	26.2	q5	9.5	15.7	21	22.5
Total	100	100	100	100	Total	100	100	100	100

**Source:** own elaboration based on ENEMDU.

Notwithstanding, the image does not appear to have changed substantially for the year 2016. Even though we can appreciate a rise in the percentages of people belonging to these excluded subgroups in the top quantiles (q5) – passing in Indigenous from 7.4% in 2007 to 9.5% in 2016, and Afro-American from 12.9% to 15.7% –, the situation down in the bottom seemed not only to stagnate but worsen with especial emphasis in Indigenous people.

In order to disentangle even more these unequal conditions, it is worthy highlighting the particular exposure of children and adolescents in households whose ethnic origin pertained to these subgroups. While in 2006 the percentage of poor children and adolescents in mestizo households was 44.1%, those of indigenous and Afro-American had 70% and 69.2% respectively. By 2016, however, all the numbers had declined maintaining relatively the same distance between them. The percentage of children and adolescents in mestizo households drop to 24.8%, the indigenous ones decreased reaching 59.1%, and finally, the

<sup>22</sup> In distributive topics it is useful to order society within equal parts according to their income. These positional measures placed each observation in an increasing pattern; from the lowest to the greatest. The magnitude of measures differs from quintiles (5 layers) to percentiles (100 layers). In our case, we divide our sample in 5 parts being the first quintile the fraction composed by the observations who earn the lowest income.

<sup>23</sup> Table 1 splits up society along the quantiles of the distribution (first column) according to the ethnic origin (first row). That is the reason why if we sum up all the percentages in each column, we will have the complete share (100%) of a particular ethnic group. For instance, in 2007, of all Indigenous just a 7.4% was situated in the upper quantile of the distribution.

number concerning Afro-American children and adolescents went down until 41.8% (OSE, 2019). The data bolster the disadvantaged situation of these ethnic groups compared to the whole population and highlight the lack of opportunities underwent by them since early stages of live cycle.

Even though net enrolment rates concerning these groups in the different educational levels have shown a substantial improvement during 2007-2016, they continue relying mostly under the national average. For primary education, whereas Indigenous passed from 87.63% in 2007 to 93.74% in 2016, Afro-American moved from 89.54% to 93.99%. In the case of secondary level, despite of a larger distance to the average, the improvement throughout the period is more evident. In fact, for the former, the rate increased from 52.18% in 2007 to 82.32% in 2016, while for the latter the percentage passed from 53.96% to 75.80%<sup>24</sup>.

On the other hand, gross university enrolment rate describes a somewhat shorter increment. The rate concerning Indigenous shifted from 7.5% in 2006 to 9% in 2014 whereas that of Afro-American moved from 14.4% to 17.4% respectively (Ponce & Carrasco, 2016).

To a certain extent, this puts forward the composition effect within education spending which has been targeted to parts of society under less favorable material and social conditions. However, the distributive impact of this educational upgrading is not determined *ex ante*. In this sense, the socioeconomic repercussions of these kind of policies are of utmost importance in order to attempt a somewhat accurate measure of how the well-being of the population has changed over time.

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<sup>24</sup> Ministerio de Educación (MINEDUC). Coordinación General de Planificación (CGP). Dirección Nacional de Análisis e Información Educativa (DNAIE).

### 3. LITERATURE REVIEW

#### 3.1. Roots of Historical Thought on Economics of Education

As mentioned in the previous chapter, in order to understand the interaction between education and income distribution the study will draw on Human Capital theory, and namely, on Economics of Education. There are two particular reasons. First, the econometric models used in this research rely on this view and build upon the ideas elucidated within this framework. And second, education, as is conceived nowadays, owns much more to this theoretical body than we usually believe. Therefore, the work will briefly mention the meaningful points that underpin this economic field.

By and large, according to this standing point, education is thought of as a private investment rather than a mere consumption insofar as it yields a monetary return to the individual. The concept of Human Capital is conceived hereinafter as the accumulation of particular types of investments, mostly measured by schooling years, which in turn increase wages due to an enhancement of labor productivity (Schultz, 1961). From a theoretical standing point, this is the mechanism whereby differentials in labor productivity translate into differentials in income (Leone & Lo Cascio, 2020). Understanding this dynamic would ultimately allow us to better capture the way in order to measure the returns of education, which is one of the main objectives of the research.

As any sort of investment – for instance, physical capital –, human capital is brought about only when the rational wealth-maximizing individual<sup>25</sup> knows that the expected return<sup>26</sup> (net internal rate of return - IRR) is greater than the market rate of interest (Fleischhauer, 2007). If the rate of interest surpasses the IRR, further investment in human capital is not warranted. Throughout this process the individual ought to incorporate the opportunity costs involved in this decision, which are time and foregone earnings. Therefore,

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<sup>25</sup> In this respect, Alonzo (1996) argues that pure individual rationality seems unlikely in society and also exhibits a major problem individuals encounter: lack of information in order to take the best maximizing decision.

<sup>26</sup> “In common usage, the coefficient on schooling in a regression of log earnings on years of schooling is often called rate of return. In fact, it is a price of schooling from a hedonic market wage equation” (Heckman *et al.*, 2006).



educational attainment influences the compositional changes in the allocation of time between market and non-market activities (Juster, 1975).

In this respect, two authors coming from Chicago School, Becker (1964) and Mincer (1958, 1974), develop the first methods and applications for the brand-new theory, back in that moment, in order to measure the extra earning of an individual before an additional year of schooling. The first scholar focuses on the analysis of Human Capital and its influence over personal earnings. Similarly, the second attempts to gauge the types of education yields and the variance of income distribution that can be explained by schooling (Sevilla, 2004). His model has been a basis for economic studies of returns to education in developing countries (Heckman *et al.*, 2006). One of its most relevant contributions is the idea of having Human Capital investment even after formal school.

Although theses methodologies were supported by empirical data, they fell short to entirely explain the interactions of the variables within the labor market. Consequently, many authors set forth several limitations of this approach<sup>27,28</sup>. For instance, one of the not yet unraveled issues in the empirical analysis is the order of causality between education and earnings. In other words, which one is the dependent variable. Furthermore, another rough point is the restriction to embed unobserved characteristics – either innate or acquired ability, for instance –, as explanatory variables inducing most of the time an upward bias to education. In a nutshell, whether higher observed labor revenues for certain workers can be explained by their high education or, on the contrary, individuals with innate ability – and higher earning capacity – select to acquire more education (Fleischhauer, 2007).

As a result, from 1970, a second generation<sup>29</sup> of authors emerge. They both question certain assumptions anchored in the theory – including the cornerstone of this field of economics: the connection education-productivity-wages<sup>30</sup> – and put forward several counterproposals. A non-negligible number of brands of research are issued from this new generation.

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<sup>27</sup> For an epistemological critic see Alonzo (1996).

<sup>28</sup> See Blaug (1985).

<sup>29</sup> Blaug (1985).

<sup>30</sup> Sevilla (2004).

The theory of selection or filters understands education as a mechanism that allows employers to determine the potential productivity of individuals, this includes Arrow (1973), Spence (1973) and Stiglitz (1975). Moreover, Thurow (1972) and his theory of competition for jobs or tail theory. The idea is that employers build a list of potentials workers according to the expected training costs and therefore organize their priorities in terms of these expenses. And finally, Doeringer & Piore (1971), with the theory of internal and segmented labor markets which are mainly due to technological differentials. In a nutshell, whereas the entry to an internal market is subject to certain rules that limit the vacancies for a determine job, the promotions across the professional hierarchy are normed by tighter measures capping even the internal wage structure.

Regardless of all the critics and limitations, Economics of Educations' theory has nonetheless proved to explain satisfactorily, in a micro level, the dynamics within the labor market as well as the interaction among its key components – education and earning differentials. It has also contributed to elucidate the role of education in the macroeconomic performance mostly through the use of endogenous growth models.

In fact, theory of Human Capital provides the justification of public investment in education (Leone & Lo Cascio, 2020). In this sense, however, policy advisors usually take for granted that, among other benefits<sup>31</sup>, a generalized educational expansion will immediately bring to the table a reduction of income inequality. Yet, at least at short term, this might not be necessarily the case.

### **3.2. The Impact of Education on Income Distribution**

Contrary to what common sense might suggest, an educational upgrading could possibly have unequalizing effects in the distribution of labor incomes. Bourguignon *et al.* (2005) first named this apparently contradictory dynamic as the “Paradox of Progress”. Even an equalizing increase in schooling – or moderately biased toward less educated groups – could cause an expansion of income gaps at the expense of lower quantiles of the distribution (Battistón *et al.*, 2014). One could also think of a scenario of increasing income inequality

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<sup>31</sup> Such as “promotion of rights, gender equity, child education, child and own health, fertility decisions, job search efficiency, technological change, social cohesion, crime reduction” (Fasih *et al.*, 2012).

even with a reduction of inequality in the distribution of education<sup>32</sup> (Bourguignon et al., 2005).

Lately, a comprehensive literature has been developed in order to address this issue. These efforts have attempted to shed light over the underlying causes behind such apparently striking performance of the heterogeneous effects of education (For empirical evidence see Girma & Kedir, 2005; Heckman et al., 2006; Martins & Pereira, 2004). For policymakers, this is crucial information since education-wage differentials – or returns to schooling – tell them what kind of skills the market values and therefore which type of programs should they expand or shut down (Fasih et al., 2012). Thus, spending decisions could be oriented towards more efficient paths. In order to answer these questions, we will concisely overview the plausible explanations that best fit with the empirical results.

During the beginning of the 2000s empirical literature for Latin America focused on the performance of skill (education) premium – or put it differently, the returns to primary, secondary, and tertiary education vs no schooling or incomplete primary schooling – as the underlying cause of heterogeneous returns<sup>33</sup> (Binelli, 2008) (See Lopez-Calva & Lustig, 2010; Gasparini & Lustig, 2011; Levy & Schandy, 2013; Lustig et al., 2013). This dynamic is shaped to a large extent by changes in labor supply underwent in the region.

Although this explanation fits the labor market performance on average among the region, the net impact of this variable upon the income distribution remains ambiguous. During the 1990s and 2000s, whilst the drop of returns to schooling fueled an inequality decline at the bottom of the distribution it had no effect in the upper quantiles (Fernandez & Messina, 2018). This can be explained by the divergence performance in the different educational level ratios related to the inverted U-shaped curve in schooling. At the same time that the high school/primary wage gap fell throughout the whole period, the college/high

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<sup>32</sup> The most important assumption in this statement is that returns to education – or wage structure – keep constant (Bourguignon et al., 2005). In other words, this approach needs to use a partial equilibrium framework. Consequently, the analysis restricts to the short-term period since it is not plausible to believe that returns remain unaltered throughout a more extended lap of time.

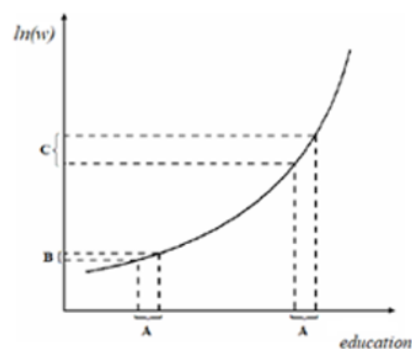
<sup>33</sup> Surprisingly, although playing a prominent role, the evolution of experience premium has received overall considerably less attention in literature. For a more in-depth research see Fernandez & Messina (2018).

school one increased considerably during the 1990s with a tipping point at the beginning of the 2000s.

A possible preliminary explanation could be the association of the Kuznets curve to the schooling distribution (Kanbur, 2000). In one word, initially, throughout a process of generalized educational upgrading, inequality in the distribution of number of years of schooling would increase. Thus, widening the differential of labor monetary returns among the quantiles. Right after, it will reach some maximum in certain segments of society, and as a consequence, schooling would start spreading to the rest of the population. Authors such as Alejo (2012) thinks of this as the distributive effect of education. The bottom line is that the impact of education on income inequality resides in the dynamic of the distribution of years of schooling.

Bourguignon *et al.* (2005) question this approach pointing out that it does not coincide with the empirical evidence. According to the authors, there are two meaningful mechanisms of transmission from education to households' labor income. The first mechanism is the convexification of the wage profile, that is, wage earnings are a convex function of years of schooling.

**Figure 6 - Hourly Wage and Schooling**



Source: Larrea & Fabris (2017)

In this point, Binelli (2008) enumerates three drivers that would potentially exacerbate this convexification. The first concerns the observables characteristics such as level of education, gender, work, experience, sector of employment, etc. The effect can be split up into changes in the composition, linked to the differences in the covariates (Firpo *et*

*al.*, 2018) and changes in their returns, the wage structure linked to the differences in the coefficients (the betas) of these covariates.

Moreover, the second driver is a change in the ability composition by level of education, within workers with intermediate and high education. This implies that the schooling expansion impacts unevenly on the mean ability (unobservable characteristic<sup>34</sup>) according to the educational level, decreasing observed wages at intermediate level and increasing at the higher one (Binelli, 2008).

Finally, the third driver accounts for a change in the prices of education through the interaction of supply and demand of skill. Put it differently, this means a shift in the market incentives on whether to invest in human capital or not. The curvature of this relationship depends on the distribution of characteristics associated with labor qualification and capital requirements – or type of tasks. If capital has a greater dispersion than the distribution of available skill levels, then there is a relative shortage of more skilled workers. Therefore, the market will be willing to pay increasingly more for them leading to a growing and convex relationship in the wage equation (Alejo, 2012).

In line with Battistón et al. (2014), the convexity in returns to education is a widespread characteristic in the majority of Latin American labor markets. The authors point out that the underlying mechanism of this process is associated with trade and market reforms, more specifically, trade liberalization policies implemented during the 1990s. The first channel might be the liberalization per se, which means that it could have shifted demand towards raw materials (natural resources) intensive industries at the expense of unskilled-intensive industries. The second, given its high complementarity with skilled labor force, inflows of investment in capital could have also changed the way in which the market rewards the unskilled. Last but not least, financial liberalization probably benefited more large firms that demanded skilled labor (Battistón et al., 2014).

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<sup>34</sup> This is related with another potential factor regarding the convexification process stated by Alejo (2012), which associates this phenomenon to the heterogenous returns in the labor market due to unobservable characteristics such as personal ability, intelligence, and talent. In a nutshell, in a scenario with two individuals having the same observable characteristics, there is always a gap in their remuneration, since the two of them can have different professional skills (unobservable factors).

This in turn shows the relevance of the term of years of schooling in the Mincer equation<sup>35</sup>. Empirical results exhibit that the mean of this coefficient in the countries of the region is significant at 1% level of confidence for the period 1990-2009. In this sense, the convexification process has been deepening progressively with special emphasis throughout the last years of the millennium (Binelli, 2008). The above-mentioned could be exacerbated when we incorporate into the analysis the economic cycle. Leone & Lo Cascio (2020) claim that the regressive impact of education across the quantiles of the distribution worsens during economic crisis widening the real income differentials.

On the other hand, the second mechanism of transmission stated by Bourguignon *et al.* (2005) is the negative impact produced by a school enhancement on labor supply within a short-term framework. This happens most notably in lower income households essentially because it supposes the withdrawn of a meaningful income source coming from members of the family – the majority underage – which is not available anymore.

Although this sacrifice means an investment insofar as more educated members of the family might compete for future better labor positions and therefore, higher incomes, the immediate reduction of the family income entails a widening in the gap with respect to the upper quantiles in the income distribution.

In other words, the redistributive effect will be for oncoming generations. That is the reason why, in another work, Bourguignon & Rogers (2007) advice to gauge Human Capital investment in an inter-temporal or intergenerational accounting in order to capture its whole effect<sup>36</sup>. According to the authors, this will be the proper way to enact an impact policy study. Unfortunately, even though enriching from an empirical point of view, this approach goes beyond the scope of this research.

### **3.2.1. LATAM and Ecuador: Labor Market Stylized Facts**

For a more comprehensive analysis it is necessary, first of all, to bring to the table the relevant features of the labor markets in the region and particularly, in Ecuador. To a certain extent, these labor systems are the result of heterogeneous and poorly diversified productive

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<sup>35</sup> Further in the study we will detail the most relevant features of this particular equation.

<sup>36</sup> This would “identify the explicit tradeoff between greater future earnings equality and a present worsening of the well-being of poor populations” (Bourguignon & Rogers, 2007).

structures. In a way, this stresses and shapes their main characteristics: prevalence of informality, low quality employment, lack of protection in terms of labor laws to a major part of society, high rotation rates and persistent ethnical, racial and gender gaps (CEPAL, 2018).

Even though the economic performance is closely related to the conditions in the labor market, this was not the case for the 1990s, where in spite of a non-negligible rate of economic growth, employment indicators not only remained unaltered but eroded systematically (Weller, 2017). In this respect, there were two main causes that acted behind this dynamic. On the one hand, the economic reforms enacted during the period. On the other, the restricted way by which the region incorporated novel technics and productive transformations in the worldwide economy.

In the aftermath of systemic crisis suffered by different countries in the region, the period 2003-2010 showed an expansion phase (Weller, 2017). Powered by redistributive reforms the continent underwent a sustained enlargement of the domestic market as well as a soaring demand for wage goods. Consequently, the unemployment rate fell steadily from 10.7% in 2000 to 6.3% in 2013 where it reached its minimum – suffering a stagnation until 2015 with a value of 6.5% (ILO, 2016). In parallel, a rise of the employment population ratio occurred, which means that employment growth overcame working-age population growth. During the same period, labor force participation mildly moved from 64.4% to 65.2%.

However, transformations in what respects structural compositions within Latin-American labor markets have fallen short<sup>37</sup> of expectations. Not only the shift towards high-skilled jobs has been marginal (ILO, 2016) but also the supply of skills has proved to be inadequate exposing the absence – on average – of generalized improvements in skills and schooling in the region.

Shaped by different domestic nuances, Ecuador described a similar trend compared to what we have described in regional terms. In fact, during the 1990s both the reduction of the government and a set of implemented measures searching for an ease in hiring rigidities changed radically the structure of the Ecuadorian labor market on the way out of one of the

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<sup>37</sup> It is worth to highlight that during 2000-2015 the share of agricultural sector slightly decreased from 17.5% to 15%. Moreover, whereas the size of the service sector passed from 60.8% to 63.3%, the share of employment in industry stagnated at 21.6% (ILO, 2016).

worst socioeconomic and political crises underwent by the country in 1999 (BCE, 2010). As a result, the productive apparatus – the labor demand – has shown deficiencies in order to absorb a growing labor supply.

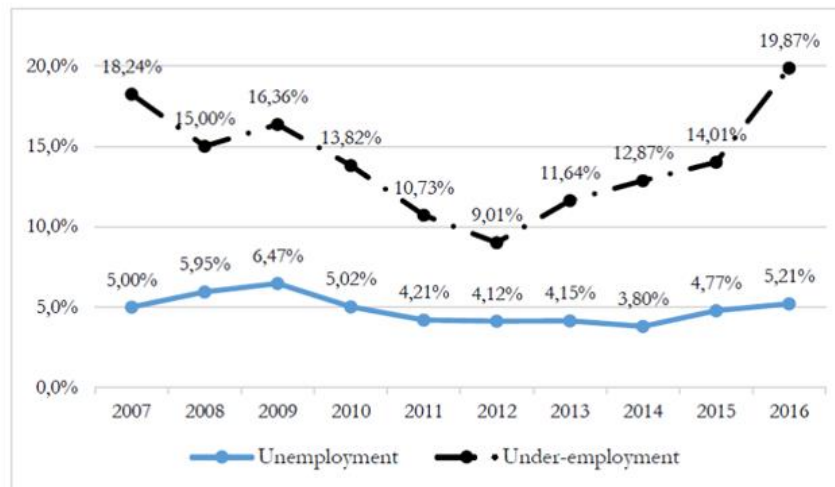
However, from 2007 to 2016, the labor supply described a different pattern. The first stage of the U-shaped curve was due essentially to two factors. On the one hand, an increase in workers retirement within a context of changes on the demographic structure. On the other, a growing number of students enrolling in the education system (Muñoz Bravo, 2017). Both dynamics contribute to a departure of people from the economic realm. The breakpoint, nevertheless, was reached in 2014, where more persons began to reenter in the labor market, in a way, to offset the economic crisis impact and therefore maintaining the consumption households' level. Needless to say, the upward slope continued until 2016.

In the same vein, the unemployment rate, showed in Figure 7, followed a similar dynamic with a downward tendency from 2007 (5%) to 2014 (3.8%) increasing however in 2016 (5.21%) (Muñoz Bravo, 2017). Simultaneously, the formal employment rate increased in 51% during the period 2007-2016. The main driver was the soaring employed population with social security affiliation<sup>38</sup> (Muñoz Bravo, 2017). In this sense, during the subperiod of major expansion, 2007-2014, the adequate employment increased from 43.2% to 49.3% (Carrillo, 2019). However, from 2015 the qualitative expansion seems to slow down. In fact, inadequate employment started to increase at the expense of adequate employment (Olmedo, 2018).

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<sup>38</sup> “The increases in the social security affiliation were led by institutional changes such as reforms to the Labor Code where it was eliminated the possibility of hiring workers by hours. Moreover, the Labor Code made compulsory a clear dependent relationship between employer and employee, so outsourcing workers for the core business of the firm were completely banned” (Muñoz Bravo, 2017).



**Figure 7 - Unemployment and Underemployment in Ecuador 2007-2016**

Source: Muñoz Bravo (2017)

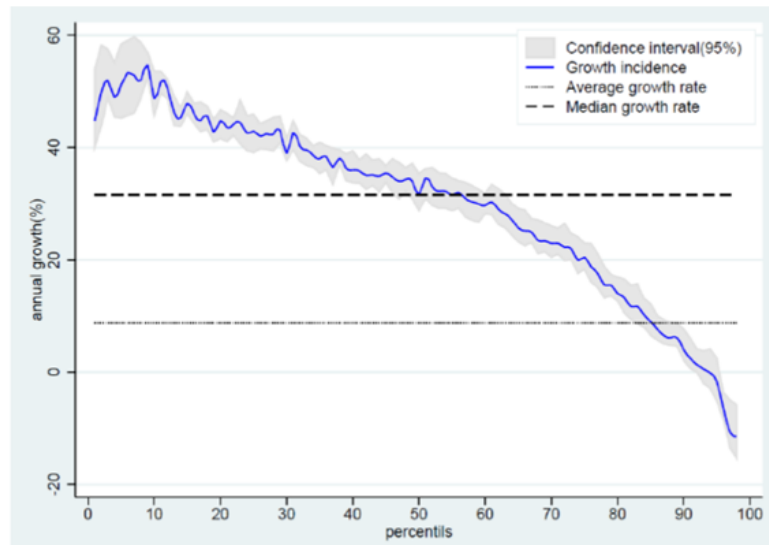
Moreover, as most Latin American economies, informality plays a vital role when it comes to define the stylized facts of the Ecuadorian labor market. If we use the correct and more accurate methodology to measure informality – which focuses on the job conditions and security of the workers, informal employment – in 2016 the percentage reached the 60.7% of the total labor force. This is an alarming information since it gets through the upper quantiles of the distribution as well (Atuesta *et al.*, 2016). Yet, this number seems rather positive when compared with the percentage of 2007: 74.1%.

Analyzing labor market characteristics is of vital importance since those are the mechanisms whereby people transit from poor to non-poor situation (Olmedo, 2018). Improvements in labor market conditions not only mean more jobs in the economy but also gains in their quality. There is a tight relationship between these features and the alleviation of poverty, extreme poverty, and inequality reductions.

Although the period under analysis accounted for pro-poor growth – measured by the Growth Incidence Curve (GIC)<sup>39</sup> (See Figure 8) (Muñoz Bravo, 2017) – the alleviation of most of the poverty indicators reached its maximum in 2014 with a fainter performance thereafter.

<sup>39</sup> “The GIC measures the changes in a welfare variable (income or consumption) across different percentiles of the respective distribution” (Muñoz Bravo, 2017).

**Figure 8 - Income growth incidence in Ecuador 2007-2016**



Source: Muñoz Bravo (2017)

This turning point coincides with the set of external shocks that the economy suffered in 2015. The economic recession was mainly due to the drop of international oil prices, exchange rate appreciation of the dollar<sup>40</sup>, and the further earthquake that impacted the country in 2016.

Precisely, throughout the more virtuous period, that is 2007-2014, according to Atuesta et al. (2016), the main driver of poverty and inequality reductions was the soaring labor income of a salaried working class<sup>41</sup>. This means, in other words, that the lower quantiles of the distribution have benefited proportionally more from this upgrade than the upper tail. When decomposing the labor income improvements, they found that changes in the returns – wage structural effect – rather than changes in endowments – composition effect – were the main contributors to this dynamic. Put it differently, the way the market rewarded the salaried workers according to their socioeconomic, educational and job characteristics played an enormous role. It is worth highlighting those changes in returns to un-skilled

<sup>40</sup> The American dollar is the legal currency in Ecuador from 1999.

<sup>41</sup> The authors hypothesize about four underlying causes: human capital, economic growth based on labor intensive sectors, public investment and structural change, and institutional factors.

occupations<sup>42</sup> were higher than those witnessed in skilled demanding sectors (Atuesta et *al.*, 2016).

Apart from an outstanding economic performance among all the indicators during 2007-2014 – which in turn meant a thriving development of the private sector in terms of job creation – the reasons why economic growth was mostly absorbed by the lower quantiles were institutional changes (notably minimum wage and social security) and public investment. The former equals to legal reforms that are likely to shift workers preeminently not registered and in the informal sector – the majority belonging to the lower quantiles of the distribution – towards more adequate jobs with better labor conditions and therefore higher payments. To a large extent, the latter fuels low-skilled occupations such as construction that, given the non-negligible quantity of public resources poured on the economy during 2007-2014, could have reconfigured the market rewards system inherited from the 1990s.

### **3.2.2. Empirical Studies**

Throughout the last decades, especially in the 2000s, a series of works aimed at understanding the dynamics and determinants that shape the income distribution have appeared, all of which are framed in the field of micro econometrics. These works have mostly focused on the compositional analysis – mostly quantitative – of several labor market variables and the accumulation of Human Capital when it comes to describe the performance of the allocation of income through market mechanisms in different societies.

Simultaneously, a vast methodological development has provided tools to the theoretical approach of Human Capital vis-à-vis an increasing interest for the assessment and evaluation of a broader number of study cases, most notably those of developing countries. To a certain extent, among all, Latin American countries have provoked a particular attention since they are considered being part of one of the regions where income inequality is among the highest (Birsdall et *al.*, 2011).

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<sup>42</sup> Such as commerce and service workers or elementary occupations.

Far from presenting an exhaustive list of every single study enacted in recent literature, the work attempts to concisely show an equilibrated and recent sample, which puts forward the current importance of distributive analysis in research particularly in the region.

To start with, Montenegro (2001), based on the methodology of Conditional Quantile Regressions<sup>43</sup> (CQR), analyze gender differentials in the returns to education and experience for the Chilean case for the period 1990-1998 divided in five cross-section data issued from the national survey. The results bolster their hypothesis: there is a systematic difference in the returns to education controlling by gender on the conditional wage distribution.

