LUND UNIVERSITY
School of Economics and Management

Master in Economic Development and Growth

Gender Wage Gap in Urban Nicaragua: Evidence from Decomposition Analysis

Eduardo Camilo Pacheco Medina
eduardo_camilo.pacheco_medina.469@student.lu.se

Abstract: This paper empirically investigates explanations to the gender wage gap in urban Nicaragua for 2005 and 2009. For this task, using data from the EMNV survey, we applied an Oaxaca-Blinder (1973) decomposition (standard and correcting for selection bias) of the mean wage and the novel Recentered Influence Function (RIF) regression method introduced by Firpo, Fortin, and Lemieux (2009) for the wage distribution. In this way, we explore in detail which factors influence the mean wage gap and the presence of a "sticky floor effect". The results show that the wage structure accounts for a large share of the differences in mean wages and across the distribution. We do not find evidence that selection bias affects this result for the mean. Moreover, we found a reduction in the wage gap and in discrimination during the period of study, especially at the lower and upper part of the distribution. We argue that the mean gap and the differences at the upper half are driven by taste-based discrimination outlined in Becker's (1971) view. In contrast, the sticky floor effect is driven by occupational segregation due to discrimination in commerce and service activities. Meanwhile, at the upper part of the distribution this effect appears in sales and clerical occupations.

Keywords: Gender wage gap, Nicaragua, discrimination, Oaxaca-Blinder, RIF-regressions.

EKHR92

Master Thesis (15 credits ECTS)

June 2013

Supervisor: Jonas Helgertz

Examiner: Anders Nilsson

Acknowledgements

I would like to thank my Supervisor, Jonas Helgertz for excellent guidance and helpful comments. Also, I would like to thank Jonas Ljungberg for his guidance and support during my studies in Lund. I acknowledge comments and suggestions provided by Dalia Fadly, Laura Giles, Tania Guerra, Juan Pablo Bermeo and Andrea Papini, especially for giving me a better understanding of the labor markets in the developing world.

Also, I am particularly indebted to Kathya Ríos, Alda Cecilia Castro and Alvaro López, for sharing invaluable information and their views regarding the household surveys in Nicaragua.

I am especially indebted to my family, my father, my mother and my sister for their spiritual support, advice and encouragement over these two years of my studies abroad. I will be always indebted to Dalia Fadly for all her love, support, teaching, encouragement and thousand other reasons that are impossible to enumerate. You will always be in my heart.

I am also grateful to Jilber Urbina, Eduardo Medina, Gabriela Centeno and Samantha Bendaña for their support, advice and encouragement at different stages of my studies.

Last but not least, I would like to dedicate my thesis to my grandparents. In their persistent struggle in life, I have found inspiration and admiration. I hope to follow their example and always strive to achieve my goals.

Any mistakes or inaccuracies are my sole responsibility.

Contents

List of Tables

List of Figures

1 Introduction

After a period of economic stagnation, rising unemployment and hyperinflation during the mid-1980s and early 1990s, Nicaragua has experienced sustained economic growth during the period 1994-2009 (see figure 10 in appendix).[1] Despite these improvements, a high level of inequality still persists, as proven by the Gini index of 0.46 for 2009 (Gobierno de Reconciliación y Unidad Nacional -GRUN-, 2012).[2] This suggests that certain sectors of the population have not benefited to the same extent from positive economic growth.

In this context, gender inequality in the Nicaraguan labor market is of special interest; as historically women have faced greater obstacles to access the labor market and lower returns to their work. Although this topic has been extensively discussed for developed countries and several Latin American countries, it is an under-researched area for Nicaragua, which is the second poorest country in Latin America (ECLAC, 2012).[3] Furthermore, the study of gender disparities in Nicaragua is more relevant nowadays; as the country is in a process of change in the gender roles towards a greater labor division within the household. As a result, women are able to participate more actively in the labor market (Agurto, Guido, Alaniz, Sandino, Acevedo and Michell, 2008).

The existing literature on the prevalence of gender wage differentials in Nicaragua is very scarce. In particular, the few studies that exist have not analyzed beyond the mean wage based on the Oaxaca-Blinder decomposition (1973) and extensions. This approach divides the mean wage gap into two components: composition (explained part) and wage structure (unexplained part) effect. The first, measures differences in observed characteristics between men and women, whereas the latter accounts for the differences in the returns to these characteristics, which are generally attributed to the effect of discrimination (Oaxaca, 1973; Fortin, Lemieux and Firpo, 2010). Indeed, it has been the wage structure effect which has prevailed as the major determinant of the gender wage differentials in Nicaragua to date (see e.g. Agurto et al. 2008; Enamorado, Izaguirre and

[1] According to data from the Central Bank of Nicaragua (BCN), the average real GDP growth (%) of Nicaragua over the period 1994-2009 was 3.8%.

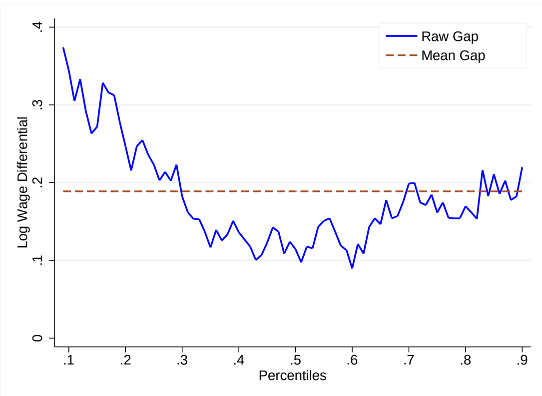
[2] Although Nicaragua has high levels of income inequality, it has been reduced over the last years. The Gini index fell from 0.51 in 2005 to 0.46 in 2009 (GRUN, 2012). Furthermore, Nicaragua has been one of the Latin American countries with greater decrease in inequality in recent years (Economic Comission for Latin America and the Caribbean -ECLAC-, 2012).

[3] According to ECLAC (2012), the incidence of poverty in Nicaragua, measured as the proportion of the population living below the poverty line, is 58.3% in 2009. This figure is only higher in Honduras, in which the incidence of poverty is 67.4% in 2010.

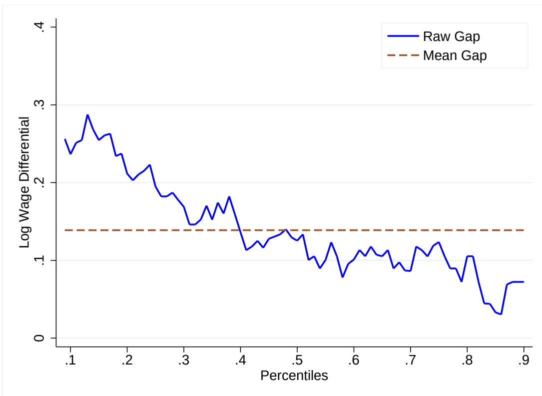
Ñopo, 2009). Thus, previous evidence reveals that "pure discrimination" and not the difference in workers' endowments is the main reason behind the gender wage gap. In this context, pure gender discrimination can be defined as the unequal treatment (different wages) to women with the same productive capabilities as men (Altonji and Blank, 1999). Nevertheless, discrimination appears due to different reasons such as employer's taste, statistical discrimination or occupational segregation.

Moreover, the wage gap is not homogeneous across the entire wage distribution. In fact, looking at different percentiles (see figure 1) we observe that the disparity in wages in urban Nicaragua for 2005 have some sort of a U-shaped form. The gaps are larger at the bottom and the top of the distribution, although the largest difference is observed at the lower percentiles. This is known as a "sticky floor effect" (Arulampalam, Booth and Bryan, 2007). Meanwhile, for 2009 the gaps have been reduced at both extremes of the distribution. The largest difference is still observed at the bottom of the distribution.

Figure 1: Gender Wage Gap in Urban Nicaragua



2005



2009

Source: Author's calculation based on EMNV 2005 and 2009.

Taking into account these issues, this research seeks to go beyond the existing literature by analyzing in detail the determining factors of the gender wage gap in urban Nicaragua for 2005 and 2009. In so doing, we aim to extend the existing literature in several ways. Firstly, we perform a detailed decomposition of the mean wage gap for 2005 and 2009. In this way, it is possible to capture the different forms that discrimination takes. Secondly, we update the determinants of the wage gap for 2009, which have not been explored before. Thirdly, we control for potential sample selection bias using the two-step procedure proposed by Heckman (1979). A large literature stresses that standard techniques may produce biased estimates when using only samples of working individuals. In this manner, it is acknowledged that the estimated wage differentials and the decomposition might be different when accounting for the effect of labor market participation. Fourthly, we provide a better understanding of the labor market in Nicaragua by exploring the determining factors of labor market participation in the urban area, which has not been addressed before - at least to the best of our knowledge - from a gender perspective.[4]

Finally and more importantly, we carry out detailed decompositions for the wage distribution rather than only for the mean. In so doing we are the first study - to the best of our knowledge - that applies this type of decomposition for Nicaragua. Recent studies (see e.g. Albrecht, Björklund and Vroman, 2003; Chi and Li, 2008) have stressed the importance of this type of analysis, as the gender wage gap tends to be different across the distribution, as observed in figure 1 for the case of urban Nicaragua. The detailed decomposition allows us to estimate the specific effect of different factors to the wage differential and evaluate if the impact is the same across the distribution. This was not possible to carry out in a holistic manner until the recent development of the Recentered Influence Function (RIF) regression by Firpo, Fortin and Lemieux (2009). This technique performs a detailed decomposition of the wage distribution in the same vein of the traditional Oaxaca-Blinder method. More importantly, the decomposition results are based on unconditional quantiles, so it computes the direct effect of a given factor on a specific percentile of the distribution, which is of particular interest in applied economics (Firpo, Fortin and Lemieux, 2009).

In order to capture the different forms that discrimination can take and to test if observed characteristics such as human capital have an impact along the wage distribution, we study the effect of the differences in educational attainment, experience, regions and job-related characteristics on the gender wage gap. The latter variables allow us to analyze the relation between occupational segregation and discrimination.

By means of these contributions, this study aims to answer five questions: Does participation into the labor market affect the differences in wages by gender? Are discriminatory levels in average wages been reduced between 2005 and 2009? Does discrimination

[4]Previous research has analyzed the probability of working in a given job (see Gutierrez, Paci and Ranzani, 2008) and the probability of working of the youth who chose not to study (see Central Bank of Nicaragua -BCN-, 2012).

have the same effect on the wage gap along the distribution? What are the factors in which discrimination takes form? Does differences in endowments play a role in offsetting discrimination in mean wages and across the distribution?

