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Gender Wage Gap in Ecuador: Exploring the Gender Wage Differential Across the Distribution

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RESUMEN

Este trabajo de investigación estudia el comportamiento de la brecha estructural (no explicada) de la diferencia salarial de género en el área urbana del Ecuador durante los años 2007-2017. Usando la metodología de "Regresiones Cuantílicas Incondicionales" (Firpo et al., 2009), mostramos que los retornos de los determinantes del ingreso varían dependiendo del nivel salarial (cuantiles 10, 50 y 90). En la parte media de la distribución salarial (cuantil 50), a lo largo del período de análisis, el tener un título universitario, el número de horas trabajadas y la experiencia presentan un retorno favorable para las mujeres, mientras que estar casado, en unión libre o haber estado casado tienen un retorno favorable para los hombres. En el cuantil 10, el retorno de años de educación tiende a favorecer a las mujeres, si bien el retorno de un título universitario es no significativo. En el cuantil 90, el retorno de los años de educación favorece a los hombres, al igual que un título universitario; mientras que estar casado o en unión libre favorece a las mujeres. El retorno estructural total está determinado principalmente por las características no observadas junto con el efecto del grupo omitido. De esta forma, existe un mayor retorno salarial para los hombres en la parte inferior de la distribución y para las mujeres en la parte superior (excepto para 2017).

Palabras Clave: Brecha salarial de género, Regresiones Cuantílicas Incondicionales, Recentered Influence Functions (RIF), descompocición distribución salarial, Regresión de Mínimos Cuadrados Ordinarios, Oaxaca-Blinder(OB).

ABSTRACT

This research work studies the behavior of the gender wage gap structure effect (unexplained) in the urban area of Ecuador during the years 2007-2017. Using the methodology of “Unconditional Quantile Regressions“ (Firpo et al., 2009), we show that the salary determinants' returns vary depending on the wage level (10th, 50th, and 90th quantile). In the middle part of the wage distribution (50th quantile), throughout the analyzed period, having a university degree, number of hours worked, and experience present a favorable return for women, while being married, in free union or previously married have a favorable return for men. At 10th quantile, the return of years of education tends to favor women, although the return of a university degree is not significant. At 90th quantile, the return of years of education favors men, as does a university degree; while being married or in free union favors women. The total structure effect return is determined mainly by the unobserved characteristics and the omitted group effect. In this way, there is a greater wage return for men at the lower part of the distribution and for women at the upper part (except for 2017).

Keywords: Gender wage gap, Unconditional Quantile Regressions, Recentered Influence Functions (RIF), wage distribution decomposition, Ordinary Least Square Regressions, Oaxaca-Blinder (OB).

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Introduction

Gender labor income[1] differentials are an important indicator of equality within the labor market. The wage gap between men and women has been an active investigation subject, where the factors that cause this divergence have been changing over time. Initially, this salary difference was attributed to purely discriminatory acts towards women. However, nowadays studies show that there are many explanations to the existence of this gap regarding the changes that have taken place in family structure, career and occupations selection, and women's preferences.

Ecuador, being a developing country, does not have many studies on the behavior of the gender wage gap. Despite, it has been adopting interest on this subject due to the rise of feminist movements (Saunders, 1995) and socio-economic development's research. With that motivation, this paper studies the gap between female and male earnings throughout the distribution for the last decade.

In order to understand the gender wage gap behavior, it is commonly used the Oaxaca-Blinder decomposition method (1973), which decomposes the differences between men's and women's wage using multivariate regression analysis (Fortin et al., 2011). This technique applies to the decomposition of the gap at the average and does not work for other distributional statistics such as quantiles (Chi and Li, 2008). For this reason, Firpo et al. (2009) developed a decomposition method for the entire distribution known as Unconditional Quantile Regression, which is based on Recentered Influence Functions (RIF). This methodology allows estimate the marginal effect of independent variables on the desired unconditional quantiles.

Using these RIF unconditional quantile estimates, we proceed to decompose the gender wage gap at different quantiles into explained and unexplained effects, which in turn are decomposed into the contribution of each independent variable. This enables us

[1] In Ecuador there are important differences beyond salaries, so in this work labor income is set up by adding all monetary earnings, discounts, and species or services received by employers. However, for editorial purposes, throughout the work we will use income, earnings, salary, and wage as synonyms of labor income.

to determine the difference between female and male specific characteristics that lead to the explanation of the gender wage gap. This paper emphasizes in the analysis of the structural wage gap in order to determine the differences in the determinants' returns.

Results show that the covariates of the structure wage effect gap vary at different points of the distribution. For the studied period, at 10th quantile, years of education give women a higher return, where the university degree return is not statistically significant; while men in free union and previously married receive a higher return. At 50th quantile, having a university degree, hours worked and years of work experience favors women with a greater return; whereas being married, in free union or previously married favors men. At 90th quantile, the return of years of education is higher for men, as well as a university degree; while the return of being married and in free union is higher for women. This result's divergence, depending on the distribution level, helps explain the structural gender wage gap, but what mainly determine this gap are the unobserved characteristics and the omitted group effect captured in the constant. In this way, men have a greater wage return at the lower part of the distribution and women at the upper part (except for 2017).

Literature Review

2.1 General perspective

The wage gap between men and women has been a well investigated subject for several decades and continues being an innovative and active research area (Blau and Khan, 2016). Its importance lies on the fact that it is a key indicator of gender equality (Dupuy et al., 2009). Across the world, the wage gap reflects the fact that men enjoy higher income than women. This gap is interpreted as the result of the difference between the relative price of labor, paid by employers, to men and women (Dupuy et al., 2009). Even though the long-term trend suggests a substantial reduction in the gender wage gap, both in the United States and in other economically advanced nations (Blau and Khan, 2008), gender wage-inequality persists worldwide (Kleven et al., 2018).

Over the past half-century, women have experienced significant gains in the labor market, where the gender gap in labor force participation and the gender gap in income have declined (Bertrand et al., 2013). Over time, the wage gap has gradually diminished; especially in the upper part of the salary distribution compared to the middle and lower part (Blau and Khan, 2016). This can be corroborated by the increase in the rate of women participation in the labor force and by the reduction in gender occupational segregation.

The convergence between men and women regarding traditional human capital factors has played a relevant role in reducing the gender wage gap. However, these factors together explain relatively little of the difference in income. Indeed, currently women tend to outperform men in terms of educational attainment, which has also allowed for a reduction of the gender experience gap. The gender pay gap has been attributed to a series of factors such as the endowment of human capital, women's career interruptions, employers' discrimination, labor characteristics, self-selection of labor, and labor market institutions (Dupuy et al., 2009). However, some authors argue that its presence is mainly due to changes or trends in global perspectives that include access to education, work hours, work experience, tasks and occupations at work, participation in the workforce, and type of company (Blau et al., 2014).

Over time, several theories about the gender wage differential have emerged. Some of them are focused on the human capital theory and the gender division of housework, while others on discrimination. In the first case, the distribution of human capital is believed to influence the allocation of time between household work –which implies a non-market activity– and work –which implies a market activity– (Mincer and Polachek, 1974). Following this line, the gender wage gap could be understood as a result of women's low educational and work training, who are assumed to interrupt their careers during motherhood and face a depreciation of their human capital while they raise their children (Mincer and Polachek, 1974). This women's withdrawal from the labor market will result in a skills' deterioration and thus a lower wage, compared with the one before the withdrawal. (Mincer and Ofek, 1982).The fact that women have a shorter working life and more interruptions than men may be due to their preferences or the discriminatory social norm, which would generate fewer working years' experience and consequently fewer job training opportunities. Historically, women have worked fewer years than men and in a disrupted way as a result of their family role and motherhood (Juhn and McCue, 2017).

As mentioned before, human capital differences may be a cause of wage gaps. On the one hand, individuals invest in education and skills formation with the aim of achieving a desired return in the labor market. On the other hand, employers are guided by the signals issued by potential workers, their characteristics and behavior patterns. To select qualified workers, employers use years and quality of education as a proxy for their potential ability and productiveness, which makes investment in human capital attractive for individuals (Blaug, 1976). Apart from education, other aspects such as congeniality, pliability, and skin color are also considered as proxies of the work performance of individuals (Cain, 1976), where prejudice and discrimination against certain groups can be generated.

More recently, the conventional human capital variables (education and experience) as a whole do not explain much of the wage divergence between men and women; unlike industry and occupation (Blau and Khan, 2016). Despite this, the cut in hours and female interruption in labor force continue being important when analyzing gender income differences, as well as the industry and occupation variations due to gender roles and division of labor activities. In this sense, research based on experimental evidence strongly suggests that discrimination cannot be completely ruled out (Blau and Khan, 2016). Therefore, the wage gap becomes a waste that cannot be explained by the differences between men and women's endowments. For this reason, it is generally assumed that at least past of the gender wage gap –which cannot be explained– is the result of gender discrimination by employers (Dupuy et al., 2009).

One of the main drivers of the wage gap is segregation in employment and economic sectors (Commission, 2017). In some industries such as manufacturing, construction, science, and transport, women are less represented. Likewise, the clear divergence between companies, industries, occupations, and tasks, in which women are employed, has a great significance in the wage difference and should not be considered as a discriminatory act since it may be due to preferences (O'Brien and Williams, 2016). Even though the discriminatory component has lost relevance, it has not been ruled out completely over time since occupational segregation has decreased in recent years due to the evolution of women's education (Blau and Khan, 2016). However, vertical segregation is present in the labor field; where women are less likely to be promoted and obtain management responsibilities. Although women now finish their studies with better qualifications than men, in ten member states of the European Union, women younger than 34 years old have a 10% lower income than men (Commission, 2017).