Similarly, for the Ecuadorian case, Puebla (2018) addresses the gender income gap by regarding the monetary returns according to the occupation and firm size. He finds that both the conditioned average wage gap – controlled by the characteristics above-mentioned – is four times the unconditional average gap and that it increases along the distribution of wages. Overall, women have labor characteristics associated with better wages, yet they receive lower returns.

Without taking into account gender differentials, Zuluaga (2007) conducts a similar approach for the Colombian case putting particular emphasis on poverty reduction (See Blom *et al.* (2001) and González & Miles (2001) for inequality studies for Brazil and Uruguay, respectively).

Likewise, for the Mexican case, Winters & Chiodi (2008) analyze the impact of a conditional cash transfer (CCT) program lead by the central government called “Oportunidades” – originally launched in 1997 as “Progresa” – not only on the improvement of Human Capital development but also on changes in the selection of income-generating activities in the poorest households of the rural part of the country. By using a probit model, the authors examine the choice of participating in different income-generating activities<sup>44</sup> and the role that some key factors, such as schooling, play in defining those behaviors. For instance, how educational returns vary according to location and asset position (Winters & Chiodi, 2008). Among several interesting results, they find that higher levels of education

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<sup>43</sup> The in-depth description of this methodology will be further discussed in next chapters.

<sup>44</sup> Self-employment, agricultural wage employment, non-farm wage employment, transfers, and other income sources (Winters & Chiodi, 2008).

are negatively associated with agricultural wage employment participation. Thus, this sector seems to absorb those workers with limited educational levels. In fact, schooling is linked with more lucrative non-farm wage employment. Finally, the proximity to population centers – this is, the location factor – leads in general to greater wage employment.

In the past years, the Ecuadorian case has raised enormous interest in the impact of public investment on several labor market variables. Atuesta et al. (2016) use a CQR approach to gauge the change in market returns for the real labor income in different occupational variables across the quantiles of the consumption distribution for the period 2006-2014.

Although returns increased overall, occupation with low-skilled qualifications – elementary occupations, plant operators and assemblers, etc. – witnessed a higher growth compared to those with high qualifications – CEO’s and managers, for instance. Even more, within occupations with low-skilled qualifications, the biggest shift in level pertains to the lower quantiles of the consumption distribution. Notwithstanding, when disentangling the socioeconomic characteristics of workers, the study concludes that the labor variables whose return increased the most were experience, salaried employment, and industry<sup>45</sup> (Atuesta et al., 2016). Again, this phenomenon was higher for the lower quantiles. Authors hypothesize that public investment might have changed the way market rewards salaried workers – wage structure effect – during this period.

Leal & Chacón (2017) focus on a particular subgroup in the region, the Andean countries, among which one of the most distinctive factors is – surprisingly, even in the Latin American region – the level of informality in their labor markets. The period is 2015-2016, right after the commodity boom. Through CQR the authors search for a monetary income premium between self-employed workers and those wage earners across the income distribution. Put it differently, the idea is to verify the existence or not of “incentives” for workers to move to self-employment jobs. As expected, despite some domestic nuances according to the country, whereas in the bottom 25% of the distribution there is a negative income premium – a market punishment – the top 25% enjoys of large positive income

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<sup>45</sup> The dependent variable in this case is the log of the real monthly labor income.

premium. This coincides with empirical studies that show the lack of formal job opportunities for the lower quantiles of the distribution who are to a large extent low-skilled workers.

Moreover, in a more holistic study, Patrinos *et al.* (2009) examine the quantile returns of education for eight Latin American countries and eight Asian countries. The research finds increasing returns for the former along the quantiles – similar to the situation of Europe/North America – and a decreasing return for the latter. Therefore, Latin American region would meet the premise of Human Capital theory; that is, the higher the education and unobserved ability, the higher the wages. Paradoxically, however, the average rate of return – that of OLS estimation – for another year of schooling for males is similar in East Asia and Latin America ranging from 10.2% to 11.6%, respectively<sup>46</sup>. Thus, the underlying difference does not reside on the average effect of earnings on education. In order to address this issue, we should shift our attention towards the quantiles of income distribution insofar as educational impact on earnings varies within education groups. East Asia has an equalizing pattern across the quantiles, the lower ones bear for higher returns, or at least flat returns. On the contrary, Latin American countries present decreasing returns to lower quantiles. This divergence occurs despite of the fact that both regions have no significant differences in educational endowments (Patrinos *et al.*, 2009). According to the authors, these dissimilar situations could be related to difference in labor markets. In other words, asymmetrical exposures to market forces and the link between monetary payments and productivity.

In this concern, they highlight the enormous importance of the public sector in East Asia, which is the largest employer in most of those countries. Empirical results seem to support the hypothesis that this sector is the responsible for the overall decreasing pattern witnessed in this region<sup>47,48</sup>. At the same time, increasing wage effects are still observed within the public sector in the group of Latin American countries, albeit with a lower dispersion compared to the private sector (Patrinos *et al.*, 2009).

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<sup>46</sup> In fact, educational attainment in formal sectors seems not to vary considerably across regions. Whilst in East Asia the average for those male aged 25-65 is 9.8 years and for females 9.9 years, in Latin America the average for male and females goes from 9 to 10.2 years accordingly (Patrinos *et al.*, 2009).

<sup>47</sup> “Evidence suggests that the public sector pay premium is declining as one moves up the conditional wage distribution, suggesting that the profitability of public sector employment is higher in the lower end of the wage distribution” (Patrinos *et al.*, 2009).

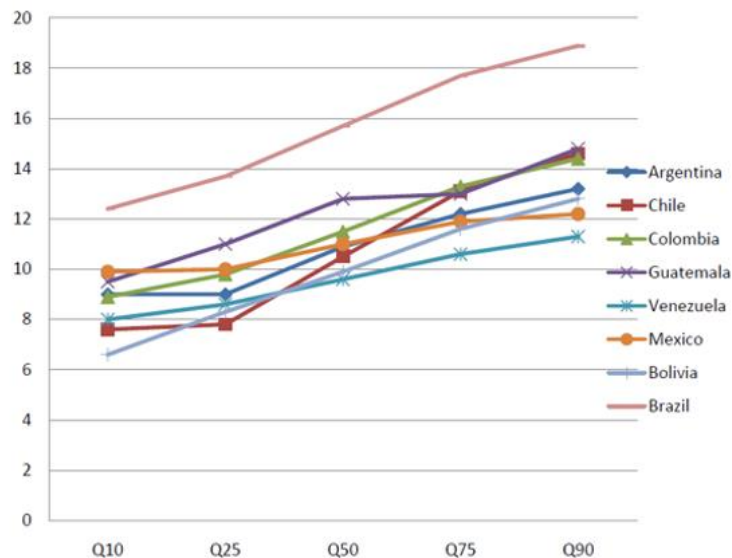
<sup>48</sup> Idem. While the impact of education on earnings within the private sector is non-decreasing.

Moreover, Martins & Pereira (2004) examine the impact of education on inequalities through the same methodological approach, which according to them, unlike the Ordinary Least Squares (OLS) approach, would allow a complete characterization of the conditional distribution of the dependent variable (the income distribution).

The authors use a sample of 16 countries – most of Western Europe – during the 1990s, using cross-sectional databases from national surveys to test their hypotheses (See also Brunello *et al.*, 2009). Accordingly, they extract some rather interesting results, notably that schooling can have a positive impact on wage inequalities within groups, as the distribution of returns increases for higher levels of education. This relationship could be shaped as well by the country's development stage according to the labor market characteristics between developed and developing countries.

In this sense, Fasih *et al.* (2012) document increasing returns of education as one move towards the upper end of the earning distribution – but with important divergence among regions –, being Latin America a continent with a steep slope along the quantiles during the period 2000-2003.

**Figure 9 - Quantiles Returns to Schooling by Country (LAC)**



Source: Fasih *et al.* (2012)

However, a new methodological approach was proposed by Firpo *et al.* (2009), which allows to take into account the impact of any variable on the unconditional distribution of

earnings. Research has remarkably shifted towards this method since the final goal of distributive analyzes is to assess the impact of any variable on the entire (marginal) distribution. The methodology based on the Re-centered Influence Function (RIF) advocates the use of Unconditional Quantile Regressions (UQR).

We briefly remark the differences between CQR and UQR with respect to our variable of interest: education. In fact, schooling enhancement is composed by two effects: an increase in expected earnings and a rise in their dispersion for each level of education. In short, more educated groups deal with a (conditional) distribution of earnings that is both placed to the right and more disperse (Alejo et *al.*, 2014). Therefore, the distributive effects of education on earnings depend not only in schooling returns but also in the initial distribution of education.

In sum, earnings distribution is composed by the (conditional) distribution depending on the level of education – how disperse is it across the quantiles – and the marginal (unconditional) distribution of it. Then, earnings inequality embodies the interaction of inequality in education – the ex-ante educational endowment –, and the way earnings are affected by education – schooling returns. The partial perspective of CQR resides precisely in the fact that this approach apprehends the second channel, while UQR is modeled by both.

Although fleshed out thereafter in the methodological section more profoundly, it is worthwhile to point out that the ongoing research draws on this approach in order to assess the quantitative impact of education on income distribution for the Ecuadorian case. We believe that the comprehensive scope of this methodology enables to gauge the complexity of the Andean labor market which, as already discussed, underwent several structural changes during the decade 2007-2016.

Moreover, for the Argentinian case, we can find two studies that have been the most robust concerning the problematic. On the one hand, Alejo et *al.* (2014) which falls within the period 1992-2008. On the other hand, Groisman (2012) takes the years 2003 and 2011.

Both theoretical starting points are similar; because of the convexity of the Mincer curves, education could lead to a negative effect on inequalities. To achieve this, the works



use the UQR approach with the same cross-sectional database<sup>49</sup>. Groisman (2012) highlights that over the period of analysis there has been a change in the educational profile of private employees towards those with better qualifications, which has not nonetheless translated into a rise in their wages. Contrary to what one might think, he mentions that this period was characterized by a reduction in wage differences.

According to the results of Alejo et al. (2014), during the 1990s, heterogeneous returns to education further improved and positively co-shifted with observed increases in inequality. Meanwhile, the results for the year 2008 suggest that this uneven effect has diminished considerably, revitalizing the role of education as a powerful policy variable to improve well-being (Alejo et al., 2014).

In a more recent study, Larrea & Fabris (2017) analyze the performance of the distributive effect of education – measured both by years of schooling and educational level – on the income distribution for the Argentinean case, notably on the real hourly wage. The selected period (1992-2015) comprises two different decades in terms of labor market regulations and state intervention; the 1990s and the 2000s. By using cross-sectional data, the authors draw on UCR methodology in order to arrive to two major conclusions. First, when education is gauged by years of schooling, over time its distributive effect tends to be more equalizing. Second, if we select educational level two conclusions emerge. On the one hand, primary education holds an equalizing effect throughout the whole period with more pronounce influence in the last years of the sample. This goes in line with empirical research in the region<sup>50</sup>. On the other, although unequalizing from tail to tail, higher education seems to soften its regressive effect over income distribution from 2008 to 2015.

Given the two potential effects of education, increasing incomes and inequalities, they point out that the latter substantially loses strength during the second section of the period (2008-2015) turning education – to a large extent, across all the educational levels – a desirable policy for social welfare (Larrea & Fabris, 2017).

In the Brazilian case, we have witnessed a vast literature recently deployed. Ferreira et al. (2017) focus on studying the causes, and even determinants, of a substantial decline in

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<sup>49</sup> Encuesta Permanente de Hogares (EPH).

<sup>50</sup> See Gasparini et al. (2013).

labor income inequality in Brazil between 1995-2012. The tool chosen by the authors is the UQR approach, which makes it possible to disentangle the quantitative impact of five explanatory variables, namely, Human Capital, labor market institutions, demographic characteristics of workers, spatial segmentation and finally the distribution of the workforce into sectors (Ferreira *et al.*, 2017). According to their estimates, the decline was motivated by changes in the structure of remuneration in the Brazilian labor market, rather than directly by changes in the distribution of worker characteristics.

Also, Maurizio (2014) frames her analysis for the two Latin American countries described above in the period 2003-2011. The author examines the formalization of employment as an explanatory cause for the decrease in inequalities in Argentina and Brazil. Among the different methodological components used with regard to the estimation of the wage gap, the author chooses the UQR concluding that the formalization process, in a context of strong job creation, played an extremely important role.

In an article devoted to the theoretical development of econometric decomposition analysis, in particular the UQR approach, Firpo *et al.* (2018) take the case of the polarization of wages between men and women in the United States between 1988 and 2016. The strategy permits to better illustrate the methodological framework. This is how the authors aim to study the problematic using a series of causes that they believe have exacerbated the gap<sup>51</sup>. On the other hand, Schneck (2019) examines the German case for 2015, in particular the condition of self-employment and its impact on income distribution. Through income polarization, the increase in self-employment in the labor market increases inequalities.

Finally, among a considerable group of works emphasizing a comparative analysis between different sets of countries (Battistón *et al.* (2014)<sup>52</sup>; Coady & Dizioli (2017)<sup>53</sup>; Fernandez & Messina (2018)<sup>54</sup>) we will briefly discuss the one carried out by Fournier & Koske (2013) that has interesting empirical results.

Indeed, in a comprehensive work the authors make an effort to depict the channel whereby educational composition of the workforce exerts an influence on the distribution of

<sup>51</sup> De-unionization, education, occupations, and changes in industry (Firpo *et al.*, 2018).

<sup>52</sup> Could an Increase in Education Raise Income Inequality? Evidence for Latin America.

<sup>53</sup> Income Inequality and Education Revisited: Persistence, Endogeneity, and Heterogeneity.

<sup>54</sup> Skill premium, labor supply, and changes in the structure of wages in Latin America.

labor income. In this regard, the authors use a sample of 32 countries<sup>55</sup> using national surveys for the years 2005-2008 depending on the country. Having as its goal a fairly broad understanding of the phenomenon, the work is interested not only in the UQR approach but also in that provided by CQR (Fournier & Koske, 2013). There are many results that the authors extract from it. First, the number of hours worked is a determinant of income inequality. Then, the returns of age are higher as we get closer to lower quantiles. Finally, the relationship between education and income inequality at the theoretical level remains ambiguous.

In a more current work Ariza et al. (2018) frame their analysis of the distributive effects of informality and schooling in a group of Latin American countries<sup>56</sup> for the period 2002-2014. The set of methodological tools on which they rely is made up of the Machado-Mata algorithm (Machado & Mata, 2005), the UQR and CQR approaches, and quantile regressions with random coefficients. In all countries, it is found that the reduction in wage inequality can be explained by improvements at the bottom of the income distribution. This perfectly meets with the two main drivers that Birsdall et al. (2011) envisage concerning the substantial reduction of inequality in most countries of the region in the first years of the new millennium. On the one hand, a decline of the skill-premium – with special emphasis in higher education – driven mostly by a considerable expansion of basic education, which in turn has diminished the wage income distribution (Chiodi, 2021). On the other, the implementation of social and progressive public policies targeting households at the bottom of the income distribution. Both movements had as a result the enhancement of a vast middle class whose size is usually proposed as a measure of well-being (Chiodi, 2021).

At the same time, Maurizio (2019), using a somewhat larger sample of Latin American countries<sup>57</sup>, questions exclusively the effect of informality and its distributive impact through low wages and the absence of security social services. Indeed, the author ends up showing the strong relationship between the variables mentioned above.

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<sup>55</sup> Including Europe, Asia, and Latin America. For the detailed list review Fournier & Koske (2013).

<sup>56</sup> Including Argentina, Brazil, Colombia, and Mexico.

<sup>57</sup> Apart from those studied in (Ariza & Montes-Rojas, 2018) the author takes Chile, Costa Rica, Ecuador, Paraguay, and Peru.

To conclude, there is not still a wide-spread consensus about the extent and strength of the distributive effects of education. First, because their impacts are not neutral since they affect people's live unevenly (Gasparini *et al.*, 2013). As any social program, there are always beneficiaries – persons who are directly better off after the intervention –, for instance, children of low-income households, and losers of the policy – in a hypothetical scenario, top income households that indirectly fund this public expenditure through a more direct tax system.

Second, the diverse scenarios according to the particularities of each country in terms of economic systems, political structures, institutions, and idiosyncratic traits – such as costumes or culture – make this task even harder to achieve.

## 4. RESEARCH DESIGN

### 4.1. Empirical Strategy

In this section we will focus on the stylized facts of the quantitative methodology derived from micro econometric theory. Taking into account the complexity of it, we will attempt to concisely synthesize the underlying concepts that lay behind.

The foundation upon which the framework will be built is the Recentered Influence Function – RIF (Firpo *et al.*, 2009). From this departure point we will be able to initially dive into the cornerstone equation of Economics of Education – Mincer equation – pointing out its methodological limitations when it comes to express results beyond the expected conditional mean of a sample. Then, we will move forward to address the main differences, with their respective weaknesses and strengths, of both models: Conditional Quantile Regressions (CQRs) and Unconditional Quantile Regressions (UQRs). We will finally conclude highlighting the usefulness, in distributive topics, of unconditional Quantiles versus those conditional. This is sustained mainly because although both show the computation for the full sample, the former tackles the whole marginal distribution (Firpo *et al.*, 2018; Alejo *et al.*, 2014; David, 2015).

The selection of this pack of models (Mincer equation, CQRs and UQRs) responds to an illustrative and comparative strategy. Even though the objective of the research is to show the benefits of UQRs – since they capture in more proper way the heterogeneity and complexity of the impact of education upon the income distribution –, we believe that setting first the departure point on Mincer equation and CQRs will complement the analysis.

Each time we move forward the idea is to incorporate more complexity to the interpretation of the estimators so as to better capture the interaction of our two variables of interest. Mincer equation estimators tell us the effect of education on the expected conditional mean. Moreover, CQRs estimators add to this the differences that might arise along the quantiles. Hence, the interpretation gains in scope. However, the coefficients are still limited to the distributive impact of education conditional to either the years of schooling or the educational level. Finally, UQRs go a little bit further integrating the heterogeneity to the entire distribution of income. We believe this approach will consistently assess the

complexity of the Ecuadorian labor market thus easing a better comprehension of the phenomenon.

#### 4.1.1. RIF Methodology

The seminal article written by Firpo *et al.* (2009) opens up a whole series of methodological tools enriching the field of study of distributive analyzes. Building on this, the research will attempt to disaggregate the heterogeneous impact of education on income inequality.

When analyzing social welfare, inequality, or poverty, empirical research might sometimes encounter lack of information issues, such as not knowing of each individual of the sample. However, we could possibly count on the relative position of all the individuals compared to the rest of the population – the Cumulative Distribution Function (CDF) ( $F$ ) – or how frequent it is to observe an individual with any given level of income – Probability Density Function (PDF) ( $f$ ). If our outcome of interest can be referred to as:

$$y = [y_1, y_2, y_3, \dots, y_n] \quad (0)$$

Where each  $y_i$  is the value of the  $i$ th person – in our case, the logarithm of the real wage – then, if we have access to these vectors of information ( $y, F, f$ ) any distributional statistic can be derived:

$$\hat{\theta} = \hat{\theta}(F) \quad (1)$$

Where  $\hat{\theta}(\cdot)$  is the functional that uses the information contained in those vectors in order to estimate a distributional statistic of  $y$ . Formally, this functional can estimate statistics relevant to distributional or policy analysis like the mean, the  $\tau$ -quantile, poverty indices or inequality indices (Gini, Theil, etc.) (Ríos Avila, 2019).

If we want to assess the impact a change in the income distribution due to education will have on the distributional statistic, it is necessary to compare the indices from the observed (ex-ante) distribution  $F$  to the ex-post distribution  $F_\lambda$ :

$$\Delta \hat{\theta} = \hat{\theta}(F_\lambda) - \hat{\theta}(F) \quad (2)$$

We can then think this change of as a schooling expansion at a particular educational level of the original distribution function  $F$  by a small mass of probability  $\lambda$ . Particularly,  $\lambda$  represents the magnitude of the change from one distribution to another when the shift tends to zero. With this definition we are able to build up the distribution that would be observed after a schooling expansion ( $F_\lambda$ ) combining the observed distribution from  $F$  and  $\delta_y$ :

$$F_\lambda = \lambda\delta_y + (1 - \lambda)F \quad (3)$$

Where  $\delta_y$  denotes a point mass at  $y$ . The expression quantifies the change in the distribution when passing from  $F$  to  $F_\lambda$  by an infinitesimal change (Ríos Avila, 2019). Thus, the influence function of the distributional statistic  $\hat{\theta}$  at the original distribution  $F$  at a specific value  $y$  will be:

$$IF_{\hat{\theta}}(y, \hat{\theta}(F)) = \lim_{\lambda \rightarrow 0} \frac{\hat{\theta}(F_\lambda) - \hat{\theta}(F)}{\lambda} \quad (4)$$

In one word, the Influence Function (IF) tells us what will happen to our statistic  $\hat{\theta}$  if we expand education at  $y$  to the distribution  $F$ . Furthermore, instead of using the IF directly, Firpo et al. (2019) propose to use the recentered version of this statistic, the so-called Recentered Influence Function (RIF)<sup>58</sup>:

$$RIF_{\hat{\theta}}(y, F) = \hat{\theta}_F + IF_{\hat{\theta}}(y, F) \quad (5)$$

A small change in the distribution of education will generate a change in the unconditional distribution of the hourly income wage ( $\Delta F_y$ ), which in turn will be traduced into a change in the distributional statistic – the Gini or the quantiles, for instance. Finally, thanks to the linearity assumption, we can use the Ordinary Least Squares (OLS) method to capture the way changes in the distribution – due to education enhancement – relate to changes in in our statistic of interest (Ríos Avila, 2019):

$$E[RIF(y, \theta) | X] = \beta X + \varepsilon \quad (6)$$

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<sup>58</sup> Both expressions, IFs and RIFs, share the same statistical properties. On the one hand, the expected value of IF is equal to zero. This property is what allows the IF to avoid the inconvenience of the non-compliance of the law of repeated expectations, which in fact, is fulfilled for the mean, but not for other statistics, such as the conditional quantiles of the regression (Larrea & Fabris, 2017). On the other, the one concerning the asymptotic variance of the estimator under the probability distribution  $F$ . In other words, the RIF measures the influence of each observation on the change of the distributional statistic and also makes it possible to estimate its asymptotic behavior.

Put in another way, the authors suggest replacing the variable of interest with its RIF and perform a regression on the explanatory variables<sup>59</sup> by OLS. If we apply it to a certain quantile, for example the median, the technique is to replace the variable of interest by the RIF of the median of the logarithm of the real wage and return it to the explanatory variables by OLS.

Nevertheless, the RIF-OLS coefficients obtained from this regression are interpreted in a slightly different way compared to those of OLS. Given a change in the years of schooling, holding constant the other variables, such that the unconditional average increases by one unit, the expected change in the distributional statistic is equal to  $\beta$ .

The advantages of this methodology are multiple. RIF-regression methods provide a simple way of performing detailed decomposition analysis for any distributional statistic (Fortin et al., 2010). One gets a simple regression, which is easy to interpret. It also implies that an analysis based on two different times is not necessary, but rather that the coefficients can be estimated from a single database. This makes possible to draw on cross-sectional data. On the other hand, the marginal impact of a change in variable on a distributive statistic can be calculated directly, corresponding to the entire – marginal – distribution<sup>60</sup>.

#### 4.1.2. Mincer Equation

In order to better understand the most important features of quantiles – conditional or not on education – we must first briefly review the standard and central function in the theory of Economics of Education: the Mincer equation. Thus, we present the reduced form for the Mincerian equation, which assumes the linear dependent relationship between the logarithm of earnings and years of schooling, so:

$$y = \ln(W_i) = \beta_o + \beta_1 S_i + \beta_2 year2_i + \beta_3 year3_i + \beta_4 SE_i + \beta_5 DEM_i + \beta_6 Esec_i + \varepsilon_i \quad (7)$$

Where  $y_i$  denotes the logarithm wage of the individual  $i$ ,  $S_i$  stands for years of schooling. Therefore,  $\beta_1$  can be interpreted as the rate of return to investment on education. Moreover,  $year2_i$  and  $year3_i$  are the ranges of the age of the population that proxy the work

<sup>59</sup> The reduced form with all the covariates selected will be fully detailed in the next section.

<sup>60</sup> A more subtle advantage is that linearization permits not to worry about the global impact evaluation at all points of the distribution, and thus not be concerned about monotonicity. Consequently, the decomposition is path independent (Fortin et al., 2010).



experience ( $year1_i$  remains as the default variable). The scales are the following: between 15 and 24, between 25 and 45, and more than 45 (Maurizio, 2014; Ríos Avila, 2019). This subdivision permits to a large extent to capture the concavity of earnings profile.

$SE_i$  represents some socioeconomic characteristics of the individual  $i$ , such as, marital status, gender, and occupational category. Likewise,  $DEM_i$  captures demographic characteristics, namely dummy variables for region and urban/rural areas. Furthermore,  $Esec_i$  is a variable that allows to control for economic sectors. Finally,  $\varepsilon_i$  is the disturbance term<sup>61</sup>. Generally, and it would be the case of this research, this regression is implemented through OLS.

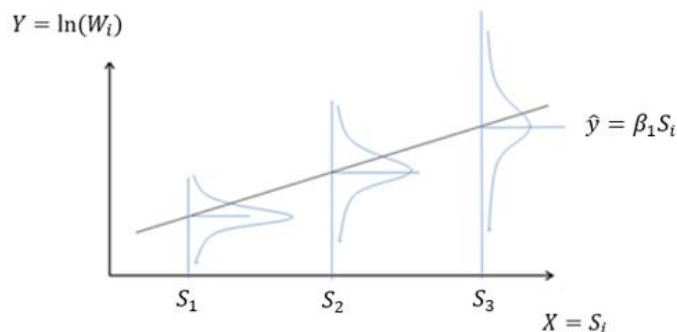
Among all the benefits, this equation provides a simple way to quantify the effect that one variable has on the logarithm of the hourly wage, isolating it from the possible concurrent effect that other factors may have (Sosa Escudero, 2005). Therefore, the effect that education has on our dependent variable is:

$$E(\ln(W_i) | S_i) = \beta_1 S_i' + \varepsilon \quad (8)$$

Where  $\varepsilon$  stands for the error term that ultimately is composed by the unobservable attributes not captured by the model. In fact, if there is not interaction between  $S_i$  and the error term (exogeneity assumption, which is considered to be a strong hypothesis), the effect that years of schooling has upon the expected conditional value of  $\ln(W_i)$  coincides with that of  $S_i$  has directly over the dependent variable.  $\beta_1$  measures the effect on  $E(\ln(W_i) | S_i)$  of marginally modifying years of schooling, *ceteris paribus* the rest (Sosa Escudero, 2005). Notwithstanding, Figure 10 shows the limitation of the estimate, it only manages to measure the conditional expectation:

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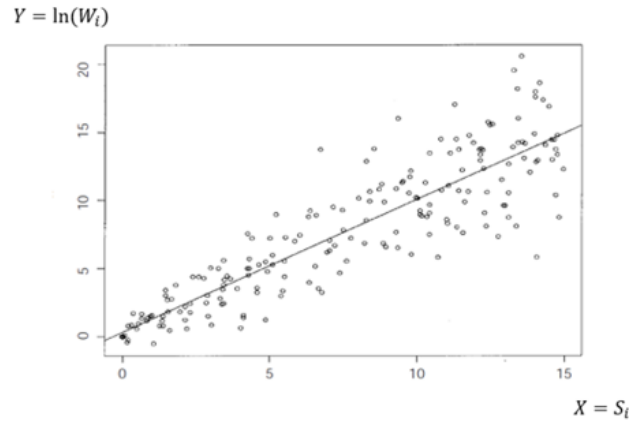
<sup>61</sup> By construction, this term is assumed to be exogenous, this is, independent of all covariates. In mathematical terms, this means that  $E(\varepsilon | S_i, X_i) = 0$ .