In order to answer these questions, we apply decomposition methods using data from the National Household Living Standards Survey (EMNV) for 2005 and 2009. Nicaragua provides an interesting scenario to study the gender differences in wages during this period because in 2007, Daniel Ortega in representation of the Frente Sandinista de Liberación Nacional (FSLN) party, came into office. Since then, a new package of policies towards social issues including gender equity were implemented in substitution of the trickle-down approach based on the Washington Consensus. Thus, our data does not only provide an updated view of the wage gaps but also might capture some of the effects of the policy shift under Ortega's administration.

The paper is organized as follows. Section 2 reviews the literature that analyzed the gender wage gap in Latin America with special focus in Central American countries and especially Nicaragua. Section 3 discusses the theoretical framework. Section 4 describes the data of the National Household Living Standards Survey (EMNV). Section 5 explains the empirical strategy. Section 6 discusses the results of the decompositions. Finally, conclusions will be presented in section 6.

2 Literature Review

A large extensive literature has analyzed the determining factors of inequalities in the labor markets.[5] Extensive research into this topic is based on decomposition methods, which allows for studying of the differences in wages by population groups. This literature has its origins on the seminal papers of Oaxaca (1973) and Blinder (1973) which are inspired by Becker's (1971) work on discrimination. From these contributions, many scholars have extended this approach by looking at differences in mean wages (see e.g. Reimers, 1983; Neumark, 1988; Cotton, 1988; Fortin, 2008) and recently at changes across the distribution (see e.g. Juhn, Murphy and Pierce, 1993; DiNardo, Fortin and Lemieux,

[5] An alternative approach explores the inequalities at household level (focused on income), which is practically an extension of the literature on wage distribution (see e.g. Bourguignon, Ferreira and Lustig (2005) and Bourguignon, Ferreira and Leite (2008).

1996; Machado and Mata, 2005; Firpo, Fortin and Lemieux, 2009).[6]

Gender wage disparities have been of special interest. Although most of the studies on this issue have been applied on the developed world, there is growing interest in understanding the determinants of women's participation in the labor market in Latin America, and the explanations of a wage gap favoring men. An early contribution on this topic for the region can be found in Psacharopoulos and Tzannatos (1992), who compile case studies for 15 Latin American countries during the 80s. Using national household surveys, most of the studies reviewed apply an Oaxaca-Blinder decomposition, correcting for potential sample selection bias in the way suggested by Heckman (1979). The decompositions are done based on a Mincer-type equation which uses hourly wages or monthly earnings as dependent variable and years of schooling, experience, experience squared and hours worked -in some cases- as regressors. Among the overall findings, most of the differences in wages between men and women are attributed to unexplained factors, which Psacharopoulos and Tzannatos (1992) argue represent an "upper bound to discrimination". This is because there are other factors that might influence wages which are not included in the estimations, consequently the level of discrimination would be upward biased.

A recent attempt to summarize the findings on gender wage gaps in the region is in Atal, Ñopo and Winder (2010), who survey the literature for 18 countries in a multi-country approach and country-specific studies. Three important considerations can be derived from their review. Firstly, cross-country heterogeneities avoid reaching a consensus whether disparities in earnings by gender in the region have been reduced over time or not.[7] Secondly, the mixed evidence suggests that wage gaps are still present even when women have increased their participation in the labor market. Thirdly, although discrimination seems to have declined over time, it still plays an important role in wage differentials. Moreover, as the gender gap in schooling has narrowed (Duryea, Galiani, Ñopo and Piras, 2007), other observed factors such as experience or labor market segregation, might have more relevance in determining the wage gap.

For Central American countries, Psacharopoulos and Tzannatos (1992) and Atal, Ñopo

[6] Comprehensive reviews on this topic can be found in Bourguignon, Ferreira and Leite (2008) and Fortin, Lemieux and Firpo (2010), especially regarding regression-based decompositions.

[7] Ñopo and Hoyos (2010) find a reduction in the wage gaps for the same 18 Latin American countries as a whole between the early 90s and the mid-2000s.

and Winder (2010) have found relatively low gender wage gaps compared to other Latin American countries. Nevertheless, the determinants of the earnings gap are different across countries. In Psacharopoulos and Tzannatos (1992) it is found that females earn about 80% of males earnings for 1989 in Costa Rica, Honduras, Panamá and Guatemala. For the first three countries, these differences appear to be mainly accounted by unobserved characteristics, including discrimination. Meanwhile, half of the earnings differentials in Guatemala is explained by endowment factors, although discrimination appears to be more important in the formal sector (Arends, 1992). In accordance with these results, Tenjo, Ribero and Bernat (2005) also find evidence of discrimination in Costa Rica and Honduras for 1989 and 1998, although for the case of Honduras this effect is being offset by higher women endowments.[8].

Some limitations in the studies compiled by Psacharopoulos and Tzannatos (1992) and in Tenjo, Ribero and Bernat (2005) is that the potential non-linear relation between earnings and educational attainment, as well as the effect of occupational segregation in wages are not explored. Regarding the latter, it has been shown that the presence of segregation in the labor market in some Latin American countries (see e.g. Deutsch, Morrison, Ñopo and Piras, 2005). This might influence wages of women and men if segmentation comes from differences in skills or job-preferences (Polacheck, 1985; Anker, 1997). Furthermore, segmentation may also arise as a result of discrimination on the choice of occupations (Altonji and Blank, 1999).

Aware of this issue, Atal, Ñopo and Winder (2010) include job-related characteristics in a framework that uses matching comparisons in order to analyze the earnings gaps in 18 Latin American countries.[9] Nevertheless, different from previous research, they do not find evidence that segregation is a relevant determinant of the earnings gap for the 18 countries analyzed. They also observe that Central American countries show lower gender gaps compared to the rest of the countries in Latin America. Moreover, it is found that a greater share of the wage gap is accounted by unobserved characteristics. This suggests that discrimination might still play an important role. The same consideration is given by Enamorado, Izaguirre and Ñopo (2009).

[8]This argument is built on the results of an Oaxaca-Blinder decomposition using a standard Mincerian earnings function

[9]The authors include variables that capture the type of employment, formality, occupational category and firm size. For further reference on the matching procedure see Ñopo (2004).

Despite extensive discussions about the role of women in the Nicaraguan labor market, there is little knowledge about the gender wage gap and its determinants.[10] Monrroy (2008) observes that the difference in average wages between men and women (as percentage of men wages) is 19.8% for 2005. Meanwhile, Agurto *et al.* (2008) estimate that women earn about 79% of men wages in 2006. Using their calculations, the differences in wages between men and women (as percentage of men wages) is 21.0% for 2006. Contrary to these findings, Atal, Ñopo and Winder (2010) find a much lower wage gap (as a percentage of women wages) of 1.5% also for 2005. In addition, Enamorado, Izaguirre and Ñopo (2009) estimate a reduction in the wage gap (as a percentage of women wages) from 5.1% in 1998 to 2.6% in 2005. Furthermore, they report a greater gap of 17.2% among urban workers in 2005.

There is a problem of comparability in these studies, which influences the large discrepancies among the estimated gaps. First, Agurto *et al.* (2008) use a household survey undertaken by the *Fundación Internacional para el Desafío Económico Global* (FIDEG) in 2006.[11] In contrast, Monrroy (2008), Atal, Ñopo and Winder (2010) and Enamorado, Izaguirre and Ñopo (2009) use the National Household Living Standards Survey (EMNV). Second, while Atal, Ñopo and Winder (2010) select a sample that covers individuals between ages 18-65, Monrroy (2008) and Agurto *et al.* (2008) include individuals from 10 years old onwards and between ages 11-64 respectively. In a more flexible selection, Enamorado, Izaguirre and Ñopo (2009) account for all the individuals in the sample that show positives hourly wages. Third, Monrroy (2008) assess differences in mean wages between men and women using males as reference group, while Atal *et al.* (2010) chose women as reference.

Although the existing evidence shows mixed estimations of the raw gap, the determinants of the gender gap seem to be similar in these studies. In Agurto *et al.* (2008) an Oaxaca-Blinder decomposition is implemented in the same way as in Psacharopoulos and Tzannatos (1992).[12] They argue that unobserved characteristics including discrimination against women explains 91.2% of the earnings gap (in favour of men) and the differences in endowments account for the remaining 8.8%. Moreover, they observe that

[10]Tinoco and Agurto (2003) and Agurto *et al.* (2008) are specialized researches on socio-economic status of women in Nicaragua.

[11]FIDEG is an independent think tank specialized on socio-economic research.

[12]Instead of estimating the model by OLS, a tobit (truncated) regression model is computed in order to control by self-selection due to non observed earnings.

men have higher returns to schooling and (potential) experience compared to women. Consistent with this view, using a matching procedure, Atal, Ñopo and Winder (2010) and Enamorado, Izaguirre and Ñopo (2009) report that a significant share of the wage gap is accounted by unexplained factors (including discrimination), with this effect being greater in urban areas.

Some limitations in these studies exist; it is only possible to identify the aggregate decomposition and it does not account for potential sample selection bias. Regarding the latter, standard techniques may produce biased estimates when using non-random samples. Therefore, a large number of studies have addressed this issue by applying a sample selection correction.[13] In this paper, we correct for potential sample selection bias using the two-step procedure proposed by Heckman (1979) and we discuss the sensibility of the results by comparing it with the standard Oaxaca-Blinder method.

Furthermore, since most of the evidence relies on the Oaxaca-Blinder method, there is no formal discussion about the gaps across the earnings distribution. Some considerations can be found in Monrroy (2008), who find that unskilled workers such as laborers and farm workers show the smaller gap and the largest gap appears to be in the agricultural and fishing sectors. Moreover, Ñopo and Hoyos (2010) find that the unexplained gap is greater at the top of the distribution and has increased at the top half of the earnings distribution (45th-100th percentiles) between 1993-2005.

In our case study for urban Nicaragua, the determinants of the wage gap at different points of the distribution using the Recentered Influence Function (RIF) regression method introduced by Firpo, Fortin and Lemieux (2009) are explored. As mentioned before, the RIF regression is a novel method that has begun to take place in the empirical literature that addresses wage inequalities.[14] Regarding gender wage gap, this approach has been useful for understanding the factors that explain the presence of "sticky floor" and "glass ceiling" effects.[15] The advantage of this approach is that allows us to compute a detailed decomposition as in a standard Oaxaca-Blinder decomposition. In this way, it

[13]See Vella (1998) and Beblo, Beninger, Heinze and Laisney (2003) for an extensive discussion of the methods that deal with the sample selection problem.