Another recent explanation for gender differences in individual income is attributed to the psychological characteristics or non-cognitive abilities of men and women (Blau and Khan, 2016). These differences suggest that women have lower non-pecuniary costs of investing in college, that have traditionally excelled in academic performance, and that find school less difficult or unpleasant than men (Goldin et al., 2006). Contrary, men have a much higher incidence of school disciplinary and behavior problems, and are two to three times more likely to be diagnosed with attention deficit hyperactivity disorder (Goldin et al., 2006).

Furthermore, current investigations continue to find evidence of a maternity penalty for women and a marriage bonus for men; where the division of labor in the family is a key driver of the gender difference in income (Blau and Khan, 2016). Economic and sociological studies show that a child birth generates a negative effect on women's labor market participation, due mainly to the social conception according to which men are expected to specialize in labor market activities while women in domestic production, especially after becoming mothers (Fouarge et al., 2010). Family environment thus plays a key role in the formation of women's preferences, but not of men's, in terms of professional career and family structure (Kleven et al., 2018). Because of this, once women have children, they look for jobs that are more family friendly where they can spend more time at home. This in turn leads to more flexible jobs with less workload and/or work from home, which carry lower remunerations.

In addition to this, within the family, the norms of gender identity and especially the idea that a man must and is socially expected to earn more than a woman because of their sex, has a great social and economic impact. Thus, the predominance of this norm can clearly be an explanation for the prevalence of an unequal distribution of income between men and women. This aversion to a situation in which women earn more than men impacts on marriage formation and satisfaction, likelihood of divorce, participation in the labor market, and division of domestic production activities between husbands and wives (Bertrand et al., 2013). However, these norms have evolved according to new generations, where family formation and the effect of children on woman's salary now depends on the generation to which the woman belongs. In regions with a higher concentration of young women, the probability of continuing working more hours after becoming mothers is higher compared to older generations (Fouarge et al., 2010).

Following this analysis, there are two ways in which the gender wage gap can be considered. One is before children, where there would be an anticipated fertility effect, and the other is after children, where it would be an effect of realized fertility (Kleven et al., 2018). In the first case, women, foreseeing that they will be mothers, can select careers that in the future will allow them to devote more to their home and to their children's care. Also, they can decide to invest less in education under the idea that once they have children, this would not be very applicable since they would stop working or they would not see the expected returns on this investment. In the second case, due to the preferences of women, they choose to stop working or to shift to jobs that are more motherhood-friendly: either with fewer hours of work, with different work modalities, or to another company. In this last case, the term "child penalty" arises, which can be understood as the percentage by which women's salaries fall below men's salaries when they have children[2]. In this way, "child penalty" becomes a clear dynamic impact for women in the labor market, type of occupations, promotion to managers, and familiarity with the company (Kleven et al., 2018).

Under the assumption that growing children require less demanding care, working hours for mothers generally increase as children grow (Sommerfeld, 2009). In this way, there should be a continuous growth in the supply of work after a child's birth. In a study for Germany, it was determined that the supply of female labor drops drastically at the time of giving birth, by around 12%, and only increases slowly thereafter (Sommerfeld, 2009).

Additionally, mothers with only one child have a greater labor attachment than mothers with more children. The central explanation for this mothers' behavior is that the economic incentives matter for them only after two years of childbirth. This occurs since, in general, mothers' monetary incentives are not above their family wellness and care nor relevant when their children are little (Sommerfeld, 2009). That is why it is important for this analysis to consider the wage evolution for both men and women taking into account the household structure.

In Denmark, the study carried out by Kleven et al. (2018), shows that once people have children, the gender wage gap that is generated by infants is approximately 20% in the long term during the studied time period (from 1980 to 2013). This divergence in wages is driven by the participation in the labor force, working hours, and salary rates; where the fraction of wage inequality by gender caused by "child penalty" increased from 40% in 1980 to 80% in 2013.

Due to women's preferences regarding family and children, they opt more frequently for part-time jobs, where this kind of jobs not only represent a lower workload, but also

[2] This term can be also interpreted as a fine that includes the costs of the children born after the first one, and how this penalty increases as the number of children is greater.

a lower remuneration. However, women who later want to return to full-time work –having a record of part-time employment– earn significantly less since there is a sequel effect of partial employment on current salary. Furthermore, part-time workers also incur higher income losses in specific-skill jobs, which makes them less likely to return to full-time jobs. Consequently, the effect of a lower salary is emphasized and the existing wage gap widens; this could be attributed to the lack of institutional and social support for part-time work, allowing it to be of lower quality, attracting people with less skills, and offering lower salaries. (Fouarge and Muffels, 2009)

When analyzing women's preferences, women are much more likely than men to participate in activities that are not highly remunerated but have a great social impact. This occurs since they are psychologically more altruistic and seek common welfare instead of being selfish in the desire to seek their own improvement and achievements (Babcock et al., 2017). These attitudes would be decisive in terms of income difference by gender, and because of preferences, they would not allow a wage convergence to be reached.

Finally, and for all the above mentioned, it is possible to notice the importance of the analysis of the gender wage gap. This since, although the causes have been changing with the passage of time, where some have strengthened more and others have weakened, it is an issue that generates concern and that is increasingly reinforcing in terms of the field of study and the methodologies used for its analysis. Despite the reduction in the gender wage gap, it still persists and researchers are constantly looking for an explanation. There have been important changes over time regarding to family structure, number of children, career selection, occupations, among others that highlight a change in women's preferences, which consequently has an effect over the behavior of the wage gap.

2.2 Latin America and Ecuador

Even though the differences in income by gender are present worldwide and have some common characteristics, they vary across countries due to different institutions, language, culture, traditions, geographic location, among others. In Latin America, the increasing women's labor participation has contributed to the reduction in gender inequalities, just as in other regions (Psacharopoulos and Tzannatos, 1992). Also, there has been a shortening of the educational gap with women having more years of education than men, which has likewise contributed to women's greater presence in the labor market (Duryea et al., 2007). Despite these changes in favor of women, during the last years the differences in gender wages remain considerable large when they refer to informal, self-employed, less educated and old female employees (Atal et al., 2009).

Besides, women's labor market participation has been affected by market regulations, the rigidity of the system, and women's preferences. This is partly due to the continuous increase in female unemployment, the inadequate social benefits' coverage for women, the high concentration of women in informal jobs, and the low labor participation of poor and less educated women (Abramo and Valenzuela, 2005).

Among well-paid Latin American occupations, occupational segregation may not be prejudicial for women (Tenjo et al., 2005). Nevertheless, this does not assure a reduction in the wage gender gap because there might be differences within women's and men's occupations and tasks, which would imply earnings divergence (Tenjo et al., 2005). Although segregation contributes to the earnings gap, its effect is not significant relative to the effects of human capital endowments and discrimination. This is the case especially in Uruguay, Ecuador, and Costa Rica (Deutsch et al., 2002).

Importantly, the gender wage gap can differ when analyzing the upper or lower part of the earnings distribution. A greater wage gap at the top of the distribution, where women in upper-income levels receive a lower pay than men, is known as a glass ceiling effect (Arulampalam et al., 2007). Conversely, a wider wage gap at the bottom of the distribution, where women have disadvantages in working conditions compared to men, is known as a sticky floor effect (Booth et al., 2003).

Looking at these effects in Latin American countries, in Peru wages show a glass ceiling effect keeping women away from corporate managing positions despite of their achievements and qualifications (Ñopo, 2008). This inequality is even more marked among employees that have a high educational level and that are married (Ñopo, 2008). In Colombia, apart from the glass ceiling effect on wages, there is a discriminatory employment pattern that keeps women at the bottom of the job scale, understood as the sticky floor effect. These differences in wages between women and men are boosted by the high concentration of individuals in the informal sector and the decision or discrimination of women in the allocation of labor and household activities (Badel and Peña, 2010). In Argentina, it is highly difficult for women to get into well-paid jobs as a result of vertical segregation, being unable to achieve jobs above a certain rank because of their gender (Esquivel, 2007). In Chile, the effect of education and experience for women and men is different depending on the part of the distribution that is being examined. At the bottom part of the distribution, the returns of experience for women are similar to that of men, while the returns of education are higher for women (Montenegro, 2001). On the contrary, at the top of the distribution, the returns of experience are lower for women, while the returns of education are similar for women and men (Montenegro, 2001).

In Ecuador, previous research shows that the gender wage gap has narrowed over time but, even though women have more years of education than men, they continue receiving on average lower earnings partly because they belong to a minority group and are more concentrated in small businesses (Rivera, 2013). When analyzing the earnings distribution, the differences between men's and women's wages are larger in the upper part regardless of the fact that these two groups have the same characteristics (Guerra, 2013). In the same way, the gender gap is highly pronounced at the lower extremes of the earnings distribution, where differences in human capital characteristics explain only a small fraction thereof (Gallardo and Ñopo, 2009). This income gender inequalities are no longer attributable to human capital dissimilarities so it is thought that they are due to differences in the salary structure between women and men (Alvarado and Cortés, 2012). In conclusion, the findings of previous studies on the wage gap for Ecuador show that, despite the greater participation of women in Ecuador's labor market, there are still stigmas of unequal treatment between genders.

