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GENDER LABOR INCOME GAPS IN COSTA RICA

BRECHAS DE GÉNERO EN EL INGRESO LABORAL EN COSTA RICA

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ABSTRACT

Women have lower average labor income than men around the world, despite having more years of education. In developing countries, this situation is often even worse. Women not only face wage gaps compared to men who have the same productivity and the same job, but they also face disadvantages regarding the type and conditions of employment, job stability, unemployment rates, and their caregiving burden. This research analyzes the differences in labor incomes by gender and informality in Costa Rica. To do so, we use the Encuesta Continua de Empleo (ECE) from the first quarter of 2023 to estimate various statistical and econometric methodologies. The analysis is conducted by estimating three econometric methodologies: Mincer's equations, the Oaxaca-Blinder decomposition, and Mincer's equation considering the semi-parametric quantile regression estimation.

KEYWORDS: INCOME GAPS, GENDER, LABOR MARKET, COSTA RICA, LABOR DISCRIMINATION.
JEL CLASSIFICATION: C31, J31, J71.

RESUMEN

Las mujeres tienen ingresos laborales promedio inferiores a los hombres en todo el mundo, a pesar de que tienden a tener más años de educación. En los países en desarrollo, esta situación suele ser aún peor. Las mujeres no solo enfrentan brechas salariales en comparación con hombres que tienen la misma productividad y el mismo trabajo, sino que también enfrentan desventajas en cuanto al tipo y condiciones de empleo, la estabilidad laboral, las tasas de desempleo y su carga como cuidadoras. Esta investigación analiza las diferencias en los ingresos laborales por género e informalidad en Costa Rica. Para ello, se utiliza la Encuesta Continua de Empleo del primer trimestre de 2023 para

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estimar diversas metodologías estadísticas y econométricas. El análisis se realiza estimando tres metodologías econométricas: las ecuaciones de Mincer, la descomposición de Oaxaca-Blinder y la ecuación de Mincer considerando la estimación de regresión de cuantiles semi-paramétrica.

PALABRAS CLAVE: BRECHA DE GÉNERO, GÉNERO, MERCADO LABORAL, COSTA RICA, DISCRIMINACIÓN LABORAL.
CLASIFICACIÓN JEL: C31, J31, J71.

I. INTRODUCTION

All over the world, women have increased their participation in the labor force. It is a trend related to the changes in demographic composition, public policies, and cultural and social transformations. Nevertheless, there remains a gap in the labor income between women and men. Although women have, on average, higher years of education, they have systematically lower average earnings.

Gender discrimination is a crucial issue that governments and institutions have tried to address. Many studies and institutional statements have underlined the urgency and importance of eliminating the gender gap, particularly in the labor market (Comisión Económica para América Latina y el Caribe, 2019; Organisation for Economic Co-operation and Development [OECD], 2019; International Labour Organization [ILO], 2018). It is even one of the Sustainable Development Goals: Gender equality and women's empowerment, and its first target is to End all forms of discrimination against all women and girls everywhere (United Nations, 2015). Also, the 100th agreement of the ILO on income equity states the necessity to guarantee "equal remuneration for men and women workers for work of equal value". (ILO, 1951).

In the last decades, Costa Rica has achieved some relevant landmarks in terms of gender equality: according to the OECD gender gap indicator (2023) Costa Rica has the second smallest gender gap indicator for all the organization, second only to Belgium. The indicator defined "as the difference between median earnings of men and women relative to median earnings of men" has a value of 1.4% for Costa Rica vs. an average of 11.9% for the OECD. In 2021 Costa Rica was the fifth country of the OECD with the highest share of women in parliament, and second regarding the share of women in Ministerial positions (OECD, 2021). Nevertheless, despite the progress archived, the country still faces serious challenges in terms of gender equality, as revealed by the relatively low rate of women´s participation in the labor market: 38% (OECD, 2023). These challenges can also be seen in the relatively low percentage that women´s employment represents of total employment: 37.6% in 2021 in comparison with an average percentage of 44.7% for the OECD countries.

This research will analyze the income gender gap from a quantitative perspective for Costa Rica. To address the problem three econometric methodologies are applied: The Mincer's equations; the Oaxaca-Blinder decomposition; and Mincer's equation considering the semi-parametric quantile regression estimation.

The present paper aims to contribute in several ways to the existing literature on the gender wage gaps in Costa Rica. First, it applies the analysis on recent data, which provides insights regarding the post-pandemic scenario. Second, to our knowledge it is the first study to apply quantile regression to analyze the phenomenon in Costa Rica, therefore the paper contributes to the understanding of how the earnings gender gap changes as income levels vary, providing a clearer picture of different segments of Costa Rican society.

II. LITERATURE REVIEW

Labor discrimination is the different treatment that workers receive based on personal characteristics (gender, race, birthplace, age, etc.). There is labor discrimination if workers with the same characteristics related to productivity have different earnings (Ehrenberg & Smith, 2017). As it will be detailed in this review two main approaches have been taken to explain this phenomena. The first one addresses the topic from the perspective of the labor market demand side: where firms' dynamics and labor market institutions explain the existence of the gap. The second one explains the difference between wages emphasizing the differences in the labor supply: education, experience, and individual decisions of the labor force.

If women have less labor income this can happen because of direct discrimination, because they can have less human capital and work in certain sectors of lower productivity (indirect discrimination), but also due to the influence of social conventions and roles. As explained by Blau and Kahn (2017), this indirect discrimination is the result of social norms and gender roles that push women into "traditionally female occupations such as nursing or K–12 teaching that are generally less lucrative than traditionally male professions". In this research, we analyze the gender income gaps in general, those generated by differences in characteristics (productivity), and gender gaps due to potential labor discrimination.

Different perspectives have studied the role of discrimination in the labor market. The starting point is the fact that a labor market with discrimination is non-competitive, and the workers' wages do not equal their productivity. Thus, productivity or human capital is not the unique factor that explains labor incomes (Hellerstein et al., 2002). There is no perfect substitution between workers with the same skills and some arbitrary criteria based on prejudice can be considered when an employer demands labor (Reich et al., 1973).

One of the most influential approaches to the study of labor discrimination was proposed by the Nobel Laureate in Economics Gary Becker (1971). According to his Taste for Discrimination Theory, discrimination is the result of preferences. Employers, consumers, and even the same workers can have some reason to treat or be treated in different ways. Therefore, that preference (prejudice) could be more important than the actual productivity of workers: If a worker is discriminated her wage is lower than its productivity.

Finally, labor discrimination has been related to market power and potential segmentation (Fields, 2009). Workers who belong to a discriminated population group can be hired in a "secondary" market with lower incomes, worse conditions, and higher unstable jobs. If employers have market power in the labor market, it implies that they can pay their workers arbitrarily and consequently, they can get higher profits if they pay the discriminated group lower wages.

This base literature review of earnings gender gaps reveals a consensus about the idea that labor markets are not perfectly competitive, and everyone does not have complete information. Consequently, wages do not depend exclusively on productivity, and one of the reasons why two workers with the same productivity can have different wages is because there is a different treatment between women and men.

Grimshaw and Rubery (2007) analyze the situation of the UK. They verify the existence of an income gap related to gender and propose three main causes: discrimination, women's unequal share of responsibilities, and occupational segregation. These last two elements can be understood as part of the indirect discrimination in which women are traditionally employed in positions in which their labor is traditionally undervalued. As the authors explain: "Women may be low paid because they are concentrated in employing organizations that have a low ability to pay. In some cases, they may be located in organizations that have low 'willingness to pay".

The gap between women and men is a topic that applied econometricians and labor economists have analyzed deeply. Plenty of the literature about earnings differentials[4] has considered the gender gap as a reference. Oaxaca (1973) and Blinder (1973) proposed the now classical decomposition of income differentials between women and men, underlying that there are two possible components of the gap: the characteristics of workers and their jobs, and the different treatment in the labor market, potentially associated to discrimination.

Goldin (2014) synthetizes how this decomposition has been used: "most of the gender wage gap studies have produced estimates of an "explained" and a "residual" portion. The "residual" is often termed "wage discrimination" since it is the difference in earnings between observationally identical males and females". In its analysis, Goldin also concludes that professions where remuneration has a linear relation with the number of hours worked, like the case of pharmacists, have smaller gender wage gaps. While, professions where there is an additional penalty for working fewer hours, like in the business sector, the gender wage gap is greater.