[14]There are other methods that also decompose the entire distribution of wages. Some of them can be found in DiNardo, Fortin and Lemieux (1996), Machado and Mata (2005) and Chernozhukov, Fernandez-Val and Melly (2009). See Fortin, Lemieux and Firpo (2010) for a deeper discussion on these approaches.

[15]Albrecht, Björklund and Vroman (2003) define the glass ceiling effect as a larger wage gap at the upper part of the distribution.

is possible to evaluate if the effects of different factors are the same across the distribution.

Other authors have looked these issues using the RIF method and found different results. For example, Chi and Li (2008) found a sticky floor effect in urban China during 1987-2004. This effect is driven by lower returns to education for women, which suggest evidence of discrimination at the bottom of the distribution. Moreover, the gap at the upper end of the distribution is mainly accounted by difference in human capital. In contrast, Salardi (2013) found the presence of both effects (sticky and glass ceiling) for Brazil during 1987-2006. She observes that these effects are driven by the wage structure, especially at the bottom of the distribution, although it has declined over time. A different approach is taken by Adireksombat, Zheng and Sakellariou (2010), who analyze changes in the wage differences by gender over time (1991-2007) for Thailand. They found the presence of sticky floors effects, which are mainly explained by discrimination. However, they also report a reduction in gender inequality during the period of study.

As mentioned before, previous research for Nicaragua provides only suggestive evidence of the patterns of the wage gap along the distribution. In this paper, we go beyond by performing a detailed decomposition of the differences in wages across the distribution. Even when previous evidence shows that discrimination accounted for a large share of the mean wage gap in 2005 and 2006, our study is an initial effort to test if this view is the same at different percentiles for 2005 and 2009 and which form of discrimination prevails.

3 Why Do Women Have Lower Wages than Men?

Economists have since long studied the determining factors of the gender wage gap based on a Mincer-type (1958) earnings equation,

$$ln(w_i) = \alpha + \gamma_s s_i + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i \tag{1}$$

where w is the hourly wage of worker i, s corresponds to the schooling level and x is the work experience. α is a constant term and ε is an error term that included unobserved characteristics, which are assume to be uncorrelated with the explanatory variables $[E(\varepsilon|s,x) = 0]$.

Equation (1) has been extended over time by including other covariates and relaxing the functional form. In this regard, economic theory emphasizes that differences in human capital (education, experience, skills), preferences, occupational segregation and discrimination may explain why women may have lower wages than men (see Becker, 1971; Anker, 1997; Altonji and Blank, 1999). Thus, following Oaxaca (1973), all the observable individual characteristics that capture these issues (X) are included in the right hand side of the equation,

$$Y_i = X_i\beta_i + \varepsilon_i \tag{2}$$

where Y corresponds to $ln(w)$. i is composed of males A and females B. ε is assumed to be independent of the covariates ($E[\varepsilon_i|X] = 0$).

Based on equation (2), the mean wage gap is given by,

$$E(Y_A - Y_B) = E(X_A)\beta_A - E(X_B)\beta_B \tag{3}$$

Subsequently, we add and subtract the counterfactual $\beta_A X_B$, which is the average wage that females would have if they had the same returns to observed characteristics as males. Thus, equation (3) can be rearranged as follows,

$$E(Y_A - Y_B) = \underbrace{[E(X_A) - E(X_B)]\beta_A}_{\text{Composition effect}} + \underbrace{E(X_B)[\beta_A - \beta_B]}_{\text{Wage structure effect}} \tag{4}$$

Based on equation (4), the determinants of the wage gender gap can be divided into two main sources, one is attributed to differences in observed characteristics (composition) and the other to differences in the returns between groups, under the assumption that they share the same characteristics (wage structure). The latter is related to differences due to discrimination. We build our empirical strategy following this framework, which we discuss next.

3.1 Composition Effect

3.1.1 Human Capital Theory

One of the sources of the gender wage gap is the differences in the composition of the workforce. The human capital model states a positive relation between educational attainment, experience and earnings (Altonji and Blank, 1999). Therefore, to the extent that women have lower endowments than men, they may be less paid. A key factor in this model is that investment in human capital depends on how much time the individual expects to devote to market and non-market work (Altonji and Blank, 1999). This decision might be influenced by marital status, child-bearing and child-caring, as these factors determine the division of labor in the household and therefore market work decisions over the life-cycle (Polachek, 2004). If the individual expects to work less hours or less years, the benefits from investing in human capital are lower and thus the incentives are smaller (Polachek, 2004).

Altonji and Blank (1999) point out that differences in human capital favoring men might also be a result of discrimination to access education, which they called as "pre-labor market discrimination". Also, discrimination towards women might arise within the family. For example, if it is perceived that boys' are more likely to be more economically active than girls, parents may prefer to invest more in boys education (Das Gupta, 1987).

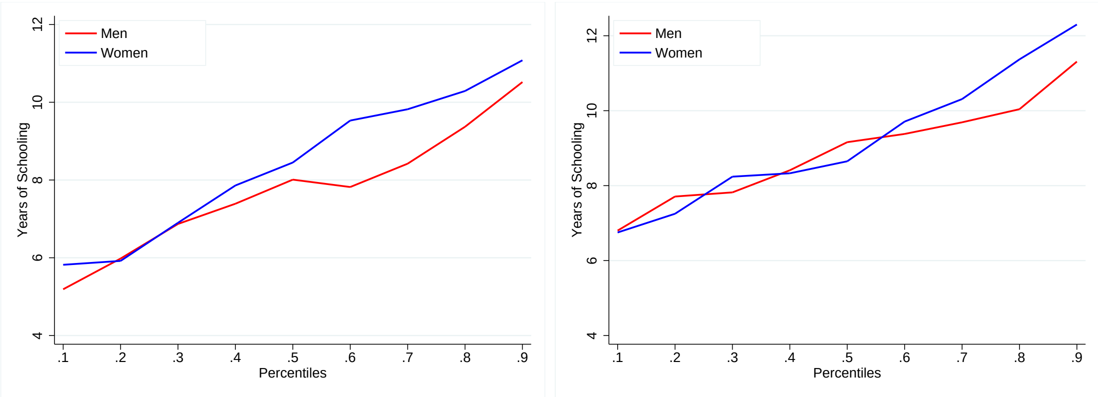
It has been argued that it is difficult to separate the effects of these sources of discrimination from the effects predicted by the human capital model (see Altonji and Blank, 1999). Nevertheless, this might not be the case for urban Nicaragua. Firstly, Monrroy (2008) observes that female participation in the labor market is higher in the urban area. Secondly, women labor market participation in urban areas has increased from 35.6% in 1993 to 45.6% in 2005 (Monrroy, 2008). Thirdly, fertility rates have decreased from 7.3 births per woman in the early 60s to 2.7 births per woman in 2009 (The World Bank, 2013). According to the human capital theory, we would expect rising educational attainment of women over time. This is also observed in the dataset. Women in Nicaragua show higher level of education since the 90s (Enamorado, Izaguirre and Ñopo, 2009). For 2005 and 2009 working women in urban area have on average 9.23 and 9.52 years of education, while working men have on average 8.62 and 8.97 respectively. This picture is similar across the wage distribution for 2005, although for 2009 women have greater educational attainment at the top half of the distribution (see figure 2).

Moreover, since women tend to devote more time to family (child-bearing and child-caring), they are more likely to withdraw temporarily from the labor force or work less hours. Therefore, accumulation of experience tend to be lower for women compared to men. In fact, this is observed by looking at data on occupational tenure for 2005.[16] On

[16]This data is not available for the 2009 EMNV survey.

average, men stay within the same occupation for 6.8 years while women stay it for 6.1 years (see table 7 in appendix). This difference is wider at the bottom and the top of the wage distribution (see figure 3). This might suggest that differences in job-training might explain part of the wage gap by gender at different points of the distribution.

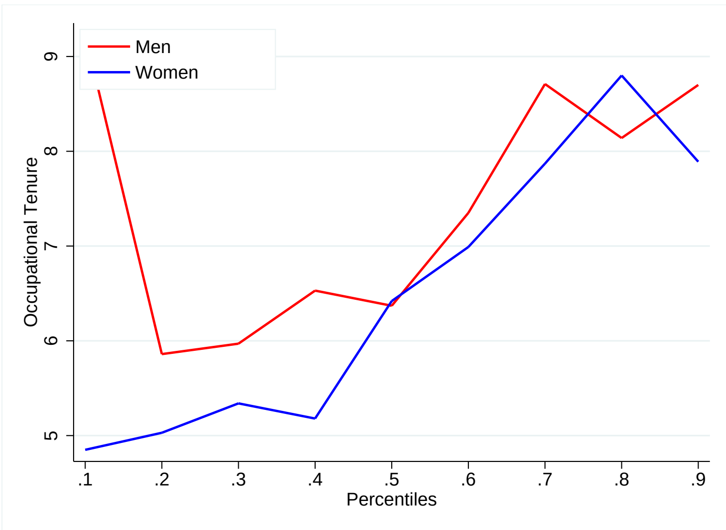
Figure 2: Educational Attainment Across the Wage Distribution



2005 **2009**

Source: Author's calculation based on EMNV 2005 and 2009.

Figure 3: Occupational Tenure in 2005 Across the Wage Distribution



Source: Author's calculation based on EMNV 2005.

3.1.2 Occupational Gender Segregation

Occupational segregation might appear due to different factors. One is related to the human capital model. Polachek (1985) points out that since women are more likely to be out of the labor force at different points of the life-cycle, they will choose occupations with less barriers to access; usually these occupations demand lower skills and have smaller returns to job-training. In competitive labor markets, "overcrowded" sectors by females will pay lower wages. In contrast, "male occupations" will be less competitive and thus wages will be higher (Bergmann, 1974).

Differences in preferences have also been considered as a source of gender occupational segregation. If women are willing to work in a pleasant job environment and are averse to work in certain occupations, while men are not averse to work in risky jobs, then there may be a wage premium for men. This is known as the compensating differentials model (Anker, 1997). Altonji and Blank (1999) stresses that it is difficult to identify the roots of the preferences by gender. This could be due to cultural and social processes or as a result of discrimination. Nevertheless, differences in wages due to occupational segregation are easy to identify (Blau and Kahn, 2000).