Methodology

3.1 Unconditional Quantile Regression

There are significant limitations when we analyze the wage distribution using only measures of central tendency such as the mean, the median, or the mode. The same occurs with measures of dispersion such as the variance, the Theil coefficient, or the Gini coefficient. The central problem is that all these measures provide very little information about what happens across the distribution, which represents an important weakness of the literature that analyzes changes in income inequality, since many explanations of the observed changes have particular implications for specific points of the distribution (Fortin et al., 2011). This occurs with the original method of Oaxaca-Blinder, which provides a wage decomposition only in terms of the distribution's mean[3].

As a result, it is imperative to go further in order to understand the sources of labor income differences between men and women. The most common approach for achieving this is preforming a decomposition for various quantiles of the distribution (Fortin et al., 2011). A method that allows this type of decomposition is the Unconditional Quantile Regression developed by Firpo et al. (2009) known as Recentered Influence Function (RIF) Regressions.

[3]Other distributional methods, going beyond the mean, is the variance decomposition, which cannot explain the contribution of variables in the divergence of women's and men's wages, but gives a more general perspective of the gender wage distributional gap (Molina, 2017).

To describe gender wage differentials across the distribution it is useful to use a kernel smoothing technique in order to estimate men and women's log-wages distributions per year. With this technique, it is possible to estimate the gender wage disparity at each quantile, which serves as an approximation of the raw gender wage gap across the distribution (Chi and Li, 2008).

In order to implement the RIF-Regression method, we need to decompose the distribution in quantiles and study the effect of an explanatory variable across all the population (unconditional quantiles) instead of the effect on a subsample with certain characteristics (conditional quantiles) (Chi and Li, 2008). To achieve this, an influence function (IF) is used to capture the influence of an observation, in this case wage, on a specific quantile (τ). The influence function is thus defined as:

$$IF(W,q_\tau) = \frac{\tau - \Pi\{W \leq q_\tau\}}{f_w(q_\tau)}, \tag{1}$$

where $IF(W,q_\tau)$ is the influence function, τ is the specific quantile, W is the log-wage observation, q_τ is the quantile's τ population of W's unconditional distribution (sample quantile), $\Pi\{\cdot\}$ is an indicator function that is equal to 1 when W is below q_τ and 0 when it is greater, and $f_w(q_\tau)$ is the density function of W at point q_τ.

The first step consists in creating the recentered influence function (RIF) variable, which will be the transformed outcome variable. This will substitute the log-wage dependent variable in the model. The RIF is composed by two components, the quantile's τ population of W's unconditional distribution and the influence function, as follows:

$$RIF(W,q_\tau) = q_\tau + IF(W,q_\tau) \tag{2}$$

Decomposing the RIF into its elements can be expressed as:

$$RIF(W,q_\tau) = q_\tau + \frac{\tau - \Pi\{W \leq q_\tau\}}{f_w(q_\tau)} \tag{3}$$

In this way, the RIF is a simple calculation, considering that is the sum between the sample quantile (q_τ) and the influence function, which in turn is composed by the quantile (τ), a dummy variable ($\Pi\{\cdot\}$), and a density function ($f_w(q_\tau)$) (Salardi, 2012). As a result, the RIF variable can be used to estimate an Ordinary Least Square (OLS) Regression, which is a method that estimates the parameters of a multiple linear regression model by minimizing the sum of squared residuals (Wooldridge, 2013). Thus, the RIF variable, that is available for each observation, can be used to estimate an OLS regression on a vector of covariates for female and male, where the expected value is seen as an unconditional quantile regression.

The OLS regression model would look as follows:

$$RIF(W, q_\tau)_{ig} = \beta_{g0} + \sum_{k=1}^{K} X_{ik}\beta_{gk} + e_{ig}, \quad g = m, f \tag{4}$$

where g corresponds to gender (male and female), β_{gk} is the vector of coefficients, and the outcome variable RIF_{ig} which, for individual i for each group g, is linearly related to the vector covariates (X_{ik}) that are detailed below in the Variables Used subsection and the error term e_{ig}, which is conditionally independent of X_{ik} ($\mathbb{E}(e_{ig}|X_{ik}) = 0$).

As the coefficients of the unconditional quantile regression are computed for each group, then they can be used to calculate the equivalent of the Oaxaca-Blinder (1973) decomposition for each quantile. In order to obtain the gender wage gap at a specific quantile, the process to follow is just as the Oaxaca–Blinder (1973) decomposition at the average.

The difference in gender wages per quantile would be defined as follows:

$$\hat{\Delta}_\tau = \overline{RIF}_{\tau m} - \overline{RIF}_{\tau f}, \tag{5}$$

and can be written as:

$$\hat{\Delta}_\tau = \underbrace{(\hat{\beta}_{m0} - \hat{\beta}_{f0}) + \sum_{k=1}^{K} \overline{X}_{mk}(\hat{\beta}_{mk} - \hat{\beta}_{fk})}_{Unexplained\ Effect} + \underbrace{\sum_{k=1}^{K} (\overline{X}_{mk} - \overline{X}_{fk})\hat{\beta}_{fk}}_{Explained\ Effect}, \tag{6}$$

where $(\hat{\beta}_{m0} - \hat{\beta}_{f0})$ represents the omitted group effect, the unexplained effect can be understood as the wage structure effect and the explained effect as the composition effect.

Regarding the methodological approach to measure the gender wage gap, the most commonly used tool is the Oaxaca-Blinder decomposition method, which decomposes the differences between men's and women's salaries using Mincer regressions for each group (Ayala, 2017). This decomposition technique, developed by Oaxaca (1973) and Blinder (1973), helps explain the gap between the groups, which is broken down into two parts. One of them is the part that is due to the group differences in the magnitudes of the determinants, and the other part is the one of the group differences in the effects of these determinants (O'Donnell et al., 2008). In other words, one part explains the difference between the observable explanatory variables between the two groups (composition effect), while the other part explains the difference between the unobservable characteristics of the groups (structure effect) (Vicens Otero, 2012). Thus, with the Oaxaca-Blinder method, there would be a regression for the wages of men and women and, when calculating the difference between both, the gender wage gap would be obtained, incorporating the two, observed and unobserved factors. This work uses this methodology, where the decomposition approach will be in different parts of the wage distribution, and not in the average as it is conventionally.

For this study the RIF-Regression model method was used, which provides a simple way of carrying out detailed decompositions for any distributional statistic. There are several advantages of the linearity of the RIF-Regressions. One of them is the simplicity of inverting the proportion of interest by dividing by the density, where the inversion can be done locally, so it is not necessary to evaluate the whole impact at all points of the distribution and be concerned about monotonicity. Other is the easiness of interpreting the results got from the simple regression. Therefore, the resulting decomposition is independent of the methodology (Fortin et al., 2011).

Regarding the limitations of this, and other decomposition methods, RIF-Regressions assume the invariance of the conditional distribution, in other words, no general equilibrium effects (Fortin et al., 2011). Also, the decomposition results are sensible to the chosen wage structure, and in case of an omitted variable or measurement error in the regressors, the discriminatory component will capture the omitted effect (Cotton, 1988). Consequently, the wage structure effect could no longer be considered as discrimination, instead it would be treated as an unexplained gap (Oaxaca, 2007).

Sample selection bias[4] is another limitation of this method, where the unobserved factors and individuals' preferences, that determine its participation in the labor market, affect the wage function, and thus the estimated coefficients (Oaxaca, 2007). Additionally, there is a specification error in the decomposition based on the RIF method because, with it, quantiles are linearly estimated, but actually they behave as a non-linear distribution function (Salardi, 2012).

3.2 Data

In order to analyze the gender labor income differential in Ecuador, we used a national survey from 2007 to 2017. This period of analysis was chosen because from 2007 onwards, the methodology and the format of this survey were unchanged. In this way, we avoid inconsistencies in the research and ensured that the data for each year could be matched with those of the other years of the studied period of time.

The data was obtained through the National Institute of Statistics and Censuses (INEC), which carries out a quarterly Ecuadorian employment survey called ENEMDU (National Survey of Employment, Unemployment and Underemployment) (INEC, 2018).

[4]At the average, Heckman (1979) developed a correction for this problem.

This survey collects significant economic and socio-demographic information such as income, sources of income, number of hours worked, years of education, years of work experience, area to which the individual belongs (urban or rural), gender, family composition, number of children per household, occupations, among others. Hence, it allows to estimate labor market indicators and structural factors that affect the distribution's behavior of wages by gender.

For the purposes of this study, the database was constructed using the December ENEMDU survey of every year (from 2007 to 2017). This is because the data for urban and rural households is published only in this month and also because it is representative at the provincial level. In order to make a yearly analysis of the gender wage gap, the information from the December survey (which recovers information for the previous four weeks (INEC, 2018)) was multiplied by twelve.

As stated above, the ENEMDU offers a significant amount of information of the Ecuadorian labor market. However, it has some limitations from an econometric perspective. The main one is the impossibility of incorporating certain variables (particularly job type and occupation sector) into the analysis because of the large number of missing values. If this type of variables are incorporated in the modeling, the model results would have a large bias due to the non-response and a reduction in the sample size.