Blau and Kahn (2017) developed a wide literature review and studied the changes in the gender wage gap between 1980 and 2010. They found a general decrease in the gap, but they identified that the decrease has been lower in the top segments of the wage distribution, they conclude therefore that there has been a glass ceiling. The authors use a traditional Oaxaca–Blinder decomposition to decompose the gender wage gap into a part explained by differences in characteristics and an unexplained component. The authors conclude that improvement in women's education has had an important role in reducing the gap as it explains between 38% and 40% of the gap reduction.

Regarding the indirect discrimination experienced by women Blau and Kahn (2017) indicate that the nature of the occupations and the industries in which women tend to work has an important role in explaining the gender wage gap. They argue that there is a set of social roles and norms attaching women to these positions. Deviation from these norms implies a cost for individuals, generating incentive status to reproduce the status quo. In this sense, the authors highlight the existence of structural and institutional factors that interact with individual decisions.

In general, there is quantitative evidence that confirms the existence and relevance of an income-gender gap. Weichselbaumer and Winter-Ebmer (2005) summarize the international gender wage gap through a meta-analysis. They found 263 published articles[5] and 1535 different estimations from 1960 to 2000 all over the world. The average earnings gender gap was 33%, and the unexplained component (potential discrimination) was 20% for the total period. However, a decline in the gap has been observed, but because of the increase in the human capital of women. Meanwhile, over the period the measure of potential discrimination[6] has reduced from 23% to 19%. That survey included 8 papers for Costa Rica, with an average gap of 13% against women (Weichselbaumer & Winter-Ebmer, 2005, p. 502).

Many methodologies have been applied to check the gender earnings gaps. Madalozzo (2010) for Brazil, Couppié et al. (2014) for France and Fuchs et al. (2021) for Germany, estimate the Oaxaca-Blinder decomposition. The gap is lower for the European countries, but the unexplained component is similar to the figure for Brazil. Those authors coincide with

4 Earnings differentials can be considered with several comparative groups, but by far the most studied is the gender gap. Perhaps because the political and social relevance, but also because it is a binary category available in many data sources

5 One interesting data is that only 28% of the authors were women.

6 There is called "potential discrimination" to the unexplained gap. It could be the result of different treatment for women, reducing their labor income, but it also could be "the effect of unobservable factors that can lead to males and females receiving different returns for the same characteristics" (Xiu & Gunderson, 2014, 308).

Weichselbaumer and Winter-Ebmer (2005), regarding the decline in the total gap, but in the persistence of the potential discrimination (unexplained differences between women and men).

There is a possible selection bias in the estimation of earnings, due to the fact that some people are out of the labor market when they could potentially be working (Heckman, 1979). That bias can be higher when considering the presentation of women into employment because there is a higher relationship between their participation in the labor market and characteristics associated with higher wages (education, experience, household characteristics) (de la Rica et al., 2008). Olivetti and Petrongolo (2008) analyzed the role of selection bias in the estimation of earning gaps for the United States and some Western European countries and implementing the two-step Heckman's method they found a considerable effect of sample selection. On average, the gap rises from 18% to 24% after correcting for selection bias (Olivetti and Petrongolo, 2008). Nevertheless, many studies have questioned the reliability and accuracy of the methodology to correct this potential econometric issue. The seminal article of Angrist & Krueger (1994) concludes that when implementing instrumental variables (IV) (quarter of birth as instrument) there is not a statistically significant difference between the conventional OLS estimation and IV estimators, as they tend to be biased in the same direction. Specifically, for the gender earnings gaps, Bar et al. (2015) discuss the actual relevance of selection bias, while Neuman and Oaxaca (2004) show the different interpretations that the selection bias could have.

The gap can be different through the wage distribution, which has been estimated with the quantile regression method. The idea is that there are two different situations: glass ceiling when larger gaps are at the top of the distribution, and even though women have high incomes they are not paid as men with the same productivity; and sticky floor, that is the result of exclusion and potential discrimination of women that are in the bottom of the income distribution, situation than can be related in developing countries with maternity and the role within the household (Dah & Fakih, 2016; Xiu & Gunderson, 2014).

Huffman et al. (2017) apply an unconditional quantile regression method to understand how the wage gender gap varies through income distribution and how the impact of policies to address it varies according to the income level in Germany. Their results indicate that the "gender gap follows an inverted U-shaped pattern with higher inequality in the tails of the distribution". The authors also found that the policies to reduce the gap have a greater impact in the case of women with lower income in the distribution.

The results are noticeably different depending on the features of the labor market. Developing countries have higher gender income gaps at the bottom of the distribution (Dah & Fakih, 2016; Xiu & Gunderson, 2014), while European countries have higher gaps at the top, verifying the existence of glass ceiling (Arulampalam et al., 2007). However, there is no deterministic rule, Chzhen and Mumford (2011) found that there are no significant changes in the gap for different points of the distribution in the British case, and Sakellariou (2004) concludes that Singapore presents sticky floor and no glass ceiling.

For Costa Rica, several studies have addressed the gender wage gap. Jiménez Cordero and Morales Aguilar (2012) applied the Oaxaca-Ransom method to evaluate the gender wage gap during the nineties and declined to use the 2 stage Heckman correction method. They describe how the share of women taking part in the labor market increased from 30% in 1990 to 34% in 2000. The authors concluded that the wage gap estimated by the Oxaca-Ramson technique decreased from 11.6% in 1990 to 1.6% in 2000. However, the authors also found that during the whole period, there was an unexplained component of the gap (attributable to discrimination) that oscillated between 0.2% and 0.15%

Rodríguez Zúñiga and Segura Díaz (2015) applied the Oaxaca-Blinder decomposition without the Heckman selection method for the year 2013. The authors calculated the decomposition using the quantile regression method and concluded that the gender gap is negative (women have lower wages) for women in the percentiles 10 and 25, while the gap becomes positive in favor of women for percentiles 50, 75, 90, and 95. In contrast, they found that the non-explained component of the gap is negative in general for women with values between 3% and 9% for the different percentiles.

Torres and Zaclicever (2022) applied the Oaxaca-Blinder decomposition with the Heckman correction method for the years 2001 and 2019. They found some particular results, with the explained gap being 24% and 25% against women for 2001 and 2019 respectively, while the unexplained gap was positive in favor of women with 30% and 34% of the hourly wage in 2001 and 2019.

Blanco (2023) realizes an analysis of the gender wage gap for the employees of the University of Costa Rica and finds that men´s hourly wage is 7.8% greater than women´s. After reviewing the nature of the University´s wage scale and structure, Blanco concludes this can be explained by differences in the accumulation of human capital.

In synthesis, there is a well-known and established methodology to analyze the income gaps between men and women. The methodology has been applied to countries all around the world with robust results, including the country of analysis. In Costa Rica, the results vary. Most of the studies find the existence of an explained gender gap, but in terms of the unexplained gender gap, some studies found a positive unexplained gender gap and others a negative one.

The current study analyzes the gender wage gap for 2023 and tries to provide a new approach to the problem by estimating several Mincer equation specifications and by applying the quantile regression method to understand the changes in the gender wage gap across the income distribution.

III. METHODOLOGY

Applied studies that estimate the gender income gaps usually regress labor income over a set of variables that do not necessarily explain productivity but affect labor earnings. Some of those variables are gender, relationship with the head of household, children in the household, non-labor income, labor contract, informality, and so on. Given our objective, we will analyze the effect of gender[7] on earnings and how it interacts with other explanatory variables.

According to the Oaxaca-Blinder decomposition earnings differences between women and men can be the result of endowments (human capital, better employment conditions, different household microfeatures) or different retribution for those endowments, the latter is called[8] "potential discrimination" (Xiu & Gunderson, 2014).