Other scholars view occupational segregation as a result of "stereotypes". Gender theories state that women are seen as subordinates and linked roles related to family care (Anker, 1997). Therefore, they tend to be located in occupations that demand lower human capital. For example, it has been shown that domestic help in Nicaragua is an occupation performed exclusively by women. Women are trained on this type of occupation since a young age as they devote time for household care. This is a result of the labor division at home (Agurto *et al.* 2008; Tinoco and Agurto, 2003). Furthermore, this theory can be related with the models of discrimination, which are discussed next.

3.2 Wage Structure Effect

The gender wage gap is not only determined by differences in observed characteristics, but also by the returns to these characteristics. In applied economics, researchers have analyzed this issue under the assumption of equality in endowment between groups. This is known as the wage structure effect and is analyzed based on theories of discrimination (see second term in equation (4)). Based on Altonji and Blank (1999), gender discrimination can be defined as the unequal treatment (different wages) to women with the same productive characteristics as men. There are several views about discrimination, but in our study we consider the following as the more suitable to the Nicaraguan context: taste-based discrimination (Becker, 1971), statistical discrimination (Phelps, 1972; Arrow, 1973) and occupational segregation due to discrimination.

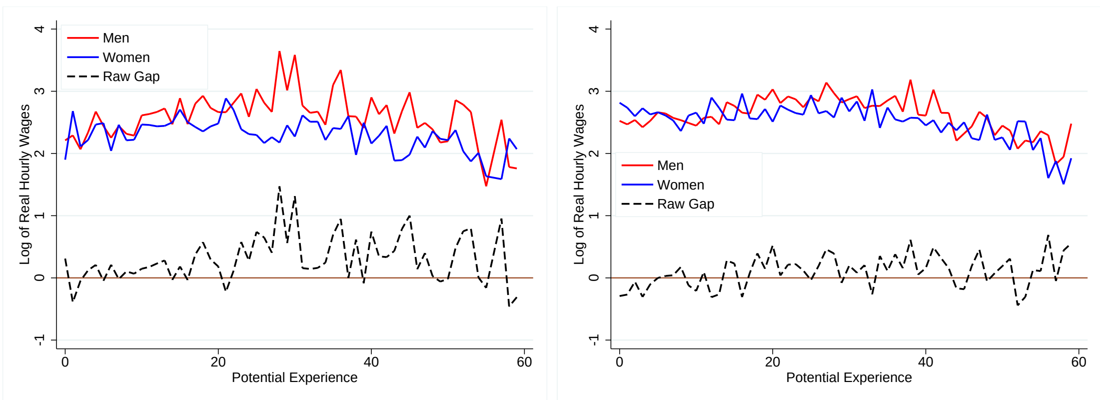
Becker's (1971) theory states that discrimination arises from the "taste for discrimination" by consumers, workers and employers. The latter has received more attention in the context of the gender wage gap (Tenjo, Ribero and Bernat, 2005). In this model employers discriminate a minority group (women), therefore, they are willing to pay less wages to women even if they share the same productive characteristics as men (Cain, 1986). Becker's model also predicts that in competitive markets non-discriminatory firms would have higher profits than discriminatory firms and eventually would be out of the market. This would imply a reduction in the wage gap, although Altonji and Blank (1999) stress that this is not what has been observed in the empirical literature. Furthermore, it has been argued that in non-competitive markets it is possible that the taste for discrimination will be persistent. This could be the case for example in the presence of monopolies and under imperfect information (Cain, 1986). Regarding the latter, this model states that women face greater search cost in markets where there is imperfect information about the employer's taste for discrimination. This will reduce women's wage reservation relative to men and therefore their wages will be lower (see Black, 1995).

As an alternative to Becker's theories, the statistical discrimination model was proposed by Phelps (1972) and Arrow (1973). This framework states that differences in wages result from employers' discrimination based on judgements (prior beliefs) or the expected productivity of men and women. In presence of imperfect information, employers rely on stereotypes or on average information of individuals' productivity in order to determine wages (Aigner and Cain, 1977). Statistical discrimination is difficult to test in practice, as the way in which employers form their expectations is uncertain and statistical discrimination might also be confused with taste-based discrimination (Altonji and Blank, 1999). Nevertheless, some scholars have found evidence of statistical discrimination using decomposition methods (see e.g. Tenjo, Ribero and Bernat, 2005).

Finally, a framework that has drawn attention is occupational segregation due to discrimination. According to Altonji and Blank (1999), overcrowded occupations by females are due to social processes, institutional restrictions and employer's discrimination. However, social processes might also be shaped by pre-market discrimination. For example, the educational system or the family can influence women's preferences by raising them based on discriminatory beliefs regarding the role of women in economic activities (Altonji and Blank, 1999). Meanwhile, both the taste for discrimination and stereotypes might determine employer's discrimination. This subject has been largely debated among scholars, as segregation may be influenced not only by non-cognitive skills, ability and preferences but also by different forms of discrimination (Antecol and Cobb-Clark, 2010). This issue challenges the precision of the attempts to measure the level of discrimination that women suffer by using decomposition methods.

Despite the difficulties to differentiate among different types of discrimination, it is possible to identify from the data for urban Nicaragua some level of discrimination in a broad sense. For example, looking at the earnings profiles over the life-cycle, proxied by potential experience, we observe an inverted U shaped pattern as the human capital model predicts (see figure 4).[17] More importantly, the wage structure at the same level of experience is higher for men in almost all stages of the life-cycle for 2005, especially from 20 years onwards. In contrast, these gaps seem to have narrowed for 2009, which may suggest a reduction of discriminatory levels.

Figure 4: Returns to Experience



2005 **2009**

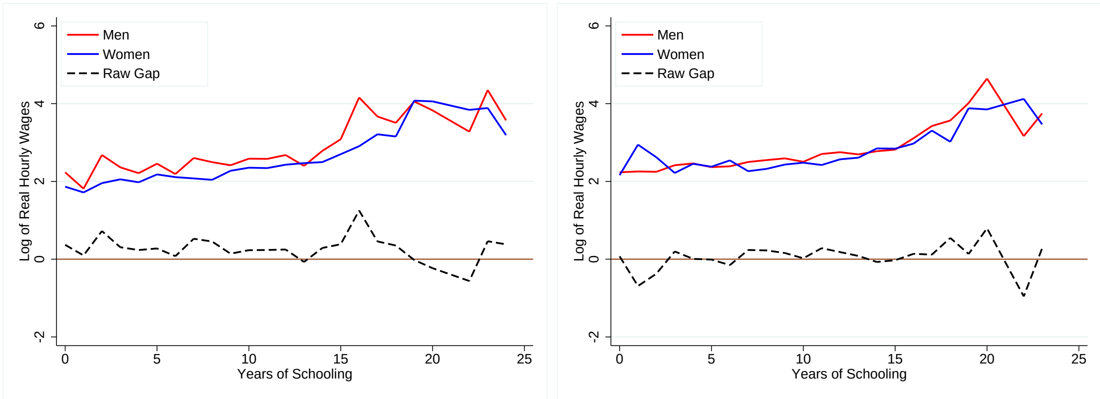
Source: Author's calculation based on EMNV 2005 and 2009.

The picture is quite similar by exploring the returns at the same level of education (see figure 5). For 2005, returns to education are greater for men up to university levels. This

[17]Potential experience is constructed as age minus years of education minus six.

suggests that there might not be an unequal treatment at postgraduate level. Meanwhile, the differences in payments are marginal for 2009.

Figure 5: Returns to Schooling



2005 **2009**

Source: Author's calculation based on EMNV 2005 and 2009.

4 Data

The data used in this study come from the National Household Living Standards Survey (EMNV) for 2005 and 2009 conducted by the National Institute for Development Information (INIDE) of Nicaragua.[18] The EMNV surveys include a random sample with national coverage and provide cross-sectional information on household consumption, income and poverty.[19] The design of the survey is based on the methodology developed by the World Bank under the project Living Standards Measurement Study (LSMS).[20] Despite some minor divergence in the questionnaires, both surveys should be compatible and comparisons over time can be derived using a set of harmonized variables.

The datasets contain information for 36,612 individuals from 6,882 households for 2005 and 30,432 individuals from 6,515 households for 2009. Information is available on the characteristics of the individuals such as sex, age, region (Managua, Pacific, Central, Atlantic), area of residence, civil status and educational attainment. Moreover, it is

[18] *Encuesta de Hogares sobre Medición del Nivel de Vida.*
[19] We use the sampling expansion factor of each survey in order to represent the working and non-working population of the country.
[20] 5 surveys have been undertaken for the years 1993, 1998, 2001, 2005 and 2009.

possible to compute household characteristics such as number of persons living in the household, number of children younger than 14 years old and number of persons employed. Data on labor market characteristics includes information on the numbers of hours worked, labor income and number of individuals by occupational category, economic sector and occupational classes.

We restrict our analysis to the urban area. We adopt this approach because analyzing urban and rural areas as a whole might provide a misleading view of the gender wage gap in Nicaragua. This could be because labor market characteristics in rural area differ from the urban in terms of productivity and remuneration. Furthermore, employment is different in the rural area as it depends to some extent on the harvest season.

By focusing on the population in urban areas we obtain information for 17,287 and 21,698 individuals for 2005 and 2009, respectively. We restrict the analysis to individuals between ages 14 and 65 years old in order to avoid the influence of education and retirement choices in labor market participation (Beblo, Beninger, Heinze and Laisney, 2003). Unpaid family and non-family workers and disabled individuals are also excluded. Moreover, while in previous research a minimum age for work of 10 or 11 years has been used (see e.g. Monrroy, 2008; Agurto *et al.* 2008), we use the minimum age of 14 years old established in the Code of Childhood and Adolescence and by the Ministry of labor.[21] We do this because less than 2.0% of the children between ages 10-13 in both samples are working. This implies that most of these children are full-time students and their selection into labor market may be different from the rest of the individuals in the sample. Finally, individuals from which there is any missing value in the variables used in the analysis are excluded. The final sample for 2005 includes 3437 working men, 2551 working women, 1481 unemployed men and 3238 unemployed women. Meanwhile, the sample for 2009 covers 4421 working men, 3545 working women, 2193 unemployed men and 4036 unemployed women.