The sample analyzed includes employed and self-employed individuals between 15 and 65 years of age for the urban sector, who reported positive earnings in the survey. It is relevant to comprise both groups in the research because both of them are part of the principal occupation market, due to the fact that changes in the labor market may have affected the size of employed and self-employed population during the studied period of time.

The independent variables that are included in this study were selected based on the gender wage gap literature and the availability of them in the ENEMDU survey. These variables are detailed in the next subsection and have a descriptive character over the wage. The selection of the variables was made according to their importance in describing individuals in terms of educational, labor, family, and demographic characteristics. In this way, the vector of covariates allows controlling the individual effects of the wage over the gap.

3.3 Variables Used

The focus of this research is to examine gender earnings differentials among employed and self-employed individuals. For this purpose, wage becomes the main variable of study and we analyze its components and behavior. In order to construct the total labor income variable for the principal occupation from the ENEMDUs, it is necessary to consider all income breakdowns for both employees and self-employees.

For self-employed individuals, labor income is set up by adding the amount of money the respondent received in November (the income reported is from the month before the publication of the survey) for the sale of its products and the amount that he/she withdrew from it, and subtracting what the individual spent in the operation of his/her business. On the other hand, for employed individuals, income is set up by adding the liquid money that the individual received in November for salary and other income, all the discounts for contributions such as social security (IESS) and income tax, and species or services like food, housing, and clothing received associated with his/her main activity.

The calculation of the total labor income was done in real terms. To achieve this, the nominal income of each year was transformed into a real one using the Consumer Price Index (CPI) deflator taking 2014 as the base year. The CPI was constructed by dividing the CPI of November of each year by the CPI of November 2014. Then, the real total income was multiplied by twelve to have an annual estimation for the sample individuals. At the end, the natural logarithm was applied to the income, as this is a common practice in the literature and helps the income distribution to be less asymmetric. This log-income variable is the one that was used for the central analysis of this study.

Besides income, other variables must be considered in the analysis of the gender gap. We included educational variables such as years of education, highest level of higher education approved (technical career education, university education, and postgraduate education), and knowledge of a foreign language. The importance of these variables is that they are a proxy of education and more of it implies a higher probability of having better wages and of being able to enter and stay in the labor market.

We also included labor variables as the number of hours worked and the years of work experience. Both of them are related to the type of job and its characteristics, taking into account the different aspects of the individual's labor force activity. This, in turn, is a determinant of the wage given the demands and requirements of the job type. Since it is thought that the years of work experience have a non-linear relationship with wage, the square of this variable was incorporated, where this non-linearity is due to the fact that, as the person has more years of work experience, the effect of experience over wage decreases.

Additionally, marital status variables were considered. Hence, we included married, free union and previously married as explanatory variables. This last one was constructed with separated, divorced and widowed individuals; leaving as the omitted category single individuals. In the literature, marital status constitutes an important factor when explaining gender wage gap, because it affects women and men's earnings in different magnitudes. Usually for women, marriage is an indicator of motherhood, whereas for men it is a signal of responsibility.

Finally, the demographic variables added in the model were race and area. Regarding the first one, a variable called ethnic minority was created. This includes people who identify themselves as indigenous, blacks, afro-descendants, mulattos, montubios, and others. The ethnic majority is the omitted category, which contains mestizo and white individuals. It is important to consider that this variable corresponds to the respondent's self-denomination according to its own identification, instead of an assigned category based on pre-stablished criteria depending on the respondent's physical appearance, culture, and customs. Finally, the area variable was divided into principal provinces of the country. We include Pichincha, Azuay, Guayas, and Manabí; being the first two provinces of the Highlands region and the other two of the Coastal region. In this case, the omitted category is all other provinces. We made this distinction between provinces because salaries vary depending on the place where the individual is working, since the opportunities, types of job, and earnings are different.

Results

4.1 Descriptive Analysis

Table 1 presents the characteristics of urban employed and self-employed Ecuadorian population by gender for 2007, 2012, and 2017. During these years of study, there is not much difference between the average years of education of men and women. However, in 2017, women had marginally more years of education than men.

Over the years, the percentage of men and women who have a technical career increased, as well as that of those who complete a postgraduate degree. The opposite occurs in the university degree, where the percentage of female and male participation decreased over time. The decrease in university participation may be due to an increase in the requirements to enroll in universities, where most public universities now have entrance exams (Molina and Rivadeneyra, 2019). Also, with the aim of increasing the quality of education, by 2016, 15 poorly performing universities were closed, and so the supply of higher education decreased (Molina and Rivadeneyra, 2019). Regarding postgraduate degrees, over time the percentage of both men and women who have such a degree has increased. However, men have more postgraduate education for all years than women, but this difference has declined over the years.

Over time, fewer men and women know a foreign language. This may be that in fact they have stopped studying new languages, which can be related to the decrease of people who obtain a university degree, since it is in the university where the largest

Table 1: Urban population characteristics by gender, 2007–2017

	2007		2012		2017	
	Male	Female	Male	Female	Male	Female
Educational Characteristics						
Years of education	11.18	11.03	11.75	11.69	11.67	11.84
Technical career	0.91%	1.00%	0.94%	1.18%	2.05%	1.91%
University	23.11%	22.68%	24.91%	26.81%	19.21%	23.43%
Postgraduate	1.27%	0.63%	1.23%	1.07%	1.51%	1.46%
Foreign language	4.69%	3.84%	3.10%	3.08%	2.44%	2.49%
Labor Characteristics						
Hours worked per week	47.36	40.15	44.46	39.24	42.72	35.50
Years of work experience	9.26	7.24	9.62	7.98	10.05	7.84
Marital Status						
Married	36.60%	35.97%	33.00%	32.76%	31.73%	31.31%
Free union	17.99%	17.39%	16.79%	16.31%	23.79%	22.84%
Previously married	6.44%	15.64%	7.95%	17.44%	6.60%	15.41%
Single	38.97%	31.00%	42.26%	33.48%	37.88%	30.44%
Demographic Characteristics						
Ethnic minority	7.55%	6.68%	7.54%	7.52%	11.27%	10.68%
Ethnic majority	92.45%	93.32%	92.46%	92.48%	88.73%	89.32%
Pichincha	26.01%	26.12%	25.17%	25.10%	20.81%	20.51%
Azuay	3.89%	4.38%	4.33%	4.36%	4.34%	4.35%
Guayas	34.47%	33.61%	34.18%	34.10%	30.30%	29.94%
Manabí	8.17%	7.92%	8.33%	8.01%	8.23%	8.06%
Other provinces	27.45%	27.97%	28.00%	28.43%	36.32%	37.13%
Number of observations	12,594	13,858	13,018	14,287	20,797	22,778

Note: Results were obtained with expansion factors

number of people learn a foreign language. Besides, individuals may have become aware that knowing a little bit about a foreign language does not imply that they actually know it.

On average, men work more hours than women, where the former work more than the 40 hours that correspond to a full time job. In the analyzed period, there is a decreasing pattern of hours worked due to the fact that overtime payment was formalized, so employers cut back the working hours. Furthermore, as salaries and other benefits have increased, the demand for labor has declined. As with hours worked, men have more years of work experience compared to women.

In terms of marital status, the share of married men and women has diminished over time, contrary to what has happened with free unions. In both of them there is not much difference between men and women. With regard to previously married people, the female percentage is greater; unlike single ones, where the share of men is higher. This difference between previously married men and women is due to the fact that the female percentage of widows is largely superior to male's, since women have a longer life expectancy.

The share of individuals that categorize themselves as belonging to an ethnic minority increased approximately by three percentage points from 2012 to 2017, for both men and women. This increase is explained by the ethnic empowerment and rising sense of belonging that the government promoted during those years. Finally, the distribution by gender in the main provinces is quite similar over time, where the majority of the population is concentrated in Pichincha and Guayas, then in Manabí, and last in Azuay. In 2017, the percentage of women and men in Pichincha decreased due to the fact that in 2015 the Santo Domingo canton separated and became a new province. The same process occurred with Santa Elena, which separated from Guayas.

Tables 2 and 3 show the average gender salary from 2007 to 2017 by individual characteristics. The ratio of women's average labor income to men's increased from 70% in 2007 to 81% in 2012, and decreased to 80% in 2017. These results illustrate a general improvement in the gender wage gap. This behavior of earnings is consistent for all characteristics, where the wage gap increases from 2007 to 2012 and decreases from 2012 to 2017. There are some exceptions in which the income gap tends to close over time. This happens for those who have a university degree, know a foreign language, work more than 40 hours a week, have between 5-10 years of experience, are in free union, belong to an ethnic minority, and are from Pichincha. The only case in which the wage gap increases over time is for individuals who have only finished primary school.

Women have lower average earnings than men in each group. There are some exceptions in which female earnings are superior than men; such as women with primary school in 2007, women with a technical career in 2012, single women for the three years analyzed, and women who lived in Manabí in 2012.

Also, there are groups of women that are in a better position than others, i.e. whose F/M ratio is higher. These women are those who work between 20-40 hours a week, are single, belong to an ethnic majority, and live in Manabí. On the other hand, women who work less than 20 hours per week, were previously married, belong to an ethnic minority, and live in Azuay are at a greater disadvantage.