**Figure 10 – Conditional Mean Expectation**

**Source:** Larrea & Fabris (2017)

In this particular situation the figure exhibits the distribution of the logarithm of the hourly wage (axis  $y$ ) according to the level of education (axis  $x$ :  $S_1, S_2$  and  $S_3$ , for instance). The more we increase the level of education, the greater the disturbance of the observations. According to Lemieux (2006) this could be easily explained since returns to schooling to all quantiles are linked. Hence, the groups who experience relative increase in the average wages – those who are more educated – undergo an increasing wage dispersion within-group (with the same educational level) (See also Metzler, 2008).

Furthermore, we move now to Figure 11. The graph shows a hypothetical plot of some sample distribution according, in this case, to the average year of schooling (axis  $x$ ) and the logarithm of the hourly wage (axis  $y$ ). In fact, education increases both the level and the dispersion of wages (Firpo *et al.*, 2018). Consequently, the effect of schooling on wages is not homogenous. Thus,  $\beta_1$  although it is a good measure of the effect that  $S_i$  has on  $E(\ln(W_i) | S_i)$ , it is a somewhat restricted summary of the effect of  $S_i$  on  $\ln(W_i)$ . In particular, it tends to underestimate the effect that the former has on the latter at the top of the conditional distribution, and the opposite on the bottom end. In conclusion, there is not such a thing as a “single return to education”, but rather a variety of heterogenous impacts across society (Lemieux, 2006).

**Figure 11 – Heteroskedasticity**

Source: Sosa Escudero (2005)

#### 4.1.3. Conditional Quantile Regressions: beyond the Mean Effect

The impact of education on earnings is likely to differ across individuals. That is the case of Latin America, for instance, where overall primary school – a low educational level – tends to be pro-poor, whereas higher education, in most of the countries, benefits more the upper quantiles of the distribution. Standard OLS techniques overlook this heterogeneity providing just an estimate of the mean effect. Thus, information in these models typically remains poor, specially, for policy purposes (Fasih et al., 2012).

In response to this, based on the seminal article of Koenker & Bassett (1978), a vast literature has leaned over a technique that seeks to incorporate such differentials across samples: the (Conditional) Quantile Regressions (CQRs).

These models allow for a parsimonious way to fully characterize the conditional distribution of the dependent variable, thus enriching the analysis if the relationship between the regressors and the independent variable evolves across its conditional distribution (Martins & Pereira, 2003). In fact, this is clearly the case of education and earnings. Following equation (9) we present the model:

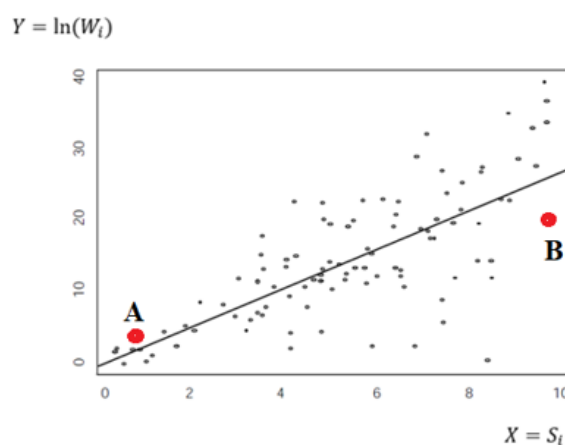
$$Q_{y|x}(\tau) = \beta_0(\tau) + \beta_1(\tau)S_i + \beta_2(\tau)age2_i + \beta_3(\tau)age3_i + \beta_4(\tau)SE_i + \beta_5(\tau)DEM_i + \beta_6(\tau)Esec_i + \varepsilon_i(\tau) \quad (9)$$

Where  $\tau \in (0,1)$  and  $\beta_1(\tau)$  is a vector of K coefficients. The notation  $Q_{y|x}(\tau)$  draws on the  $\tau$ -quantile of the conditional distribution of wages on years of schooling,  $S_i$ . The  $\tau$ -quantile is a number in the distribution such that the occurrence probability of lower values

is  $\tau$  (Sosa Escudero, 2005). For instance, when  $\tau = 0.50$ ,  $Q(\tau) = 0.50$  is the value that split up the distribution in equal parts, thus leaving to the left 50% of the full sample distribution<sup>62</sup>.

Now, let us compare points  $A$  and  $B$  in Figure 12.  $A$  is a high point in the conditional distribution of  $\ln(W_i)$ , as it is above the bold line, yet, it has an extremely low position in the unconditional distribution. The opposite occurs with point  $B$ . In other words, point  $A$  corresponds to a person who, despite having low earnings within the whole population, holds a relatively high income compared to those with the same education (Sosa Escudero, 2005).

**Figure 12 – Limitations of the Mean**

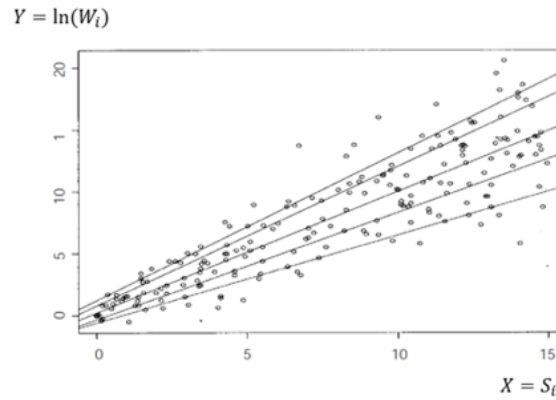


**Source:** Sosa Escudero (2005)

The key point is that the coefficients  $\beta(\tau)$  are not restricted to be equal. On the contrary, equation (9) shows a family of regression models to better capture the complex phenomenon of the heterogenous impact of education on (conditional) income distribution.

Likewise, Figure 13 traces several lines according to each quantile of the conditional distribution; it is clear that the upper lines (quantiles) have a steeper slope compared to those of the bottom. As we already discussed, the effect of education ( $S_i$ ) on the logarithm of real wage –  $\ln(W_i)$  – is not homogeneous:

<sup>62</sup> For the sake of comparison, the set of regressors is the same already presented in the previous subsection for the case of the Mincerian equation.

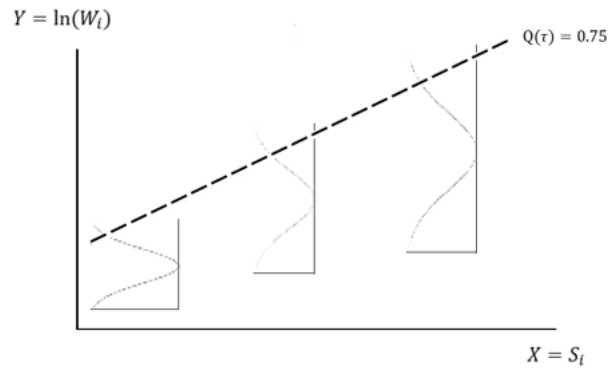
**Figure 13 – Family of Conditional Quantiles**

Source: Sosa Escudero (2005)

For illustrative purposes, let us consider the case of  $\tau = 0.75$  for just one regressor (years of schooling) in the model:

$$Q_{\log(W) | S}(0.75) = \beta_o(0.75) + \beta_1(0.75)S_i \quad (10)$$

This function joins the quantiles 0.75 of the earnings distribution given the year of schooling as the latter varies imposing a linear relationship. Graphically, equation (10) will stand for:

**Figure 14 – Conditional Quantiles:  $\tau = 0.75$** 

Source: Sosa Escudero (2005)

In one word,  $\beta_1(\tau)$  is the effect that an infinitesimal change in  $S_i$  has upon the  $\tau$ -quantile of the conditional distribution of earnings. In Figure 14, since the dispersion of the

observations in the distribution increases with the level of education, the coefficients in the upper quantiles would be bigger proving a steeper slope.

However, when it comes to interpret the results, there are few precautions to bear in mind. They only suggest that, after controlling for the explanatory variables (the ones in the reduced form already presented), the set of quantiles of the conditional distribution increases when education is improved, but at an increasing rate for higher quantiles.

Moreover, the greater heterogeneity of the upper conditional quantiles does not necessarily imply greater inequality in the upper quantiles of the marginal distribution. In other words, this does not indicate that the dispersion is greater for those with higher income.

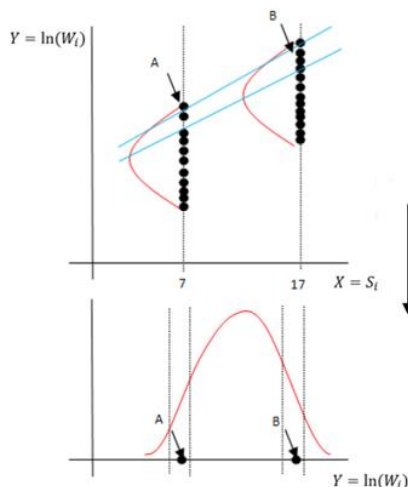
In this respect, a common difficulty associated with the interpretation is that the top (bottom) of the conditional distribution does not coincide with the top (bottom) of its unconditional counterpart. In fact, the positive and heterogeneous effects of CQRs do not imply that education has a stronger effect for the rich, for example, but for the conditionally rich (conditional upon their educational level), after controlling for the set of explanatory variables (Alejo *et al.*, 2014).

#### **4.1.4. Unconditional Quantile Regressions: the Marginal Distribution**

This kind of regressions, by contrast, focus on the unconditional quantile of an individual. That is, his/her earning quantile in the overall earning distribution (Fournier & Koske, 2013).

Figure 15 presents the complete picture of what we recently saw in Figure 10, this time adding up the unconditional distribution. The main difference between the two panels is that the upper one shows multiple distributions of the logarithm of the hourly wage (y axis) conditional to years of schooling (x axis). The bottom panel, on the contrary, distributes increasingly (from the lowest to the greatest) all the observations solely in function of their logarithm of the hourly wage (x axis) (marginal distribution); they are not conditional to any covariate.

**Figure 15 – Conditional vs. Unconditional Distribution**



Source: IIEP-BAIRES. UBA-CONICET (2017)

In the top panel on Figure 15 persons A and B belong to the same top quantile  $\tau$ , which means that they are the conditionally rich – upon their level of education. In this case, with 7 and 17 years of schooling, respectively. For instance, among all the subsample counting on 7 years of schooling, individual A holds the highest earning. However, when regarding the unconditional or the so-called marginal distribution of income (the bottom panel on Figure 15), a completely new scenario comes up. In effect, person A is placed on the bottom of the unconditional distribution, whereas person B is situated on the top of it.

In intuitive terms, the distribution of the logarithm of real wage can be thought of as factored by its conditional distribution given  $S_i$ , and the marginal distribution of  $S_i$ . Then, inequality in the logarithm of the hourly wage represents the interaction of inequality in education and the way  $\ln(W_i)$  is affected by  $S_i$ . CQRs can be thought of as those that model the second channel, while UQRs integrate both (Firpo *et al.*, 2018). In other words, whereas CQRs captures the growing inequality in income distribution as education increases, UQRs adds to it the inequality in education levels, resulting in an even more heterogeneous effect. When using both methodologies, this research aims to stress the impact of the distribution of educational endowments, conceived as a second channel whereby education models inequality.

For each unconditional  $\tau$ -quantile of the distribution,  $Q_\tau$ , the RIF is obtained by adding the quantiles to its influence function (Maurizio, 2014). Therefore:

$$RIF(y, Q_\tau, F) = Q_\tau + \frac{\tau - I\{y \leq Q_\tau\}}{f(Q_\tau)} \quad (11)$$

Where  $f(Q_\tau)$  is the marginal density function of  $y$ . Likewise, the RIF of a quantile is simply the indicator variable  $I\{\cdot\}$  for whether the earnings are smaller or equal to the quantile  $\tau$ . Unlike CQRs, the expectation of the RIF is the quantile itself. Consequently, it is possible to measure the response of an unconditional quantile to a marginal shift in education. Hereinafter, we are able to record the marginal changes that occur in the quantiles – or, in any other distributional statistic such as the Gini – of the initial unconditional distribution due to unit changes in education.

This approach allows for a more direct and straightforward interpretation of the coefficients. Since the unconditional quantile of an individual is the share of individuals in the sample population whose earnings are lower than the earnings of the individual of interest, the results of UQRs are easier to understand (Fournier & Koske, 2013).

For instance, this method can provide a sound answer to what would be the impact on median earnings ( $\tau = 0.5$ ) of a generalized shift in the population to the right of one year of schooling. Effectively, this is the type of concern a policy maker might have before enacting an educational expansion through public expenditure, for instance.

## 4.2. Data

In this work we will limit the sample to men and women aged 15 to 65<sup>63</sup> in Ecuador during the decade (2007-2016) being economically active. More specifically, those who are part of the occupied sample that is encompassed in the EAP<sup>64</sup> – the population in working age – during the implementation of the surveys. At the same time, the research will try to go beyond the national aggregate by describing the trajectories experienced by certain ethnic groups from society, namely Indigenous and Afro-American<sup>66</sup>.

<sup>63</sup> Those are the lower and upper bounds of the Working Age Population according to ENEMDU.

<sup>64</sup> The Economically Active Population.

<sup>65</sup> Based on Muñoz Bravo (2017). See Annex I.

<sup>66</sup> For a detailed analysis of the comprehensive list of distributional indicators when addressing population by its ethnic origin see Aranda & Ratzlaff (2018).



The reference individual income is the one that comes from any labor source<sup>67</sup>. More particularly, following Ariza et al. (2018) and Ferreira et al. (2017), the measure of earnings is the real hourly wage defined as the nominal wage earned in the last month divided by the number of hours worked and finally deflated by a price index. In this respect, we will use the consumer price index (CPI) since we find it a representative index of the households' consumption. Therefore, all the values are expressed in current dollars as of December 2016<sup>68</sup>. Using real magnitudes provides a sound basis for time comparisons within samples because it leaves aside the nominal movements caused by price fluctuations.

Regarding the period under analysis, and thanks to the use of the methodology which was profoundly explained in the previous subsection –, we focus on a comparison between three specific years, 2007-2012-2016, through the use of cross-sectional data. This particular type of data could resemble a picture of society in a given moment of time. However, although concise and synthetic, showing information this way could carry on several methodological drawbacks that one should take into account regarding econometric estimations. These issues will be further discussed.

The selection of the period responds to the complete tenure of the same political movement (2007-2016<sup>69</sup>), the formerly called Alianza País<sup>70</sup>. Moreover, we do not consider previous years both because of the substantial methodological change enacted in the national Household Survey during 2007 onwards, and because of the structural breakpoint in terms of institutional arrangements, economic policies and State intervention that took place in this year, which we previously fleshed out.

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<sup>67</sup> See Larrea & Fabris (2017).

<sup>68</sup> It is worth to highlight that the reference year's selection is arbitrary. Thus, we could have chosen either 2007 or 2012.

<sup>69</sup> First of all, it is worth to highlight that, in Ecuador, the executive tenure, as well as the legislative one, lasts 4 years and, if elected, each authority has a maximum of two ruling periods. However, just one year after arriving to power, the government called for a Constituent Assembly whose main objective was to create a new constitution. In particular, this constitutional reengineering both implemented new elections in 2009 and allowed popular election authorities in the two branches (deputies and president) to start their maximum of two rounds election periods from scratch. Essentially, this meant that Rafael Correa could run for president in 2009 as if it were his "first" election. Thus, the whole period can be subdivided in three segments: 2007-2008 (before the Constituent Assembly), 2009-2012 (the "first" tenure), and 2013-2017 (the second tenure).

<sup>70</sup> Nowadays, due to judiciary and political problems, the party has shift to another name: "Revolución Ciudadana".

The choice of 2012 is based on comparative purposes. The main thrust of the analysis is to evaluate the labor market conditions and the schooling distribution on the two tails of the period (2007 and 2016). Picking up a year situated in-between – and equidistant from each tail – would present the estimations and results in a smoother way. It also coincides with the end of the first term of Alianza País (2009-2012), and therefore, the beginning of the second one, which, albeit an extension of the administration programmatic plan, meant both a deepening in the implementation of a set policies and the realignment of some others (Benito Gil, 2017).

Finally, we do not take into account other years of the period in order to better show changes throughout time. Although a yearly series is feasible with these data, a year-to-year comparison would not put forward structural movements, rather it will present the smooth trend during the decade.

#### **4.2.1. Survey Characteristics**

The research draws on a household micro database provided by a continuous application survey with a nationwide coverage, divided according to the geographical area (urban and rural) among all the provinces in Ecuador: 'ENEMDU (Encuesta Nacional de Empleo, Desempleo y Subempleo). This survey, whose target population is all private households in Ecuador, makes part of a wider data framework called SIEH (Sistema Integrado de Encuestas de Hogares).

Using this statistical tool, we are able to extract information on geographic phenomena, the employment situation in the country, the characterization of the labor market, the economic activity of Ecuadorians and income sources of the population.

In 2007, the Instituto Nacional de Estadísticas y Censos (INEC) carried out a methodological change in what concerns the construction of indicators<sup>71</sup>. It can be briefly divided in three modifications: 1) the sampling frame: where the representativeness is extended to the regional, urban-rural level and five main cities<sup>72</sup>, 2) procedures in field operations concerning the information gathering, and 3) conceptual reframing that affected

<sup>71</sup> “With two fundamental objectives: i) to unify the labor statistics derived from the gathering of information by an external entity, and ii) adhere to international standards suggested by CIET” (Castillo & Salas, 2018).

<sup>72</sup> Quito, Guayaquil, Cuenca, Machala and Ambato.

the conception of the EAP through changes in the survey forms from which the labor indicators are constructed. Even though this adjustment brought a more accurate assessment among variables and eased the international comparison, it hampered the possibility to smoothly analyze the labor market performance through a continuum of time due to the lack of comparability of the figures (Castillo & Salas, 2018).

Regardless of the multiple methodological changes underwent by the survey from that year – this equally includes the incorporation of a new sampling framework in 2013, the enlargement of the sample size in 2014, etc. – INEC has provided researchers of homogenized databases at least for the period 2007-2020<sup>73</sup> (INEC, 2021).

Furthermore, the waves have been quarterly since June 2007 (March-June-September-December), which makes it possible to count on periodic windows. In effect, this panel-type survey is supposed to measure the evolution of indicators in consecutive quarters and years, as well as capture seasonality effects over time (INEC, 2018)<sup>74</sup>.

Concerning the frame and sample design we need to mention that it is a probabilistic type and composed by two stages: on the one hand, the selection of primary sampling units (conglomerates) (UPM) by stratum. On the other, the selection of occupied dwellings<sup>75</sup> within each of the conglomerates selected in the first stage (INEC, 2018).

Each UPM belongs to an array which in turn is constituted by seven households. The arrays' rotation follows a quarterly scheme 2-2-2. This means that an array is visited by interviewers during two consecutive quarters followed by no visits in the two subsequent quarters. Finally, the array receives a second visit on the two last quarters (INEC, 2019).

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<sup>73</sup> The reference year upon which all the variables were homogenized is September 2018.

<sup>74</sup> The number of observations for the three years 2007, 2012, 2016 is 76,922; 73,686; and 114,086, respectively.

<sup>75</sup> Considered as the Secondary Sampling Unit (SPM).

Moreover, the Survey enables to extract information about the ethnic origin of the population, which ultimately permits the study to apprehend the two sub-groups of interest: Indigenous and Afro-American<sup>7677</sup>.

On the other hand, as it is the case for this particular type of Survey, there are some biases than might arise as a product of the information gathering process. Among others, an underestimation problem is likely to occur due to the self-identification method used in ethnic origins questions<sup>78</sup>. Because of historical reasons explained in previous chapters – systematic exclusion and social discrimination upon Indigenous and Afro-American – it is plausible to have a biased trend in the responses of self-identification towards the Mestizo category. By and large, the latter refers to a large and diverse group where a variety of cultures converge being those who are descendants of Andean Indigenous and Spanish the most representative. Since there is a generalized and embodied social rejection towards Indigenous and Afro-American (See section 2.2.2), whoever effectively belongs to them would avoid a self-identification in the category within the frame of a Survey. This issue would overestimate the mestizo's group biasing the results<sup>79</sup>.

Finally, although the Andean country is composed by four regions; coast, mountain range, amazon, and insular, we will remain only with the first three. This decision is based

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<sup>76</sup> Technically, based on the form, in the 2016's Survey there is a specific question targeting these two subgroups. It asks the respondents: "How do you identify (...) according to your culture and customs?". In the Survey this question is labeled as "p15". The possible answers that unfold are: Indigenous, Afro-Ecuadorian, or Afro-Descendent, Black, Mulato, Montubio, Mestizo, White and Other (which?). Taking into account the similarities among certain ethnicities we have decided to gather Afro-Ecuadorian or Afro-Descendent, Black and Mulato in one single category labeled "Afro-American".

<sup>77</sup> For 2007 the unfolded options concerning "p15" are less. This is, Indigenous, White, Mestizo, Black, Mulato, Other (which?). With the same criterion, the ethnicities Black and Mulato were gathered in a single one. The way we proceed enables us to homogenize the answers regarding a proper comparison of the estimations.

<sup>78</sup> This method is widely use in Latin American countries as the primary way for determining the ethno-racial categorization (Aranda & Ratzlaff, 2018).

<sup>79</sup> Another relevant fact concerning this particular question is the creation of the option "Montubio" in the year 2011. This ethno-racial category refers to the people with morphological features of the littoral region as well as the subtropical zones of Ecuador. The issue might affect the estimates for the first year of study, 2007. However, in a population distribution analysis according to the self-ethnicity perception Castillo & Andrade (2016) conclude that in 2006 approximately 4% of persons that self-identified as White and 2% as Mestizo were for 2016 actually Montubio. Thus, we consider this percentage could not be by any mean a source of bias that might jeopardize the results.

on the fact the insular region (Galapagos' Islands) is not included in the cross-sectional data for 2007 and 2012<sup>80</sup>.

### 4.3. Specification of the Model

#### 4.3.1. Covariates' Selection

As we mentioned in the beginning of this section and following reference works such as those of Ariza & Montes-Rojas (2018) and Ferreira *et al.* (2017), our dependent variable would be a particular measure of labor earnings, the real hourly wage of the population in working age. Although there are other sources of income – cash transfers, capital incomes or subsidies – the one coming from the labor realm fits the best with respect the analysis envisaged in this research.

The reason is the following. In modern societies, channels studied in the theoretical frameworks discussed above between skill differentials – proxied mostly by educational attainment – and earning differentials are carried out through market means. Indeed, to a large extent, labor revenues will be representative of the market reward structure at a particular point in time<sup>81</sup>.

Moreover, in light of the discussion fleshed out in the initial chapters, we select a set of regressors attempting to explain the performance of the real hourly wage: sex, marital status, educational attainment, age (potential experience), occupational categories, sector of activity, urban/rural, and regional dummies.

Marital status is a dummy variable indicating whether the individual is married or not. Furthermore, we will split the effect of schooling by using first years of formal education and then, the highest educational level attained. This responds to another approach of Human Capital theory that casts doubt on the implementation of years of schooling as its proxy. In

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<sup>80</sup> Notwithstanding, the representativeness of this geographical area in demographic terms is negligible. In fact, in 2016 it stands for the 0.23% of the total population. As a result, we believe this methodological decision will not undermine the final results.

<sup>81</sup> “Labor earnings are the main source of income for most households. On average, they account for 75% of all income reported in Latin American household surveys” (Galiani *et al.*, 2017).

this sense, the “Parchment Theory”<sup>82</sup> draws on the maximum educational level attained in individuals as the reference and measurable category.

Since real labor experience is not an observable characteristic – unfortunately, it is not captured by the Survey we draw on –, we rely on potential experience, which is proxied by the age of individuals. The subdivision of this category in three levels allows us to capture the concavity of earnings profile<sup>83</sup>: experience returns to the hourly wage are increasing until they reach a tipping point from which their contribution starts to decline.

Moreover, we include to the regressions dummy variables for occupational categories such as boss, self-employed and wage earner. Sector of activity presents the economic area where individuals work (9 categories). Finally, we control for dummies variables not only by rural and urban zones, but also by region of three geographical areas of the country: coast, mountain range and the amazon.

Based on several previous works (Alejo et al., 2014; Firpo et al., 2018; Larrea & Fabris, 2017; Maurizio, 2014; Ríos Avila, 2019) we believe that this set of regressors can fully explain the hourly wage’s dynamic. Furthermore, the inclusion of control variables such as geographical regions as well as urban/rural zones permit to capture the particular features of the Andean country. Finally, occupational categories and economic sectors precisely describe both labor market and the productive matrix features. For instance, the relative importance that holds “self-employment” in an economy such as the Ecuadorian.

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<sup>82</sup> “This view suggests that the rate of return to education is higher for those who finish their studies and obtain a degree than for those who drop out before obtaining it, even though they have been on the verge of obtaining it” (Sevilla, 2004).

<sup>83</sup> In order to capture this nonlinear relationship other studies rely as well on a quadratic term of the variable years. See for instance Fournier & Koske (2013).

## 5. RESULTS<sup>84</sup>

In this chapter, we first describe the evolution of different microeconomic variables of the Ecuadorian labor market and the educational system during 2007-2016 with the aim of contextualize the socioeconomic situation of the country. This will better elucidate its performance in terms of education and labor income distribution, our variables of interest. Next, we will move towards the models' assessments by employing the set of models already discussed – the Mincerian equation, CQRs, and drawing on RIF methodology, UQRs – for the three years selected. Finally, through the use of the estimates as input, the research will attempt to extract conclusions that will help understand this complex interaction between education and wage distribution.

### 5.1. Descriptive Statistics

As mentioned in previous sections, throughout the period under analysis, the country experienced a somewhat virtuous circle in many macroeconomic indices that consequently impacted in the microeconomic realm, such as labor market variables. In fact, this upward trend was particularly meaningful in the first subperiod (2007-2014), where the real GDP increased 4.4% on average, boosted by a favorable international context, and a set of economic policies embodied in a significant public intervention (See Chapter 2). Several external shocks, nonetheless, slowed down the upward path in 2015, which in turn caused a stagnation of the previously thriving economy.