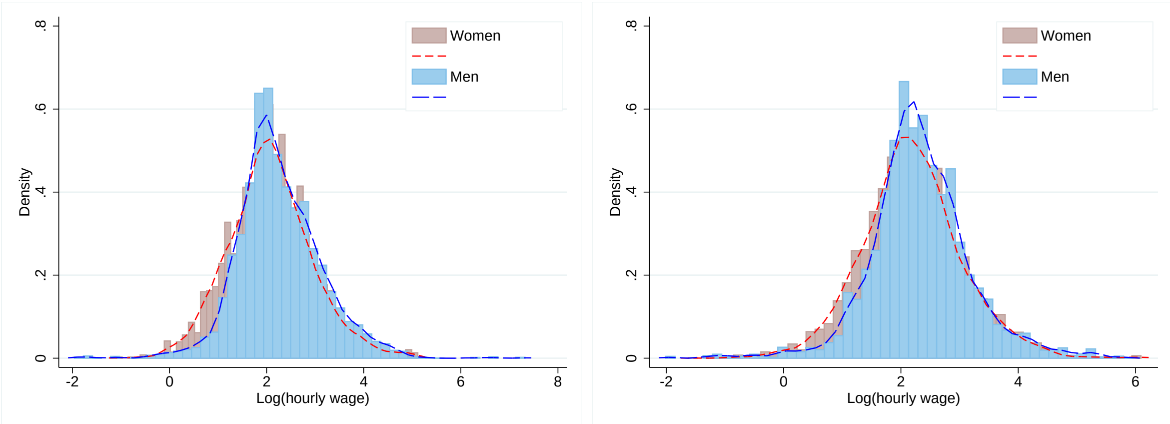
Working individuals are classified as those who reported positive hours and earnings.[22] Wages are computed using the labor income from the primary occupation. Earnings are reported in several frequencies (daily, weekly, biweekly, monthly, quarterly, semester and annual). Therefore we standardize the data to a weekly frequency as the survey show

[21] *Código de la Niñez y la Adolescencia* (Law No. 287) and *Ministerial Agreement JCHG-010-06-07* approved on May 23, 2007 by the Minister of labor of Nicaragua.

[22] Observations with outliers in hours and earnings are also excluded.

information on the usual hours worked per week.[23] Hourly wages are then obtained by dividing wages by the number of hours worked. In order to allow for comparability between the 2005 and 2009 surveys nominal hourly wages are transformed to constant values of 2005 using the national consumer price index (CPI).[24]

Figure 6: Kernel Densities of Log Real Wages per Hour



(a) 2005 **(b) 2009**

Note: Kernel density functions using Epanechnikov kernel function.

Source: Author's calculation based on EMNV 2005 and 2009.

Figure 6 shows the Kernel density estimates of the logarithm of real wages per hour for 2005 and 2009. Looking at these plots we get a preliminary view of the raw gender wage gap. In overall, the distribution of hourly wages by sex is different in both years. Men's wage density is skewed to the right, especially for 2009. Moreover, the gaps do not seem to be constant across the distribution over the period of study. For 2005, the gap looks greater at the bottom of the wage distribution, but there is also a marked gap at the top. For 2009, the gaps are greater at the bottom and at the middle of the distribution but is marginal at the top. These figures give support to the idea of exploring the determinants of these gaps across the distribution rather than exclusively at the mean.

Educational attainment is constructed based on the educational level and last year succeeded reported in the survey. Complete primary education is 6 years and complete

[23]Based on Ahmed and Maitra (2010), the daily wage is converted to a weekly frequency assuming that individuals work 6 days during the week. Furthermore, we assume that there are 4.3 working weeks per month.

[24]The CPI published by the Central Bank of Nicaragua is in base year 2006=100, thus the index is transformed to a base year 2005=100.

secondary is 5 years. Technical (vocational) education includes basic, middle, superior and teacher training. Tertiary education includes college, master and doctorate level. We exclude individuals with special education. Based on this criteria we construct 4 dummy variables: none or primary incomplete; primary complete or secondary incomplete; secondary complete, tertiary or technical incomplete; and tertiary and technical complete. In this way, we capture potential non-linearities in the returns to education.

Potential experience is approximated in the traditional way: *experience = age - years of education - 6.* The number of years of education is not reported in the survey and there is no official publication - at least to the best of our knowledge - that established the minimum required of years of education to access different stages of educational level. Taking into account this limitation, we estimate the years of education by assuming that the minimum required to access to secondary education and teacher training is 7 years of education, basic technical education is at least 8 years, middle technical education is 9 years, superior technical education and university is 12 years, master degree is 17 years and doctorate level 19 years. Meanwhile, at age 6 children are supposed to start attending school. Potential experience is modelled as dummy variables that capture experience groups. A valid concern regarding this variable is that it tends to overstate the experience; it does not account periods in which individuals are absent from the labor market. This overstatement tend to be greater for women as they are more likely to temporarily withdraw from the labor market due to child caring (Arends, 1992; Scott, 1992). This is in agreement with the graphical inspection performed in figure 3.

Another variable that captures working experience is occupational tenure. This information is available for the 2005 survey but not for 2009. Therefore, we chose to explore the role of occupational tenure for 2005 instead of potential experience and we discuss how the results are sensitive to the inclusion of this variable. It is worthy to emphasize that potential experience and occupational tenure do not account for the same effect, as the latter does not necessarily capture experience during the life cycle.[25]

Several dummy variables were constructed in order to capture job-related characteristics. Occupational category is divided in self-employed, employee and employer. Economic activity classes are constructed using the Standard Classification of Economic Activities of

[25] Ñopo and Hoyos (2010) explore the role of job tenure for six Latin American countries as a whole (including Nicaragua) for the early 90s and middle 2000.

Nicaragua, which is based on the International Standard Industrial Classification of All Economic Activities (ISIC) published by the United Nations. Meanwhile, occupations classes are constructed using the Standard Classification of Occupations of Nicaragua which is based on the International Standard Classification of Occupations (ISCO - 88) published by the International labor Organization (ILO).

We address selectivity in participation using Heckman's correction (1979) and by analyzing the decision of entering into the labor market. There is no consensus on how to classify the labor market participation. Beblo *et al.* (2003) exclude unemployed individuals as they show different characteristics from those individuals "voluntarily not employed". In contrast, other scholars state that an individual participates in the labor force if he/she is working, searching for a job or temporarily unemployed (see e.g. Ng, 1992). In this study, we chose to follow both approaches and we discuss the sensitivity of the results to a different definition of labor market participation.[26]

The validity of Heckman's method lies on satisfying the exclusion restriction. This consists of the selection of appropriate instruments for the equation of participation in the labor market. Basically, valid instruments are those variables that influence the participation decision but not the "offered wage" (Puhani, 2000). In practice, it is difficult to choose appropriate instruments for the Heckman's procedure. Ahmed and Maitra (2010) underline that identification of the instruments usually lies on intuition and data availability.

Taking into account this issue in this paper we chose 5 variables: age groups (5-year intervals) in order to capture non-linearities in the probability of participating in the labor force; a dummy variable that takes the value 1 if the individual is married and zero otherwise (single, divorced and widowers); the "need for income" is measured by the number of persons living in the household, number of children younger than 14 years old and number of persons employed excluding the respondent.[27]

Labor market characteristics by gender are presented in tables 5 and 6 in appendix and job-related characteristics are reported in table 7 in appendix. Moreover, table 1 shows that females' wages represent 79% and 87% of males wage rate in urban Nicaragua for 2005

[26] In practice, the difference between both approaches is given by excluding unemployed individuals from the sample.

[27] In this definition we consider as married those people that reported to be married or cohabitating.

and 2009, respectively. Although these figures show that there have been improvements towards gender equity on average, in overall women have lower wages compared to men among different groups (see table 1).

Looking at different groups we observe various patterns in the gender wage gap. For example, greater gaps appear among self-employed and employers compared to employees. The ratio female-to-male wages is higher in Managua (capital city) compared to the rest of the regions. In addition, men tend to earn more than women in all educational levels and almost in all age groups.[28] By economic sector, we observe greater gaps in the industrial and service sectors compared to the commerce activities. By occupational classes, women's wages tend to be higher than men among non-skill workers, while we find the opposite case among the rest of occupations analyzed. These figures suggest marked differences in the wage gap across the distribution. Furthermore, between 2005 and 2009 we observe a reduction in the mean wage differences in almost all the groups analyzed.

[28]Exceptions are found in ages 14-24 for 2005 and ages 30-34 and 55-59 for 2009.

Table 1: Gender Wage Gap in Urban Nicaragua, 2005-2009

	Real Hourly Wages (2005 C$)					
	2005			**2009**		
	Male	**Female**	**F/M**	**Male**	**Female**	**F/M**
All	15.21	12.01	0.79	15.51	13.54	0.87
Age group (%)						
Age 14 to 24	8.85	8.96	1.01	10.26	9.38	0.91
Age 25 to 29	14.77	11.18	0.76	16.01	12.63	0.79
Age 30 to 34	15.11	11.73	0.78	14.26	14.92	1.05
Age 35 to 39	17.05	14.80	0.87	17.89	14.48	0.81
Age 40 to 44	17.87	14.73	0.82	19.58	14.56	0.74
Age 45 to 49	22.45	12.97	0.58	20.77	18.01	0.87
Age 50 to 54	30.09	11.09	0.37	18.34	13.77	0.75
Age 55 to 59	16.26	12.84	0.79	12.28	14.11	1.15
Age 60 to 65	12.02	10.50	0.87	17.77	10.31	0.58
Education levels (%)						
None or Primary Incomplete	9.52	7.84	0.82	11.34	9.42	0.83
Primary Complete or Secondary Incomplete	12.71	10.03	0.79	13.06	10.07	0.77
Secondary Complete, Tertiary or Technical Incomp.	13.50	10.88	0.81	16.16	13.69	0.85
Tertiary and Technical Complete	39.06	24.13	0.62	30.03	24.19	0.81
Region (%)						
Managua	15.83	14.75	0.93	15.70	14.80	0.94
Pacific	14.58	10.48	0.72	15.61	13.07	0.84
Central	14.75	9.16	0.62	14.72	10.85	0.74
Atlantic	15.57	11.52	0.74	16.25	15.86	0.98
Occupational category (%)						
Employee	12.57	11.74	0.93	13.44	13.12	0.98
Self-employed	13.96	10.61	0.76	18.43	13.85	0.75
Employer	46.70	30.14	0.65	39.51	33.58	0.85
Economic sector (%)						
Industry	14.02	9.57	0.68	12.79	10.37	0.81
Commerce	14.01	11.91	0.85	14.42	13.75	0.95
Service	17.91	13.25	0.74	19.66	14.51	0.74
Occupation classes (%)						
Non-skill workers	8.47	8.83	1.04	9.20	9.41	1.02
Professional, Technical and Managerial	29.56	22.24	0.75	28.71	23.60	0.82
Sales and Clerical	13.95	9.85	0.71	14.87	12.25	0.82
Operational and Services Workers	15.40	8.76	0.57	14.76	10.88	0.74

Note: The wage gap in each category is computed as the ratio of females mean wage over males mean wage (F/M). Real hourly wages are in Córdobas at 2005 prices.
Source: Author's calculations based on EMNV 2005 and 2009.