It is important to underline that there is always potential bias in the estimation of the gender gap because there are omitted variables that are not available and can be related to the gender but also and more importantly there is a sample selection bias that is related to the gender. After all, women who are out of the labor market have different endowments than women working and men who do not work (Bar et al., 2015). Nevertheless, most of the applications to this topic have recognized that the ways to correct sample selection bias are still in discussion, and there is still not a consensus regarding the techniques, as explained by Blau and Kahn: "Possible selection

7 We consider a restricted approach to gender based on the availability of information: the conventional male-female identification of gender.

8 It is called "potential" at least for two reasons: first, the source of information is given by workers, who are discriminated; second, there are not enough information to verify if the gap is the result of discrimination or because of omitted variables.

bias in measuring the gender wage gap is an important and complex issue. Thus, it may not be surprising that efforts to address it have not yet achieved a consensus" and "continued research, and perhaps new methodologies, are needed to resolve the debate" (Blau and Kahn, 2017). We acknowledge the existence of possible selection bias as an important limitation of the present study, and we leave it as a fundamental area of analysis for future research.

In terms of the subsample selection, we use the approach proposed by Juhn et al. (1993), we take a subsample of the survey to apply the analysis. The criteria for the subsample are: Paid workers between 18 and 55 years old, who have worked at least 12 hours per week and have daily labor income at least equal to one dollar (567.17 colones per dollar in the first quarter of 2023).

The rest of this section will briefly summarize the three econometric methods applied.

Mincer Equations

The fundamental econometric approach is called "Mincer equations" (Mincer, 1974). The equation [Eq. 1] takes the hourly labor income (natural logarithm) as explicated variable and a set of independent variables are included (vector X) considering that they can affect the variability of income. Gender is included as an independent (dummy) variable and its coefficient indicates the level and significance of the average earning differential between women and men (ceteris paribus).

$$\omega_i = \ln(w_i) = X_i^T \beta_i + \varepsilon_i \,; \mathrm{E}(\varepsilon_i) = 0 \qquad \text{[Eq.1]}$$

It is needed to guarantee unbiased estimations, so we need to assume that the conditional mean of errors is zero $E(\varepsilon_i|X_i) = 0$.

To obtain a broader approach, interpret different relationships, and check robustness, six different specifications are estimated, changing control variables, quadratic (non-linear) relationships, and including interaction terms. The explained variable is always the natural logarithm of hourly wage, and the vector of independent variables changes over the specification. The set of explanatory variables are:

i. Specification 1: gender (dummy variable equals 1 if the worker is a woman), education (years of education), experience (years of experience, calculated as the age of worker minus years of education minus five), informal (dummy variables equals to 1 if the worker has informal employment, given the official definition for Costa Rica) and regional controls (n-1 dummy variables: 6 for Costa Rica).

ii. Specification 2: The same specification 1 including household controls. There are three characteristics of households that potentially can affect the wage and at the same time are correlated with gender: marital status (4 dummy variables: living together, single, widowed, and divorced or separated, taking "married" as a base variable/category), relationship to the head of household (4 dummy variables: spouse or partner, child, grandchild, and other, taking "head of household" as a base variable/category), and number of children in the household (under the age of 16).

iii. Specification 3: The same specification 1 including square education and square experience (checking non-linear relationships with wages).

iv. Specification 4: The same specification 3 including household controls explained in specification 2.

v. Specification 5: The same as specification 2, including two interactions: gender and education, and gender and experience (exploring differences in the returns of education and experience between women and men).

vi. Specification 6: The same specification 5 including square interactions.

There are some features of the specifications that need to be explained:

• Interpretation of the gender coefficient: This is our primary data collected because it quantifies the average earning gap between women and men. Given that the base group is men (gender=1 if woman), the gap will be equal to:

$$\frac{E[w_{Fem}] - E[w_{Male}]}{E[W_{male}]} = e^{\hat{\beta}\,\text{gender}} - 1$$

If the coefficient is negative, the expected average wage is lower for women than men. For instance, a coefficient of -0.15 means that the earnings of women are, on average, and ceteris paribus, ($e^{-0.15} - 1 = 0.8607 - 1 = 0.1393$), 13,9% lower than the earnings of men.

• Experience variable: Although experience is an essential variable to explain productivity, it is not available in most microdata. Hence, many empirical applications have calculated it as age minus years of education minus 5 and we adopt this approximation. Some assumptions can be weak. For example, there are no unemployment periods or periods out of the labor market, and there are no differences by gender in that situation. The likely bias that this approach can have is recognized, however, that discussion is beyond our scope. Regan and Oaxaca (2009) discuss extensively this issue.

• Categorical variables: There are categorical variables in some specifications. To avoid misspecification, they are included as dummy variables. To do so, one category is considered the reference and is not included (avoiding multicollinearity).

• Household controls: They are included to avoid probable bias for omitted variables because those variables can affect the wages and are correlated with the gender of the worker.

• Square terms: There are square variables of education and experience in some specifications because it is conventionally recognized probable non-linearity between education and wages, and experience and wages. The marginal effect of years of education (experience) is different when the worker has basic, secondary, or professional education.

• Interactions: This is a preliminary approach to quantify differences in the return of education and experience between women and men. If there is potential discrimination the market returns of those variables can be different. An extension of this is done in the Oaxaca-Blinder decomposition.

Oaxaca-Blinder Decomposition

One of the most used methodologies to split up the gap between the component related to characteristics and the one that is explained by differences in remuneration is the decomposition proposed by Oaxaca (1973) and Blinder (1973). Gender earnings gaps can be the result of lower levels in variables that are positively correlated to productivity (education, experience), but they can also be the product of different treatment (remuneration) to workers with some personal distinction (gender, ethnic group, nationality). Consequently, women can have lower incomes because they have lower years of education and experience (explained gap), but there can be an unexplained component and that is the potential discrimination that they face. There are two Mincer's equations estimated by gender, but in this case, the dummy variable that identifies gender is excluded:

$$\omega_l = \ln(w_l) = X_l^T \beta_l + \varepsilon_l \,; E(\varepsilon_l) = 0 \qquad \text{[Eq.1]}$$

Equation 1 is the simple Mincer estimation, where X_l is the variable data vector, β_l is the coefficient vector, ε_l is the error, and l is a group sub-index for women [F] and men [M]. Thus, the average gap between women and men is given by the mean difference in the expected value of the linear predictions:

$$\bar{\omega}_F - \bar{\omega}_M = \bar{X}_F^T \hat{\beta}_F - \bar{X}_M^T \hat{\beta}_M \quad \text{[Eq.2]}$$

If we add and subtract $\bar{X}_F^T \hat{\beta}_M$ on the right-hand side in equation 2, we obtain the Oaxaca-Blinder decomposition (Oaxaca, 1973), considering men as the reference group:

$$\underbrace{\bar{\omega}_F - \bar{\omega}_M}_{\text{Total gap}} = \underbrace{[\bar{X}_F^T - \bar{X}_M^T]}_{\text{Endowments}}\hat{\beta}_M + \bar{X}_F^T \underbrace{(\hat{\beta}_F - \hat{\beta}_M)}_{\text{Unexplained gap}} \quad \text{[Eq.3]}$$

The first right-hand side term measures the component of the gap that can be explained by differences in the endowments like education or experience. A negative value indicates that women have lower endowment when the variable is positively correlated to wages ($\hat{\beta}_M > 0$). The second term quantifies the difference in the level of remuneration between women and men that is not explained by endowments (unexplained gap), if there is a negative difference is because women are treated in such a way that they receive lower wages even though they have the same potential productivity.

This division of the gender income gap, allows us to understand what part of the gap can be explained by differences in factors such as experience or education (endowments) and which part is unexplained and therefore can be attributed to potential discrimination.