Table 2 shows how the Gini coefficient of the hourly wage plummeted drastically passing from 0.52 in 2007 to 0.43 in 2012. In other words, economic growth had an equalizing effect during these years (see Figure 8). Notwithstanding, due to the negative impacts on the economy, as well as a reduction in public expenses, this coefficient slightly increased in 2016. Despite of this economic slowdown, the real hourly wage measured in American dollars increased with a high pace throughout the period, albeit with a more pronounced dynamic in both the median ( $q50$ ), moving from USD 1.6 in 2007 to USD 2.3 in 2016, and the top quantile ( $q90$ ), from USD 5.5 to 5.9, respectively. Therefore, most of

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<sup>84</sup> For the synthetic version of the Do Files used in the estimation process (through the software STATA) see Annex V.

this movement took place in the upper part of the distribution. Yet, this performance coexists with the distributional improvements already mentioned.

Likewise, changes in education were also dramatic. Schooling dispersion – understood as the distribution of years of schooling among the members of society – in the sample decreased during the period (from 0.29 to 0.27). This might have been caused by the expansion of the share of primary and secondary education in the poorer households that usually lack of Human Capital accumulation.

**Table 2 - Variables' Summary**

Variable						
Wage per hour*						
Year	Mean		Gini	q10	Median	q90
2007	2.8		0.52	0.5	1.6	5.5
2012	2.9		0.43	0.7	2.1	5.6
2016	3.2		0.44	0.7	2.3	5.9
Years of Education						
Year	Mean		Gini	q10	Median	q90
2007	10.0		0.29	4.0	10.0	17.0
2012	10.8		0.28	5.0	11.0	18.0
2016	10.9		0.27	6.0	12.0	18.0
Educational Level						
Year	No Education	Primary	Basic Education	Secondary	Middle Education	Higher
2007	4.1%	36.7%	5.5%	30.1%	3.4%	20.3%
2012	3.3%	31.6%	4.4%	32.7%	4.1%	23.9%
2016	2.2%	30.3%	5.2%	31.5%	9.3%	21.5%
Region						
Year	Mountain Range		Coast		Amazon	
2007	47.5%		47.8%		4.7%	
2012	46.5%		48.6%		4.9%	
2016	47.1%		47.6%		5.3%	
Ethnic Composition of the Population						
Year	Indigenous		Afro-American	Mestizo		White
2007	6.3%		3.7%	82.7%		7.3%
2012	5.9%		4.0%	88.6%		1.9%
2016	7.3%		4.4%	86.7%		1.7%

**Source:** own elaboration based on ENEMDU.

\* Current US Dollars of 2016

In this sense, within the period 2006-2014, the average years of schooling in the 3 inferior quintiles rose by almost one year. Depending on the quintile, these same households



have experienced a non-negligible increase in the percentage of higher education (Atuesta *et al.*, 2016). This upgrade benefited more the lower quintiles where the average of years of formal schooling passed from 4 to 6 (see Table 2). Thus, what was fueling the increase in the mean of years of education proved to be an improvement in terms of Human Capital in the more vulnerable groups: the first quantiles of the distribution. This fact coincides with Battistón *et al.* (2014), who point out that during the 2000s, education growth path in Latin America, was generally biased towards less educated people (poorer) groups. The authors called it the “break in educational gaps”. Equally, authors such as Nora Lustig call it the “democratization of education”.

Moreover, taking the maximum educational level<sup>85</sup> attained, it is evident that the declining percentage of people holding a Primary level – from a 36.7% in 2007 to a 30.3% in 2016 – was traduced in a greater share of Secondary and Higher education. The latter implies that a portion relatively bigger of the population attained higher levels of education other than Primary. Even though, the chosen period fails to be long enough in order to prove a structural change in the educational composition of the Andean country, it nonetheless captures at least an initial trend of these variables’ performance. There is not necessarily a symmetric timing between a generalized upgrading in schooling and the subsequent differentials in earnings. This synergy could probably take a longer time to crystalized. That is the reason why, a comprehensive study of education’s impact on economy beyond conjunctural distributional effects, would unquestionably need a larger period.

Similarly, the Region subsection presents the demographic composition of each of the three natural zones of the Andean country. As we can appreciate, both Mountain Range (the cities situated within the Andes) and Coast account for the majority of the population. Although extensive in area, the Amazon region is not demographically significant.

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<sup>85</sup> Primary education comprises 6 years of schooling and officially includes children from 6 to 11 years. Basic education is a broader category that incorporates Primary level and adds Middle education. Hence, it accounts for 10 years of schooling and concerns children from 5 to 14 years old. Moreover, Secondary is a period that comprises 6 years of education, adolescents in this level range from 12 to 17 years. Likewise, middle education is placed in-between Primary and Secondary accounting for 3 years and the official ages in this level move from 9 to 11 years. Finally, Higher education in this work includes tertiary, non-tertiary, and post-graduate studies. This means that the official age is from 17 years on (Ministerio de Educación, 2015).

Finally, the last section in Table 2 illustrates the ethnic composition of the Ecuadorian society for the three years under analysis. First, the Mestizo category bears for the greatest demographic share compared with the others. Its percentage is never under 82%. As we already mentioned in the previous chapter, this ethnic group is broad and diverse. Second, Indigenous and Afro-American present lower percentages exposing their relative low representation within society. Yet, their numbers have been increasing throughout the decade reaching the values of 7.3% and 4.4%, respectively.

To better understand the nuances that might arise when splitting up the sample according to the ethnic origin Table 3<sup>86</sup> shows the wage per hour for the four subgroups. Overall, the mean wage has risen during the period for every category. However, the departure levels for each one vary considerably.

**Table 3 - Ethnic Origin: Wage per Hour**

<b>Indigenous</b>					
Year	Mean	St. Dev.	q10	Median	q90
2007	1.5	1.7	0.2	1.1	3.0
2012	1.7	3.3	0.2	1.2	3.2
2016	2.0	2.2	0.3	1.6	4.0
<b>Afro-American</b>					
Year	Mean	St. Dev.	q10	Median	q90
2007	2.3	4.1	0.5	1.4	4.1
2012	2.5	3.5	0.7	2.0	4.3
2016	2.8	2.7	0.8	2.2	5.3
<b>Mestizo</b>					
Year	Mean	St. Dev.	q10	Median	q90
2007	2.8	4.9	0.6	1.7	5.6
2012	2.9	4.4	0.7	2.2	5.6
2016	3.3	9.4	0.8	2.4	6.1
<b>White</b>					
Year	Mean	St. Dev.	q10	Median	q90
2007	3.6	8.3	0.5	1.8	7.3
2012	3.9	3.9	0.6	2.6	9.4
2016	3.8	5.3	0.8	2.6	6.9

**Source:** own elaboration based on ENEMDU.

<sup>86</sup> Table 3 deploys different statistics for the wage per hour according to the ethnic origin for the three years under analysis. The mean, the Standard Deviation (St. Dev.), which shows the dispersion of a set of values, and three representative quintiles: *q10*, *q50* (the median) and *q90*.

Both Indigenous and Afro-American possessed the lowest mean in 2007, USD 1.5 and USD 2.3, respectively. The values they reached in 2016, albeit greater, remained lower than those of Mestizos and White. Moreover, these two last subgroups exhibit a high dispersion in the observations. This can be easily contrasted when regarding their first ( $q_{10}$ ) and last ( $q_{90}$ ) percentile. The former is similar in magnitude during the three years to that of Indigenous and Afro-American ranging from USD 0.6 to 0.8 for Mestizo and USD 0.5 to USD 0.8 for White. Notwithstanding, the divergence within ethnic subgroups appears in the upper percentile. While in  $q_{90}$  Indigenous and Afro-American attained for 2016 USD 4.0 and USD 5.3 respectively, Mestizo and White reached in the same year USD 6.1 and USD 6.9.

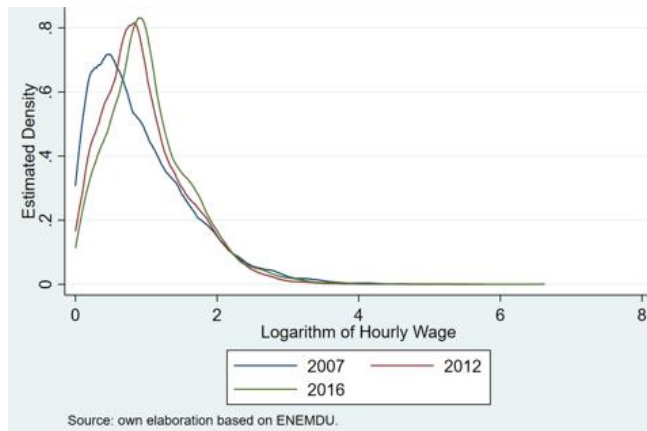
Likewise, Figure 16 exhibits the densities of the logarithm of the hourly wage measured by Kernel for the three years in the period<sup>87</sup>. It is remarkable the shift of the income distribution from 2007 to 2012. On average, the hourly wage increased, which is represented by a shift in the mean of earnings from USD 0.91 to USD 0.97. Yet, as any other average, it might hide compositional movements inside the sample since this statistic is not robust in presence of outliers or extremely great values. In this sense, an even larger change occurred in the median. Thus, the value under which is placed 50% of the sample moved from USD 0.76 to USD 0.85. Graphically, we can see that the curve for 2012 is narrower concentrating more observations – more persons – in a higher hourly wage compared to 2007. This movement coincides with the widespread improvement of all labor market indicators reviewed in previous chapters.

In what concerns the second subperiod, 2012-2016, to a certain extent, the shift of the curve is sugarcoated. Yet, it is relevant to mention a movement to the right of the distribution, which in turn means an increase in both the mean and the median.

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<sup>87</sup> For a detailed figure of each year with their respective medians and means, see Annex II.

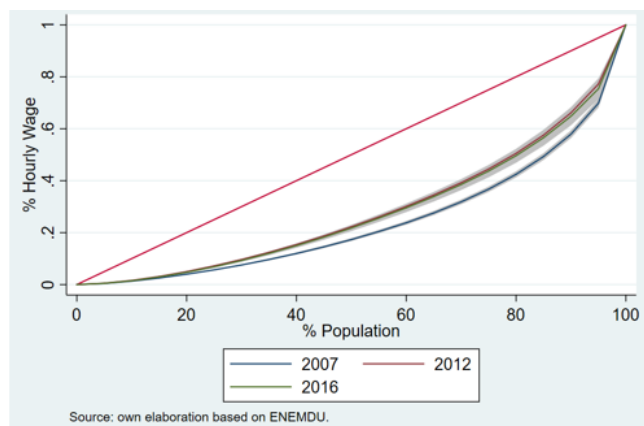
**Figure 16 - Log Hourly Wage Densities by Kernel 2007-2021-2016**



Finally, for the aggregated analysis, it is of valuable importance to present the Gini coefficient in a more graphic way. The Lorenz Curve illustrates the hourly wage distribution for each year of the selected period. The distributive situation of a particular moment of time is the area inside the curve. The smaller it is – the closer to the line of  $45^{\circ}$ <sup>88</sup> –, the more equalizing is the earning distribution.

For the first subperiod, the distributive upgrades are clear, the blue curve (2007) possesses a greater area compared to the red curve (2012). This means a reallocation of labor income towards the lower quintiles of the distribution. Notwithstanding, for the second subperiod, the change remains ambiguous exposing the stagnation of the improvement of labor market variables discussed above.

**Figure 17 - Lorenz Curve - 2007-2012-2016**

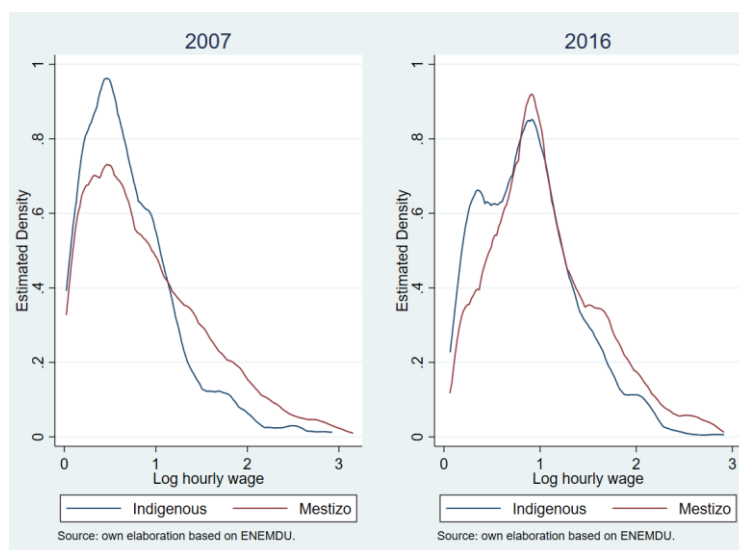


<sup>88</sup> Also called the line of “perfect equality”.

On the other hand, hourly wage distributions present significant asymmetries when divided according to the ethnic origin. This is called in specialized literature ethno-racial inequality. For that purpose, we will first compare the performance, from tail to tail, of the marginal income distribution of Indigenous against Mestizo. Then, we will address the same dynamic, but this time for Afro-American<sup>89</sup>. The reason why we contrast both ethnic subgroups with Mestizo category is straightforward. A priori the latter enjoys of social acceptance and lack of social discrimination before the population which will be traduced in different – higher – market returns (See Table 3). Hence, Mestizo will act as the reference category.

In this sense, Figure 18 sketches the estimated densities by Kernel of Indigenous and Mestizos. For presentation reasons we will solely display the two tails of the period (2007 and 2016). This in turn will help contrast the changes – if they occurred – underwent in the decade.

**Figure 18 - Estimated Densities by Kernel – Indigenous vs Mestizo**



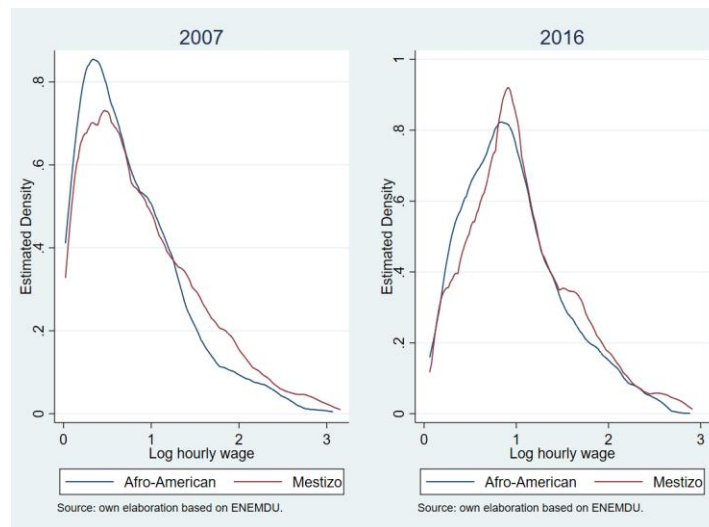
For the first year, the estimated density of Mestizo was more evenly distributed across the different values of the hourly wage. This implies that the tail had a greater importance compared to that of Indigenous. The latter nonetheless concentrates the majority of the sample in lower values of the hourly wage. In 2007, the gaping chasm in terms of earning

<sup>89</sup> For a detailed evolution of kernel densities of both Indigenous and Afro-American according to each year of analysis see Annex II.

differential between these two subgroups was enormous. Furthermore, in 2016, the pick of the kernel density of Indigenous shifted towards the right pointing out an improvement both for the mean and the median. Still, Mestizo continued enjoying a weightier tail for the upper values of the hourly wage distribution. In one word, despite of a shortening in the gaps between these ethnical groups, the differences remained in place for 2016.

Though nuanced by its own particularities, the situation for Afro-American in 2007 resembles that of Indigenous. Whereas the point around which most of the earnings gather is placed in an extremely low value of the hourly wage (less than USD 0.5), the tail for upper values shrunk drastically compared to that of Mestizo. On the other hand, for 2016 a pretty different panorama shows up. In fact, the decrease of the pick is absorbed by a relative greater importance of the tail, which means that more Afro-American started earning higher hourly wages compared to 2007.

**Figure 19 - Estimated Densities by Kernel – Afro-American vs Mestizo**



In an attempt to gauge the interaction between schooling and earning differentials we deploy Table 4<sup>90</sup>. Succinctly, it displays the composition of each quintile of the distribution, measured by the real hourly wage, across the five educational levels: No Education, Primary, Basic Education, Secondary, Middle Education and Higher Education. The information compares the situation between the two tails of the period, 2007 and 2016, respectively.

<sup>90</sup> Table 4 splits up the different quantiles of the income distribution according to their share in each educational level (6 in total) for the two tail years: 2007 and 2016. Thus the sum of each row is 100%.

The first difference between the two years is the loss of relative importance of the Primary share across the quintiles. On the one hand, in the lower quintiles (*q1* and *q2*), this downward movement was substantial and to a large extent explained the gain in relative importance in upper education levels. Whereas the shares of *q1* and *q2* in Secondary passed from 22.8% and 30.6% in 2007 to 28.5% and 33.3% in 2016, respectively, higher education grew from 4.4% and 7.7% to 6.0% and 9.6% for each quintile during the period.

**Table 4 - Income quintiles & Educational Levels**

Year		2007					
Quintiles	No Education (%)	Primary (%)	Basic Education (%)	Secondary (%)	Middle Education (%)	Higher (%)	Total (%)
q1	11.1	51.2	7.4	22.8	3.1	4.4	100
q2	5.6	46.8	6.0	30.6	3.2	7.7	100
q3	4.3	42.6	3.6	34.5	2.6	12.4	100
q4	2.2	31.8	2.2	36.6	1.8	25.4	100
q5	1.5	16.2	0.7	26.1	1.2	54.3	100

Year		2016					
Quintiles	No Education (%)	Primary (%)	Basic Education (%)	Secondary (%)	Middle Education (%)	Higher (%)	Total (%)
q1	6.8	45.5	6.0	28.5	7.3	6.0	100
q2	3.6	39.4	5.5	33.3	8.5	9.6	100
q3	1.8	33.5	4.0	36.6	10.1	13.9	100
q4	1.2	27.3	3.3	37.3	7.4	23.5	100
q5	0.5	13.0	0.9	24.6	3.4	57.6	100

**Source:** own elaboration based on ENEMDU.

**Note:** Income as USD hourly wage.

On the other hand, the upper quintiles followed a similar trend but with a different intensity. Although there was an improvement of the share of people belonging to this scale of society in Higher education, the strength of this change was somewhat modest. Among other explanations, this could possibly be the result of an explicit policy from the government to target the most vulnerable groups by focusing education expenditure on households with low Human Capital accumulation.

More particularly, it is interesting to analyze the interaction between the different shares within the educational levels according to the ethnic origin. This is precisely what

Table 5<sup>91</sup> exhibits. Regardless of the year we take, the disparity in terms of schooling accumulation underwent by both Indigenous and Afro-American compared to Mestizo and White is evident.

**Table 5 - Educational Levels & Ethnic Origin**

2007					2016				
Year					Year				
Educational Level	Indigenous (%)	Afro-American (%)	Mestizo (%)	White (%)	Educational Level	Indigenous (%)	Afro-American (%)	Mestizo (%)	White (%)
No Education	18.2	6.1	4.8	4	No Education	9.9	3.8	2.9	2.3
Primary	30.6	29.1	26.1	25.2	Primary	25.1	21.8	22.1	19.5
Basic Education	36.6	32.3	29.6	27	Basic Education	39	31.2	27.7	24
Secondary	8.4	21.8	20.3	22	Secondary	12.5	22.8	21	24.6
Middle Education	3.4	4.6	5.4	5.4	Middle Education	9.4	11.7	10.8	9.4
Higher	2.8	5.9	13.7	16.4	Higher	4.1	8.8	15.4	20.2
Total	100	100	100	100	Total	100	100	100	100

**Source:** own elaboration based on ENEMDU.

Indigenous and Afro-American are mostly placed, for 2007, in the lowest educational levels. Primary represented a 29.1% of the share of the latter, while it stood for 30.6% for the former. It is striking the marginal percentage on both ethnic categories when regarding higher education (barely a 2.8% and 5.9%, respectively). For instance, in 2007, the percentage of White people in Higher education (16.4%) was almost sixfold the number of Indigenous.

The landscape in 2016, though still asymmetric, presents a more compensated structure across the ethnic origins. Primary education in Indigenous and Afro-American lost substantially its relative importance reaching 25.1% and 21.8%, respectively. Not only the Secondary education share grew, but Higher education appears to have absorbed the majority of the schooling upgrading in these two groups moving to 4.1% and 8.8%, accordingly.

Unfortunately, this panorama exhibits a particular form whereby inequalities might occur that are clearly beyond the control of individuals: ethno-racial attributes. The data for Ecuador support what Aranda & Ratzlaff (2018) suggest for the Latin American region: due to this type of discrimination, Indigenous and Afro-American are faced with higher rates of

<sup>91</sup> Table 5 splits up the different educational levels according to their share in each ethnic origin for the two tail years: 2007 and 2016. Thus the sum of each column is 100%.



poverty, lower incomes, and access to services. In our research, we acknowledge that it is the case of education.

## 5.2. Model Assessment

In this subsection we will attempt to interpret the results of the different models used in the research. Positioning the estimates, always through a rigorous methodological criterion, in a particular socioeconomic context will help understand and disentangle the complexity interaction between our variables of interest.

### 5.2.1. Mincer Equation

The research will focus essentially on the interaction of education and the dependent variable. For comparative purposes, in this subsection we will analyzed Indigenous and Afro-American as a single group. This decision is based on the different indicators displayed below that show the similar features as well as alike trends shared by these two ethnicities.

In this sense, a first remark can be found in Table 6<sup>92</sup>. The influence of years of schooling, *ceteris paribus* the other explanatory variables, on the hourly wage is decreasing over time and statistically significant<sup>93</sup> for the aggregate sample. On the contrary, albeit still significant, the returns of schooling for Indigenous and Afro-American are slightly increasing from tail to tail<sup>94</sup>.

For the aggregate sample, whereas in 2007, a marginal change to the right of education meant an increase of the hourly wage in 5.4%<sup>95</sup>, in 2016 this impact had been reduced to 4.5%. On the other hand, for the two ethnic groups the marginal change of education was associated to a rise of the hourly wage of 2.8% in 2007 and 2.9% in 2016<sup>96</sup>. These two opposite trends can be explained simultaneously through two channels.

<sup>92</sup> In Table 6 the two columns labeled “Variable” deploy the pack of regressors used in the estimations. Our measure of education is Years of Schooling. Moreover, the subsequent columns exhibit both the estimates (the  $\beta$ 's) (Est.) and the Standard Error (S.E.) for each subsample (Aggregate and ethnicities) in 2007 and 2016.

<sup>93</sup> The three coefficients are significant with a  $p < 0.001$ .

<sup>94</sup> Both estimations were carried out including Heckman's correction. For the outputs of the auxiliary equations see Annex III.

<sup>95</sup> Technically, given the log-lin model, the coefficients are interpreted as semi-elasticities. Particularly, for education:  $\beta_1 = \frac{\% \Delta y_i}{\partial s_i}$ .

<sup>96</sup> It is worth to highlight that all the estimates for this regressor are statistically significant regardless of the period and the sample. Hence, showing the importance of education when it comes to explain the hourly wage.

**Table 6 - Mincerian equation and returns of education. Heckman's correction.**

Variable	Aggregate sample		Indigenous & Afro-American		Variable	Aggregate sample		Indigenous & Afro-American	
	2007	2016	2007	2016		2007	2016	2007	2016
	Est./S.E	Est./S.E	Est./S.E	Est./S.E		Est./S.E	Est./S.E	Est./S.E	Est./S.E
year2	0.109*** -0.02	0.124*** -0.01	0.043 -0.05	0.087* -0.04	transport	0.261*** -0.02	0.285*** -0.02	0.353*** -0.09	0.319*** -0.06
year3	0.237*** -0.02	0.155*** -0.02	-0.013 -0.05	0.089* -0.04	tourism	0.216*** -0.03	0.284*** -0.02	0.258** -0.09	0.275*** -0.05
sex	0.085*** -0.01	0.095*** -0.01	0.078 -0.04	0.073** -0.03	teaching	0.485*** -0.03	0.572*** -0.02	0.723*** -0.08	0.722*** -0.06
marital	0.107*** -0.01	0.1*** -0.01	0.086** -0.03	0.051* -0.02	public	0.705*** -0.03	0.754*** -0.02	0.928*** -0.1	0.861*** -0.05
education	0.054*** 0	0.045*** 0	0.028*** 0	0.029*** 0	others	0.301*** -0.02	0.415*** -0.01	0.439*** -0.06	0.472*** -0.04
boss	0.765*** -0.04	0.668*** -0.03	0.623*** -0.12	0.708*** -0.11	urban	0.123*** -0.01	0.095*** -0.01	0.148*** -0.04	0.143*** -0.03
self-employed	0.082** -0.03	-0.137*** -0.02	0.058 -0.09	-0.037 -0.06	coast	0.056*** -0.01	0.012 -0.01	0.116*** -0.03	0.005 -0.03
salaried	0.329*** -0.03	0.341*** -0.02	0.341*** -0.09	0.477*** -0.06	amazon	-0.018 -0.02	-0.088*** -0.01	0 -0.05	-0.056* -0.02
manufacture	0.1*** -0.02	0.179*** -0.01	0.234*** -0.06	0.187*** -0.04	lambda	-0.19*** -0.02	-0.235*** -0.02	-0.227*** -0.06	-0.219*** -0.04
construction	0.259*** -0.02	0.227*** -0.02	0.314*** -0.05	0.257*** -0.04	_cons	-0.758*** -0.04	-0.321*** -0.03	-0.589*** -0.12	-0.337*** -0.09
commerce	0.137*** -0.02	0.21*** -0.01	0.213*** -0.05	0.217*** -0.04					

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

As already mentioned in Table 2, unlike upper quantiles, educational expansion was particularly strong in the lower bounds. In fact, Human Capital among the poorest and most vulnerable workers – the quantiles with a huge component of Indigenous and Afro-American (see Table 1) –, measured by the average of years of schooling, drastically increased during this period. There was a compositional movement within the accumulation of education in the poorest from Primary to Secondary and Higher education<sup>97</sup>. Table 7<sup>98</sup> illustrates this shift comparing poor and non-poor<sup>99</sup> dynamics. The educational expansion in intermediate and higher schooling levels biased towards the poorest households could have caused an increase

<sup>97</sup> For the period 2006-2014, “among the 40% of the poorest, the percentage of workers with only basic education or less has decreased by close to 10 percentage points, which has led to groups with secondary education (around 8 points) and higher (2 points) to swell” (INEC, 2017).

<sup>98</sup> This table compares the percentage of poor and non-poor persons belonging to each Educational Level for the three years under analysis.

<sup>99</sup> INEC defines a person as “poor” if he/she is situated under the poverty line. This line is calculated through an update of the Consumer Price Index (CPI) of the official consumption poverty line. Hence, those individuals whose total per capita income, in relation to their household, is below the poverty line are identified as poor by income (INEC, 2020).

in the mean ability, and consequently an improvement in the wages at those levels. This dynamic could be the underlying cause of a rise in the return of education in the two ethnic groups.