5 Empirical Strategy

We rely on regression-based decomposition methods in order to study the difference in wages by gender. This approach has been widely used in applied economics and it has been extended in several ways in order to look at the difference in the distribution rather than only mean outcomes (Fortin, Lemieux and Firpo, 2010).

In this paper it is applied the Oaxaca-Blinder method (hereafter OB) in order to perform a detailed decomposition of the mean wage gap. The decomposition is also corrected for potential sample selection bias in the way suggested by Heckman (1979). Furthermore, we use the Recentered Influence Function regression (hereafter RIF method) proposed by Firpo, Fortin and Lemieux (2009), which allow us to compute the contribution of each factor at different percentiles.

5.1 Oaxaca-Blinder Decomposition

In the OB method, equation (2) is the starting point,[29]

$$Y_i = X_i\beta_i + \varepsilon_i \tag{5}$$

where Y is $ln(w)$. $i \in \{A, B\}$, A corresponds to males and B represents the females group. X is a vector of observable individual characteristics and β includes the intercept and the coefficients of the covariates. ε is an error term that included unobserved characteristics and is assumed to be independent of the covariates ($E[\varepsilon_i|X_i] = 0$).

From equation (5), we can compute the mean difference in wages as follows,

$$E(Y_A - Y_B) = E(X_A)\beta_A - E(X_B)\beta_B \tag{6}$$

Then, we add and subtract the counterfactual $\beta_A X_B$, which is the average wage that group B (females) would have if they had the same return as group A (males). Thus, equation (6) can be rearranged as follows,

$$E(Y_A - Y_B) = E(X_A)\beta_A - E(X_B)\beta_A + E(X_B)\beta_A - E(X_B)\beta_B$$

[29]This section is based on Fortin, Lemieux and Firpo (2010) and Jann (2008).

$$E(Y_A - Y_B) = [E(X_A) - E(X_B)]\beta_A + E(X_B)[\beta_A - \beta_B] \tag{7}$$

The components of the decomposition can be estimated by least squares or another estimator,

$$\bar{Y}_A - \bar{Y}_B = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\beta}_A}_{\text{Explained part}} + \underbrace{\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B)}_{\text{Unexplained part}} \tag{8}$$

where $\bar{X}$ represents the mean of the covariates and $\hat{\beta}$ is the estimated coefficient of β. The first term corresponds to the composition effect, which measures differences in the observed characteristics between males and females. The second term represents the wage structure effect, which accounts for the difference in the returns between males and women, under assumption that they have the same characteristics. Although this component is referred to as the difference due to discrimination, it also includes the effect of unobserved characteristics such as innate ability and non-cognitive skills (Fortin, 2008).

As can be noticed, in equation (8) we have chosen females as the discriminated group. In this specification it is assumed that there is no positive discrimination towards men. However, as Oaxaca (1973) has pointed out, the decomposition of the wage gap is sensitive to the choice of reference group. This is known as the “index number problem”. Several scholars have proposed different alternatives to deal with this problem.

One of these alternatives is using weighted coefficients (see e.g. Reimers, 1983; Cotton, 1988; Neumark, 1988; Oaxaca and Ransom, 1994; Fortin, 2008),

$$\beta^* = \Omega\beta_A + (I - \Omega)\beta_B \tag{9}$$

where β^* corresponds to the non-discriminatory coefficient, Ω is a matrix of relative weights and I is an identity matrix (Jann, 2008). The specification in equation (8) is equal to set $\Omega = I$. Meanwhile, Oaxaca and Ransom (1994) proposed the following weighting matrix,

$$\beta^* = \Omega = (X'_A X_A + X'_B X_B)^{-1} X'_A X_A \tag{10}$$

where X_A and X_B correspond to the values of the characteristics of group A (males) and B (females). Equation (10) corresponds to the coefficients from a pooled regression for the two samples (A and B), which is an approach that has also been proposed by

Neumark (1988). Based on this framework, the decomposition can be expressed as,

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}_A - \bar{X}_B)\beta^* + \bar{X}_A(\hat{\beta}_A - \beta^*) + \bar{X}_B(\beta^* - \hat{\beta}_B) \tag{11}$$

Moreover, we add to the pooled model a dummy variable that identifies the sex of the individuals. According to Fortin (2008), in this way the potential bias is avoided, which arises from the "group membership effect". This is because coefficients from the pooled model capture part of the unexplained differences by gender, overstating the results of the decomposition. Thus, the pooled model is given by,

$$Y_i = X_i\gamma + F_i\gamma_B + M_i\gamma_A + \varepsilon_i \tag{12}$$

where F_i and M_i are the female and male dummy, respectively. Moreover, in equation (12) it is applied the restriction $\gamma_B + \gamma_A = 0$. As stated in Fortin (2008), this implies that the advantage of men is equivalent to the disadvantage of women.

Using this procedure the decomposition can be written as follows,

$$\bar{Y}_A - \bar{Y}_B = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\gamma}}_{\text{Explained part}} + \underbrace{[\bar{X}_A(\hat{\beta}_A - \hat{\gamma}) - \bar{X}_B(\hat{\beta}_B - \hat{\gamma})]}_{\text{Unexplained part}} \tag{13}$$

where $\hat{\gamma}$ is the non-discriminatory wage structure.

In our study we consider the specifications stated in equations (8) and (13). In equation (8), females are assumed to be the discriminated group and the second one corresponds to the coefficients from the pooled model. Another alternative would be to consider positive discrimination towards men. However, this would imply setting the females' wage structure as the non-discriminatory group, which is not suitable in the context of Nicaragua based on previous evidence.[30]

The detailed decomposition is straightforward to compute because the total explained part is the sum of the contribution of each factor. Therefore, we can rewrite the first term

[30] Agurto et al. (2008) study different forms in which women are in disadvantage compared to men, especially regarding their role in the reproductive and productive activities.

in equation (8) as follows,[31]

$$(\bar{X}_A - \bar{X}_B)\hat{\beta}_A = (\bar{X}_{1A} - \bar{X}_{1B})\hat{\beta}_{1A} + (\bar{X}_{2A} - \bar{X}_{2B})\hat{\beta}_{2A} + ... = \sum_{k=1}^{K}(\bar{X}_{kA} - \bar{X}_{kB})\hat{\beta}_{kA} \quad (14)$$

where $k = 1, 2, ..., K$.

In the same way we can obtain the contribution of each factor in the unexplained part,

$$\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B) = (\hat{\beta}_{0A} - \hat{\beta}_{0B}) + \bar{X}_{1B}(\hat{\beta}_{1A} - \hat{\beta}_{1B}) + \bar{X}_{2B}(\hat{\beta}_{2A} - \hat{\beta}_{2B}) + ...$$

$$(\hat{\beta}_{0A} - \hat{\beta}_{0B}) + \sum_{k=1}^{K}\bar{X}_{kB}(\hat{\beta}_{kA} - \hat{\beta}_{kB}) \quad (15)$$

Finally, as discussed by several scholars (see e.g. Oaxaca and Ransom, 1999; Fortin, Lemieux and Firpo, 2010), the detailed decomposition of the wage structure is sensitive to the choice of the omitted group for the case of categorical variables. In this regard, Fortin, Lemieux and Firpo (2010) suggest the choice of a base group that provides a good economic interpretation rather than a "arbitrary normalization". Thus, based on this recommendation, each dummy variable is interpreted as the effect of a category relative to the base group.

5.2 Heckman's Correction for Sample Selection

One of the potential drawbacks in the standard OB decomposition is the non-random sample selection. There are different ways of addressing selectivity in participation. Some authors consider selectivity into occupational categories like employee or self-employed (see e.g. Stelcner, Smith, Breslaw and Monette, 1992). Meanwhile, others look at the decision of entering into the labor market (see e.g. Ahmed and Maitra, 2010; Beblo *et al.* 2003; Yang, 1992; Arends, 1992). In this study we focus on the latter.

Selection bias in participation appears if the characteristics of the working individuals considered in the sample are different from those who do not participate in the labor force or are unemployed (Vella, 1998). In this case, working individuals will not represent a random sample of the population of interest. Therefore, if the decision of participation in the labor market is correlated with the wage rate and some of the covariates (e.g. expe-

[31]This expression can be written in the same way for the decomposition in equation (13).

rience), the zero conditional mean assumption is violated. Consequently, the regression coefficients will be biased and will overstate effects like the returns to skills (Beblo *et al.* 2003).

The most popular approach to deal with this problem has been the one proposed by Heckman (1979), although alternative methods are provided in Dolton and Makepeace (1986) and Lewbel (2007). Beblo *et al.* (2003) point out that correcting for sample selection can be done in different ways depending on the problem of interest and the nature of the data. In our case study, the two-step procedure proposed by Heckman (1979) is used, as we are interested in assessing the net wage gap after accounting for selection effects and how the components of the decomposition have changed. In the first step, a participating equation is estimated. This is computed as the probability that the individual participates in the labor market conditional on a vector of observable characteristics. In the second step, we include the inverse Mills ratio as an additional covariate in order to control for potential selection bias (Heckman, 1979).

The selection equation is given by,

$$P_i = \alpha Z_i + \mu_i \tag{16}$$

where P is a dummy variable that takes the value 1 if the individual participates in the labor market and 0 otherwise (based on the definitions stated in section 4). $i \in \{A, B\}$, where A is male and B is female. Z is a vector of observable individual characteristics that determine the participation. α represents the coefficients of the parameters of interest. The error term is independent and identically distributed ($i.i.d$ $[0, 1]$). We estimate equation (16) using a probit estimator separately for men and women.

Then, the inverse Mills ratio is obtained as $\lambda_i = \frac{\phi(-\alpha Z_i)}{1-\Phi(-\alpha Z_i)}$, where ϕ and Φ correspond to the normal density and normal distribution functions, respectively. Next, we include λ as an additional regressor into equation (5),

$$Y_i = X_i\beta_i + \rho\lambda_i + \varepsilon_i \tag{17}$$

where ρ represents the correlation between the wage regression and the selection equation. We test for selection bias by looking at the t-test of the coefficient of λ. If the coefficient is statistically significant it is argued that there is presence of selectivity (Heckman, 1979). Moreover, we choose not to establish an expected sign for the selection of women and men.