Quantile regression

This methodological approach lets us explore the gender earnings gaps beyond the conditional mean (Mincer OLS) and it estimates the potential heterogeneity that can be found when different points of the distribution are considered. Koenker and Bassett (1978) proposed the following conditional quantile function:

$$Q_\theta(\omega|X) = X\beta(\theta) \quad \text{[Eq.4]}$$

Here $Q_\theta(\omega|X)$ is the θth quantile of variable ω (natural logarithm of labor income) conditional to the vector of variables X, and $\beta(\theta)$ is the vector of estimated coefficients, but in this case as a function of θ ($\theta \in [0,1]$), quantile in the distribution. Koenker and Bassett (1978) proposed that $\beta(\theta)$ is the result of the minimization of the weighted sum of the absolute value of the residuals in the regression equation:

$$\beta(\theta) = argmin_{\beta \in R^k} \frac{1}{t}\left[\sum_{t\epsilon\{t\epsilon:\omega_t \geq X_t'\beta\}} \theta|\omega_t - X_t'\beta| + \sum_{t\epsilon\{t\epsilon:\omega_t < X_t'\beta\}} (1-\theta)|\omega_t - X_t'\beta|\right] \quad \text{[Eq.5]}$$

It can be re-written as:

$$min_{\beta \in R^k} \frac{1}{t} \rho_\theta(\omega_t - X_t'\beta) \quad \text{[Eq.6]}$$

$$\rho_{\theta}(\varepsilon) = \begin{cases} \theta_{\varepsilon} & si\ \epsilon \geq 0 \\ (1-\theta)_{\varepsilon} & si\ \varepsilon < 0 \end{cases} \qquad \text{[Eq.7]}$$

Here, ε is the error term, as usual, is assumed that the conditional mean of errors is equal to zero. Based on this estimate a set of gaps are going to be found for every point of the conditional distribution and we will be able to discuss the possibility of ceiling glass and sticky floor. $\beta(\theta)$ has the same meaning as in the Mincer equation just that in this case is for a specific point of the distribution, and its interpretation is also the same as mentioned in the first part of this section. Finally, it is important to underline that this approach is going to consider only the third specification which includes the squared term of education and the squared term of experience. We choose this specification because it allows to capture the non-linear relation between the independent variables education and experience, and wage and at the same time it has a relatively simpler functional form than specifications 4, 5 and 6.

We acknowledge that one limitation of the applied methodology is that we are not controlling for employment segment or profession, which are 2 important elements to explain the gender wage gap and understand if there is a horizontal displacement of women to sectors and positions with worst labor conditions.

IV. DATA AND DESCRIPTIVE STATISTICS

The data used for the analysis corresponds to the Costa Rican Continuous Employment Survey, First Quarter 2023 (Instituto Nacional de Estadística y Censos [INEC], 2023). From the total survey data, we extract a subsample using the next criteria: we kept only paid workers between 18 and 55 years old, who have worked at least 12 hours per week and have daily labor income at least equal to one dollar (567.17 colones per dollar in the first quarter of 2023). This subsample criteria are based on the criteria proposed by Juhn et al. (1993) Next, we present descriptive statistics for the subsample.

Table 1: Descriptive statistics of the main variables for the subsample selected

	Population			
	Mean	**Standard deviation**	**Min**	**Max**
Age	37.38	9.80	18	55
Years of education	10.10	4.20	0	24
Informality	0.37	0.48	0	1
Experience	22.29	11.29	-1	50
Income	440,101	356,254	4,167	5,960,350
Hours worked per week	45	12.84	12	105
Hourly income	2,529	2217.31	74	45,139

Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Table 1 provides an aggregated summary of the data: an average age of 37.38, with 10.10 mean years of education, average income of 440 101 CRC (Costa Rican Colones), 44 hours worked per week on average, and an hourly income of 2 529 CRC (Costa Rican Colones).

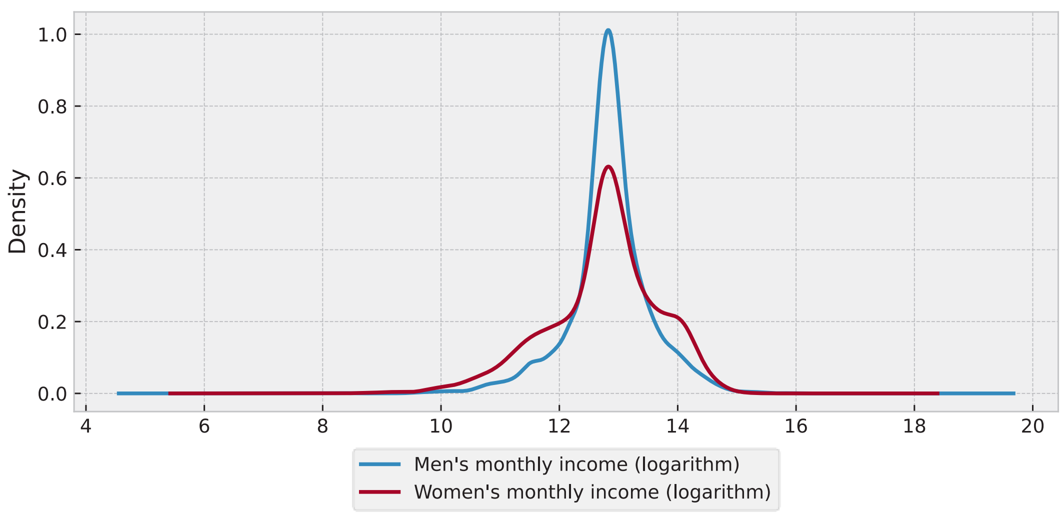
Some valuable insights can be extracted from Table 2. The disaggregation of the data by gender allows us to identify that despite having a higher hourly wage and more years of education on average, women have a lower monthly income and work fewer hours per week than men, something related to the unequal distribution of care and home responsibilities. With a mean experience of 22.95 years, men have slightly more average experience than women, who have 21.24 mean years of experience. In terms of hours worked per week, men tend to work on average 7.21 hours more per week than women. However, men have lower hourly income than women, with 2 363 vs. 2790. This reflects some of the progress made by Costa Rica in terms of gender earnings gap and can be partially attributed to the differences in the average years of education between men and women. This educational breach is reflected in the fact that women have on average 2 more years of education than men in the subsample.

Table 2: Descriptive statistics of the main variables for the subsample selected

	Males				Females			
	Mean	**Standard deviation**	**Min**	**Max**	**Mean**	**Standard deviation**	**Min**	**Max**
Age	37.27	9.95	18	55	37.55	9.55	18	55
Years of education	9.33	3.95	0	24	11.32	4.31	0	24
Informality	0.37	0.48	0	1	0.38	0.49	0	1
Experience	22.95	11.44	1	50	21.24	10.98	-1	48
Income	434,707	347,212	4,167	5,960,350	448,627	370,009	5,800	2,985,367
Hours worked per week	47.80	11.93	12	105	40.59	13.00	12	105
Hourly income	2,363	2,137	74	45,139	2,790	2,314	75	19,375

Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

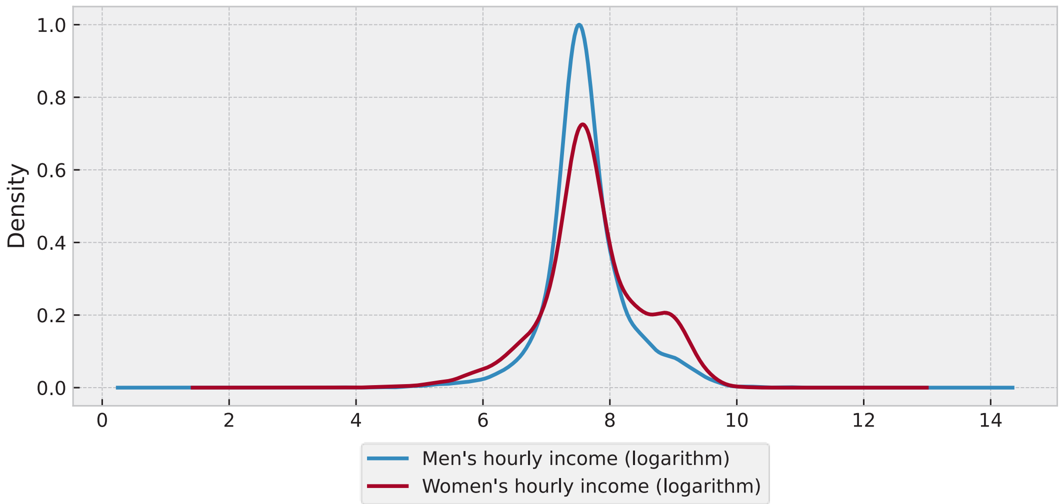
Graph 1: Kernel distribution for men's and women's hourly income



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Graphs 1 and 2 present the Kernel density for men's and women's hourly and monthly income distribution. In both cases, they allow us to identify a bigger concentration of men in the mean income, while for women we have a bigger concentration in the extreme values. This reflects a reality that will be present in the rest of the analysis: the gender income gap is not constant along the income distribution.