**Table 7 - Educational Level & Poor/Non-Poor**

Educational Level	2007		2012		2016	
	Poor	Non-Poor	Poor	Non-Poor	Poor	Non-Poor
No Education	7.9%	2.5%	7.5%	2.3%	5.0%	1.6%
Primary	53.6%	29.9%	50.6%	27.3%	46.9%	26.7%
Basic Education	9.3%	3.9%	8.9%	3.4%	10.0%	4.1%
Secondary	21.8%	33.5%	23.1%	35.4%	24.4%	33.0%
Middle Education	3.6%	3.4%	4.9%	3.9%	9.6%	9.2%
Higher	3.9%	26.9%	5.0%	27.8%	4.1%	25.3%

**Source:** own elaboration based on ENEMDU.

In fact, the income gap in returns according to the educational level shortened considerable during this period. For instance, the average labor wage of a worker with Secondary level in 2006 was 45% greater than the wage of a peer with Primary level, this differential was reduced to 35% in 2014<sup>100</sup> (INEC, 2017). The shortening of these differentials could have produced a decline in the returns of the expected value of education for the aggregate sample as a whole.

The second channel can be situated in the demand side. From this approach, the interest relies on whether economic growth was driven by labor-intensive sectors and composed by a demand for high-skill workers – skill premium. The two components shape the way the market rewards labor force, therefore, shortening or increasing the gaps among them. This dynamic can be influenced by different circumstances and actors that can model the market mechanisms. Among all, the government, through public investment, played an enormous role in economy, namely until the year 2014. Atuesta et *al.* (2016) highlight that throughout this period the low-skilled intensive sectors witnessed a great increase in their returns, even more than those of high-skilled. These activities, such as construction, are tightly related to the public scaffolding. To a certain extent, it is possible to envisage a skill-

<sup>100</sup> Similarly, the difference of average labor income between Higher and Secondary education moved from 104% to 82%, respectively (INEC, 2017).

premium mechanism operating in the opposite way. An increase in the relative demand for unskilled labor will in turn increase their remuneration, and thus reduce overall inequality.

### 5.2.2. CQRs

As already mentioned in previous paragraphs, in order to better understand the interaction between education and labor income distribution, distributional analyses ought to go beyond the mean.

Table 8<sup>101</sup> shows the estimates<sup>102</sup> for the Conditional Quantile Regressions of both the aggregate sample and the particular subgroup composed by Indigenous and Afro-American. For illustrative purposes, we display in the table only the two tails of the period (2007 and 2016) as well as representative conditional quantiles of the distribution, namely  $q10$ ,  $q50$  (the median) and  $q90$ <sup>103</sup>. Finally, the last columns for each subgroup are the estimations of MCO adjusted by Heckman showing the mean conditional expected value of education.

First, we consider the upper part of the table. For the aggregate sample, in 2007 the increasing returns of education along the conditional quantiles are pretty clear. In this sense, it is possible to appreciate a greater reward of schooling (the last regressor labelled “education”) for the top quantile. An additional year of schooling in  $q90$  is associated to an increase of 6.2% of the hourly wage conditional to education. However, in 2016, there were several substantial differences. On the one hand, the average return of education declined (from 5.4% to 4.5%). This shift is compatible with the decrease of the skill premia (Chiodi, 2021). On the other, although the increasing returns remained along the quantiles, the

<sup>101</sup> In Table 8 the column labeled “Variable” deploys the pack of regressors used in the estimations, in this case solely the first part of the list. Our measure of education is Years of Schooling. Moreover, the subsequent columns exhibit both the estimates (the  $\beta$ 's) (Est.) and the Standard Error (S.E.) for each subsample (Aggregate and ethnicities) in 2007 and 2016 according to representative quantiles (namely  $q10$ ,  $q50$  and  $q90$ ) and the mean.

<sup>102</sup> In the body section we limit to display de estimates only for the main regressors. The model includes nonetheless other control variables such as occupational categories (Boss, Self-employed, Salaried), economic sectors (Manufacture, Construction, Commerce, etc.), zone dummies (Urban and Rural), region dummies (Mountain Range, Coast and Amazon). The comprehensive model is presented in Annex IV.

<sup>103</sup> For a detailed version of the results through the use of this decomposition method see Annex IV where we exhibit the estimates of the three years of the period and for all the quantiles of the distribution ( $q10$ - $q90$ ).

range<sup>104</sup> slightly decreased moving from 0.09 to 0.08, which might be bolstering the fact of a more equalizing distribution for this year.

**Table 8 - Conditional Quantile Regressions (CQRs) - Years of Schooling**

Variable	Aggregate Sample							
	2007				2016			
	q10	q50	q90	Mean	q10	q50	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
year2	0.231*** -0.03	0.194*** -0.02	0.196*** -0.02	0.109*** -0.02	0.275*** -0.02	0.201*** -0.01	0.262*** -0.02	0.124*** -0.01
year3	0.274*** -0.03	0.326*** -0.02	0.444*** -0.03	0.237*** -0.02	0.28*** -0.02	0.246*** -0.01	0.375*** -0.02	0.155*** -0.02
sex	0.23*** -0.02	0.153*** -0.01	0.09*** -0.02	0.085*** -0.01	0.196*** -0.02	0.128*** -0.01	0.127*** -0.01	0.095*** -0.01
marital	0.121*** -0.02	0.097*** -0.01	0.141*** -0.02	0.107*** -0.01	0.122*** -0.02	0.115*** -0.01	0.111*** -0.01	0.1*** -0.01
education	0.053*** 0	0.053*** 0	0.062*** 0	0.054*** 0	0.048*** 0	0.044*** 0	0.056*** 0	0.045*** 0
Variable	Indigenous & Afro-American							
	2007				2016			
	q10	q50	q90	Mean	q10	q50	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
year2	0.13 -0.07	0.167*** -0.05	0.124* -0.06	0.043 -0.05	0.233*** -0.07	0.214*** -0.04	0.18*** -0.04	0.087* -0.04
year3	-0.016 -0.08	0.118* -0.05	0.211** -0.07	-0.013 -0.05	0.202** -0.08	0.247*** -0.04	0.218*** -0.05	0.089* -0.04
sex	0.223*** -0.06	0.166*** -0.04	0.112* -0.05	0.078 -0.04	0.182*** -0.05	0.123*** -0.03	0.019 -0.03	0.073** -0.03
marital	0.199*** -0.06	0.09* -0.04	0.077 -0.05	0.086** -0.03	0.123* -0.05	0.057* -0.03	0.106*** -0.03	0.051* -0.02
education	0.032*** -0.01	0.03*** 0	0.034*** -0.01	0.028*** 0	0.038*** -0.01	0.035*** 0	0.034*** 0	0.029*** 0

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:** p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

Second, when analyzing the trajectories of the two ethnic groups, there are several particularities we need to point out. In 2007, the increasing returns along the quantiles, albeit present, were to a large extent less pronounced, they did not increase considerably when moving towards the upper quantiles. As a result, the range was barely 0.002. Moreover, for 2016 not only the average return increased, but also the system reward was reversed. In other words, education had a greater impact on the hourly wage for the bottom quantiles. Whereas a marginal increase of a year of schooling in  $q_{10}$  rose the hourly wage 3.8%, it represented

<sup>104</sup> The difference in absolute value between the highest and lowest quintile,  $|r| = |q(90) - q(10)|$ .

a gain of 3.4% for  $q_{90}$ . These estimates might be indicating a possible equalizing role of education over the conditional distribution of income.

Furthermore, Table 9<sup>105</sup> displays the CQRs for the three years under study, but this time we focus exclusively on the educational levels<sup>106107</sup>. The idea is to incorporate in the critic of the “Parchment theory” already discussed in the previous chapter. We show solely three levels of education: Primary, Secondary and Higher. The reason is based on the fact these categories are the more representative in terms of enrollment during the whole period (See Table 2).

In line with many empirical works for the region – for instance, Gasparini *et al.* (2013) – the distributive effect of primary education is overall equalizing for the aggregate sample in Ecuador throughout the period 2007-2016. Consequently, the impact for the lower quantiles hourly wage was greater than the one of the upper parts. Nevertheless, insofar as we move to 2016, the equalizing effect deepens, which means that the range, in absolute terms, was also expanded. In effect, it moved from 0.101<sup>108</sup> in 2007 to 0.164<sup>109</sup> in 2016. At the beginning of the period, a marginal expansion of Primary education entailed an increase of the hourly wage in 30.9% for the lowest quantile, while in the end it was worth it 33.2%. Simultaneously, the conditional mean return, assessed by MCO, declined in this educational level.

Likewise, when reducing the sample to Indigenous and Afro-American groups, Primary education still presents an equalizing effect for the whole period. Even though for 2007 its impact in most of the quantiles was not statistically significant, in 2016 it stood for a  $p < 0.001$  in all the estimates indicating a gain in importance as explanatory variable of

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<sup>105</sup> In Table 9 the column labeled “Variable” deploys the pack of regressors used in the estimations, in this case solely the Educational Levels Primary, Secondary and Higher, which are this time our measure of education. Moreover, the subsequent columns exhibit both the estimates (the  $\beta$ 's) (Est.) and the Standard Error (S.E.) for each subsample (Aggregate and ethnicities) in 2007 and 2016 according to representative quantiles (namely  $q_{10}$ ,  $q_{50}$  and  $q_{90}$ ) and the mean.

<sup>106</sup> The reference category, and thus, the one omitted in the estimation is “No Education”. It is worth highlighting that this methodology is used in order to avoid problems of multicollinearity. Moreover, we restricted the presentation to three educational levels: Primary, Secondary and Higher education. Both Basic and Middle education with the 3 years can be appreciated in Annex IV.

<sup>107</sup> In terms of covariates, this model includes the same explanatory variables that those of Table 8.

<sup>108</sup>  $|q(90) - q(10)| = |0.208 - 0.309|$

<sup>109</sup>  $|q(90) - q(10)| = |0.168 - 0.332|$

the hourly wage. In fact, before an infinitesimal rise of this level, earnings increased 36.8% for the bottom quantile. Thus, the range attained a striking value of 0.202.

**Table 9 - Conditional Quantile Regressions (CQRs) - Educational Level**

Variable	2007				2016			
	q10	q50	q90	Mean	q10	q50	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>								
Primary	0.309*** -0.04	0.235*** -0.02	0.208*** -0.03	0.247*** -0.02	0.332*** -0.04	0.227*** -0.02	0.168*** -0.03	0.238*** -0.02
Secondary	0.491*** -0.04	0.43*** -0.02	0.479*** -0.04	0.474*** -0.02	0.517*** -0.04	0.368*** -0.02	0.355*** -0.04	0.402*** -0.02
Higher	0.877*** -0.05	0.899*** -0.03	1.053*** -0.04	0.943*** -0.03	0.831*** -0.04	0.737*** -0.02	0.903*** -0.04	0.8*** -0.02
<i>Indigenous &amp; Afro-American</i>								
Primary	0.108 -0.07	0.144** -0.05	0.111 -0.07	0.128** -0.04	0.368*** -0.07	0.302*** -0.04	0.166*** -0.05	0.258*** -0.03
Secondary	0.176 -0.09	0.243*** -0.06	0.317*** -0.09	0.273*** -0.06	0.459*** -0.08	0.384*** -0.04	0.272*** -0.05	0.347*** -0.04
Higher	0.474*** -0.13	0.606*** -0.08	0.686*** -0.12	0.578*** -0.08	0.768*** -0.1	0.713*** -0.06	0.645*** -0.07	0.658*** -0.05

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:**  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Another completely different situation unfolds in Higher education. The unequalizing effect over labor income distribution stands for the whole period, both in the aggregate sample and in the two ethnic subgroups. The returns of a marginal gain in Higher education increased vis-à-vis the quantiles. This situation has provoked an intense debate not only in academy, but also in the policy realm, since public efforts for a schooling enhancement mostly in University could finish by benefiting the richest groups in society (Gasparini *et al.*, 2013).

In the aggregate sample, the monetary returns for the  $q90$  associated to an increase of one year of education moved from 105.3% in 2007 to 90.3% in 2016 reinforcing the idea above mentioned. However, the gap in those returns between the two tails of the labor income distribution has been drastically reduced. In this sense, the range passed from 0.176 in 2007 to barely 0.072 in 2016. Despite its regressive feature, Higher education's impact has been compensated for the lower quantiles.

Although the data provided by CQRs are clear on the effects of education on wages, it is necessary to be careful with the interpretations. It means that, once controlled for the rest of regressors, a rise in the years of Higher education brings with it a positive return in all quantiles, with increasing effects in the upper part.

Finally, in our subsample composed by Indigenous and Afro-American, Higher education proved to be unequalizing in 2007 with a greater impact on the top. Yet, for 2016 the compositional structure in terms of returns changed substantially. The trend reversed bearing a greater impact on the hourly wage to the first quantile compared to the upper ones. In this last year, whereas a marginal gain of Higher education in the  $q10$  increased the hourly wage 76.8%, it implied a 64.5% for the  $q90$ .

### 5.2.3. UQRs

The main limitation of the CQRs nonetheless is that the top (bottom) of the conditional distribution does not necessarily coincide with the top (bottom) of the marginal distribution. Therefore, for the moment we are able to assert that throughout the period, education has been traduced in a quantitative improvement of the impact not over the poor, but over the conditionally poor. Hence, the picture about the interaction between education and hourly wage remains limited. In this sense, drawing on RIF methodology we can address our two distributional statistics of interest: the unconditional quantiles and the Gini coefficient.

UQRs have a more reliable interpretation of the coefficients since the upper quantiles do represent the richest layers of the distribution. Table 10<sup>110</sup> exhibits the estimates by using RIF regressions both on the unconditional quantiles and the Gini coefficient. Again, for practical reasons we restrict the table just to the two tails of the period, and the most representative quantiles<sup>111</sup>. The last column – in both the upper and lower parts of the table

<sup>110</sup> In Table 10 the column labeled “Variable” deploys the pack of regressors used in the estimations, in this case solely the first part of the list. Our measure of education is Years of Schooling. The category “Indicator” shows the Gini value decomposed for each quantile as well as the total Gini in the last column. Moreover, the subsequent columns exhibit both the estimates (the  $\beta$ 's) (Est.) and the Standard Error (S.E.) for representative quantiles (namely  $q10$ ,  $q50$  and  $q90$ ) and our distributional statistic (the Gini) in 2007 and 2016.

<sup>111</sup> For a detailed version of the results through the use of this decomposition method see Annex IV where we exhibit the estimates of the three years of the period and for all the unconditional quantiles of the distribution ( $q10$ - $q90$ ). Likewise, it will be display of the whole set of regressors used in the model which are the same as the ones in CQRs.



–, this time, indicates the impact of each covariate on our particular distributional statistic of interest: the Gini coefficient. Therefore, a positive estimate means that the regressor has an unequalizing effect on the income distribution rising the Gini. The opposite occurs with a negative sign.

In 2007, education had a more heterogenous effect along the quantiles for both the aggregate sample and the two ethnicities. While for the first group, a rise in years of schooling – the last variable labelled “education” – meant an increment of the hourly wage in the  $q10$  of 3.9% and 9.4% in the  $q90$ , this shift is traduced in an increase of the hourly wage of 1.9% and 5.9%, respectively. Another way to approach this issue is the magnitude of the ranges. In both cases, the difference between the highest and lowest quantile is bigger than that estimated by CQRs<sup>112</sup>.

The fact that this second estimate is markedly more heterogeneous than the first can be explained by the different phenomena they capture. While the CQRs incorporate only the growing inequality in income distribution as education rises, the UQRs adds to this the inequality in education levels, resulting in an even more heterogeneous effect (Larrea & Fabris, 2017).

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<sup>112</sup> 0.055 for the aggregate sample and 0.04 for the ethnic subgroup.

**Table 10 - Unconditional Quantile Regressions (UQRs) - Years of schooling**

Variable	Aggregate sample							
	2007				2016			
	q10 Est./S.E.	q50 Est./S.E.	q90 Est./S.E.	Gini Est./S.E.	q10 Est./S.E.	q50 Est./S.E.	q90 Est./S.E.	Gini Est./S.E.
Indicator	0.51	1.62	5.48	52.14	0.73	2.35	5.94	44.45
<i>Marginal Effects</i>								
year2	0.165*** -0.03	0.239*** -0.02	0.167*** -0.02	-4.2*** -1	0.207*** -0.03	0.216*** -0.01	0.242*** -0.01	0.3 -1
year3	0.082* -0.04	0.33*** -0.02	0.621*** -0.03	6.4*** -2	0.104** -0.03	0.233*** -0.01	0.457*** -0.02	2.5 -2
sex	0.322*** -0.03	0.116*** -0.01	0.093*** -0.02	0 -1	0.381*** -0.02	0.073*** -0.01	0.103*** -0.01	-8.4 -8
marital	0.106*** -0.03	0.108*** -0.01	0.162*** -0.02	2.9** -1	0.096*** -0.02	0.102*** -0.01	0.135*** -0.01	2.2 -2
education	0.039*** 0	0.046*** 0	0.094*** 0	1.4*** 0	0.04*** 0	0.034*** 0	0.069*** 0	1.5* -1
Variable	Indigenous & Afro-American							
	2007				2016			
	q10 Est./S.E.	q50 Est./S.E.	q90 Est./S.E.	Gini Est./S.E.	q10 Est./S.E.	q50 Est./S.E.	q90 Est./S.E.	Gini Est./S.E.
Indicator	0.27	1.25	3.30	48.53	0.42	1.88	4.50	42.80
<i>Marginal Effects</i>								
year2	-0.003 -0.09	0.118* -0.05	0.196** -0.06	4.9 -4	0.191* -0.07	0.287*** -0.04	0.248*** -0.04	-3 -3
year3	-0.351*** -0.1	0.012 -0.05	0.523*** -0.08	16.7* -7	0.075 -0.09	0.256*** -0.04	0.434*** -0.05	-0.3 -3
sex	0.334*** -0.09	0.152*** -0.04	0.018 -0.06	2.6 -5	0.323*** -0.07	0.111*** -0.03	-0.003 -0.04	-2 -2
marital	0.299*** -0.09	0.089* -0.04	0.065 -0.05	-4.2 -5	-0.057 -0.06	0.14*** -0.03	0.078* -0.04	0.2 -2
education	0.019* -0.01	0.024*** 0	0.059*** -0.01	2* -1	0.034*** -0.01	0.027*** 0	0.049*** 0	0.3 0

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:** p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

Although reduced compared to 2007, education still had an increasing impact on the hourly wages along the quantiles for 2016. However, given the different mechanisms that UQRs capture these estimates remain more heterogeneous in comparison to those of CQRs.

Finally, we will focus on the RIF of the Gini. For this estimation we take the hourly wage level and not the logarithm since this function tends to smooth the distribution resulting in an artificially lower Gini (Alejo, Gabrielli, & Sosa-Escudero, 2014).

The underlying reasoning is the following. In 2007, a marginal shift of education to the right had a regressive impact statistically significant over the income distribution since it

increased the Gini in 1.4 points. Surprisingly, this behavior remained practically unchanged for 2016, where the rise was 1.5 points, though with a loss in significance measured by the  $p$  value. This stresses the unequalizing overall effect of education. However, we can appreciate that for Indigenous and Afro-American, this regressive effect measured by the Gini was even greater for 2007 reaching the 2 points. In the case of 2016, schooling lost the strength in its impact and therefore, the extent of the unequalizing effect was reduced to 0.3 points. It is worth pointing out nonetheless that the estimate is not statistically significant. In a way, this could be signaling the decreasing importance of the regressor compared to the others.

We will move finally to the last estimates. In effect, this time, Table 11<sup>113</sup> displays the unconditional quantiles for the different educational levels. Similarly, the last column shows the impact of each one of them on the Gini coefficient<sup>114</sup>.

Primary education had an heterogenous effect across the quantiles for the aggregate sample benefiting considerably more the lower parts of the distribution. This applies for the three years under analysis. For instance, in 2007, while a marginal enhancement of schooling within this educational level represented an increase of the hourly wage in 48.2% for the lowest quantile, it barely incremented in  $q90$  a 11.9%. Equally, the range widened progressively during this time<sup>115</sup>, even more than that of CQRs. Again, the greater extent of these differentials might be explained because UQRs capture not only the movements in income distribution, but also the shifts of the distribution in educational endowments. Consequently, we could affirm that for 2016 operated a more equal distribution of educational levels among society (see in Table 3 and Table 4). The impact on the Gini is undoubtedly progressive for the three years implying a reduction of 8.7 points of this synthetic distributional indicator for 2016.

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<sup>113</sup> In Table 11 the column labeled “Variable” deploys the pack of regressors used in the estimations, in this case solely the Educational Levels Primary, Secondary and Higher, which are this time our measure of education. The category “Indicator” shows the Gini value decomposed for each quantile as well as the total Gini in the last column. Moreover, the subsequent columns exhibit both the estimates (the  $\beta$ 's) (Est.) and the Standard Error (S.E.) for representative quantiles (namely  $q10$ ,  $q50$  and  $q90$ ) and our distributional statistic (the Gini) in 2007 and 2016.

<sup>114</sup> The extended version of the table with the three years under analysis as well as the 5 educational levels (with Basic and Middle education) are presented in Annex IV.

<sup>115</sup> It reached, for instance, 0.672 in 2016.

**Table 11 - Unconditional Quantile Regressions (UQRs) - Educational Level**

Variable	2007				2016			
	q10	q50	q90	Gini	q10	q50	q90	Gini
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>								
Indicator	0.51	1.62	5.48	52.14	0.73	2.35	5.94	44.45
<i>Marginal Effects</i>								
Primary	0.482*** -0.07	0.186*** -0.02	0.119*** -0.03	-4.3*** -1	0.674*** -0.08	0.13*** -0.02	0.002 -0.02	-8.7*** -2
Secondary	0.664*** -0.07	0.409*** -0.02	0.381*** -0.03	-2.6 -2	0.849*** -0.08	0.282*** -0.02	0.14*** -0.02	-8.7*** -2
Higher	0.792*** -0.07	0.748*** -0.03	1.395*** -0.05	16.5*** -4	0.967*** -0.08	0.533*** -0.02	0.953*** -0.03	13.9* -7
<i>Indigenous &amp; Afro-American</i>								
Indicator	0.27	1.25	3.30	48.53	0.42	1.88	4.50	42.80
<i>Marginal Effects</i>								
Primary	0.113 -0.13	0.096* -0.05	0.141* -0.06	-1.5 -2	0.632*** -0.13	0.24*** -0.04	-0.043 -0.04	-6.5*** -2
Secondary	0.262 -0.14	0.228*** -0.06	0.333*** -0.09	6.4 -4	0.666*** -0.13	0.319*** -0.05	0.128* -0.06	-4.5 -2
Higher	0.184 -0.17	0.422*** -0.08	1.224*** -0.17	44.6* -21	0.747*** -0.14	0.495*** -0.06	1.041*** -0.11	9.6* -4

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:**  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Moreover, when regarding our ethnic subgroups, the returns of Primary education increased along the quantiles exposing the slightly unequalizing effect of it during 2007<sup>116</sup>. Notwithstanding, the trend reversed for 2016 where the impact was bigger and statistically significant on the lowest quantile ( $q10$ ) 63.2%. Although not significant for the first year, the impact of Primary education on the wage distribution was equalizing. In 2016, a marginal shift to the right of this educational level implied a statistically significant reduction of 6.5 points of the Gini.

On the other hand, Higher education played a completely different role in terms of distributive performance. In the aggregate sample its effect was heterogenous and unequalizing across the quantiles, which meant that the upper ones benefited more of a potential educational expansion in this educational level.

<sup>116</sup> However, its coefficients are not strongly significant.

Surprisingly, in 2016, the downsizing in the gaps across the quantiles finished by reverting the trend. The lowest quantile stood for a higher, albeit slightly, return compared to the top quantile; 96.7% to 95.3%, being both estimates statistically significant. Furthermore, the distributive impact presents a regressive scenario. Even though the effect of Higher education on the Gini declined over time, it still played an unequalizing role. For instance, it rose the indicator on 13.9 points for 2016.

Finally, Higher education had heterogenous and unequalizing effects along the two years for Indigenous and Afro-American people. However, the gap between the lowest and highest quantiles considerably shortened, moving from 1.04 in 2007 to 0.294 in 2016. What is also worthy to mention is the remarkable decline of the regressive effect of this variable throughout the period. Whereas an infinitesimal shift of Higher education in these two subgroups meant an increase of 44.6 points of the Gini coefficient in 2007, it barely represented a gain of 9.6 points in 2016. Overall, this might suggest a restructuring of returns of educational levels fueled mainly through redistribution of Human Capital assets among society in a more equalizing way.

#### **5.2.4. Overall Comparison**

To conclude, Figure 20 sketches a handy way in order to interpret the different results of our three models: the conditional mean (Mincer), CQRs and UQRs. On the vertical axis (y) we find the return, already set in terms of percentage, a marginal shift of education – holding constant the other covariates and under the exogeneity assumption – has on the real hourly wage. Moreover, the horizontal axis is divided in each one of the quantiles of the wage distribution ( $q_{10}$ - $q_{90}$ ). In other words, we just plot the estimates obtained through the regression of the models for our variables of interest (years of schooling or educational level). The blue line is the expected conditional mean of the Mincer equation, which is completely flat since it is the average expected value of the return of education. The orange line graphs the effect of the conditional quantiles. Finally, the grey line illustrates the marginal returns of the unconditional quantiles. The first group of figures is composed by the results of years of schooling for the years 2007-2012-2016, the second, those of Primary education, and the third of Higher education.

Overall, Figure 20 exposes the limitations and the consequent partial picture that the Mincer estimates might offer in distributive analysis being a somewhat simplistic way of apprehending the interaction. The return of each of the variables is constant along the quantiles. However, since the influence of education on the hourly wage varies vis-à-vis the different quantiles, the expected conditional mean fails to be a proper representation of the heterogeneity of this relationship. Furthermore, we need to remark that UQRs curves are more pronounced – both upwards (unequalizing) and downwards (equalizing) – compared to those of CQRs for the three years and in the three groups since the former captures another potential source of inequality: the distribution of educational endowments.

To start, considering years of formal schooling, the mean of education falls from tail to tail. The order of magnitude of the impact associated to an increase of an additional year of education on individuals diminished consistently. Yet, the expected mean remains limited when it comes to fully understand the process.

That is why the use of UQRs could facilitate a more in-depth analysis exhibiting compositional changes on the variable within the distribution. Hence, it is remarkable the flattening process of these curves throughout the period. The one of 2007 started with a pronounced heterogeneous effect across the quantiles – probably incorporating a pre-existent unequal distribution of education among society – and finished in 2016 with a lower steep. This implies that the unequalizing effect of schooling softened throughout the period. Even though the upper quantiles still enjoy of a greater return to their hourly wage, the gap with the lower ones narrowed considerably. Results suggest that policy intervention targeting more vulnerable and excluded groups could model the distributional effect of education turning it pro-poor or at least diminishing its unequalizing impact.