Despite the wide applicability of Heckman's correction method in many empirical studies, there are some concerns about the robustness of the results provided by this estimator.[32] We focus on two particular issues that have relevance in the context of decomposition methods. Firstly, including the inverse Mills ratio as an additional covariate might produce multicollinearity in the results, which can lead to large standard errors (Puhani, 2000). Collinearity may appear when the variables used in the selection equation are the same as the ones used in the wage regression. Puhani (2000) suggests incorporating exclusion restrictions as a potential solution to diminish collinearity. In practice, this is done by including in the first step variables that influence the participation decision but not the "offered wage". Thus, following this recommendation, we include these variables as instruments: age groups, marital status, household size, number of children within the household and number of working members in the household (excluding the respondent).[33] Furthermore, following Puhani (2000), we test for potential collinearity by looking at the R-squared of a regression of the inverse Mills ratio on the covariates of the wage regression.

A second concern is the sensitivity of the coefficient of λ to the specification of the participation equation, which is also related to the validity of the instruments (Beblo *et al.*, 2003). Lauer and Steiner (2000) try to address this issue by testing the sensitivity of the results to different specifications, although it is difficult to assert if the selected instrument is good enough. Nevertheless, we follow this approach for the left-hand side of the equation.

There are several ways to introduce the selection correction into the OB decomposition.[34] As mentioned before, we chose to compute the net wage gap. Therefore, the

[32]See Puhani (2000) for a depth discussion of the drawbacks of Heckman's method.

[33]It is worth mentioning that by construction, age is strongly correlated to experience, but this is not necessarily the case for the age groups and experience groups.

[34]A formal discussion on selectivity issues in decomposition methods can be found in Neuman and Oaxaca (2004).

selection term is introduced in equation (8) as follows,[35]

$$\bar{Y}_A - \bar{Y}_B = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\beta}_A}_{\text{Explained part}} + \underbrace{\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B)}_{\text{Unexplained part}} + \underbrace{(\hat{\rho}_A\hat{\lambda}_A - \hat{\rho}_B\hat{\lambda}_B)}_{\text{Difference in selectivity}}$$

$$\underbrace{(\bar{Y}_A - \bar{Y}_B) + (\hat{\rho}_B\hat{\lambda}_B - \hat{\rho}_A\hat{\lambda}_A)}_{\text{Net difference}} = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\beta}_A}_{\text{Explained part}} + \underbrace{\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B)}_{\text{Unexplained part}} \tag{18}$$

The left hand side of equation (18) corresponds to the difference in wages net of selection effects, which is also known as the "offered wage gap" (Beblo *et al.* 2003).

5.3 RIF Method

The RIF regression method proposed by Firpo, Fortin and Lemieux (2009) computes a detailed composition for distributional statistics such as median, gini, variance, quantiles and percentiles. The procedure provides unconditional quantile estimates, which are of interest in applied economics (Chi and Li, 2008).

The procedure is divided in two steps. The first one consists of computing a recentered influence function (RIF) for the quantile $q(\tau)$ and to use this variable instead of the outcome of interest, i.e., wage (Y). Following Fortin, Lemieux and Firpo (2010), the RIF is given by,[36]

$$RIF(y; Q_\tau) = Q_\tau + \frac{\tau - 1\{y \leqslant Q_\tau\}}{f_Y(Q_\tau)} \tag{19}$$

where Q_τ corresponds to the population in the τ-quantile, $1\{\centerdot\}$ is the indicator function of whether the wage observation (y) is at or under the quantile τ and $f_Y(\centerdot)$ is the density function of Y.

The RIF for each observation $[\widehat{RIF}(Y_i; \hat{Q}_\tau)]$ is obtained by estimating the sample quantile $\hat{Q}_\tau$ and computing the density $\hat{f}_Y(\hat{Q}_\tau)$ using a kernel estimation. Then, it is estimated the effect of a change in the distribution of a given covariate on the marginal quantile τ of Y (Firpo, Fortin and Lemieux, 2009, pp. 957), in a specification that takes the form,

$$E[RIF(Y_i; Q_\tau)|X_i] = X_i\beta_i \tag{20}$$

[35]The adjusted decomposition can be written in the same way for the specification that uses the coefficients from a pooled model (see equation (13)).

[36]Firpo, Fortin and Lemieux (2009) define the RIF as $RIF(y; v) = v(F_Y) + IF(y; v)$, which adding the quantile back can be also expressed as $\int RIF(y; v) \centerdot dF(y) = v(F_Y)$, where $IF(y; v)$ is the influence function of the observation y for the quantile $v(F_Y)$.

The parameters of interest (β) can be estimated by OLS or any other estimator,[37]

$$\widehat{RIF}(Y_i;\hat{Q}_\tau) = X_i\hat{\beta}_i \quad for \;\; i = A, B \tag{21}$$

where $\hat{\beta}$ captures the "unconditional quantile partial effect" of X.[38]

Using the estimates from equation (21) we can compute an OB decomposition for each unconditional quantile as follows,

$$\hat{Q}_\tau(Y_A) - \hat{Q}_\tau(Y_B) = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\beta}_{A,\tau}}_{\text{Explained part}} + \underbrace{\bar{X}_B(\hat{\beta}_{A,\tau} - \hat{\beta}_{B,\tau})}_{\text{Unexplained part}} \tag{22}$$

As in the OB decomposition, the first term is the composition effect and the second one is the wage structure effect. In this specification, females are assumed to be the discriminated group. We do not computed the decomposition using the coefficients from a pooled model. We chose this specification because we expect our results to serve as a baseline for future research, in which a reweighting approach combined with the RIF method can be computed in the way suggested by Fortin, Lemieux and Firpo (2010). In the reweighting approach, the counterfactual for the distribution of women wages is constructed based on what the distribution would be if women possess the same distributional characteristics of men (Fortin, Lemieux and Firpo, 2010).

We can get the contribution of each factor in the same way that in the OB method (see equations (14) and (15)). The standard errors for the decomposition are computed using bootstrapped standard errors with 100 replications. Finally, for the detailed decomposition we mainly focus on the 10th, 50th and 90th percentiles.

According to Fortin, Lemieux and Firpo (2010), one of the advantages of the RIF regression is that the decomposition is path independent, as the inversion of the proportions back to quantiles is done locally. In this way, it is straightforward to compute and interpret decompositions at specific points of the distribution. They also point out that the main concern with this approach is regarding the precision of the linear approximation of the decomposition.

[37] Firpo, Fortin and Lemieux (2009) suggest three methods: OLS, logistic estimator and a non-parametric estimator.

[38] The rest of the subscripts are indicated as in the previous sub-sections.

5.4 The Wage Equation and Issues in Decomposition Methods

Decomposition methods provide a good understanding of the contribution of several factors to the differences in wages by gender. Fortin, Lemieux and Firpo (2010) stress that the wage structure effect, under certain assumptions, can reflect treatment effects in the spirit of the impact evaluation framework's. Nevertheless, they also point out that these methods only provide descriptive results of the differences in the labor market and it is difficult to derive structural relations and obtain causal estimates from them. In practice, the assumption $E[\varepsilon_i|X_i] = 0$ is not likely to hold, thus Fortin, Lemieux and Firpo (2010) assume "ignorability", which basically states that the decomposition is valid if the bias is the same for males and females. Moreover, even when we account for potential sample selection bias at the mean, this is not done for the case of quantiles. To the best of our knowledge, there is no methodology yet that controls for sample selection in detailed decompositions for quantiles. Therefore, considering these issues, the results of the decompositions should be interpreted with cautious.

Based on the discussion in section 3, the covariates included in the wage equation are 4 dummies of schooling, potential experience and its squared value, regional dummies (Managua, Central, Pacific and Atlantic), dummies of occupational category (employee, self-employed and employer), 4 dummies of occupational classes and 3 dummies of economic sectors. The reference category is secondary complete, tertiary or technical incomplete for the educational groups; Pacific and Atlantic regions for the regional dummies; employee for occupational category; operational and services workers for the occupational classes; and industry for the economic sectors.

In section 4, we addressed some of the practical problems that appear in the available data. However, other concerns arise in the specification of the wage regression. According to Blau and Kahn (2000), it is difficult to measure the actual effect of discrimination, as unobserved factors such as innate ability are not accounted in the estimation. In this regard, the discrimination level resulted from the decomposition would be overstated if men have greater ability than women. In contrast, as noticed by Oaxaca (1973), controlling for occupational classes and economic sector might provide an understated measure of discrimination if gender segregation is the result of discriminatory practices in the labor market. This would also be the case if women suffer from barriers to access and have greater ability than men (Blau and Kahn, 2000). Aware of this issue, we discuss whether the discrimination is being understated in our results based on the effects of occupational categories.

6 Which Factors Explain the Gender Wage Gap?

6.1 Determinants of Labor Market Participation

Selection into the labor market is estimated using a probit model. The regressions are computed separately for men and women in each year. We specify the model taking into account the availability of information for both surveys (2005 and 2009) and previous evidence for Latin American countries (see e.g. Psacharopoulos and Tzannatos, 1992). As mentioned previously, we use two variables as measures of labor market participation. The first one is a dummy variable that takes the value 1 if the individual is working and zero if is voluntarily unemployed (*definition 1*). The second one takes the value 1 if the individual is working, searching for a job or temporarily unemployed and zero otherwise (*definition 2*). As explanatory variables we chose two demographic variables: age (groups) and marital status. The variables that capture the need for income are household size, number of children and number of working members in the household (excluding the respondent). Finally, the effect of human capital on the labor supply is measured through schooling dummies.

Urban labor market characteristics are reported in tables 5 and 6 in appendix. A large share of the unemployed individuals (voluntary and non-voluntary) is in the age group 14-24 years old. In addition, more than two third of the voluntarily unemployed individuals are women. This is not surprising as women tend to withdraw from the labor force at the different points of the life-cycle due to child-bearing and child-caring (Polachek, 2004). Furthermore, working and temporarily unemployed women are more educated than men; voluntarily unemployed men show higher schooling than women in this category.