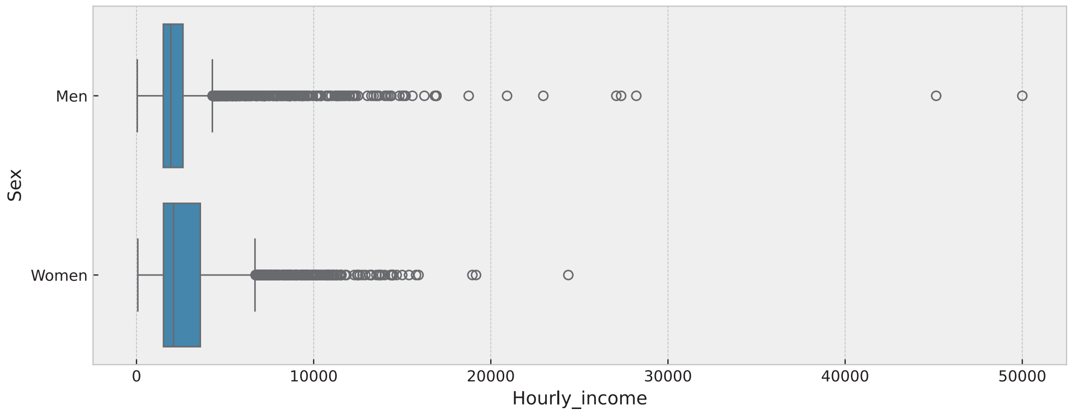
Graph 2: Kernel distribution for men´s and women´s monthly income



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Finally, we present in Graph 3 the box plot of the hourly wages for men and women. Graph 3 provides important insights to understand the behavior of hourly income across different quartiles for men and women. It is important to highlight that the first 2 quartiles present similar behavior for men and women, with the last quarter starting at a higher hourly income level for women, and a small group of men with particularly high hourly incomes in the last quartile.

Graph 3: Boxplot for the Hourly wage of subsample men and women



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

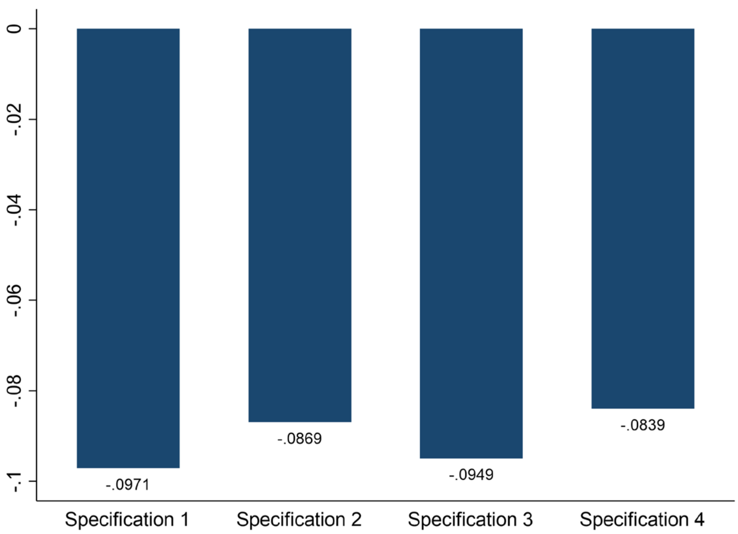
V. RESULTS AND ANALYSIS

This section will analyze the main results of the estimations, focusing on the gender gap. The analysis will be organized sequentially as in the previous section: first the results of Mincer equations and some extensions; secondly, the results of Oaxaca-Blinder decomposition; and lastly, the semi-parametric approach of quantile regression.

Mincer equations

Graph 3 presents the gender gap measured by the equation $\frac{E[w_{Fem}]-E[w_{Male}]}{E[W_{male}]} = e^{\hat{\beta}\text{ gender}} - 1$, where $\hat{\beta}$ gender is obtained from the estimation of each specification. The results reveal that there is a clear gender wage gap in Costa Rica: Women have an hourly wage that is on average between 8.77% and 10.22% lower than men keeping all other factors constant.

Graph 4: Estimated gender gap coefficient for the first 4 specifications of the Mincer equation for the first quarter of 2023



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

The general results of the 6 specifications are presented in Table 3

First, we compare the 6 different specifications using the Akaike and Bayes information criteria. The results show that specifications 4 and 6 have the best results in terms of the information criteria and the best fit according to the R square, we will also comment on specification 5, as the interaction terms provide rich results for the analysis. Therefore, our analysis will be focused on those 3 specifications.

As explained in section III, specification 4 regresses hourly wage as a dependent variable over years of education, years of education squared, years of experience, years of experience squared, and informality as independent variables (additionally, regional and household controls). The results show that the 6 parameters are statistically significant with 99% confidence, except for the years of education parameter, which is statistically significant with 95% confidence.

The estimation for specification 4 indicates that women earn on average 8.768% less than men keeping all other factors equal. Informality has a heavy weight on the determination of the hourly wage, as informal workers earn on average 36.52% less than formal workers. It is a worrisome result given that around 45% of workers in Costa Rica are informal.

In the case of education, the estimation is done with a quadratic specification, revealing that the average marginal effect of one additional year of education increases with the number of years of education. In the case of the experience variable, the estimation also uses a quadratic form, however, the results are different and indicate a decreasing marginal effect of experience in the hourly wage, this is consistent with the literature.

Table 3: Mincer equations estimated by OLS

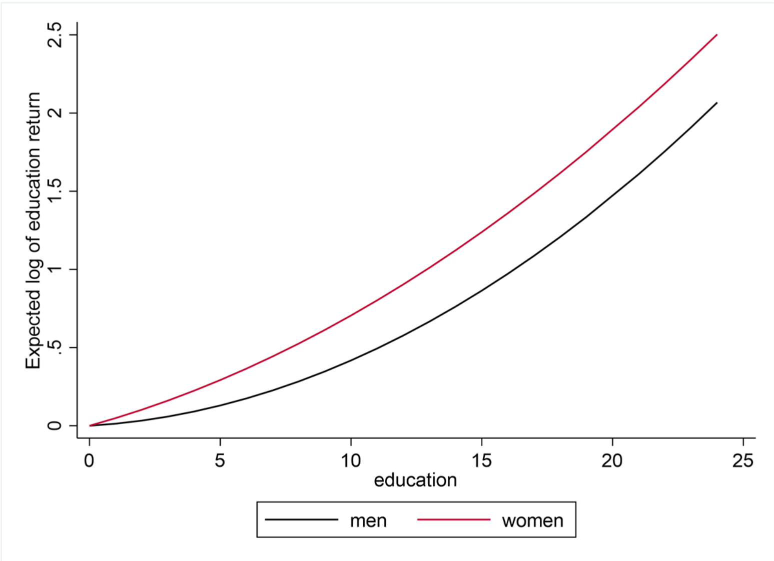
	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	Specification 6
gender (1=women)	-0.1021755***	-0.0909636***	-0.0997513***	-0.0876823***	-0.4635401***	-0.4560407***
	(0.0137)	(0.0146)	(0.0135)	(0.0145)	(0.0603)	(0.1007)
Education (years)	0.0969677***	0.0941222***	0.018486**	0.018217**	0.083921***	0.0100632
	(0.0019)	(0.0019)	(0.0064)	(0.0065)	(0.0024)	(0.0079)
Education square	-	-	0.0032248***	0.0031123***	-	0.0031702***
	-	-	(0.0003)	(0.0003)	-	(0.0003)
Interaction (education and gender)	-	-	-	-	0.0252672***	0.0363242**
	-	-	-	-	(0.0036)	(0.0136)
Interaction square (education and gender)	-	-	-	-	-	-0.0007569
	-	-	-	-	-	(0.0005)
Experience (years)	0.0120857***	0.0086497***	0.0227613***	0.0168144***	0.0068481***	0.0151005***
	(0.0007)	(0.0008)	(0.0024)	(0.0025)	(0.0009)	(0.0031)
Experience square	-	-	-0.0002915***	-0.0002291***	-	-0.0002208**
	-	-	(0.0001)	(0.0001)	-	(0.0001)
Interaction (experience and gender)	-	-	-	-	0.0045749**	0.0028461
	-	-	-	-	(0.0014)	(0.0049)
Interaction square (experience and gender)	-	-	-	-	-	0.0000256
	-	-	-	-	-	(0.0001)
Informal (1=informal)	-0.3599674***	-0.3637265***	-0.363155***	-0.3651828***	-0.3580581***	-0.360638***
	(0.0142)	(0.0141)	(0.0140)	(0.0140)	(0.0141)	(0.0140)
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	Specification 6
Household controls	No	Yes	No	Yes	Yes	Yes
R square	0.4167	0.4274	0.4328	0.4412	0.4318	0.4435
AIC	9282.375	9185.643	9112.597	9037.371	9141.216	9019.623
BIC	9349.718	9313.596	9193.41	9178.793	9282.639	9187.983