Although these results are only descriptive, they show that there are differences in the gender wage gap, which may even be greater for certain groups of women. This suggests that income discrimination may occur not only by gender, but by individuals' characteristics.

Table 2: Descriptive urban gender wage gap, 2007–2017

	2007			2012			2017		
	Male	Female	F/M	Male	Female	F/M	Male	Female	F/M
Mean Wage	7,013.92	4,875.99	70%	6,751.82	5,455.07	81%	6,852.39	5,498.98	80%
Mean Wage by Educational Characteristics									
Less than primary school	4,335.46	2,651.79	61%	4,681.59	3,377.50	72%	4,986.48	3,244.76	65%
Primary school	2,419.59	2,717.58	112%	3,235.44	2,720.93	84%	3,515.74	2,609.81	74%
Less than secondary school	4,747.44	3,077.61	65%	5,028.24	3,361.73	67%	5,058.72	3,323.94	66%
Secondary school	6,394.51	4,607.37	72%	6,940.41	4,588.86	66%	6,371.19	4,460.54	70%
Technical career	12,066.62	5,834.38	48%	7,751.56	8,386.42	108%	10,689.72	6,004.01	56%
University	12,534.74	7,745.93	62%	9,731.21	7,610.73	78%	10,019.90	8,248.32	82%
Postgraduate	19,471.24	15,028.37	77%	17,117.75	15,120.90	88%	21,372.24	15,118.46	71%
Foreign language	19,171.19	11,664.30	61%	14,295.80	9,677.11	68%	16,144.97	11,584.34	72%
Mean Wage by Labor Characteristics									
Number of hours worked									
<20 hours	2,479.48	1,426.30	58%	2,624.04	1,474.10	56%	2,690.96	1,424.11	53%
20-40 hours	6,448.27	5,284.49	82%	6,635.98	5,886.70	89%	6,994.41	6,247.70	89%
>40 hours	7,738.93	5,455.33	70%	7,068.74	5,411.86	77%	7,230.72	6,112.02	85%
Years of Experience									
Experience <5 years	5,506.66	3,848.36	70%	5,629.01	4,688.16	83%	5,630.49	4,565.34	81%
Experience 5–10 years	7,362.66	5,238.77	71%	6,801.44	5,452.68	80%	7,161.93	5,911.15	83%
Experience 10–15 years	8,321.94	5,737.24	69%	7,060.32	6,013.55	85%	7,913.95	6,123.68	77%
Experience 15–20 years	7,931.44	6,395.40	81%	8,141.37	6,096.65	75%	7,691.31	6,233.84	81%
Experience 20–25 years	8,992.69	7,080.23	79%	7,685.70	7,187.65	94%	7,872.02	6,656.81	85%
Experience >25 years	8,462.41	7,684.21	91%	9,107.78	7,473.82	82%	7,566.75	7,259.37	96%

Note: "F/M" indicates the ratio of female's average wages over male's. Wages are changed to real values in 2014 USD.

Table 3: Descriptive urban gender wage gap Cont., 2007–2017

	2007			2012			2017		
	Male	Female	F/M	Male	Female	F/M	Male	Female	F/M
Mean Wage by Marital Status									
Married	9,402.24	5,953.16	63%	8,116.09	6,415.88	79%	8,508.56	6,311.17	74%
Free union	5,261.29	3,652.82	69%	6,014.90	4,342.12	72%	6,099.79	4,529.73	74%
Previously married	6,885.41	4,340.17	63%	7,687.73	4,734.09	62%	6,401.40	5,119.80	80%
Single	4,424.44	4,605.25	104%	5,085.71	5,560.79	109%	5,219.75	5,569.17	107%
Mean Wage by Demographic Characteristics									
Ethnic minority	5,339.37	3,605.70	68%	5,386.16	3,965.55	74%	6,130.34	4,894.05	80%
Ethnic majority	7,158.39	4,968.01	69%	6,869.37	5,570.13	81%	6,948.00	5,565.92	80%
Pichincha	9,070.22	5,792.15	64%	8,228.71	6,272.68	76%	8,035.97	6,746.57	84%
Azuay	8,289.94	5,161.63	62%	7,668.35	5,825.56	76%	8,232.42	6,135.48	75%
Guayas	6,579.37	4,548.81	69%	6,193.91	4,715.09	76%	6,308.00	4,670.09	74%
Manabí	4,883.31	3,913.57	80%	5,022.08	5,286.56	105%	5,477.77	4,864.52	89%
Other provinces	6,157.06	4,486.10	73%	6,620.38	5,603.21	85%	6,857.07	5,468.60	80%

Note: “F/M” indicates the ratio of female’s average wages over male’s. Wages are changed to real values in 2014 USD.

4.2 Gender wage differential across the distribution

Figure 1 panels (a), (b), and (c) present the kernel density estimates of the wage logarithm for 2007, 2012, and 2017, respectively. These functions show the gender labor income differences across the income distribution for men and women at different quantiles. A common characteristic in the three years is that the male distribution is slightly displaced to the right with respect to the females' one. However, over the years, the peak of the men's distribution has become wider, while the peak of the female log-wage distribution presents a change that suggests a bimodal distribution.

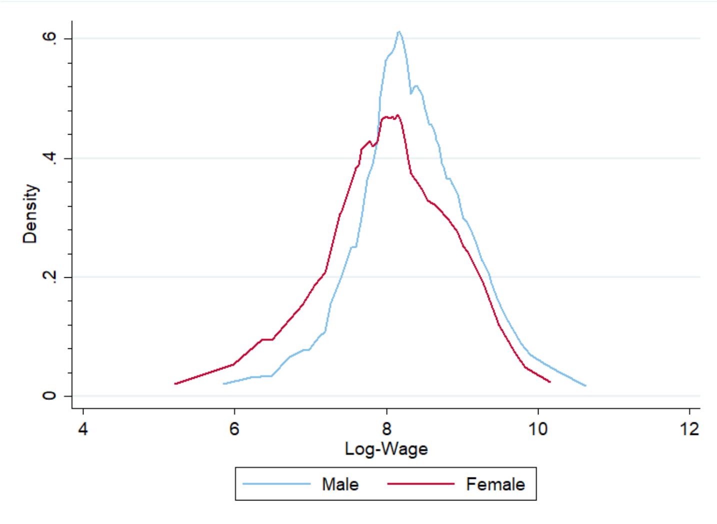
This change in the female wage distribution represents the formation of two local wage maximums, which indicates that two different groups are forming. In this way, a group of women with a higher salary level has come into existence, who are even reaching and possibly overcoming the male salary distribution. This may be an indication that, at high income levels, the differences between male and female earnings are narrowing.

4.3 RIF unconditional quantile regressions for men and women

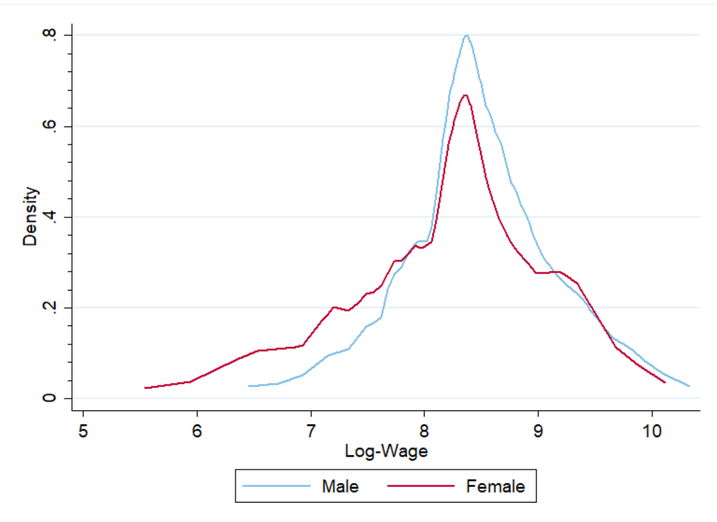
Tables 4, 5, and 6 show the RIF unconditional quantile regression estimates by gender at the 10th, 50th, and 90th income quantiles for 2007, 2012, and 2017, respectively. These tables report the coefficient estimates of Equation (4), which can be understood as the marginal effects of the explanatory variables, expressed as semi-elasticities.

The results show that the return of years of education on income is always positive and significant for all years and quantiles. At the 10th quantile the difference between male and female returns diminishes over time, which indicates that the gap is narrowing. At the 50th and 90th quantiles the estimates decrease over time, which suggests that the return of an additional year of education is falling. The highest level of higher education approved has no effect at the 10th quantile. Just the opposite, at the 50th quantile, these degrees are statistically significant for men and women, especially in 2012 and 2017.