In what concerns Primary education, we can reaffirm the equalizing effect on the wage distribution for the three years. In other words, the lower quantiles benefit proportionally more than the top. Notwithstanding, this progressive impact gained in strength during the period intensifying the equalizing role of this educational level. In graphic terms, we see a steeper and decreasing slope in 2016 (the grey line) compared to the one in place for 2007.

Furthermore, whereas in 2007 the impact of Higher education was markedly heterogeneous and increasing along the quantiles (both conditional and unconditional), for 2016 we can appreciate a more compensated curve between the marginal return at the top and the bottom of the distribution. In other words, the range narrowed exposing a somewhat convergence in terms of returns of the lower and upper quantiles. This means that, throughout this period, the return of Higher education improved relatively more for the bottom part.

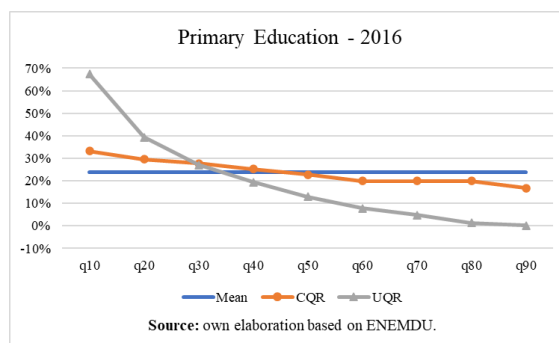
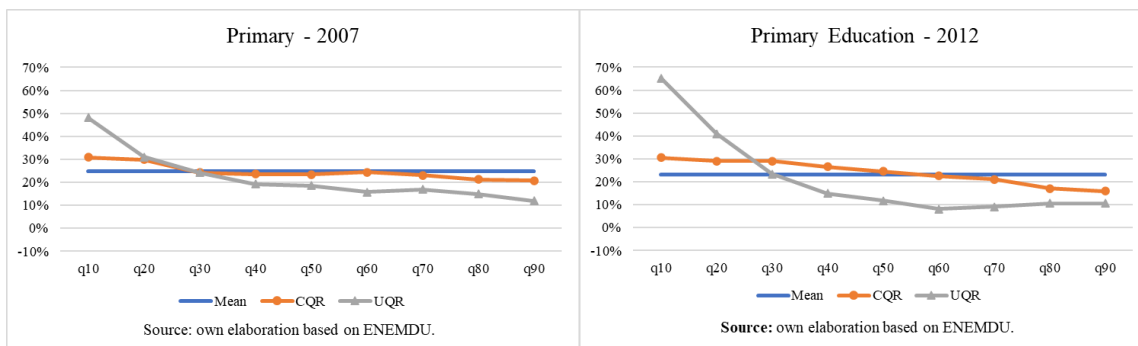
Finally, estimates for educational levels in a way confirm the thesis of Gasparini *et al.* (2013), which states that, in Latin American region, Primary education is pro-poor while Higher education is pro-rich. Nevertheless, these two levels' effects were far from being unaltered during the period. On the contrary, we witnessed an evolving dynamic in their heterogeneous impacts. In the final part of the decade, Primary became even more pro-poor while Higher education underwent a softening in its regressive influence. This could open an interesting debate that cast doubt on the sometimes-unquestionable idea that Higher education – regardless of time, place, and type of implementation – has an unequalizing effect on wage distribution.

**Figure 20 - CQRs, UQRs, Conditional Mean (Mincer)**

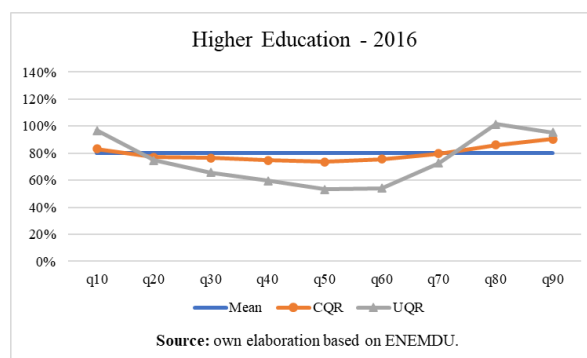
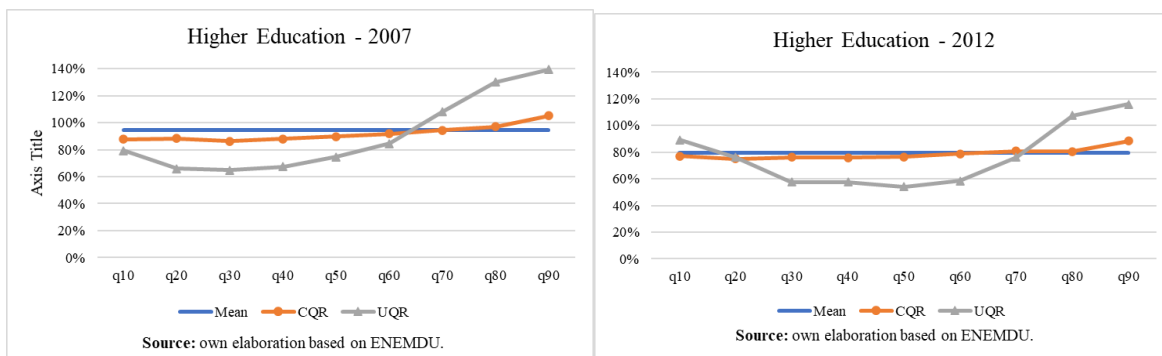
### Years of Schooling 2007-2012-2016



## Primary Education 2007-2012-2016



## Higher Education 2007-2012-2016





## 6. LIMITATIONS

Although the work leads to insightful results regarding the distributive performance of Ecuador during 2007-2016, there are several restrictions and limitations that must be pointed out. This exercise implies not only an acknowledgement of the scope of the tools used in the research, but also a potential opportunity for future works that seek to incorporate novel and better methods.

### 6.2. Empirical Shortcomings

To start, relying on survey data could be most of the time enriching since the study can draw on multiple questions that ultimately shape the socioeconomic conditions of the sample in a given moment. However, as these data are nourished by private respondents through the intermediation of an interviewer, some drawbacks might arise. The latter includes non-respondents<sup>117</sup>, wrong responses<sup>118</sup> and the impossibility to observe the most extreme parts of the distribution, such as top income earners (Fournier & Koske, 2013). In our case, two inconvenients might arise. On the one hand, the probability of an over-estimation of the category Mestizo – produced by a deliberate decision of not being self-recognized as Indigenous or Afro-American<sup>119</sup>. On the other, the under-estimation of the individual wage – usually, witnessed in the top part of the distribution –, which could entail a bias in the estimations.

Moreover, the selection of the type of data always brings to the table a tradeoff situation. Often this is not a decision since the researcher needs to adapt himself to the available information. Even though one of the benefits of RIF regressions is a simpler assessment of the model by using cross-sectional data – a snapshot of the sample in a given moment –, this feature can lead to methodological challenges<sup>120</sup>. Ideally, it would of utmost importance to make a follow up of the same person year to year in order to isolate fixed effects from changes in labor market variables through the use of longitudinal or panel data.

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<sup>117</sup> Usually, the research assumes that the personal decision not to respond to the survey is exogenous from both the dependent and explanatory variables.

<sup>118</sup> As mentioned before, this might not entail a big issue since the methodology is robust to outliers.

<sup>119</sup> See Section 2.2.2.

<sup>120</sup> “Measuring inequality and poverty in a society may thus be misleading if one uses only a snapshot of income disparities at a point of time instead of individual income sequences” (Bourguignon & Moreno, 2020).

This in turn would help compute consistent estimates (Fortin *et al.*, 2010) as well as permit to deal with problems such as endogeneity when no instrumental variables are available<sup>121</sup>.

In this sense, ENEMDU is a cross-sectional survey whose results are released quarterly. However, given its rotating array design (See Section 4.2.1.), there are follow-up arrays (households' groups) that can offer longitudinal data estimations<sup>122</sup> (INEC, 2019) – selected households are interviewed in successive moments of windows.

Drawing on similar type of data, for instance, Moreno (2020) constructs a series of short-term synthetic panels<sup>123</sup> to study long-term distributive performances for the Mexican case in the past 30 years. The author circumscribes his analysis to the association between macroeconomic dynamics and income mobility<sup>124</sup> through different indicators. Results lead to the conclusion that during the period under analysis, the country witnessed low level of intra-generational mobility. In this sense, a similar approach could be used in further research to assess the effect of educational attainment on income distribution within a larger period of time.

Second, in this work we attempted to isolate the effect of years of schooling (CQRs and UQRs) and dispersion of Human Capital endowments (UCRs) on the interaction with labor income distribution. In order to shed light over a complex phenomenon, the empirical strategy sought to restrict the evaluation to single-variable performance: education. Further analysis nonetheless must widen the scope introducing and studying the influence of other variables, and the existing relationships among them when it comes to gauge distributive dynamics. For instance, it would strengthen the research assessing the impact of minimum wage or job formalization on earnings distribution, and the way they interact, for instance, with an educational expansion.

Third, the selection of income exclusively from labor source, our dependent variable, was mostly based on two criteria. On the one hand, data sources in a country with a poor

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<sup>121</sup> “Panel data can be used to impute wages for years where an individual is not participating in the labor market” (Fortin *et al.*, 2010).

<sup>122</sup> This scheme ensures a 40.7% overlap of the arrays in two consecutive periods.

<sup>123</sup> These panels are based on matching individuals with the same time-invariant attributes in consecutive cross-sections (Bourguignon & Moreno, 2020).

<sup>124</sup> The particular definition used in this work understands income mobility as “a transformation from an initial, or first, income distribution to a second, or terminal, income distribution” (Moreno, 2020).

information system – concerning microeconomic performance – restricted the research to circumscribe the analysis to this particular type of income. Unfortunately, this inconvenient is a common thread among the majority of the countries in the region. On the other, one of the main channels that affect income distribution are the labor market returns through education (Galiani et al., 2017). This particularly applies to the short-term assessment because earnings are the key source of income of most households. Nevertheless, the monetary approach leaves aside multiple levels of analysis. For instance, in a country that experienced an enormous increase of public education provision such as Ecuador (See Chapter 2), labor income might be a biased measure since it is under-estimated<sup>125</sup>.

Therefore, a complementary approach that assess educational improvement' effect on equality of opportunity, rather than equality of income, might be insightful (Bourguignon et al., 2007). To a certain extent, this could be solved as well with the incorporation of more comprehensive indices that go beyond the mere monetary measure adding up living standards, health, or well-being.

Fourth, the link between education and income distribution is complex not only from a theoretical point of view (Fournier & Koske, 2013) but also in the empirical field (See Chapter 3). Besides causation discussions – already addressed in previous sections – the distributive effect of education is far from being fully understood. For instance, the traditional income-expense analysis overlooks the potential profits of a schooling expansion for those who are not directly beneficiaries of this change and the factors employed to provide those services. Not taking into account externalities hampers the possibility of measuring the effects and repercussions in a wider approach such as the general equilibrium framework (Gasparini et al., 2013).

Furthermore, given the complexity of the interaction a short-term method fails to consistently estimate the effects of education upon income distribution. Intrinsically, schooling enhancement is an investment for future generations (Bourguignon & Rogers, 2007). Increasing public expenditure in education do not necessarily means immediate income gaps reduction. On the contrary, they might be worsened at first (Paradox of

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<sup>125</sup> Overall, this is the case of countries where the provision of public goods is non-negligible. A considerable part of household expenses is assumed by the Government, therefore a household has much more income left.

Progress). Probably, not even a change in consumption from the poorest households is expected before the presence of imperfect capital markets<sup>126</sup>. Even though the selected period depicts a clear picture of the income-education performance, it would be desirable to enlarge the time window to better capture the trade-off above-mentioned.

Finally, it will be of high interest to link these decomposition microeconomic models to a bigger framework searching for a detailed analysis of external shocks produced either by policies or exogenous movements. Putting forward this connection will permit to understand the underlying causes of, for instance, a schooling enhancement. In this sense, a suitable proposal could be the macro-micro approach. This method is carried out usually by a particular methodology: the Computable General Equilibrium (CGE) models (Gasparini *et al.*, 2013). The usefulness resides on the potential information that we can extract in order to evaluate different policy alternatives with a considerable degree of accuracy.

### 6.1. Methodological Drawbacks

To conclude, in this subsection we are going to discuss several methodological inconvenients concerning the educational estimates in the particular decomposition models developed in previous chapters. First, the work will briefly summarize the theoretical, and thus general, problems that cause deficient estimates of education. Second, given the socio-economic features of the case study, we will examine concrete sources of bias that might arise when carrying on the estimation process as well as possible solutions for further research.

Typically, within our models' framework<sup>127</sup>, there are two main sources of bias regarding all the estimators: self-selection, endogeneity.

First, self-selection specially concerns Mincerian equations. In the wage allocation model, the logarithms of the hourly wage of individuals are explained by observable socioeconomic and demographic characteristics. These regressions have a bias because the observed wage turns out to be a banned variable, since the salary corresponding to the people

<sup>126</sup> In economic jargon this is called "moral hazard". Imperfect capital markets make impossible to borrow against the human capital of one's descendant (Bourguignon & Rogers, 2007).

<sup>127</sup> We talk about the three models we will rely on: the Mincer equation, centered on the conditional mean, and both, CQR and UQR (through RIF methodology), centered on the quantiles of the conditional and unconditional distribution, respectively.

who decide not to enter the labor market cannot be observed and thus, remains in the error term. The decision to work or not (which is not observable) operates as a self-selection mechanism<sup>128</sup>.

One way to overcome this issue is to consider this bias caused by missing data as a problem of omitted variables<sup>129</sup>. In this respect, literature suggests running an auxiliary regression that estimate those unobservables. The two-steps procedure relies initially on a Probit model used to assess the probability of participation in the labor market including the variables that are expected to influence income levels (Winters & Chiodi, 2011). The intensity of participation is calculated through the inverse Mills ratio (IMR), which constructs the Heckman variable  $\lambda$ <sup>130131</sup>. Afterwards, we include this ratio as another regressor of the Mincerian equation. In this way, according to Maurizio (2019), it is possible to avoid sample selection bias.

A second source of bias, this time specifically for education variable, is the presence endogeneity in the regression<sup>132</sup>. By and large, this means that there is no conditional independence between schooling ( $S_i$ ) and the error term,  $E(\varepsilon|S_i) \neq 0$ . Hence, years of schooling could potentially be related to the error term through an unobservable determinant – for instance, unobserved ability –, of the hourly labor income. In fact, one can think that more skillful people would tend to attain higher educational levels and thus, earn greater wages.

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<sup>128</sup> This may not only arise from female labor participation (Maurizio, 2019) – vastly documented by the gender wage gap literature –, but also from ethnic discrimination in the labor market (Fortin et al., 2010).

<sup>129</sup> Heckman (1979).

<sup>130</sup> It is explained by variables that can be the same as those of the Mincer regression, with the addition of some extra variables that do not explain the salary but does explain the participation, and thus can define the convenience or not of working given the market wage.

<sup>131</sup> As Winters & Chiodi (2011) point out there are some inconvenients when using this approach. Particularly, “it requires instruments in the instruments in the first stage that predict participation in the income-generating activities but do not influence the level of income earned” In order to overcome these issues, in this investigation we will use the number of children in the household as such variable for female labor participation, understanding that the greater the number of young children, the lesser the propensity to work.

<sup>132</sup> Typically, there are three sources of endogeneity: a) specification errors (Angrist et al., 2006), b)  $S_i$  is not accurately measured (Montes-Rojas, 2011), and c) simultaneity:  $y_i$  and  $S_i$  are determined within a system.

The conventional method used in micro-econometric theory is Instrumental Variables (IV). In this specific case, this means to find a valid instrument<sup>133</sup> for years of schooling. Usually, literature has attempted to use IV such as the IQ test in order to capture the potential unobservable heterogeneity. However, this test might not only encompass ability, but also other factors that ultimately will produce inconsistent estimates (Wooldridge, 2010).

Moreover, beyond the conditional average analysis, when regarding CQRs<sup>134</sup>, exogeneity means that the position of an individual in the ranking is randomly assigned (Alejo et al., 2021). Though still in an early phase, Alejo et al. (2021) have attempted to focus on this unresolved methodological issue. They propose a first-stage model to evaluate the association between the IV and the endogenous regressors. Ultimately, what is at stake is the IV validity for specific quantiles.

Likewise, some authors suggest that the IV method could also apply for UQRs estimated through RIF methodology<sup>135</sup>. However, Firpo et al. (2009) disregard the issue reducing their set of parameters solely to those that capture changes on unconditional quantiles in the presence of exogenous regressors. Bearing this in mind, Alejo et al. (2014) refrain diving into the effect of treating education as an endogenous variable. Unlike conditional mean results, in distributive effects, methods handling with this inconvenient are still premature. It is still not clear ex-ante nonetheless that methodological concerns affecting the mean estimates could translate into other type of functionals, as the quantiles<sup>136</sup>. As a result, although a relevant route for further exploration in order to enact more comprehensive studies, this methodological drawback remains beyond the scope of this research.

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<sup>133</sup> Being  $z_i$  a proposed instrument for  $S_i$ , it has to satisfy two conditions: a) range condition:  $E(z_i S'_i) \neq 0$ , and b) orthogonality:  $E(z_i u_i) = 0$ . In other words, we search for an instrument that has to be strongly related to the endogenous variable and, at the same time, it has to be unrelated to the error term (Wooldridge, 2010).

<sup>134</sup> The same sources of endogeneity for the conditional average apply for the quantiles.

<sup>135</sup> Frolich & Melly (2014), for instance, within an impact policy evaluation framework, advice to use IV estimators for unconditional Quantile Treatment Effect for compliers as a powerful tool to identify causal effects.

<sup>136</sup> "When the interest lies in inequality, a biased counterfactual distribution that arises by ignoring endogeneities does not necessarily biased the functional of interest for distributive purposes. For example, if neglected endogeneities bias the whole conditional distribution up (or down), this negatively affects the estimation of the mean effect, but not necessarily that of distributive effects, which depend on distances between quantiles and not on their levels." (Alejo et al., 2014).

Scaling down to the national boundaries we will now discuss some possible sources of bias in the estimation of the education's coefficient for Ecuador during the period 2007-2016. Given the socioeconomic features of the Andean country, it is possible to encounter several underlying mechanisms through which a down (up) ward estimation might be in process. Of course, the oncoming reasoning could be extended to other nations in the Latin American region since they have numberless traits in common.

First of all, the huge rate of investment concerning the educational expansion deeply fleshed out in this work would have held a limited impact if a somewhat similar allocation of resources in teaching workforce had never been implemented. When building up solid foundations in an educational system teachers and professors play a meaningful role. In this respect, during the period 2007-2016 the number of professors with a post-graduate level incremented 23% (SENPLADES, 2017). Simultaneously, 19.586 scholarships for studies abroad were granted<sup>137</sup>. The number of teaching professionals within the Primary and Secondary level (children from 5 to 17 years old) in the public system moved only in the period 2009-2014 from 135.593 to 146.500<sup>138</sup>. Particularly, higher education underwent structural changes throughout the decade. Professors with post-graduate studies by 2008 represented 29% of the total while for 2015 the percentage soared to 80.9%. Moreover, the ratio of full-time jobs in universities passed from 39.5% to 58.2% (SENPLADES, 2017). Likewise, the plan Prometeo<sup>139</sup> brought 507 international academics all over the world to give classes and advocate research.

This other side of the coin – a quality enhancement of the educational system from the provision part of the service – is probably capture neither by the average years of schooling nor by the educational level attained. The students' academic performance is undoubtedly related to the professor's educational level. Such a determinant variable nonetheless remains in the error term and hence biases upwardly our estimate  $\beta_1$ . In order to overcome this artificial overestimation we could think of an IV that incorporates the teaching

<sup>137</sup> In the previous period (1997-2006) only 237 were granted (SENPLADES, 2017).

<sup>138</sup> Source: Ministerio de Educación (MINEDUC). <https://educarecuador.gob.ec/visualizador-estadistico/>

<sup>139</sup> “The plan consisted of hiring academics and professionals, through a rigorous selection process, to strengthen the competencies of the Ecuadorian university and other areas of the public sector” (Benito Gil, 2017).

improvement occurred during the period. This can be for instance the results of a national evaluation through the construction of an indicator for each of the selected years.

Another relevant factor that potentially can bias the estimation is the impossibility to split up the education variable into public and private source. As we have seen all along the work, during the period under analysis, Ecuador has witnessed an unprecedented educational expansion compared to previous decades. However, the actor that mostly fueled this dynamic was the government through the provision of this public good. Whereas from the total final consumption in education in 2007 a 54% was provided by the government, in 2016 the number increased to 58.9% (INEC, 2019). At the same time, the educational demand underwent non-negligible changes as well. The expansion of the public apparatus was due not only by an increasing educational supply but also by the rise of the demand. Given the quality improvements in the public provision children, adolescents and young people who previously were part of the private system moved to the former. Within the aggregate Primary and Secondary levels the public enrolment passed from 50.2% in 2009 to 71.5% (Ministerio de Educación, 2018). Similarly, public University enrolment represented for 2016 the 57.85% of the total enrolment. Moreover, this percentage for public non-tertiary level was in 2015 72% (SENESCYT, 2018).

Consequently, the inability to disaggregate the provision of education is overestimating the unequalizing and heterogenous effects of schooling in both CQRs and UQRs. We believe that, if possible, this separation could lead to even more impressive results regarding the compositional change of education along the decade. This might be the case as well for higher education that could perhaps show a sharper decline of its regressive effects on the income distribution.

Finally, the last factor proposed here that future research should take into account is the malnutrition of great part of children, adolescents, and young people in age of attending classes specially for the public educational system. Chronic malnutrition leaves serious consequences. Among all, one of the most serious is the impact on mental and intellectual development, which will affect school performance and the capacities of children, as well as their possibilities of accessing to higher educational levels in the future (OSE, 2019). Although the country experienced some progress – between 2009 and 2016 the



multidimensional poverty<sup>140</sup> for children and adolescents plummeted from 60% to 42% – there are still structural problems. For instance, in 2012, the national average of chronic malnutrition for children younger than 5 years old was of 25%. This panorama worsens drastically for children pertaining to Indigenous households where the percentage accounted for 42% in the same year. Surprisingly, Afro-American households showed a smaller number, barely a 18% (OSE, 2019).

Inasmuch as this underlying dynamic, whose scope clearly surpasses the educational realm, is not capture by the models – hence, it remains in the error term – our  $\beta_1$  is underestimated. This downward bias hampers a correct estimation of the impact of education on the hourly wage. Unfortunately, the Multidimensional Poverty Index, a feasible way to overcome this issue, was implemented in 2016, hence it does not cover the period under analysis.

To conclude, we believe that rather than empirical limitations, these points ought to be seen as further lines of research. Their improvement will unquestionably help shed light over the complex dynamic addressed in this paper leading to a better apprehension of the phenomenon.

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<sup>140</sup> It is an index constructed from 4 dimensions each of one weight 25%: education, work and social security, health, water and food, and habitat, housing, and healthy environment. Two subdimensions concern exclusively children ageing 5 to 17 years old: “basic education and high school non-attendance”, and “child and adolescent employment” (Castillo & Jácome, 2016).

## 7. CONCLUSIONS

This work addressed a particular interaction between two variables, that of education and income distribution. Through the use of modern statistical technics we attempted to shed light over the distributive impact of a schooling enhancement.

Nevertheless, it is necessary to bear in mind two meaningful aspects. First, the estimations correspond to a particular case in a given moment of time. As any other nation, Ecuador entails a variety of socioeconomic, demographic, and historical characteristics that model a specific context. Second, the link of education and inequality is far from being straightforward (Battistón *et al.*, 2014). On the contrary, both the length and the sign of the relationship can differ substantially according to the theoretical approach and the empirical study case.

In this sense, the research contributes to a developing literature that has recently gained in strength. Although representative of the regional average (Cetrángolo *et al.*, 2018), the Ecuadorian pattern of educational expansion underwent during the decade 2007-2016 stands for its own particularities.

The findings in this analysis suggest that education plays a vital role in determining the hourly labor income with a high statistical significance along all the quantiles. As supported by a vast literature, Human Capital accumulation rises monetary returns consistently during time. However, as already discussed in previous sections, the impact is heterogeneous and increasing once we move to the upper part of the distribution. Yet, we demonstrated that the unequal effect of education decreased considerable shortening the return gap between the bottom and the top.

The expected average return of schooling towards the hourly income sharply dropped from 2007 to 2016. Not only this variable lost its relative importance compared to other socioeconomic attributes of individuals but also the way market rewards it underwent a compositional change. This is particularly interesting when focusing on the two ethnicities. Although we can appreciate a similar declining movement from tail to tail, the level and the extent of the schooling return is considerably smaller. Put it differently, Human Capital accumulation does not entail the same reward through market mechanism for Indigenous and

Afro-American. This kind of inequality is complex to address since it is based on biases that are beyond the control of individuals (Aranda & Ratzlaff, 2018).

Moreover, the flattening process of the unconditional quantiles is likely to be explained by the direct intervention of the State by a twofold mechanism. On the one hand, a schooling expansion whose target lied in the lowest quintiles of the income distribution – who are mostly the least educated –, which in turn meant an increase of the average educational level. The fact coincides with the empirical study carried out by Galiani *et al.* (2017). The authors point out a remarkable drop in the wage premium to education witnessed in the region with special emphasis during the first decade of the 2000s (See also Birdsall *et al.*, 2011). On the other, a soaring public expenditure whose main sectors were construction and services. This shift towards less skilled-labor industries reconfigured the market returns at the expenses of high-skilled workers. Hence, the two dynamics implied not only a rise in the mean hourly wage but also an enlargement of observations around this value (See Figure 16). This dynamic could have compensated the second mechanism of the Paradox of Progress mentioned by Bourguignon *et al.* (2005). Namely, the loss of household income due to the insertion of children and young in the education system, especially in those families placed in the lower quantiles of the distribution, might have been offset by the increment in terms of salaries witnessed in the low-skilled sectors of economy.

Concerning educational levels we appreciate different performances according to the category we select. Primary education remained strongly equalizing, albeit with a more accentuated slope in the last part of the period. Overall, its impact is greater in the lower quantiles of the distribution. Moreover, higher education started the decade with a heterogeneous and increasing effect upon labor income. The situation bolsters the widespread consensus about the regressivity of this educational level (Gasparini *et al.*, 2013) and the attention policy makers are advised to put when allocating resources here. Notwithstanding, surprisingly, the effect of higher education reverted by the last year, which means that before such an expansion the lower quantiles of the distribution would benefit more economically<sup>141</sup>.

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<sup>141</sup> This could be clearly the result of an educational investment that was mostly concentrated in Primary and Higher Education at the expense of, for instance, Secondary level (See Section 2.2.1.).