Source: Own elaboration based on the Encuesta Continua de Empleo first quarter 2023 (INEC, 2023)
Note * corresponds to 10% significance, ** to 5% significance and *** to 1% significance levels

Specification 5 introduces interaction terms between the variable gender and the number of years of education and experience, this allows us to understand if women experience higher returns of education than men. The results show that women experience an average return 2.53% higher than men for one additional year of education. Graph 4 presents the different returns of education for men and women.

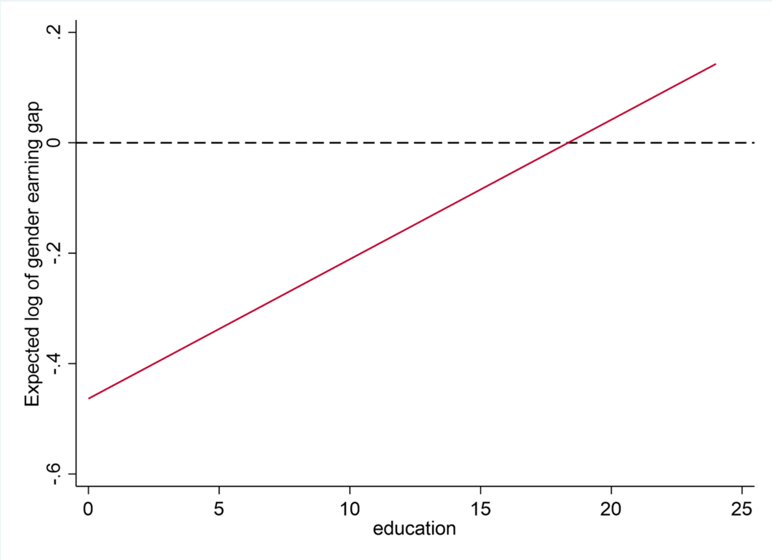
Graph 5: Expected return of education for men and women using Specification 4



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Using this difference in the education return, we can model the behavior of the gender gap for different education levels. As seen in Graph 5, this difference in the return of education implies that the gender earning gap is reduced as women have a higher level of education.

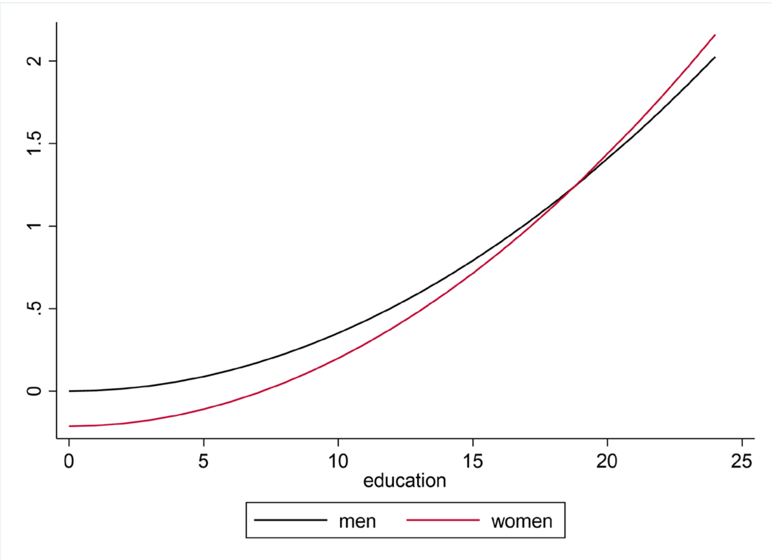
Graph 6: Expected gender earning gap according to the education level



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Specification 6 has introduced interaction terms between gender and the squares of education and experience. This allows us to enrich the analysis by introducing different decreasing factors to the marginal effect of education on men and women. Graph 6 represents this result, as seen, men obtain on average a higher return of an additional year of education. However, there is a point between 15 and 20 years where the relationship changes, and women begin to obtain a higher return.

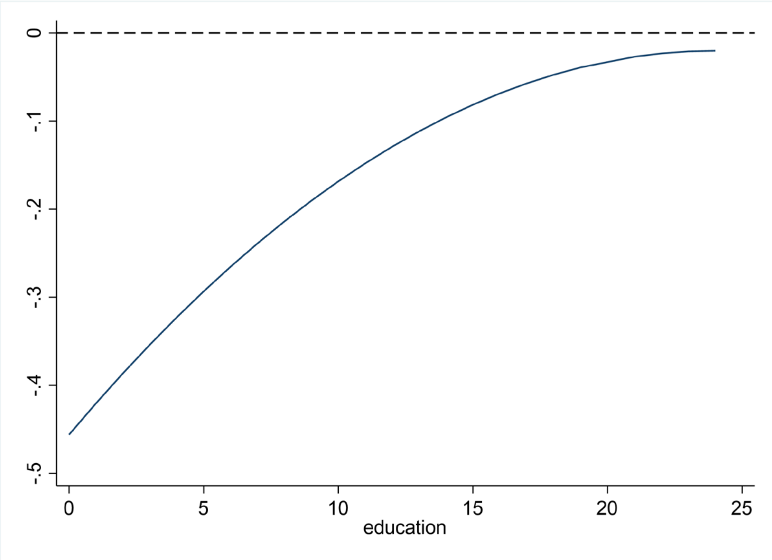
Graph 7: Expected return of education for men and women Specification 6



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

We use the values of specification 6 to simulate the gender gap as a function of the number of years of education. The results are presented in Graph 7. In contrast with the results obtained for specification 5, the results show that even when the gender earnings gap is reduced with the years of education, it is never reduced to zero.

Graph 8: Expected gender earning gap according to the education level specification 6



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Oaxaca-Blinder decomposition

The Oaxaca-Blinder decomposition allows us to divide the gender gap into 2 parts: one explained by the difference in endowments like education and experience, and the second one that can be attributed to gender discrimination. The first result we obtained is that the overall gender gap is positive, this means that on average women have higher hourly wages than men. This result is consistent with the descriptive statistics of section IV, according to which women have a mean hourly wage 15.3% higher than men for the subsample.

However, more important than the overall gap, the main focus of this study is its decomposition. As explained in section III this gap can be decomposed into 2 factors: endowments that refer to elements like qualifications or experience, and an unexplained component that can reflect the existence of gender-based discrimination. All four specifications analyzed indicate that women have a higher level of endowments. This is consistent with the data exposed in section IV, according to which women have on average 2 years more of education than men.

Once we isolated the effect of women´s higher endowments, we obtained the unexplained component of the gender earnings gap, which can be attributed to gender-based discrimination. All 4 specifications arrive at the same conclusion: assuming the same levels of endowments, women have on average lower hourly wages than men. As seen in Table 6, all 4 specifications indicate the existence of an unexplained gap superior to 10%, with a gap of -11.89% for specification one, -11.42% for specification two, -11.11% for specification three, and a lower -10.75% for specification 4.