(a) 2007



(b) 2012



(c) 2017

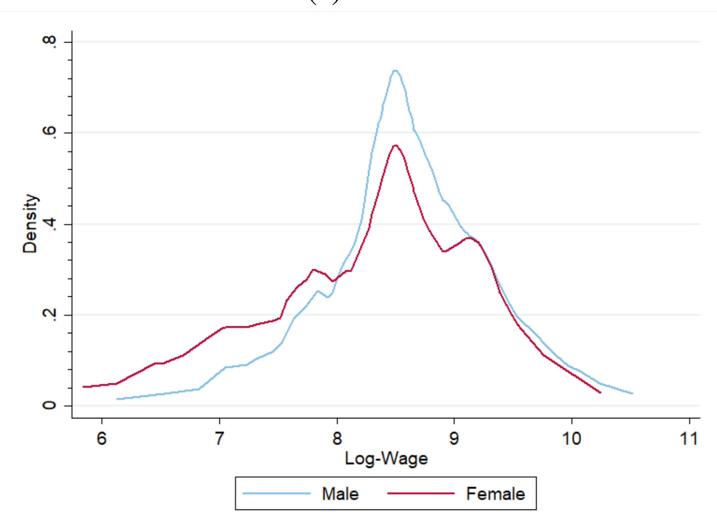


Figure 1: Kernel density estimates of the log-wage distribution by gender

At the upper part of the distribution (90th quantile), the returns vary depending on the type of higher education reached. A technical career has virtually no impact on income, and is even negative for women; university education is only meaningful for men; and postgraduate education has its largest effect for both genders. For those who know a foreign language, in the lower part of the distribution (10th quantile) this knowledge is irrelevant, contrary to what happens at the upper part (90th quantile), where it shows a higher return for men than for women.

The number of hours worked has a positive effect on the salary, with the exception of the 90th quantile, where it has a negative one. This may be due to the loss of variability of the hours worked in this part of the distribution.

Regarding the return of years of work experience, there is not much variation between genders. The only exception is for the 50th and 90th quantiles in 2007, where its effect is larger for women than for men. The negative estimate on the squared years of work experience shows, as expected, that work experience has diminishing marginal returns.

For the 10th quantile, married, free union, and previously married men have positive returns whereas women have mostly negative ones. These findings change for women in the 50th and 90th quantiles, where married women receive positive earnings' returns. Besides, at the 90th quantile, men in free union and previously married women and men have a disadvantage in labor income returns compared to other marital status groups.

In general, men and women that identify themselves as belonging to an ethnic minority are penalized with a negative return on their wages, with the exclusion of women in the 50th quantile of 2007. In addition, those individuals that live in the four principal provinces often receive a higher income return that those who do not. This changes over time at the 90th quantile, where for 2017, male and female earnings' returns are lower compared to those who do not live in these four provinces.

In this analysis, there are not only differences between the female and male salary returns, but also between the wage quantile to which the individual belongs. This is because depending on the part of the analyzed distribution, individuals have different personal characteristics and labor market features.

Table 4: Unconditional quantile regression by gender, 2007

	10th		**50th**		**90th**	
	Male	Female	Male	Female	Male	Female
Years of education	0.040***	0.067***	0.059***	0.057***	0.077***	0.036***
	(0.005)	(0.010)	(0.003)	(0.004)	(0.005)	(0.007)
Technical career	0.190**	-0.009	0.107	0.144*	0.002	-0.219
	(0.077)	(0.164)	(0.081)	(0.087)	(0.217)	(0.196)
University	0.034	0.025	0.086***	0.193***	0.136*	0.021
	(0.046)	(0.076)	(0.029)	(0.036)	(0.070)	(0.064)
Postgraduate	-0.000	-0.156	0.111**	0.254***	1.091***	1.205***
	(0.053)	(0.096)	(0.052)	(0.061)	(0.236)	(0.248)
Foreing language	-0.001	0.070	0.135***	0.093*	1.075***	0.371**
	(0.047)	(0.052)	(0.043)	(0.053)	(0.156)	(0.145)
Hours worked/100	0.033***	0.064***	0.012***	0.017***	-0.004	-0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
Years of work experience	0.021***	0.025***	0.027***	0.042***	0.029***	0.046***
	(0.005)	(0.007)	(0.003)	(0.004)	(0.006)	(0.007)
Years of work experience^2/100	-0.065***	-0.059***	-0.057***	-0.079***	-0.051***	-0.049**
	(0.015)	(0.021)	(0.007)	(0.011)	(0.016)	(0.022)
Married	0.231***	-0.081	0.295***	0.100***	0.058	0.303***
	(0.040)	(0.062)	(0.020)	(0.027)	(0.051)	(0.067)
Free union	0.179***	-0.230***	0.085***	-0.085**	-0.306***	-0.041
	(0.048)	(0.084)	(0.028)	(0.036)	(0.053)	(0.072)
Previously married	0.076	-0.139**	0.148***	-0.098***	-0.201***	-0.294***
	(0.073)	(0.058)	(0.036)	(0.032)	(0.073)	(0.068)
Ethnic minority	-0.163***	-0.074	-0.036	-0.075*	-0.028	-0.072
	(0.055)	(0.099)	(0.029)	(0.043)	(0.061)	(0.084)
Pichincha	0.210***	0.204***	0.205***	0.233***	0.201***	0.003
	(0.038)	(0.061)	(0.028)	(0.040)	(0.075)	(0.070)
Azuay	0.130**	0.302***	0.186***	0.210***	-0.007	-0.100
	(0.051)	(0.067)	(0.038)	(0.039)	(0.078)	(0.098)
Guayas	0.004	-0.037	-0.006	-0.011	0.020	-0.137**
	(0.039)	(0.072)	(0.028)	(0.032)	(0.055)	(0.065)
Manabi	-0.115*	-0.010	-0.060*	0.005	-0.058	-0.175*
	(0.069)	(0.107)	(0.033)	(0.052)	(0.068)	(0.098)
Constant	5.981***	4.680***	7.096***	6.847***	8.764***	9.140***
	(0.078)	(0.134)	(0.033)	(0.054)	(0.081)	(0.098)
Observations	9,858	7,265	9,858	7,265	9,858	7,265
R-squared	0.090	0.129	0.200	0.212	0.094	0.061

Bootstrapped standard errors in parentheses (100 replications)

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Unconditional quantile regression by gender, 2012

	10th		50th		90th	
	Male	Female	Male	Female	Male	Female
Years of education	0.050***	0.080***	0.042***	0.041***	0.072***	0.043***
	(0.006)	(0.011)	(0.002)	(0.003)	(0.005)	(0.006)
Technical career	0.177**	0.036	0.103**	0.203***	-0.114	0.153
	(0.087)	(0.162)	(0.052)	(0.061)	(0.171)	(0.171)
University	0.036	-0.026	0.096***	0.186***	0.401***	0.072
	(0.049)	(0.087)	(0.022)	(0.028)	(0.066)	(0.057)
Postgraduate	0.087	-0.053	0.186***	0.288***	1.778***	1.216***
	(0.061)	(0.107)	(0.031)	(0.046)	(0.199)	(0.168)
Foreing language	-0.193*	0.144*	0.051	0.069	0.562***	0.163
	(0.106)	(0.082)	(0.034)	(0.050)	(0.161)	(0.171)
Hours worked/100	0.048***	0.091***	0.011***	0.021***	-0.008**	0.003
	(0.003)	(0.005)	(0.001)	(0.001)	(0.003)	(0.002)
Years of work experience	0.013**	0.018**	0.011***	0.018***	0.028***	0.027***
	(0.005)	(0.009)	(0.002)	(0.003)	(0.005)	(0.006)
Years of work experience$^2/100$	-0.043***	-0.063**	-0.022***	-0.028***	-0.034**	-0.001
	(0.016)	(0.029)	(0.004)	(0.007)	(0.014)	(0.016)
Married	0.196***	0.198***	0.228***	0.068***	0.095**	0.303***
	(0.048)	(0.060)	(0.017)	(0.019)	(0.046)	(0.050)
Free union	0.174***	-0.071	0.104***	0.013	-0.144***	0.069
	(0.057)	(0.091)	(0.019)	(0.029)	(0.049)	(0.069)
Previously married	0.145**	0.032	0.074***	-0.090***	-0.195***	-0.267***
	(0.069)	(0.080)	(0.024)	(0.021)	(0.065)	(0.045)
Ethnic minority	-0.178**	0.248***	-0.065***	-0.027	0.067	0.161**
	(0.074)	(0.094)	(0.019)	(0.035)	(0.058)	(0.073)
Pichincha	0.195***	0.272***	0.103***	0.156***	0.094	-0.002
	(0.042)	(0.059)	(0.019)	(0.024)	(0.058)	(0.062)
Azuay	0.254***	0.234**	0.055**	-0.045	-0.087	-0.220***
	(0.047)	(0.095)	(0.027)	(0.034)	(0.091)	(0.077)
Guayas	-0.000	-0.157*	-0.020	0.064***	-0.183***	-0.155***
	(0.038)	(0.085)	(0.015)	(0.022)	(0.047)	(0.053)
Manabi	-0.139*	0.505***	-0.139***	0.078**	-0.353***	-0.343***
	(0.077)	(0.082)	(0.026)	(0.034)	(0.055)	(0.076)
Constant	5.820***	4.118***	7.540***	7.282***	8.823***	8.970***
	(0.112)	(0.169)	(0.027)	(0.041)	(0.094)	(0.085)
Observations	9,656	7,078	9,656	7,078	9,656	7,078
R-squared	0.073	0.126	0.185	0.214	0.113	0.089

Bootstrapped standard errors in parentheses (100 replications)
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Unconditional quantile regression by gender, 2017