An underlying cause of this overall equalizing pattern could probably be placed in the educational distribution. As mentioned before, the reason why UQRs estimates are markedly more pronounced than those of CQRs is because the former incorporates to the standard channel whereby education impacts the income distribution – the increasing wage dispersion as education rises<sup>142</sup> – a second mechanism: ex ante educational inequality. This dynamic might be playing a meaningful role when the direction of the impact goes the other way around. In other words, the reduction in the monetary return gaps among the quintiles could have been caused by a more equal distribution of educational endowments within all members in society.

Contrary to Bourguignon et al. (2005), we believe that the distribution of years of schooling is tightly associated with the mechanism of transmission from education to household incomes. In fact, rather than be separate these two phenomena are mutually interacting and to a large extent shaping the way Human Capital accumulation impacts inequalities.

To conclude, by and large, complexity arisen from the topic comes not only from features within national boundaries, but also from their constant change throughout time. The main thrust of future research ought to be the inclusion of these characteristics in both empirical and methodological analysis. That is the reason why the development of more study cases is urgently needed since it would shed light to underlying dynamics that are far from being understood.

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<sup>142</sup> For the underlying reasons see specifically Section 4.1.2.

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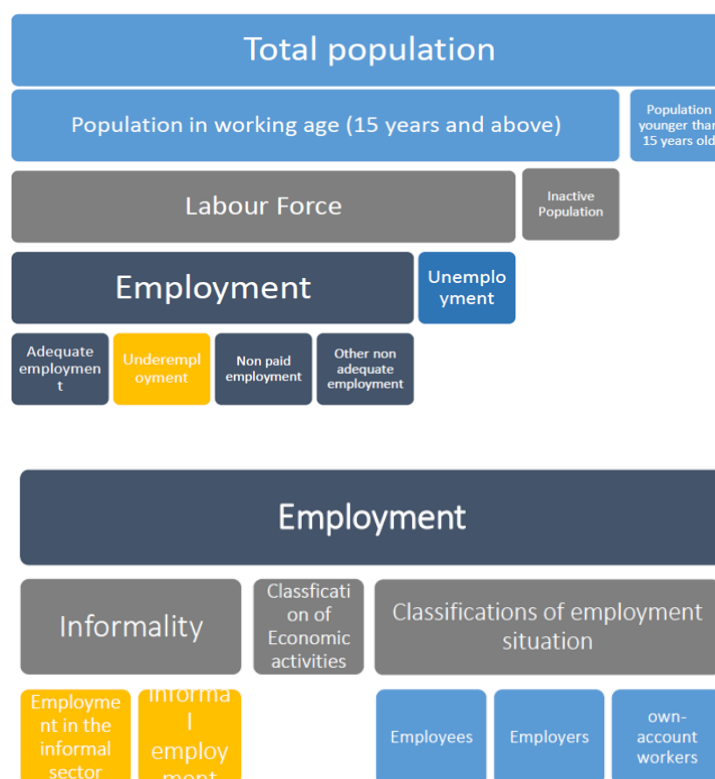
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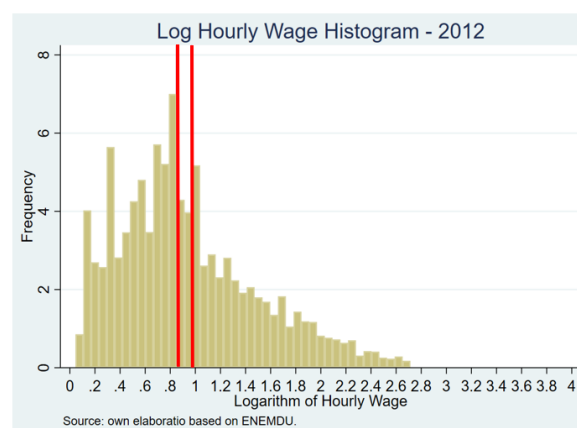
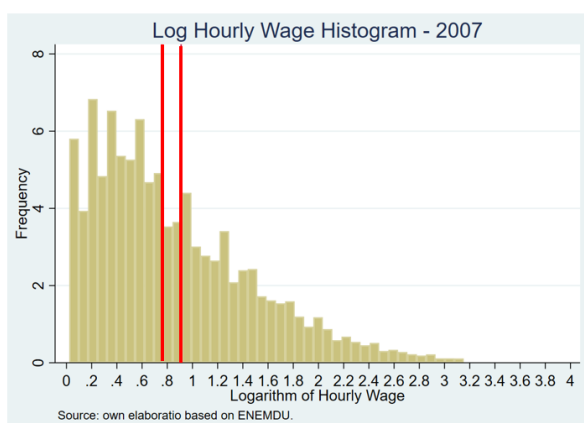
## 9. ANNEX

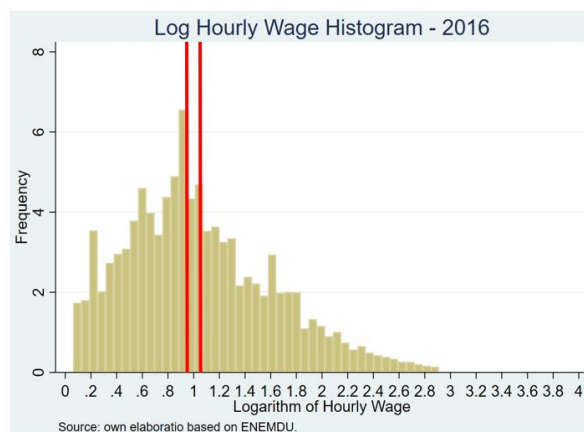
### 9.1. Annex I



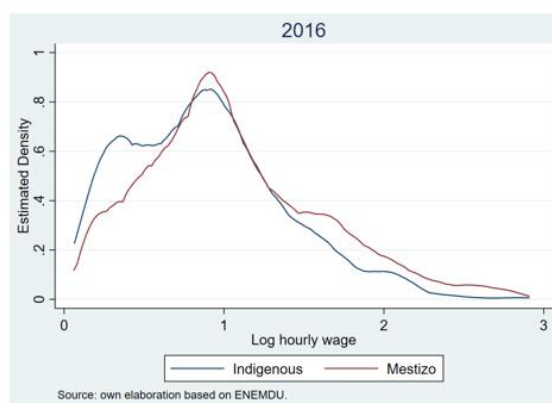
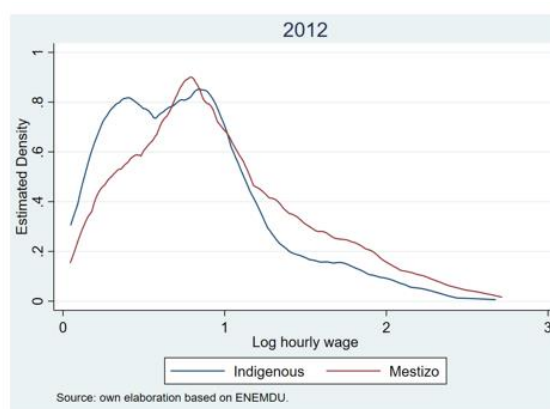
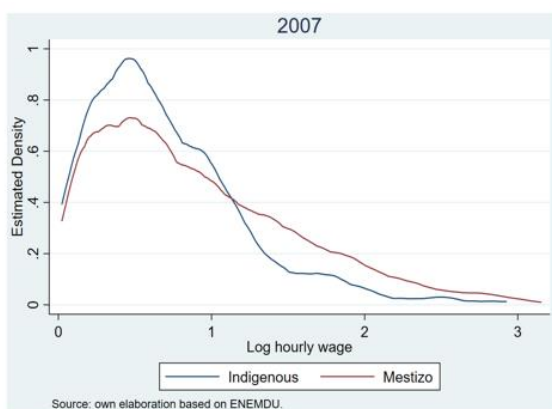
Source: Muñoz Bravo (2017)

### 9.2. Annex II

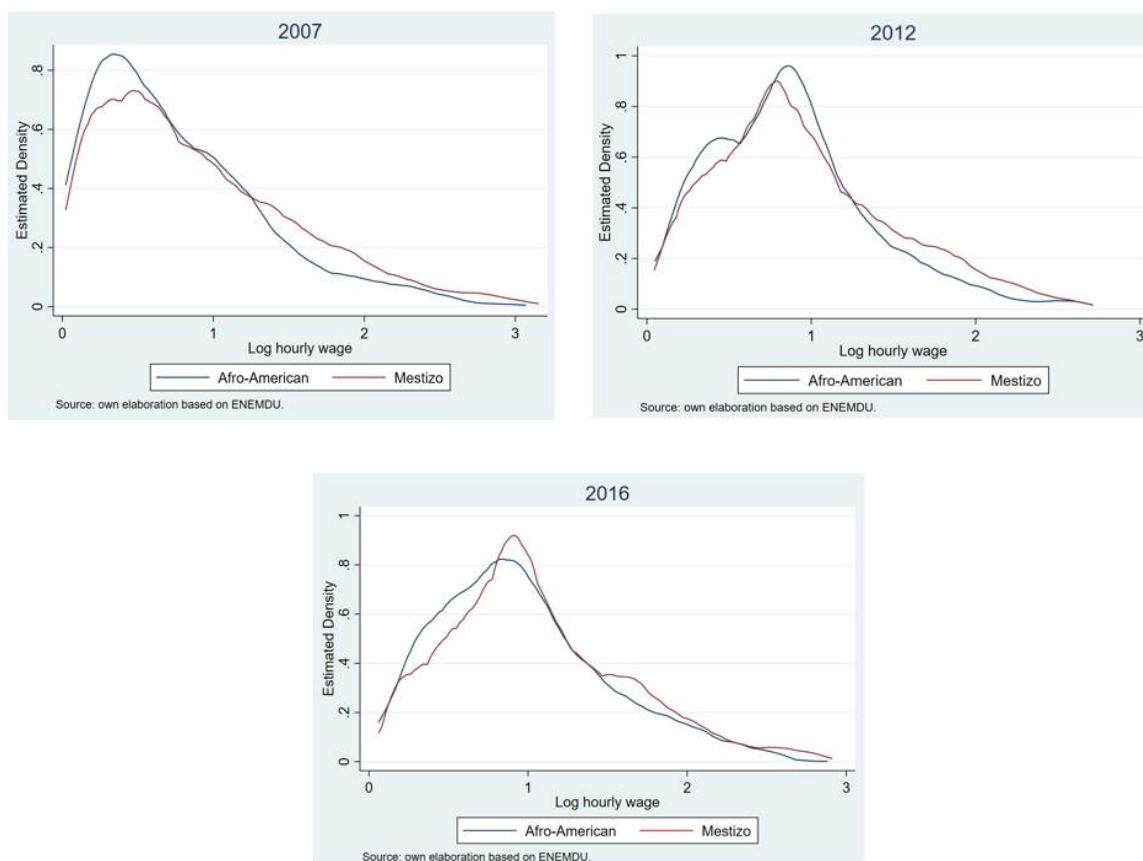




## Indigenous vs Mestizo



## Afro-American vs Mestizo



### 9.3. Annex III

#### Auxiliar Equation - Heckman's Correction

Dependent variable: Occupation	2007					
	Coef.	Std. Err.	z	P >  z	[95% Conf. Interval]	
sex	0.987	-0.010	77.377	0.000	0.962	1.012
year2	0.187	0.000	132.916	0.000	0.185	0.190
year3	-0.002	0.000	-117.148	0.000	-0.002	-0.002
education	0.028	0.000	19.986	0.000	0.025	0.031
zunderage	0.035	-0.010	6.093	0.000	0.024	0.046
zunderagesex	-0.079	-0.010	-9.382	0.000	-0.095	-0.062
_cons	-3.986	-0.030	-129.138	0.000	-4.047	-3.926

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Auxiliar Equation - Heckman's Correction**

Dependent variable: Occupation	2012					
	Coef.	Std. Err.	z	P >  z	[95% Conf. Interval]	
sex	0.987	-0.010	77.377	0.000	0.962	1.012
year2	0.187	0.000	132.916	0.000	0.185	0.190
year3	-0.002	0.000	-117.148	0.000	-0.002	-0.002
education	0.028	0.000	19.986	0.000	0.025	0.031
zunderage	0.035	-0.010	6.093	0.000	0.024	0.046
zunderagesex	-0.079	-0.010	-9.382	0.000	-0.095	-0.062
_cons	-3.986	-0.030	-129.138	0.000	-4.047	-3.926

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Auxiliar Equation - Heckman's Correction**

Dependent variable: Occupation	2016					
	Coef.	Std. Err.	z	P >  z	[95% Conf. Interval]	
sex	0.987	-0.010	77.377	0.000	0.962	1.012
year2	0.187	0.000	132.916	0.000	0.185	0.190
year3	-0.002	0.000	-117.148	0.000	-0.002	-0.002
education	0.028	0.000	19.986	0.000	0.025	0.031
zunderage	0.035	-0.010	6.093	0.000	0.024	0.046
zunderagesex	-0.079	-0.010	-9.382	0.000	-0.095	-0.062
_cons	-3.986	-0.030	-129.138	0.000	-4.047	-3.926

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

## 9.4. Annex IV

### 9.4.1. Conditional Quantile Regressions

Variable	2007									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
year2	0.231*** -0.03	0.208*** -0.02	0.182*** -0.02	0.179*** -0.02	0.194*** -0.02	0.193*** -0.02	0.201*** -0.02	0.201*** -0.02	0.196*** -0.02	0.109*** -0.02
year3	0.274*** -0.03	0.295*** -0.02	0.292*** -0.02	0.299*** -0.02	0.326*** -0.02	0.344*** -0.02	0.375*** -0.02	0.405*** -0.02	0.444*** -0.03	0.237*** -0.02
sex	0.23*** -0.02	0.199*** -0.01	0.182*** -0.01	0.177*** -0.01	0.153*** -0.01	0.153*** -0.01	0.126*** -0.01	0.118*** -0.01	0.09*** -0.02	0.085*** -0.01
marital	0.121*** -0.02	0.108*** -0.01	0.101*** -0.01	0.09*** -0.01	0.097*** -0.01	0.099*** -0.01	0.097*** -0.01	0.107*** -0.01	0.141*** -0.02	0.107*** -0.01
education	0.053*** 0	0.053*** 0	0.052*** 0	0.052*** 0	0.053*** 0	0.056*** 0	0.057*** 0	0.06*** 0	0.062*** 0	0.054*** 0
boss	0.194** -0.07	0.379*** -0.05	0.474*** -0.04	0.576*** -0.04	0.685*** -0.04	0.802*** -0.04	0.935*** -0.04	1.191*** -0.04	1.536*** -0.06	0.765*** -0.04
self-employed	-0.394*** -0.06	-0.217*** -0.04	-0.105** -0.04	-0.019 -0.03	0.077* -0.03	0.155*** -0.03	0.268*** -0.03	0.384*** -0.04	0.608*** -0.05	0.082** -0.03
salaried	0.251*** -0.06	0.296*** -0.04	0.308*** -0.04	0.297*** -0.03	0.31*** -0.03	0.314*** -0.03	0.341*** -0.03	0.369*** -0.03	0.456*** -0.05	0.329*** -0.03
manufacture	0.16*** -0.04	0.11*** -0.02	0.098*** -0.02	0.077*** -0.02	0.099*** -0.02	0.111*** -0.02	0.083*** -0.02	0.088*** -0.02	0.087** -0.03	0.1*** -0.02
construction	0.352*** -0.04	0.299*** -0.03	0.272*** -0.02	0.263*** -0.02	0.256*** -0.02	0.252*** -0.02	0.232*** -0.02	0.208*** -0.02	0.153*** -0.03	0.259*** -0.02
commerce	0.108** -0.03	0.073** -0.02	0.08*** -0.02	0.082*** -0.02	0.088*** -0.02	0.11*** -0.02	0.107*** -0.02	0.14*** -0.02	0.166*** -0.03	0.137*** -0.02
transport	0.28*** -0.05	0.255*** -0.03	0.245*** -0.03	0.209*** -0.03	0.216*** -0.03	0.232*** -0.03	0.238*** -0.03	0.231*** -0.03	0.235*** -0.04	0.261*** -0.02
tourism	0.196*** -0.05	0.217*** -0.04	0.168*** -0.03	0.141*** -0.03	0.155*** -0.03	0.201*** -0.03	0.183*** -0.03	0.178*** -0.03	0.175*** -0.05	0.216*** -0.03
teaching	0.496*** -0.05	0.52*** -0.03	0.55*** -0.03	0.547*** -0.03	0.525*** -0.03	0.495*** -0.03	0.452*** -0.03	0.408*** -0.03	0.384*** -0.04	0.485*** -0.03
public	0.769*** -0.06	0.759*** -0.04	0.732*** -0.03	0.723*** -0.03	0.711*** -0.03	0.688*** -0.03	0.657*** -0.03	0.646*** -0.03	0.623*** -0.05	0.705*** -0.03
others	0.264*** -0.04	0.241*** -0.02	0.255*** -0.02	0.253*** -0.02	0.265*** -0.02	0.297*** -0.02	0.305*** -0.02	0.328*** -0.02	0.414*** -0.03	0.301*** -0.02
urban	0.218*** -0.02	0.146*** -0.02	0.132*** -0.01	0.123*** -0.01	0.1*** -0.01	0.082*** -0.01	0.087*** -0.01	0.078*** -0.01	0.09*** -0.02	0.123*** -0.01
coast	0.052** -0.02	0.038** -0.01	0.021 -0.01	0.005 -0.01	0.013 -0.01	0.011 -0.01	0.022 -0.01	0.026* -0.01	0.044** -0.02	0.056*** -0.01
amazon	-0.001 -0.05	-0.026 -0.03	-0.03 -0.03	-0.023 -0.03	-0.024 -0.03	-0.005 -0.03	0.001 -0.03	-0.017 -0.03	-0.02 -0.04	-0.018 -0.02
lambda										-0.19*** -0.02
_cons	-1.744*** -0.06	-1.394*** -0.04	-1.16*** -0.04	-0.977*** -0.04	-0.865*** -0.03	-0.762*** -0.03	-0.654*** -0.04	-0.552*** -0.04	-0.439*** -0.05	-0.758*** -0.04

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level:  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Variable	2012									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
year2	0.265*** -0.03	0.191*** -0.02	0.18*** -0.02	0.176*** -0.02	0.186*** -0.01	0.185*** -0.01	0.19*** -0.02	0.214*** -0.02	0.198*** -0.02	0.152*** -0.06
year3	0.251*** -0.03	0.237*** -0.02	0.238*** -0.02	0.248*** -0.02	0.265*** -0.01	0.279*** -0.02	0.304*** -0.02	0.337*** -0.02	0.339*** -0.02	0.233*** -0.04
sex	0.216*** -0.02	0.194*** -0.02	0.184*** -0.01	0.171*** -0.01	0.155*** -0.01	0.136*** -0.01	0.124*** -0.01	0.114*** -0.01	0.087*** -0.02	0.132*** -0.04
marital	0.14*** -0.02	0.107*** -0.01	0.104*** -0.01	0.102*** -0.01	0.105*** -0.01	0.099*** -0.01	0.1*** -0.01	0.103*** -0.01	0.134*** -0.01	0.122*** -0.01
education	0.049*** 0	0.048*** 0	0.047*** 0	0.046*** 0	0.047*** 0	0.047*** 0	0.048*** 0	0.049*** 0	0.054*** 0	0.048*** 0
boss	0.094 -0.07	0.215*** -0.05	0.319*** -0.04	0.405*** -0.04	0.468*** -0.04	0.589*** -0.04	0.761*** -0.04	0.961*** -0.04	1.144*** -0.06	0.542*** -0.04
self-employed	-0.563*** -0.06	-0.461*** -0.04	-0.361*** -0.03	-0.248*** -0.03	-0.18*** -0.03	-0.098*** -0.03	0.023 -0.03	0.134*** -0.04	0.266*** -0.05	-0.184*** -0.03
salaried	0.227*** -0.06	0.176*** -0.04	0.164*** -0.03	0.179*** -0.03	0.169*** -0.03	0.181*** -0.03	0.227*** -0.03	0.252*** -0.04	0.26*** -0.05	0.188*** -0.03
manufacture	0.221*** -0.03	0.205*** -0.03	0.195*** -0.02	0.164*** -0.02	0.132*** -0.02	0.117*** -0.02	0.086*** -0.02	0.063*** -0.02	0.014 -0.03	0.123*** -0.02
construction	0.354*** -0.04	0.307*** -0.03	0.267*** -0.02	0.239*** -0.02	0.21*** -0.02	0.201*** -0.02	0.158*** -0.02	0.125*** -0.02	0.039 -0.03	0.224*** -0.02
commerce	0.213*** -0.03	0.179*** -0.02	0.152*** -0.02	0.125*** -0.02	0.095*** -0.02	0.097*** -0.02	0.082*** -0.02	0.067*** -0.02	0.051* -0.02	0.137*** -0.02
transport	0.351*** -0.04	0.307*** -0.03	0.253*** -0.02	0.217*** -0.02	0.19*** -0.02	0.18*** -0.02	0.161*** -0.02	0.139*** -0.02	0.089*** -0.03	0.24*** -0.02
tourism	0.266*** -0.05	0.248*** -0.03	0.223*** -0.03	0.206*** -0.03	0.179*** -0.02	0.155*** -0.02	0.162*** -0.03	0.121*** -0.03	0.045 -0.04	0.218*** -0.02
teaching	0.63*** -0.05	0.577*** -0.03	0.578*** -0.03	0.596*** -0.03	0.577*** -0.02	0.59*** -0.02	0.552*** -0.02	0.505*** -0.03	0.424*** -0.04	0.574*** -0.02
public	0.822*** -0.05	0.768*** -0.04	0.747*** -0.03	0.741*** -0.03	0.739*** -0.02	0.735*** -0.03	0.74*** -0.03	0.75*** -0.03	0.701*** -0.04	0.757*** -0.03
others	0.404*** -0.03	0.353*** -0.03	0.314*** -0.02	0.297*** -0.02	0.28*** -0.02	0.294*** -0.02	0.304*** -0.02	0.31*** -0.02	0.281*** -0.03	0.329*** -0.02
urban	0.157*** -0.02	0.115*** -0.02	0.099*** -0.01	0.098*** -0.01	0.088*** -0.01	0.089*** -0.01	0.086*** -0.01	0.088*** -0.01	0.088*** -0.02	0.118*** -0.01
coast	0.114*** -0.02	0.078*** -0.01	0.049*** -0.01	0.036*** -0.01	0.027*** -0.01	0.025*** -0.01	0.017 -0.01	0.018 -0.01	0.01 -0.01	0.088*** -0.01
amazon	-0.035 -0.04	0.01 -0.03	0.015 -0.03	0.01 -0.02	0.035 -0.02	0.044* -0.02	0.047* -0.02	0.061* -0.03	0.094** -0.03	0.036 -0.02
lambda										-0.102 -0.09
_cons	-1.424*** -0.07	-0.95*** -0.05	-0.717*** -0.04	-0.574*** -0.04	-0.433*** -0.03	-0.319*** -0.03	-0.247*** -0.04	-0.151*** -0.04	0.046 -0.05	-0.459*** -0.13

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level:  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Variable	2016									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
year2	0.275*** -0.02	0.221*** -0.02	0.207*** -0.01	0.198*** -0.01	0.201*** -0.01	0.21*** -0.01	0.219*** -0.01	0.241*** -0.01	0.262*** -0.02	0.169*** -0.04
year3	0.28*** -0.02	0.245*** -0.02	0.241*** -0.02	0.242*** -0.01	0.246*** -0.01	0.26*** -0.01	0.285*** -0.01	0.323*** -0.01	0.375*** -0.02	0.229*** -0.03
sex	0.196*** -0.02	0.162*** -0.01	0.153*** -0.01	0.138*** -0.01	0.128*** -0.01	0.123*** -0.01	0.124*** -0.01	0.122*** -0.01	0.127*** -0.01	0.123*** -0.03
marital	0.122*** -0.02	0.113*** -0.01	0.113*** -0.01	0.116*** -0.01	0.115*** -0.01	0.112*** -0.01	0.108*** -0.01	0.107*** -0.01	0.111*** -0.01	0.115*** -0.01
education	0.048*** 0	0.046*** 0	0.046*** 0	0.045*** 0	0.044*** 0	0.044*** 0	0.047*** 0	0.051*** 0	0.056*** 0	0.047*** 0
boss	0.347*** -0.06	0.303*** -0.04	0.358*** -0.04	0.449*** -0.03	0.513*** -0.03	0.662*** -0.03	0.776*** -0.03	0.945*** -0.04	1.221*** -0.05	0.655*** -0.03
self-employed	-0.439*** -0.04	-0.441*** -0.03	-0.365*** -0.03	-0.278*** -0.03	-0.202*** -0.02	-0.129*** -0.02	-0.018 -0.02	0.101*** -0.03	0.278*** -0.04	-0.152*** -0.02
salaried	0.503*** -0.04	0.333*** -0.03	0.285*** -0.03	0.274*** -0.03	0.261*** -0.02	0.255*** -0.02	0.272*** -0.02	0.295*** -0.03	0.337*** -0.04	0.33*** -0.02
manufacture	0.359*** -0.03	0.267*** -0.02	0.229*** -0.02	0.19*** -0.02	0.155*** -0.01	0.115*** -0.01	0.102*** -0.02	0.078*** -0.02	0.069*** -0.02	0.186*** -0.01
construction	0.324*** -0.03	0.298*** -0.02	0.275*** -0.02	0.239*** -0.02	0.21*** -0.02	0.175*** -0.02	0.152*** -0.02	0.124*** -0.02	0.078*** -0.03	0.238*** -0.02
commerce	0.312*** -0.02	0.247*** -0.02	0.216*** -0.01	0.185*** -0.01	0.168*** -0.01	0.141*** -0.01	0.124*** -0.01	0.111*** -0.01	0.128*** -0.02	0.214*** -0.01
transport	0.437*** -0.03	0.373*** -0.02	0.328*** -0.02	0.284*** -0.02	0.249*** -0.02	0.211*** -0.02	0.176*** -0.02	0.139*** -0.02	0.103*** -0.03	0.297*** -0.02
tourism	0.426*** -0.03	0.343*** -0.02	0.281*** -0.02	0.243*** -0.02	0.23*** -0.02	0.196*** -0.02	0.172*** -0.02	0.163*** -0.02	0.133*** -0.03	0.294*** -0.02
teaching	0.81*** -0.04	0.689*** -0.03	0.644*** -0.02	0.605*** -0.02	0.567*** -0.02	0.512*** -0.02	0.421*** -0.02	0.343*** -0.02	0.263*** -0.03	0.578*** -0.02
public	0.959*** -0.04	0.84*** -0.03	0.774*** -0.02	0.726*** -0.02	0.705*** -0.02	0.686*** -0.02	0.65*** -0.02	0.63*** -0.02	0.57*** -0.03	0.76*** -0.02
others	0.515*** -0.03	0.425*** -0.02	0.406*** -0.02	0.387*** -0.01	0.376*** -0.01	0.377*** -0.01	0.379*** -0.01	0.373*** -0.02	0.372*** -0.02	0.419*** -0.01
urban	0.098*** -0.02	0.082*** -0.01	0.081*** -0.01	0.07*** -0.01	0.065*** -0.01	0.076*** -0.01	0.077*** -0.01	0.09*** -0.01	0.094*** -0.02	0.095*** -0.01
coast	0.025 -0.02	0.014 -0.01	0.003 -0.01	-0.006 -0.01	-0.014 -0.01	-0.027** -0.01	-0.037*** -0.01	-0.051*** -0.01	-0.055*** -0.01	0.016 -0.01
amazon	-0.134*** -0.02	-0.102*** -0.01	-0.094*** -0.01	-0.096*** -0.01	-0.085*** -0.01	-0.08*** -0.01	-0.066*** -0.01	-0.069*** -0.01	-0.053*** -0.02	-0.085*** -0.01
lambda										-0.125 -0.07
_cons	-1.566*** -0.05	-0.968*** -0.04	-0.717*** -0.03	-0.516*** -0.03	-0.36*** -0.03	-0.234*** -0.03	-0.156*** -0.03	-0.083*** -0.03	0.023 -0.04	-0.455*** -0.09