Table 4: Gender earning gaps measured by the Oaxaca-Blinder decomposition

	Specification 1	Specification 2	Specification 3	Specification 4
Endowment	0.1352	0.1218	0.1375	0.1226
Coefficients	-0.1189	-0.1142	-0.1111	-0.1075
Gap	0.0468	0.0468	0.0468	0.0468

Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

Therefore, the data analyzed with the Oaxaca-Blinder decomposition provides evidence of an income gender gap against women in Costa Rica once we isolate the effects of women´s higher endowments.

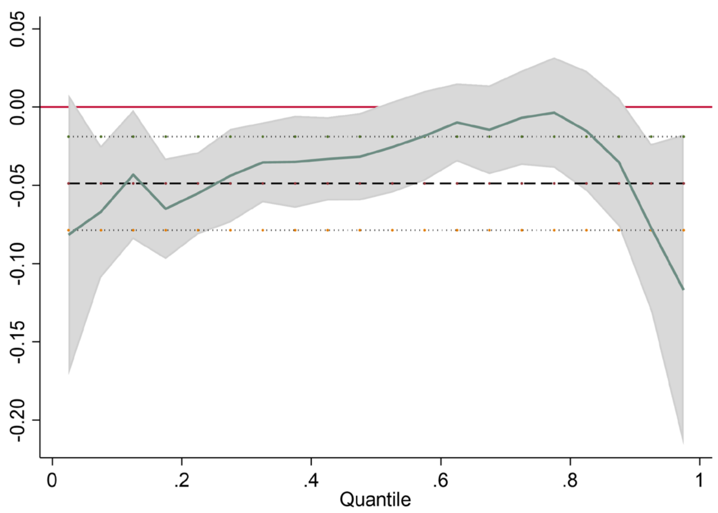
As we acknowledge in the methodology, the present study does not control for sector of employment or profession. Therefore, a possible explanation for the observed wage gaps corresponds to the segregation of women to sectors and professions with lower income. Which would correspond to an indirect mechanism of discrimination through social norms and roles.

Quantile regression

Once we analyze the existence of the gender earning gap using the Mincer equation and the Oaxaca-Blinder decomposition, we will use the quantile regression method to understand if the gap is homogeneous for all the different income levels, or if it changes according to the income level. This means that we will analyze the value for every point of the conditional distribution.

First, we run the quantile regression using specification 4 to obtain the parameter of the gender variable for the different points of the distribution.

Graph 9: Gender parameter measured by quantile regression

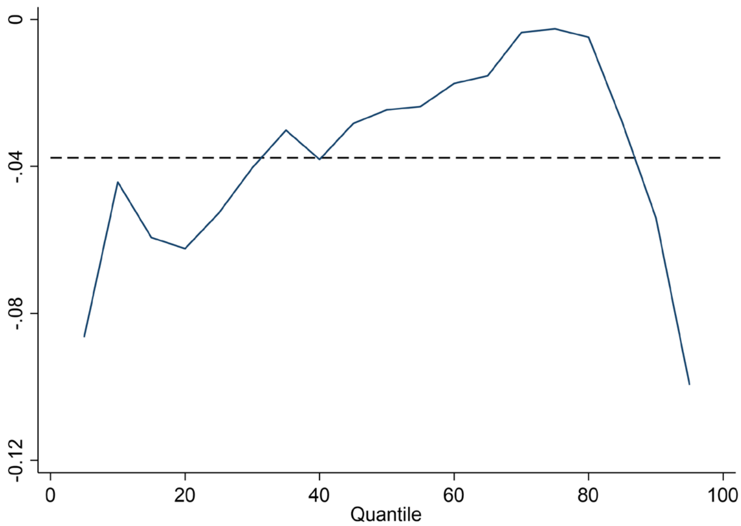


Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

On Graph 8 the red line corresponds to the value of 0, the green line corresponds to the mean value of the quantile regression result for every quantile, and the shaded area corresponds to the 5% confidence interval for the quantile regression mean on every quantile. The black line corresponds to the single mean value for all the quantiles, while the two dotted lines represent the confidence intervals of this mean for a 5% significance. The results indicate that the parameter is statistically significant between the first and the fifth decile and for the last one, which means that women from those deciles experience a gender earnings gap. In the case of the parameter for women between the fifth and ninth deciles, the confidence interval does not allow us to discard the hypothesis of the parameter being equal to 0.

However, the previous result does not provide the gender earnings gap, as the parameter must be adjusted with the formula $\frac{E[w_{Fem}]-E[w_{Male}]}{E[W_{male}]} = e^{\hat{\beta}\,\text{gender}} - 1$. Once we have made this adjustment, we obtain the following results:

Graph 10: Gender earning gap measured by quantile regression



Source: Own elaboration based on the *Encuesta Continua de Empleo* first quarter 2023 (INEC, 2023)

The values obtained by this adjustment are valid only for the deciles with parameters that are statistically significant: deciles between the first and the fifth and for the last decile.

The results of the estimation show that the gap experiences important changes according to income level. From the third to the ninth decile the gender coefficient experiences a reduction. This reduction is such that for deciles between fifth and ninth there is no statistical evidence of the gender coefficient being statistically significant. However, for the first 5 deciles and the last one, there is evidence to conclude that the coefficients are lower than 0, and therefore women experience a gender earnings gap in those groups.

This allows us to analyze the gender earning gap from the perspective of 3 groups: low-income women who experience gender earning gaps and discrimination, middle and middle-high-income for whom we did not find statistically significant evidence of gender earnings gap, and a final group of high-income women in the right margin of the distribution who, again experience negative values for the gender income gap.

The first one is associated with the existence of a sticky floors and a glass ceiling. The existence of systematic gender barriers for women of lower income has been named in the literature as "sticky floor", while the existence of sustained gender gaps for women of high-income levels has been called as "glass ceiling". The results of the quantile regression confirm the existence of both phenomena in Costa Rica. This inverted U shape for the quantile regression is consistent with the findings for Germany of Huffman et al. (2017).

As in the case of the Oxaca-Blinder decomposition, it is important to consider that the gap observed across the income distribution could be explained by the horizontal displacement of women to sectors and professions with less favorable conditions. We consider this as an important research topic to address in future research.

VI. CONCLUSIONS

The Mincer equations analysis and the Oxaca-Blinder decomposition confirm the existence of a gender income gap against women in Costa Rica. In the case of the first 4 specifications, this gap goes from -8.77% to -10.22%. In the case of the Oaxaca-Blinder analysis, the 4 specifications confirm the existence of an unexplained gender earning gap, and therefore discrimination against women: considering women and men with the same endowments, women tend to earn on average between 10.75% and 11.89% less than men.

The quantile regression indicates that the gender earnings gap changes with income level. Evidence indicates that women with lower income (first 5 deciles) experience gender earning gaps. This gap is reduced as income grows until it reaches a group of middle and middle-high-income women for whom the gender gap is not statistically different from 0. Finally, data shows that high-income women from the last decile also experience a significant gender earning gap in comparison with men. One possible explanation for this phenomenon is the existence of glass ceiling and sticky floor for high and low-income women in Costa Rica.

Another possible explanation for the gender earnings gap observed in the Oaxaca-Blinder decomposition and the quantile regression displacement of women to sectors and professions with less favorable conditions.

It is important to acknowledge two limitations of the present analysis. The first one is that it does not consider the impact of working in different economic sectors and professions on the gender wage gap. The second one is that it does not correct for possible selection bias due to the lower participation of women in the labor market. We consider these 2 limitations as key elements of future research agenda.