	10th		50th		90th	
	Male	Female	Male	Female	Male	Female
Years of education	0.045***	0.052***	0.035***	0.044***	0.057***	0.026***
	(0.006)	(0.007)	(0.002)	(0.003)	(0.004)	(0.005)
Technical career	0.120	0.086	0.161***	0.127**	0.182	-0.320***
	(0.084)	(0.107)	(0.033)	(0.053)	(0.114)	(0.088)
University	0.134**	0.129**	0.150***	0.256***	0.316***	0.071
	(0.054)	(0.056)	(0.017)	(0.028)	(0.049)	(0.050)
Postgraduate	0.233***	0.121	0.273***	0.406***	1.947***	1.074***
	(0.061)	(0.075)	(0.025)	(0.039)	(0.147)	(0.114)
Foreing language	-0.062	0.009	0.121***	0.066*	0.772***	0.398***
	(0.078)	(0.067)	(0.025)	(0.036)	(0.121)	(0.100)
Hours worked/100	0.071***	0.092***	0.016***	0.027***	-0.014***	-0.003
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Years of work experience	0.034***	0.019***	0.017***	0.023***	0.020***	0.018***
	(0.005)	(0.006)	(0.001)	(0.002)	(0.004)	(0.005)
Years of work experience^2/100	-0.105***	-0.060***	-0.040***	-0.044***	-0.033***	-0.007
	(0.017)	(0.019)	(0.004)	(0.007)	(0.010)	(0.014)
Married	0.288***	-0.162***	0.172***	0.067***	0.032	0.243***
	(0.044)	(0.052)	(0.015)	(0.018)	(0.042)	(0.044)
Free union	0.233***	-0.308***	0.056***	-0.004	-0.230***	0.011
	(0.049)	(0.064)	(0.016)	(0.023)	(0.040)	(0.053)
Previously married	0.119*	-0.186***	0.046**	-0.124***	-0.263***	-0.305***
	(0.067)	(0.062)	(0.020)	(0.020)	(0.066)	(0.044)
Ethnic minority	-0.128**	0.221***	-0.046***	0.057**	-0.023	0.142***
	(0.055)	(0.068)	(0.017)	(0.024)	(0.042)	(0.055)
Pichincha	0.331***	0.215***	0.076***	0.089***	-0.141***	-0.100*
	(0.046)	(0.053)	(0.021)	(0.023)	(0.052)	(0.055)
Azuay	0.200***	0.183**	0.082***	0.066**	-0.147***	-0.069
	(0.064)	(0.071)	(0.022)	(0.030)	(0.056)	(0.062)
Guayas	0.035	-0.118	-0.036**	-0.004	-0.195***	-0.153***
	(0.049)	(0.073)	(0.017)	(0.023)	(0.040)	(0.049)
Manabi	-0.061	-0.095	-0.118***	-0.022	-0.254***	-0.177***
	(0.071)	(0.098)	(0.020)	(0.034)	(0.051)	(0.061)
Constant	5.121***	4.629***	7.646***	7.277***	9.338***	9.437***
	(0.098)	(0.120)	(0.025)	(0.034)	(0.070)	(0.070)
Observations	15,679	12,214	15,679	12,214	15,679	12,214
R-squared	0.101	0.134	0.164	0.227	0.097	0.053

Bootstrapped standard errors in parentheses (100 replications)
*** p<0.01, ** p<0.05, * p<0.1

4.4 Decomposition with the RIF unconditional quantile regressions

Tables 7, 8, and 9 show the decomposition of the wage structure effect for 2007, 2012, and 2017, respectively. The results use the RIF-Regression estimates and the contribution of each explanatory variable on the wage decomposition. The reported coefficients show the differences in income due to differences in returns between men and women for different quantiles, so they quantify the change in women's labor income when applying the men's coefficients to the women's characteristics. In this way, a positive coefficient indicates that for that specific characteristic, men enjoy a higher return than women, and the opposite when it is negative. For example, in 2007, at the 10th quantile, if married women would have the same return as married men, they would earn 12.3% more. For the same year, however, at the 90th quantile, having the same return as married men, would imply a 9.7% lower income for married women.

The results show that, when statistically significant, the difference in labor income return for years of education and highest level of higher education approved (technical career, university, and postgraduate), favors women at the 10th and 50th quantiles but favors men at the 90th quantile. These findings are consistent for all years. Hence, despite the fact that women's years of education have been practically equalized to men's, as shown in Table 1, men continue enjoying larger returns at the top quantiles of the labor income distribution.

Although the model does not control for occupations due to the limitations of the survey, it is presumed that part of this effect can be explained by the types of occupations that are in each quantile and the female preference for some of them. Women are more related to altruistic and domestic jobs that are associated with lower remuneration (Babcock et al., 2017); hence their advantage at the 10th and 50th quantiles. On the contrary, the occupations preferred by men are more technical and mostly better remunerated, which is a possible reason for the higher returns for men at the 90th quantile. These results are in accord with those obtained in the study of Guerra (2013), where men have an income advantage for years of education at the upper part of the distribution.

Analyzing the earnings gap for years of education, at the upper part of the distribution (90th quantile), unlike at the low part (10th quantile), it decreases from 2007 to 2012 and increases from 2012 to 2017. The behavior of this gap at the 90th quantile can be a result of inequality falling between 2007 and 2011, but stabilizing thereafter (Gachet et al., 2016). This is because, as inequality decreases, the wage gender difference also does so. For example, in 2007 at the 90th quantile, women with men's return for years of education would earn 47.2% more, in 2012, 34.4%, and in 2017, 39.3%. Conversely, in 2007 at the 10th quantile, women with men's return for years of education would earn 31.7% less, in 2012, 36.2%, and in 2017, 9.5% (not statistically significant).

A similar result as highest level of higher education approved occurs with those who know a foreign language. For the three years, these variables are mostly significant only at the top of the distribution and exhibit a greater labor income return for men than for women. This is consistent with the outcomes in Tables 4, 5, and 6. The lack of significance of these variables in the low quantiles is due to the fact that they have no impact on the type of jobs and occupations that take place in that part of the distribution. This changes at the highest quantile because the degrees and knowledge of foreign languages do make a difference in terms of workers' skills, abilities, and income. Thus, human capital endowments are more important in this part of the distribution.

In the three studied quantiles, for hours worked, female labor income returns are greater than male's, which may be a result of women working fewer hours (as shown on average in Table 1). This may be the consequence of women's selection when deciding to work additional hours due to the household tasks' distribution, making women's time more valued in female-dominated occupations because of their specific capabilities.

Likewise, at the 50th quantile, years of work experience provides women with a higher income return. This, in turn, is a subject of a shorter and interrupted female work life (Blau and Khan, 2016), where the distribution of time in household and labor activities may be ruled according to women's time allocation preferences and social norm expectations on them. Given their lower work experience, there are fewer women than men who meet the needs of the labor market, that is why female experience is better paid, which implies a higher opportunity cost for them to stop working.

Regarding marital status, if married, free union, and previously married women had men's returns, at the 10th and 50th quantiles (also at the 90th quantile for previously married), they would earn more. In contrast, at the 90th quantile, they would earn less. However, the return for those individuals that are in free union is less than for those who are married, mainly because the signalling of being married is much stronger than being in free union. The fact that the return of married or free union men is higher than for women in the lower and middle parts of distribution may be due to the fact that, in those parts, there are people with lower levels of education. Thus, the perception of family formation is much more traditional, where men are the ones who work and women stay in home taking care of children and household chores.

Just the opposite occurs at the upper part of the distribution, where there are individuals, of both genders, with a higher education level and income. Therefore, the opportunity cost of not working for women is greater, particularly when they are more productive than their male partners. Thanks to these characteristics, some women and men can afford the outsourcing of children's care and household chores. Similarly, these households have adapted to the changes in the traditional view of family roles and composition, which allows women to have more time to spend working and to let the household activities be shared with their partner or with third parties.

Finally, women who are part of an ethnic minority, when the results are significant, have a higher income return than men at the 10th, 50th, and 90th quantiles of the wage distribution. These results may be related to a series of policies that were implemented by the government in the last decade, which tried to promote the inclusion of ethnic minorities, especially women, on the labor market. Also, ethnic diversity was encouraged, along with empowerment and pride of belonging to a historically marginalized group. Being this a group of scarce individuals that have had suffered from discrimination, affirmative action has been a policy measure to reduce inequalities in employment and pay. This policy was included in the Constitution of Montecristi approved in 2008, based on the principles of *Buen Vivir* (Living Well) and *Sumak Kawsay*[5] (Masala and Monni, 2017). In this way, the past government worked in ethnic minorities' labor opportunities equality, solidarity, and restitution of dignity (Masala and Monni, 2017)

In the analysis, there are some determinants that contribute more to the structure labor income effect than others, such as the returns in years of education, number of hours worked, years of work experience, and marital status variables (married, free union, and previously married). Among these variables, some of their returns favors one of the genders at the lower part of the distribution and the other at the upper part as described before.

In aggregate, at the 10th and 50th quantiles the variables' greater returns favor women. Contrary, at 90th quantile the income advantage tends to be for men (except for 2017). Despite this, the total structure or unexplained labor income effect at 10th quantile shows that if women had the same returns as men, they would earn 51.1%, 47.5%, and 38.0% more in 2007, 2012, and 2017, respectively. At the 50th quantile, women would also earn 17.6%, 5.3%, and 2.0% more in 2007, 2012, and 2017, respectively. Conversely, at 90th quantile the total structure wage effect indicates that if women would have the same returns as men, they would earn 8.5% less in 2007, but 4.5% more in 2017. In that way, the total wage structure effect is dominated by the constant (unobservable characteristics and omitted group effect), whose return favors men at the 10th and 50th quantiles, while favoring women at the 90th quantile.