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

Variable	2007									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Primary	0.309*** -0.04	0.299*** -0.03	0.243*** -0.02	0.236*** -0.02	0.235*** -0.02	0.244*** -0.02	0.231*** -0.02	0.213*** -0.02	0.208*** -0.03	0.247*** -0.02
Basic Education	0.301*** -0.06	0.292*** -0.05	0.252*** -0.04	0.246*** -0.03	0.241*** -0.03	0.258*** -0.04	0.233*** -0.04	0.225*** -0.04	0.248*** -0.05	0.265*** -0.03
Secondary	0.491*** -0.04	0.469*** -0.03	0.429*** -0.03	0.426*** -0.02	0.43*** -0.02	0.444*** -0.02	0.454*** -0.03	0.451*** -0.03	0.479*** -0.04	0.474*** -0.02
Middle Education	0.366*** -0.07	0.351*** -0.05	0.277*** -0.04	0.323*** -0.04	0.325*** -0.04	0.327*** -0.04	0.34*** -0.04	0.355*** -0.05	0.421*** -0.06	0.373*** -0.04
Higher	0.877***	0.884***	0.864***	0.88***	0.899***	0.917***	0.944***	0.971***	1.053***	0.943***

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:**  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Variable	2012									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Primary	0.306***	0.306***	0.29***	0.266***	0.246***	0.226***	0.211***	0.171***	0.16***	0.233***
	-0.04	-0.04	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.02
Basic Education	0.311***	0.311***	0.3***	0.266***	0.258***	0.253***	0.242***	0.226***	0.21***	0.276***
	-0.06	-0.06	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.05	-0.03
Secondary	0.52***	0.52***	0.457***	0.434***	0.411***	0.393***	0.377***	0.344***	0.353***	0.418***
	-0.04	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.02
Middle Education	0.365***	0.365***	0.397***	0.411***	0.38***	0.364***	0.357***	0.328***	0.331***	0.381***
	-0.06	-0.06	-0.04	-0.04	-0.03	-0.03	-0.03	-0.04	-0.05	-0.03
Higher	0.772***	0.772***	0.763***	0.76***	0.766***	0.787***	0.809***	0.806***	0.884***	0.794***

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:**  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)

Variable	2016									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Mean
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Primary	0.332***	0.295***	0.278***	0.253***	0.227***	0.199***	0.2***	0.199***	0.168***	0.238***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.02
Basic Education	0.328***	0.251***	0.244***	0.246***	0.241***	0.246***	0.256***	0.271***	0.289***	0.265***
	-0.06	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03	-0.03	-0.05	-0.03
Secondary	0.517***	0.452***	0.426***	0.4***	0.368***	0.341***	0.345***	0.356***	0.355***	0.402***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.04	-0.02
Middle Education	0.453***	0.386***	0.393***	0.371***	0.348***	0.338***	0.339***	0.341***	0.336***	0.374***
	-0.05	-0.04	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.05	-0.03
Higher	0.831***	0.771***	0.765***	0.749***	0.737***	0.756***	0.796***	0.86***	0.903***	0.8***

**Source:** own elaboration based on ENEMDU.

**Note:** sample consists on salaried workers between ages 15 and 65.

**Significance level:**  $p < 0.05$  (\*),  $p < 0.01$  (\*\*),  $p < 0.001$  (\*\*\*)



## 9.4.2. Unconditional Quantile Regressions

Variable	2007									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
Indicator	0.51	0.85	1.07	1.34	1.62	1.97	2.54	3.54	5.48	52.14
<i>Marginal Effects</i>										
year2	0.165***	0.207***	0.188***	0.216***	0.239***	0.282***	0.291***	0.259***	0.167***	-4.2***
	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-1
year3	0.082*	0.162***	0.191***	0.259***	0.33***	0.413***	0.516***	0.638***	0.621***	6.4***
	-0.04	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-2
sex	0.322***	0.224***	0.156***	0.142***	0.116***	0.104***	0.096***	0.086***	0.093***	0
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-1
marital	0.106***	0.086***	0.089***	0.104***	0.108***	0.101***	0.109***	0.147***	0.162***	2.9**
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-1
education	0.039***	0.035***	0.037***	0.041***	0.046***	0.054***	0.069***	0.085***	0.094***	1.4***
	0	0	0	0	0	0	0	0	0	0
boss	0.079	0.276***	0.422***	0.525***	0.658***	0.771***	1.046***	1.275***	1.283***	46.3***
	-0.09	-0.06	-0.04	-0.04	-0.04	-0.04	-0.05	-0.06	-0.08	-7
self-employed	-0.603***	-0.216***	0.007	0.13***	0.237***	0.315***	0.445***	0.45***	0.303***	5.3*
	-0.08	-0.05	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-2
salaried	0.234**	0.297***	0.338***	0.337***	0.359***	0.375***	0.45***	0.423***	0.269***	-2.3
	-0.07	-0.05	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-2
manufacture	0.218***	0.184***	0.145***	0.149***	0.148***	0.136***	0.081***	-0.049	-0.129***	-8.4***
	-0.05	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-2
construction	0.414***	0.381***	0.384***	0.41***	0.402***	0.315***	0.196***	-0.017	-0.091**	-7.9**
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-3
commerce	0.278***	0.166***	0.11***	0.131***	0.149***	0.141***	0.124***	0.024	-0.052	-5.4*
	-0.05	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-3
transport	0.531***	0.357***	0.294***	0.299***	0.316***	0.293***	0.265***	0.126**	-0.079	-12.6***
	-0.05	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.05	-3
tourism	0.479***	0.303***	0.219***	0.252***	0.221***	0.238***	0.211***	0.08	-0.09	-14.8***
	-0.06	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.05	-0.05	-3
teaching	0.297***	0.311***	0.325***	0.428***	0.521***	0.66***	0.845***	0.991***	0.624***	-18.8***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.03	-0.03	-0.05	-0.07	-3
public	0.291***	0.342***	0.403***	0.543***	0.712***	0.884***	1.206***	1.424***	1.108***	-9.5**
	-0.04	-0.02	-0.02	-0.02	-0.02	-0.03	-0.04	-0.06	-0.08	-3
others	0.358***	0.236***	0.201***	0.244***	0.293***	0.325***	0.386***	0.344***	0.19***	-4.4
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.04	-3
urban	0.233***	0.151***	0.129***	0.114***	0.096***	0.086***	0.098***	0.119***	0.079***	-3.1*
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-1
coast	0.265***	0.143***	0.081***	0.037***	-0.003	-0.018	-0.05***	-0.052**	-0.029	-1.2
	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-1
amazon	0.019	-0.02	-0.016	0.013	0.021	0.025	0.031	-0.045	-0.111*	0.4
	-0.06	-0.03	-0.03	-0.02	-0.02	-0.03	-0.03	-0.04	-0.05	-3
_cons	-1.793***	-1.31***	-1.068***	-1.006***	-0.957***	-0.92***	-0.964***	-0.825***	-0.178***	43.3***
	-0.08	-0.05	-0.04	-0.04	-0.03	-0.03	-0.04	-0.04	-0.05	-3

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

Variable	2012									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
Indicator	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
Indicator	0.67	1.11	1.45	1.78	2.09	2.43	2.84	3.72	5.57	43.29
<i>Marginal Effects</i>										
year2	0.19***	0.219***	0.217***	0.23***	0.202***	0.21***	0.249***	0.282***	0.191***	-1.9
	-0.03	-0.02	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.02	-1
year3	0.034	0.146***	0.184***	0.235***	0.23***	0.283***	0.387***	0.541***	0.542***	6.2***
	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.03	-2
sex	0.399***	0.291***	0.186***	0.151***	0.092***	0.085***	0.094***	0.081***	0.074***	-0.5
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-1
marital	0.165***	0.146***	0.1***	0.106***	0.09***	0.092***	0.105***	0.119***	0.144***	-2.2
	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-2
education	0.041***	0.042***	0.035***	0.038***	0.036***	0.04***	0.051***	0.072***	0.079***	1***
	0	0	0	0	0	0	0	0	0	0
boss	-0.173*	-0.086	0.16***	0.364***	0.45***	0.54***	0.939***	1.179***	1.25***	44.8***
	-0.08	-0.06	-0.05	-0.04	-0.04	-0.04	-0.04	-0.06	-0.08	-11
self-employed	-0.934***	-0.748***	-0.339***	-0.15***	-0.015	0.061*	0.304***	0.361***	0.243***	9.8***
	-0.07	-0.05	-0.04	-0.04	-0.03	-0.03	-0.03	-0.04	-0.04	-2
salaried	-0.08	0.005	0.161***	0.247***	0.253***	0.225***	0.385***	0.43***	0.262***	-4.9*
	-0.07	-0.05	-0.04	-0.04	-0.03	-0.03	-0.03	-0.04	-0.04	-2
manufacture	0.327***	0.257***	0.216***	0.241***	0.157***	0.071***	0.05*	-0.071**	-0.179***	-9.8**
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-4
construction	0.435***	0.422***	0.36***	0.348***	0.244***	0.154***	0.162***	-0.017	-0.117***	-13.4***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-2
commerce	0.361***	0.231***	0.154***	0.186***	0.122***	0.077***	0.083***	-0.011	-0.118***	-7.8***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.03	-2
transport	0.546***	0.449***	0.329***	0.318***	0.218***	0.156***	0.174***	0.024	-0.161***	-18.6***
	-0.05	-0.03	-0.03	-0.03	-0.02	-0.02	-0.03	-0.03	-0.04	-2
tourism	0.557***	0.395***	0.252***	0.256***	0.156***	0.132***	0.112***	0.032	-0.136***	-16.4***
	-0.06	-0.04	-0.03	-0.03	-0.02	-0.02	-0.03	-0.04	-0.04	-2
teaching	0.366***	0.342***	0.316***	0.467***	0.463***	0.524***	0.808***	1.087***	1.12***	-8.1**
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.04	-0.07	-2
public	0.326***	0.36***	0.362***	0.554***	0.563***	0.668***	1.034***	1.546***	1.541***	4.8*
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.05	-0.08	-2
others	0.44***	0.338***	0.288***	0.367***	0.313***	0.269***	0.336***	0.329***	0.201***	-10.8***
	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-2
urban	0.195***	0.138***	0.099***	0.096***	0.096***	0.076***	0.073***	0.088***	0.094***	-2.3
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-1
coast	0.385***	0.25***	0.094***	0.042***	-0.006	0.002	-0.022*	-0.065***	-0.111***	-7.1***
	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-1
amazon	-0.062	0.001	0.007	-0.009	-0.006	0.022	0.054*	0.078*	0.096	2.6
	-0.06	-0.04	-0.03	-0.02	-0.02	-0.02	-0.02	-0.04	-0.05	-3
_cons	-1.403***	-0.924***	-0.591***	-0.614***	-0.328***	-0.244***	-0.466***	-0.548***	0.068	43.9***
	-0.07	-0.06	-0.04	-0.04	-0.03	-0.03	-0.03	-0.04	-0.05	-2

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

Variable	2016									
	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
Indicator	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
Indicator	0.73	1.25	1.65	2.00	2.35	2.68	3.14	4.12	5.94	44.45
<i>Marginal Effects</i>										
year2	0.207***	0.244***	0.274***	0.248***	0.216***	0.229***	0.282***	0.333***	0.242***	0.3
	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	-1
year3	0.104**	0.186***	0.238***	0.241***	0.233***	0.273***	0.374***	0.507***	0.457***	2.5
	-0.03	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.02	-0.02	-2
sex	0.381***	0.27***	0.19***	0.124***	0.073***	0.074***	0.073***	0.067***	0.103***	-8.4
	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-8
marital	0.096***	0.132***	0.132***	0.124***	0.102***	0.095***	0.112***	0.137***	0.135***	2.2
	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-2
education	0.04***	0.037***	0.037***	0.036***	0.034***	0.036***	0.05***	0.071***	0.069***	1.5*
	0	0	0	0	0	0	0	0	0	-1
boss	0.162*	0.163**	0.312***	0.335***	0.381***	0.52***	0.867***	1.224***	1.203***	89.1*
	-0.08	-0.06	-0.04	-0.04	-0.03	-0.03	-0.04	-0.05	-0.06	-45
self-employed	-0.754***	-0.642***	-0.401***	-0.248***	-0.102***	0.026	0.213***	0.343***	0.276***	18.6***
	-0.07	-0.05	-0.04	-0.03	-0.02	-0.02	-0.02	-0.03	-0.03	-2
salaried	0.313***	0.297***	0.341***	0.317***	0.285***	0.275***	0.409***	0.493***	0.344***	2.1
	-0.07	-0.05	-0.04	-0.03	-0.02	-0.02	-0.02	-0.03	-0.03	-2
manufacture	0.498***	0.348***	0.318***	0.255***	0.169***	0.099***	0.056***	-0.051**	-0.115***	-13.5**
	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.02	-5
construction	0.586***	0.481***	0.436***	0.334***	0.19***	0.126***	0.036*	-0.066**	-0.111***	7
	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-17
commerce	0.52***	0.374***	0.311***	0.248***	0.173***	0.117***	0.083***	-0.008	-0.041*	-10.5
	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	-0.02	-0.02	-6
transport	0.906***	0.564***	0.416***	0.296***	0.214***	0.16***	0.126***	-0.002	-0.1***	-15.7***
	-0.04	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-2
tourism	0.841***	0.547***	0.427***	0.303***	0.19***	0.146***	0.111***	0.003	-0.06*	-19.6*
	-0.05	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-9
teaching	0.547***	0.486***	0.529***	0.559***	0.556***	0.633***	0.885***	1.109***	0.335***	-20.2*
	-0.04	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.04	-0.04	-8
public	0.507***	0.489***	0.567***	0.626***	0.641***	0.75***	1.104***	1.305***	1.053***	4.2
	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	-0.02	-0.03	-0.05	-5
others	0.657***	0.51***	0.474***	0.42***	0.349***	0.32***	0.36***	0.369***	0.276***	-9.2
	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.02	-6
urban	0.118***	0.12***	0.096***	0.08***	0.067***	0.056***	0.079***	0.098***	0.087***	0.6
	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-2
coast	0.261***	0.143***	0.043***	0	-0.051***	-0.054***	-0.089***	-0.125***	-0.14***	-5.4*
	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-2
amazon	-0.146***	-0.152***	-0.126***	-0.085***	-0.065***	-0.039***	-0.04***	-0.067***	-0.081***	0.7
	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-3
_cons	-1.73***	-1.056***	-0.807***	-0.495***	-0.183***	-0.112***	-0.337***	-0.457***	0.194***	30.6***
	-0.08	-0.05	-0.04	-0.03	-0.03	-0.02	-0.03	-0.03	-0.03	-2

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

2007										
Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Indicator	0.51	0.85	1.07	1.34	1.62	1.97	2.54	3.54	5.48	52.14
<i>Marginal Effects</i>										
Primary	0.482*** -0.07	0.31*** -0.04	0.242*** -0.03	0.192*** -0.02	0.186*** -0.02	0.158*** -0.02	0.169*** -0.02	0.15*** -0.02	0.119*** -0.03	-4.3*** -1
Basic Education	0.289** -0.09	0.146** -0.06	0.132** -0.04	0.076* -0.04	0.123*** -0.03	0.193*** -0.03	0.32*** -0.03	0.371*** -0.04	0.349*** -0.04	4.2* -2
Secondary	0.664*** -0.07	0.48*** -0.04	0.428*** -0.03	0.391*** -0.03	0.409*** -0.02	0.403*** -0.02	0.462*** -0.03	0.459*** -0.03	0.381*** -0.03	-2.6 -2
Middle Education	0.446*** -0.1	0.222*** -0.06	0.264*** -0.05	0.238*** -0.04	0.259*** -0.04	0.284*** -0.04	0.394*** -0.05	0.478*** -0.05	0.425*** -0.05	5.7 -3
Higher	0.792*** -0.07	0.661*** -0.04	0.648*** -0.03	0.675*** -0.03	0.748*** -0.03	0.845*** -0.03	1.082*** -0.03	1.301*** -0.04	1.395*** -0.05	16.5*** -4

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

2012										
Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Indicator	0.67	1.11	1.45	1.78	2.09	2.43	2.84	3.72	5.57	43.29
<i>Marginal Effects</i>										
Primary	0.653*** -0.07	0.41*** -0.04	0.234*** -0.03	0.149*** -0.02	0.118*** -0.02	0.081*** -0.02	0.091*** -0.02	0.107*** -0.02	0.107*** -0.02	-4.3*** -1
Basic Education	0.617*** -0.09	0.372*** -0.06	0.16*** -0.04	0.064 -0.04	0.076** -0.03	0.093*** -0.03	0.162*** -0.03	0.241*** -0.03	0.336*** -0.04	2.5 -2
Secondary	0.797*** -0.07	0.611*** -0.04	0.43*** -0.03	0.355*** -0.03	0.302*** -0.02	0.256*** -0.02	0.278*** -0.02	0.327*** -0.03	0.285*** -0.03	-2.2 -2
Middle Education	0.66*** -0.09	0.516*** -0.06	0.354*** -0.04	0.268*** -0.04	0.243*** -0.03	0.228*** -0.03	0.278*** -0.03	0.371*** -0.04	0.331*** -0.05	1.2 -2
Higher	0.892*** -0.07	0.763*** -0.05	0.576*** -0.03	0.577*** -0.03	0.542*** -0.02	0.584*** -0.02	0.763*** -0.02	1.075*** -0.03	1.161*** -0.04	9** -3

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

2016										
Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90	Gini
	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.	Est./S.E.
<i>Aggregate sample</i>										
Indicator	0.73	1.25	1.65	2.00	2.35	2.68	3.14	4.12	5.94	44.45
<i>Marginal Effects</i>										
Primary	0.674*** -0.08	0.393*** -0.04	0.271*** -0.03	0.194*** -0.02	0.13*** -0.02	0.079*** -0.01	0.049** -0.02	0.014 -0.02	0.002 -0.02	-8.7*** -2
Basic Education	0.619*** -0.1	0.317*** -0.06	0.127** -0.05	0.088* -0.04	0.099*** -0.03	0.102*** -0.02	0.156*** -0.03	0.21*** -0.03	0.239*** -0.03	-0.6 -2
Secondary	0.849*** -0.08	0.592*** -0.05	0.466*** -0.03	0.363*** -0.02	0.282*** -0.02	0.22*** -0.02	0.207*** -0.02	0.195*** -0.02	0.14*** -0.02	-8.7*** -2
Middle Education	0.755*** -0.09	0.484*** -0.05	0.379*** -0.04	0.283*** -0.03	0.218*** -0.02	0.179*** -0.02	0.206*** -0.03	0.24*** -0.03	0.259*** -0.03	-0.3 -2
Higher	0.967*** -0.08	0.747*** -0.05	0.658*** -0.03	0.597*** -0.02	0.533*** -0.02	0.542*** -0.02	0.726*** -0.02	1.014*** -0.03	0.953*** -0.03	13.9* -7

Source: own elaboration based on ENEMDU.

Note: sample consists on salaried workers between ages 15 and 65.

Significance level: p<0.05 (\*), p<0.01 (\*\*), p<0.001 (\*\*\*)

## 9.6. Annex V

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*****
*****ESTIMATIONS*****
*****

*Run the append dataset "2016-2012-2007_hom"

cd "C:\Users\nicol\Documents\LAGLOBE\4th Semester\2. Mémoire\Plan mémoire\7. Estimations\3.
Brouillons excel"

use "C:\Users\nicol\Documents\LAGLOBE\4th Semester\2. Mémoire\Plan mémoire\7. Estimations\1. Bases de
Datos\1. ENEMDU\2007-2012-2016_hom\2016-2012-2007_hom", clear

**We show the regressions for 2016:

*****
*****MINCERIAN EQUATIONS*****
*****

***TOTAL POPULATION

***Without Heckman's Correction

reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz if periodo==201612

***Heckman's Correction

probit ocup sexo edad edad2 educa zmenos zmenorsex if periodo==201612

drop xb

predict xb, xb

g lambda16 = normalden(xb)/(normal(xb))

reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz lambda16 if periodo==201612

***INDIGENOUS (etnia==1) & AFRO-AMERICAN (etnia==2)

***Without Heckman's Correction

reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2)

est store mco

***Heckman's Correction

probit ocup sexo edadt2 edadt3 educa zmenos zmenorsex if periodo==201612 & (etnia==1 | etnia==2)

drop xb

predict xb, xb

g lambda16_e = normalden(xb)/(normal(xb))

reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz lambda16 if periodo==201612 & (etnia==1 | etnia==2)

```

\*\*\*\*\*

## \*\*CONDITIONAL QUANTILE REGRESSIONS\*\*

\*\*\*\*\*

### \*\*YEARS OF SCHOOLING

#### \*\*\*TOTAL POPULATION

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.1)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.5)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.9)

quietly reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612

#### \*\*\*INDIGENOUS (etnia==1) & AFRO-AMERICAN (etnia==2)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), quantile (.1)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), quantile (.5)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), quantile (.9)

quietly reg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2)

### \*\*EDUCATIONAL LEVEL

#### \*\*\*TOTAL POPULATION

quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.1)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.5)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, quantile (.9)

quietly reg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612

#### \*\*\*INDIGENOUS (etnia==1) & AFRO-AMERICAN (etnia==2)

quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), quantile (.1)

```
quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ_bas Sec Educ_med Sup patron cuentprop asal
indust_man construc comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 &
(etnia==1 | etnia==2), quantile (.5)
```

```
quietly qreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ_bas Sec Educ_med Sup patron cuentprop asal
indust_man construc comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 &
(etnia==1 | etnia==2), quantile (.9)
```

```
quietly reg logingtotalh edadt2 edadt3 sexo emarital Prim Educ_bas Sec Educ_med Sup patron cuentprop asal
indust_man construc comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 &
(etnia==1 | etnia==2)
```

```
*****
```

```
**UNCONDITIONAL QUANTILE REGRESSIONS**
```

```
*****
```

```
**YEARS OF SCHOOLING
```

```
***TOTAL POPULATION
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(10)) robust
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(50)) robust
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(90)) robust
```

```
***Gini's RIF (levels)
```

```
rifhdreg ingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz [aw=fexp] if periodo==201612, rif(gini) robust
```

```
noi pctlile deciles16=ingtotalh [aw=fexp] if periodo==201612, nq(10)
```

```
noi list deciles16 in 1/9
```

```
***INDIGENOUS (etnia==1) & AFRO-AMERICAN (etnia==2)
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2),
rif(q(10)) robust
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2),
rif(q(50)) robust
```

```
quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc
comer transp hot_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2),
rif(q(90)) robust
```

```
**Gini's RIF (levels)
```

```
rifhdreg ingtotalh edadt2 edadt3 sexo emarital educa patron cuentprop asal indust_man construc comer transp
hot_rest ensen secpub otros urbano costa amaz [aw=fexp] if periodo==201612 & (etnia==1 | etnia==2), rif(gini)
robust
```

```
noi pctlile deciles16_e=ingtotalh [aw=fexp] if periodo==201612 & (etnia==1 | etnia==2), nq(10)
```

```
noi list deciles16_e in 1/9
```

```
**EDUCATIONAL LEVELS
```

```
drop deciles16
```

drop deciles16\_e

\*\*\*TOTAL POPULATION

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(10)) robust

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(50)) robust

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612, rif(q(90)) robust

\*\*Gini's RIF (levels)

rifhdreg ingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz [aw=fexp] if periodo==201612, rif(gini) robust

noi pctlile deciles16=ingtotalh [aw=fexp] if periodo==201612, nq(10)

noi list deciles16 in 1/9

\*\*\*INDIGENOUS (etnia==1) & AFRO-AMERICAN (etnia==2)

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), rif(q(10)) robust

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), rif(q(50)) robust

quietly rifhdreg logingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz if periodo==201612 & (etnia==1 | etnia==2), rif(q(90)) robust

\*\*Gini's RIF (levels)

rifhdreg ingtotalh edadt2 edadt3 sexo emarital Prim Educ\_bas Sec Educ\_med Sup patron cuentprop asal indust\_man construc comer transp hot\_rest ensen secpub otros urbano costa amaz [aw=fexp] if periodo==201612 & (etnia==1 | etnia==2), rif(gini) robust

noi pctlile deciles16\_e=ingtotalh [aw=fexp] if periodo==201612 & (etnia==1 | etnia==2), nq(10)

noi list deciles16\_e in 1/9



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## **Résumé**

Parmi tous les facteurs susceptibles d'aggraver la distribution des revenus, l'éducation a suscité un intérêt particulier dans l'académie dans la mesure où son impact distributif reste encore ambigu. Dans ce contexte, le cas de l'Équateur mérite une attention particulière pour la période 2007-2016, au cours de laquelle le pays a connu une hausse de la scolarisation jamais vue dans son histoire. Ainsi, le but principal de ce mémoire est d'analyser les effets distributifs de l'éducation sur les revenus professionnels ainsi que l'impact des niveaux d'éducation (élémentaire, secondaire, universitaire, etc.) sur les différents quantiles de la distribution globale pour l'Équateur tout au long de la décennie analysée. En d'autres termes, l'objectif est d'examiner si l'expansion de l'éducation a exacerbé les inégalités à court terme – en particulier, au profit des couches supérieures de la distribution – ou si elle a été décisive pour améliorer le niveau de scolarisation – et donc, pour réduire les écarts de revenus – pour les plus pauvres.

**Mots-clés :** éducation, répartition des revenus, Équateur.

## **Abstract**

Among all the possible transmission channels that could worsen income distribution, education has specifically provoked a significant interest in academia insofar as its distributive impact still remains ambiguous. In this context, the case of Ecuador deserves special attention for the period 2007-2016, during which the country experienced a schooling upgrading never seen before in its history. Hence, the main thrust of this master thesis is to analyze the distributive effects of education on labor income as well as the impact of educational levels (basic, primary, secondary, university, etc.) on the different quantiles of the aggregate distribution for Ecuador throughout the decade under analysis. In other words, the aim is to examine whether the educational expansion abovementioned has exacerbated short term inequalities—particularly, benefiting the upper layers of the distribution—or has been decisive in improving the schooling attainment—and therefore, narrowing income revenue gaps—for the poorer.

**Keywords:** education, income distribution, Ecuador.