VII. REFERENCES

Angrist, J., & Krueger, A. B. (1994). Why Do World War II Veterans Earn More than Nonveterans? *Journal of Labor Economics, 12*(1), 74–97. https://doi.org/10.1086/298344

Arulampalam, W., Booth, A. L., & Bryan, M. L. (2007). Is There a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wage Distribution. *ILR Review, 60*(2), 163–304. https://doi.org/10.1177/001979390706000201

Bar, M., Kim, S., & Leukhina, O. (2015). Gender Wage Gap Accounting: The Role of Selection Bias. *Demography*, *52*(5), 1729–1750. https://doi.org/10.1007/s13524-015-0418-x

Becker, G. S. (1971). *The Economics of Discrimination* (2nd ed.). University of Chicago Press. https://doi.org/10.7208/chicago/9780226041049.001.0001

Blanco, L. C. (2023). Diferenciales salariales de género y sus determinantes para el personal académico titular en la Universidad de Costa Rica. *Revista de Ciencias Económicas*, *41*(2), Article e52311. https://doi.org/10.15517/rce.v41i2.52311

Blau, F. D., & Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature, 55*(3), 789–865. https://doi.org/10.1257/jel.20160995

Blau, F. D., Kahn, L. M., Boboshko, N., & Comey, M. (2021). *The Impact of Selection into the Labor Force on the Gender Wage Gap* (Working paper series, No. 28855). National Bureau of Economic Research. https://doi.org/10.3386/w28855

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436–455. https://doi.org/10.2307/144855

Chzhen, Y., & Mumford, K. (2011). Gender gaps across the earnings distribution for full-time employees in Britain: Allowing for sample selection. *Labour Economics*, *18*(6), 837–844. https://doi.org/10.1016/j.labeco.2011.05.004

Comisión Económica para América Latina y el Caribe. (2019). *Planes de igualdad de género en América Latina y el Caribe: Mapas de ruta para el desarrollo.* (Observatorio de igualdad de género en América Latina y el Caribe; Estudios, N.° 1). Naciones Unidas. https://hdl.handle.net/11362/41014

Couppié, T., Dupray, A., & Moullet, S. (2014). Education-based occupational segregation and the gender wage gap: evidence from France. *International Journal of Manpower, 2*(1), 3–10. https://doi.org/10.1108/IJM-09-2012-0143

Dah, A., & Fakih, A. (2016). Decomposing Gender age Differentials Using Quantile Regression: Evidence from the Lebanese Banking Sector. *International Advances in Economic Research, 22*(2), 171–185. https://doi.org/10.1007/s11294-016-9574-z

de la Rica, S., Dolado, J. J., & Llorens, V. (2008). Ceilings or floors? Gender wage gaps by education in Spain. *Journal of Population Economics, 21*(3), 751–776. https://doi.org/10.1007/s00148-006-0128-1

Ehrenberg, R., & Smith, R. (2017). *Modern Labor Economics: Theory and Public Policy* (13th ed.). Routledge. https://doi.org/10.4324/9781315101798

Fields, G. S. (2009). Segmented Labor Market Models in Developing Countries. In: H. Kincaid and D. Ross (Eds.), *The Oxford Handbook of the Philosophy of Economics* (pp. 476–510). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195189254.003.0018

Fuchs, M., Rossen, A., Weyh, A., & Wydra-Somaggio, G. (2021). Where do women earn more than men? Explaining regional differences in the gender pay gap. *Journal of Regional Science, 61*(5), 1065–1086. https://doi.org/10.1111/jors.12532

Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter. *American Economic Review, 104*(4), 1091–1119. https://doi.org/10.1257/aer.104.4.1091

Grimshaw, D., & Rubery, J. (2007). *Undervaluing women's work.* (Working Paper Series No. 53). Equal Opportunities Commission.

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

Hellerstein, J. K., Neumark, D., & Troske, K. R. (2002). Market Forces and Sex Discrimination. *The Journal of Human Resources, 37*(2), 353–380. https://doi.org/10.2307/3069651

Huffman, M. L., King, J., & Reichelt, M. (2017). Equality for whom? Organizational Policies and the Gender Gap across the German Earnings Distribution. *ILR Review, 70*(1), 16–41. https://doi.org/10.1177/0019793916673974

International Labour Organization. (1951). *C100 - Equal Remuneration Convention, 29 June 1951 (No. 100).* ILO Publications. https://web.archive.org/web/20240707035200/https://normlex.ilo.org/dyn/normlex/en/f?p=NORMLEXPUB:12100:0::NO::P12100_INSTRUMENT_ID:312245

International Labour Organization. (2018). *La brecha salarial en América Latina: estimaciones para cuatro países (Costa Rica, México, Perú y Uruguay).* ILO Publications. https://web.archive.org/web/20241107223010/https://www.ilo.org/es/resource/la-brecha-salarial-en-america-latina-estimaciones-para-cuatro-paises

Instituto Nacional de Estadística y Censos. (2023). *Encuesta Continua de Empleo alprimer trimestre 2023* [Data set].

Jiménez Cordero, R., & Morales Aguilar, N. (2012). Discriminación salarial en el mercado de trabajo en los noventas. *Revista de Ciencias Económicas, 30*(2), 30–51. https://doi.org/10.15517/rce.v30i2.8006

Juhn, C., Murphy, K. M., & Pierce, B. (1993). Wage inequality and the Rise in Returns to Skill. *The Journal of Political Economy, 101*(3), 410–442. https://doi.org/10.1086/261881

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica, 46*(1), 33–50. https://doi.org/10.2307/1913643

Madalozzo, R. (2010). Occupational segregation and the gender wage gap in Brazil: An empirical analysis. *Economia Aplicada, 14*(2), 147–168. https://doi.org/10.1590/S1413-80502010000200002

Mincer, J. A. (1974). *Schooling, Experience, and Earnings* (1st ed.). National Bureau of Economic Research. https://web.archive.org/web/20220307195144/https://www.nber.org/books-and-chapters/schooling-experience-and-earnings

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review, 14*(3), 693–709. https://doi.org/10.2307/2525981

Olivetti, C., & Petrongolo, B. (2008). Unequal Pay or Unequal Employment? A Cross-Country Analysis of Gender Gaps. *Journal of Labor Economics, 26*(4), 621–654. https://doi.org/10.1086/589458

Organisation for Economic Co-operation and Development. (2021). *Government at a Glance 2021, Country Fact Sheet: Costa Rica.* OECD Publishing. https://web.archive.org/web/20210709100229/https://www.oecd.org/gov/gov-at-a-glance-2021-costa-rica.pdf

Organisation for Economic Co-operation and Development. (2023). *OECD Economic Surveys: Costa Rica 2023.* OECD Publishing. https://doi.org/10.1787/8e8171b0-en

Organisation for Economic Co-operation and Development. (2023). *Gender wage gap (indicator)* [Data set]. OECD Publishing. https://doi.org/10.1787/7cee77aa-en

Organisation for Economic Co-operation and Development. (2019). *SIGI 2019 Global Report: Transforming Challenges into Opportunities, Social Institutions and Gender Index*. OECD Publishing. https://doi.org/10.1787/bc56d212-en

Regan, T. L., & Oaxaca, R. L. (2009). Work experience as a source of specification error in earnings models: implications for gender wage decompositions. *Journal of Population Economics, 22*(2), 463–499. https://doi.org/10.1007/s00148-007-0180-5

Reich, M., Gordon, D. M., & Edwards, R. C. (1973). A Theory of Labor Market Segmentation. *The American Economic Review, 63*(2), 359–365. http://www.jstor.org/stable/1817097

Rodríguez Zúñiga, M., & Segura Díaz, M. (2015). *¿Existe un techo de cristal en la distribución salarial femenina en Costa Rica?* [Memoria de seminario de graduación para optar por el grado de Licenciatura en Economía, Universidad de Costa Rica]. Repositorio Kerwá. http://repositorio.ciem.ucr.ac.cr/jspui/handle/123456789/171

Sakellariou, C. (2004). The use of quantile regressions in estimating gender wage differentials: a case study of the Philippines. *Applied Economics, 36*(9), 1001–1007. https://doi.org/10.1080/0003684042000233230

Torres, R. & Zaclicever, D. (2022) *Brecha salarial de género en Costa Rica: Una desigualdad persistente.* (Serie Comercio Internacional, N.º 169). Naciones Unidas. https://hdl.handle.net/11362/48049

United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development (A/RES/70/1).* United Nations General Assembly. https://documents.un.org/doc/undoc/gen/n15/291/89/pdf/n1529189.pdf

Weichselbaumer, D., & Winter-Ebmer, R. (2005). A Meta-Analysis of the International Gender Wage Gap. *Journal of Economic Surveys, 19*(3), 479–511. https://doi.org/10.1111/j.0950-0804.2005.00256.x

Xiu, L., & Gunderson, M. (2014). Glass ceiling or sticky floor? Quantile regression decomposition of the gender pay gap in China. *International Journal of Manpower, 35*(3), 306–326. https://doi.org/10.1108/IJM-01-2012-0017