Once again, these results show that there are not only income differences between men and women, but also between individuals of the same gender across the distribution. Hence the importance of this type of study, where the analysis is done throughout the distribution and not only at a specific point (e.g. the mean).

[5] Andean ancestral philosophy of a full and satisfying life in harmony with nature (Gudynas, 2011).

Table 7: Decomposition of the gender wage structure, 2007

	10th	**50th**	**90th**
Years of education	-0.317***	0.022	0.472***
	(0.100)	(0.053)	(0.114)
Technical career	0.003	-0.001	0.004
	(0.004)	(0.002)	(0.004)
University	0.003	-0.032**	0.035
	(0.027)	(0.015)	(0.032)
Postgraduate	0.002	-0.002	-0.001
	(0.003)	(0.002)	(0.004)
Foreing language	-0.002	0.001	0.023***
	(0.005)	(0.003)	(0.006)
Hours worked	-0.636***	-0.116***	-0.047
	(0.059)	(0.031)	(0.067)
Years of work experience	-0.034	-0.121***	-0.138*
	(0.064)	(0.034)	(0.073)
Years of work experience^2	-0.010	0.034*	-0.004
	(0.036)	(0.019)	(0.040)
Married	0.123***	0.077***	-0.097***
	(0.027)	(0.014)	(0.031)
Free union	0.055***	0.023***	-0.036***
	(0.012)	(0.006)	(0.013)
Previously married	0.041**	0.047***	0.018
	(0.018)	(0.010)	(0.021)
Ethnic minority	-0.007	0.003	0.003
	(0.007)	(0.004)	(0.008)
Pichincha	0.001	-0.003	0.024**
	(0.010)	(0.005)	(0.012)
Azuay	-0.012	-0.002	0.007
	(0.008)	(0.004)	(0.009)
Guayas	0.006	0.001	0.022*
	(0.011)	(0.006)	(0.012)
Manabí	-0.005	-0.003	0.006
	(0.006)	(0.003)	(0.007)
Constant	1.301***	0.249***	-0.376***
	(0.118)	(0.062)	(0.135)
Total Structure Effect	0.511***	0.176***	-0.085***
	(0.028)	(0.015)	(0.033)
Observations	17,123	17,123	17,123

Bootstrapped standard errors in parentheses (100 replications)
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Decomposition of the gender wage structure, 2012

	10th	**50th**	**90th**
Years of education	-0.362***	0.015	0.344***
	(0.123)	(0.042)	(0.107)
Technical career	0.002	-0.002	-0.004
	(0.004)	(0.001)	(0.003)
University	0.021	-0.030***	0.110***
	(0.034)	(0.011)	(0.030)
Postgraduate	0.003	-0.002	0.012**
	(0.005)	(0.002)	(0.005)
Foreing language	-0.008	-0.000	0.009**
	(0.005)	(0.002)	(0.004)
Hours worked	-0.881***	-0.209***	-0.211***
	(0.090)	(0.031)	(0.079)
Years of work experience	-0.044	-0.062**	0.007
	(0.077)	(0.026)	(0.066)
Years of work experience^2	0.035	0.011	-0.057
	(0.043)	(0.015)	(0.037)
Married	-0.001	0.058***	-0.076***
	(0.028)	(0.009)	(0.024)
Free union	0.032**	0.012***	-0.028**
	(0.013)	(0.004)	(0.011)
Previously married	0.023	0.034***	0.015
	(0.020)	(0.007)	(0.019)
Ethnic minority	-0.033***	-0.003	-0.007
	(0.009)	(0.003)	(0.008)
Pichincha	-0.010	-0.007*	0.013
	(0.012)	(0.004)	(0.011)
Azuay	0.001	0.006**	0.008
	(0.008)	(0.003)	(0.007)
Guayas	0.027*	-0.015***	-0.005
	(0.014)	(0.005)	(0.012)
Manabí	-0.033***	-0.011***	-0.000
	(0.007)	(0.002)	(0.006)
Constant	1.702***	0.258***	-0.146
	(0.150)	(0.051)	(0.132)
Total Structure Effect	0.475***	0.053***	-0.018
	(0.032)	(0.011)	(0.029)
Observations	16,734	16,734	16,734

Bootstrapped standard errors in parentheses (100 replications)
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Decomposition of the gender wage structure, 2017

	10th	**50th**	**90th**
Years of education	-0.095	-0.118***	0.393***
	(0.107)	(0.039)	(0.089)
Technical career	0.001	0.001	0.013***
	(0.004)	(0.002)	(0.004)
University	0.001	-0.033***	0.076***
	(0.026)	(0.010)	(0.022)
Postgraduate	0.003	-0.004**	0.026***
	(0.005)	(0.002)	(0.005)
Foreing language	-0.002	0.002	0.011***
	(0.005)	(0.002)	(0.004)
Hours worked	-0.388***	-0.212***	-0.200***
	(0.061)	(0.022)	(0.051)
Years of work experience	0.128**	-0.054**	0.013
	(0.064)	(0.023)	(0.053)
Years of work experience^2	-0.072**	0.006	-0.043
	(0.035)	(0.013)	(0.029)
Married	0.163***	0.038***	-0.076***
	(0.024)	(0.009)	(0.020)
Free union	0.099***	0.011**	-0.044***
	(0.014)	(0.005)	(0.011)
Previously married	0.059***	0.033***	0.008
	(0.017)	(0.006)	(0.015)
Ethnic minority	-0.037***	-0.011***	-0.018**
	(0.009)	(0.003)	(0.007)
Pichincha	0.009	-0.001	-0.003
	(0.008)	(0.003)	(0.006)
Azuay	0.001	0.001	-0.005
	(0.006)	(0.002)	(0.005)
Guayas	0.016*	-0.003	-0.004
	(0.008)	(0.003)	(0.007)
Manabí	0.002	-0.005**	-0.004
	(0.006)	(0.002)	(0.005)
Constant	0.492***	0.369***	-0.098
	(0.121)	(0.044)	(0.102)
Total Structure Effect	0.380***	0.020**	0.045*
	(0.027)	(0.010)	(0.023)
Observations	27,893	27,893	27,893

Bootstrapped standard errors in parentheses (100 replications)
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

This work analyses the evolution of the gender wage gap across the log-wage distribution in urban Ecuador from 2007 to 2017. For this purpose, we used the Unconditional Quantile Regression methodology developed by Firpo et al. (2009), which constitutes another contribution to the Ecuadorian gender gap literature that provides a different dimension from which income differentials are usually studied.

Using the RIF estimates, we found that there are labor income differentials that vary according to the gender and to the part of the the income distribution we are analyzing. In the middle part (50th quantile) most results are aligned with the literature. The biggest differences are between the lower and upper part of the distribution, 10th and 90th quantile, respectively. There are some variables that contribute more to the structure income effect than others, where the returns in years of education, number of hours worked, years of work experience, and marital status variables make the largest contribution to the total labor income structure effect. Among these variables, some of their returns favors one of the genders at the lower part of the distribution and favors the other at the upper part.

At the 10th quantile, throughout the studied period of time, years of education tends to present a favorable return for women, although the university degree return is not statistically significant. At the 50th quantile, having a university degree, number of hours worked, and years of work experience favor women, while being married, in free union or previously married favor men. At the 90th quantile, years of education exhibit a favorable return for men as well as a university degree, while being married or in free union show a favorable return for women.

In aggregate, at the 10th and 50th quantiles the variables' higher returns favor women, while at the 90th quantile they favor men (except hours worked). Nevertheless, at the 10th and 50th quantiles men have a total labor income structure effect advantage, while at the 90th quantile women have an advantage (except for 2017). This result for the

90th quantile indicates that there is no glass ceiling effect. However, this finding is not inconsistent with the fact that there might be men with higher income than women at a level greater than the 90th quantile. This occurs since the wage distribution used in this paper is based on a nationally representative survey that, as every other such survey, does not capture highest-earning individuals in the country.

In this manner, the effect of the constant is the one that dominates in favor of men at the 10th and 50th quantiles and in favor of women at the 90th. Hence, we can conclude that, in this work, the omitted group effect and the unobservable characteristics are those that determine the female or male wage advantage. A possible explanation is that the constant includes important features such as occupations and Ecuadorian labor market conditions that produce this significant income divergence effect.

In this work we found that the total labor income structure effect at the 10th and 50th quantiles is decreasing over time, which means that the difference between men's and women's returns is narrowing. This finding is consistent with the gender income gap international trends. Throughout the analyzed period, at the 10th and 50th quantiles, the structural income gap favors men, while at the 90th quantile there is a change over time where it favors women in 2007 but favors men in 2017 (marginally significant). Additionally, we found elements in opposition to the literature, such as a greater return for married women at the 90th quantile.

Finally, throughout the analyzed period, the determinants of the structure wage effect gaps at different points of the distribution vary. This shows the relevance of studying the gender wage gap at different points of the distribution. Even though this work provides important insights into the female and male urban wage divergences in Ecuador across the distribution and their evolution over time, there is more to be done. In order to arrive to much more accurate and attached to reality conclusions, a future step will include a sample selection bias correction.

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