Table 2 shows the marginal effects of the probit estimations for females and males. Educational attainment is found to be an important determinant in female participation. Having a degree lower than complete secondary (reference category) reduces the probability of participation between 12-23 percentage points. Meanwhile, females with technical (incomplete) and tertiary education have higher probability of participation (15-24 percentage points). In contrast, greater educational attainment is not a key determinant of male participation, although those men with secondary and tertiary incomplete education have lower probability of participation compared to individuals with complete secondary. These effects are large and statistically significant at conventional levels.

Regarding the effect of age, the probability of participation for females and males shows a concave shaped. Those individuals in ages 14-24 and 60-65 have a lower probability of participation compared to individuals in ages 25-29 (reference category). Also, it is worth noticing that probability of participating for females increase by ageing. Furthermore, as has been shown by the literature, being married reduces the probability of participation (14-17 percentage points) of females compared to those non-married. In contrast, married males are more likely to participate (9-12 percentage points) than non-married males. These results suggest a labor division within the household, in which women are more likely to devote their time towards household production than men (Agurto *et al.* 2008).

The variables that capture the effects of the need for income are statistically significant. Higher number of individuals in the household reduces the probability of participation for males and females, being this effect higher for women (6-15 percentage points). The more the household workers, the higher the probability of participation for females (19-34 percentage points), while this effects is very low for males (3-6 percentage points). In addition, a higher number of children increase the probability of participation for males and females, although this effect is larger for women (11-15 percentage points) compared to men (2 percentage points). The fact that more children and household workers increase the probability of participation of females is an evidence of substitution in household work. According to Agurto *et al.* (2008), female children perform a large share of household tasks. This might suggest that adult women assign household activities to young children in order to work (or search for a job) and supply more financial resources to the household.

From these results we can draw some conclusions. Firstly, the estimations are quite similar using both definitions of labor market participation. Moreover, the sign and statistical significance of the marginal effects are almost analogous for 2005 and 2009. Secondly, the need for income seems to be more important in female's probability of participation compared to men. Finally, age and education appear to be key determinants of labor participation of both groups.

Table 2: Marginal Effects of Selection Equations, 2005-2009

	2005				2009			
	Definition 1		Definition 2		Definition 1		Definition 2	
	Males	Females	Males	Females	Males	Females	Males	Females
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No instruction	0.0278**	-0.2176***	0.0176	-0.2270***	0.0119	-0.1284***	0.0086	-0.1311**
	(0.01)	(0.04)	(0.01)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)
Primary complete	0.0019	-0.1692***	-0.0050	-0.1684***	-0.0266*	-0.1334***	-0.0405**	-0.1302***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.03)	(0.02)	(0.04)
Primary incomplete	0.0005	-0.1553***	-0.0072	-0.1510***	0.0027	-0.0514	-0.0026	-0.0507
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.04)
Secondary incomplete	-0.0480***	-0.1631***	-0.0481***	-0.1588***	-0.0604***	-0.1377***	-0.0545***	-0.1212***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)
Technical complete	0.0218	-0.0593	0.0040	-0.0206	-0.0584	0.0442	-0.0842*	0.0729
	(0.03)	(0.06)	(0.03)	(0.07)	(0.04)	(0.07)	(0.05)	(0.07)
Technical incomplete	-0.0368	0.2435***	-0.0691*	0.3132***	-0.0475	0.1707**	-0.0422	0.2142***
	(0.04)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.08)
Tertiary complete	-0.0131	0.1572***	-0.0369*	0.1660***	-0.0192	0.1954***	-0.0176	0.1998***
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.04)
Tertiary incomplete	-0.1034***	-0.0657	-0.1186***	-0.0885*	-0.1724***	-0.0880**	-0.1379***	-0.0493
	(0.02)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
Age 14 to 24	-0.1200***	-0.2892***	-0.1332***	-0.3627***	-0.1958***	-0.2717***	-0.2280***	-0.3207***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Age 30 to 34	0.0314*	0.0263	0.0296**	0.0599	0.0338**	0.0887**	0.0335***	0.1407***
	(0.02)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Age 35 to 39	-0.0061	0.1862***	0.0019	0.2446***	0.0083	0.2238***	0.0171	0.3011***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)
Age 40 to 44	0.0046	0.1125***	0.0065	0.1780***	0.0090	0.1323***	0.0168	0.1975***
	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.04)
Age 45 to 49	0.0038	0.1118**	0.0117	0.1817***	0.0022	0.0999**	0.0132	0.1578***
	(0.02)	(0.04)	(0.02)	(0.05)	(0.03)	(0.04)	(0.02)	(0.05)
Age 50 to 54	0.0198	-0.0005	0.0205	0.0527	-0.1169***	0.1095**	-0.0688**	0.1772***
	(0.02)	(0.05)	(0.02)	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)
Age 55 to 59	-0.0269	-0.0561	-0.0133	-0.0177	-0.1272***	-0.0527	-0.0947***	-0.0178
	(0.04)	(0.05)	(0.03)	(0.06)	(0.04)	(0.05)	(0.04)	(0.06)
Age 60 to 65	-0.3055***	-0.2162***	-0.2802***	-0.1639***	-0.5342***	-0.2065***	-0.4848***	-0.1746***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Married	0.0866***	-0.1446***	0.1026***	-0.1663***	0.0937***	-0.1383***	0.1154***	-0.1535***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Household size	-0.0153***	-0.1078***	-0.0207***	-0.1513***	-0.0110***	-0.0806***	-0.0199***	-0.1512***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
# employed persons in HH	0.0296***	0.2288***	0.0408***	0.3117***	0.0380***	0.2102***	0.0586***	0.3352***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)
# children $<$ 14 years old in HH	0.0182***	0.1073***	0.0222***	0.1488***	0.0138***	0.1098***	0.0218***	0.1548***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Number of observations	4,918	5,789	4,155	5,213	6,614	7,581	5,510	6,844

Notes: Dependent variable for *definition 1* is a dummy variable that takes the value 1 if the individual is working and zero if is voluntarily unemployed. For *definition 2* takes the value 1 if the individual is working, searching for a job or temporarily unemployed and zero otherwise.
The marginal effect for dummy variables are computed as the change from 0 to 1, holding other factors fixed at their means.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level. Robust standard errors are in parentheses.
The reference categories are: secondary complete, age 25 to 29 and non-married.
Source: Author's calculations based on EMNV 2005 and 2009.

6.2 The Wage Regression: Unadjusted versus Adjusted

The OLS wage regressions are reported in table 3, while the regressions adjusted for selection are reported in table 8 in appendix. As expected, the relation between wages and educational attainment is positive and statistically significant at 1% level. Having no instruction, primary incomplete, primary complete or secondary incomplete reduces wages compared to those who have secondary complete, tertiary or technical incomplete (reference category). Moreover, wage rates increase for those individuals with complete tertiary or technical education. The estimated returns to education are greater for men in 2005, but for 2009 this gap has narrowed considerably. This result is consistent with the graphical inspection performed in section 3.2 (see figure 5).

Experience and its squared value are statistically significant at the 1% level. Returns to (potential) experience has a concave shape, as was also observed in figure 4. Men tend to receive higher wage rates until 30-31 years, while women increase their wages up to 29 years (holding other factors fixed). As is shown in figure 7, returns to experience are higher for men than women in 2005 and 2009. Also, returns for both sex have diminished for 2009, especially for men.

Figure 7: Cumulative Returns to Potential Experience, 2005-2009

Source: Author's calculation based on EMNV 2005 and 2009.

Regarding the variables that capture job-related characteristics it is observed that self-employed and employers have higher wages compared to employee (reference group). This effect is statistically significant at conventional levels for both sex in 2005 and 2009, except for self-employed men in 2005. In addition, returns are greater for employers compared to the rest of job categories as expected. Working in professional, technical and managerial occupations increases wages compared to operational and services workers (reference group). The opposite is observed among non-skill workers, who show lower wages compared to the base group (except for women in 2005). Individuals who work in commercial activities do not have different wages compared to those who work in the industrial sector, except for males in 2009 (reference group). Meanwhile, males working in service activities earn more than industrial workers.

At the regional level, wage rates are higher for those individuals living in Managua (capital city) compared to those living in the Pacific and Atlantic regions (reference category). This effect is statistically significant at conventional level. Furthermore, individuals living the central region have lower wage rates compared the Pacific and Atlantic workers, except for men in 2009.

There is no a clear presence of selection bias. The effect of λ on the wage rate for both males and females is not statistically different from zero for either of the definitions used in the selection equations, except for males in 2005 using *definition 1* (see column 1 of table 8 in appendix). For this reason the adjusted coefficients of the regressions in table 8 appendix are almost the same to the unadjusted coefficients (see table 3). In order to test for potential collinearity in the Heckman's models, we regress the inverse Mills ratio on the explanatory variables of the wage equation. We observe that the R-squared of these regressions lies between 0.24-0.38, which is not high in order to suspect that there is presence of collinearity in the estimations.[39] Moreover, for the case of males in 2005 (using *definition 1*) a negative and statistically significant (at 10% level) coefficient of λ implies that men selected into employment have a lower wage compared to men from a random sample. For the case of females, the statistically insignificant coefficient suggests that there is no difference in wages between women selected into employment and those from a random sample of a population.

These results underline that the characteristics of the individuals that are out of the labor market might be not so different from those who are working, i.e., there is no

[39]The output is not reported as these estimations are only exploratory.

selectivity bias. We interpret these results with cautious because as was discussed before, Heckman's method is sensitive to model specification. Also selection into job-categories could be playing a more important role compared to the decision of working (or search for a job). Nevertheless, this issue goes beyond the scope of our work. Therefore, based on the current evidence, we focus the analysis on the unadjusted OLS coefficients.

Table 3: OLS Wage Equations, 2005-2009

	2005		**2009**	
	Males	**Females**	**Males**	**Females**
Variable	**(1)**	**(2)**	**(3)**	**(4)**
None or Primary Incomplete	-0.3585***	-0.4183***	-0.4121***	-0.3132***
	(0.06)	(0.07)	(0.07)	(0.07)
Primary Complete or Secondary Incomplete	-0.1412***	-0.2579***	-0.2398***	-0.2103***
	(0.05)	(0.06)	(0.05)	(0.06)
Tertiary and Technical Complete	0.5171***	0.4441***	0.2714***	0.4430***
	(0.08)	(0.06)	(0.07)	(0.06)
Experience	0.0311***	0.0176***	0.0241***	0.0172***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.0005***	-0.0003***	-0.0004***	-0.0003***
	(0.00)	(0.00)	(0.00)	(0.00)
Managua	0.2005***	0.2066***	0.0718**	0.0995***
	(0.03)	(0.05)	(0.04)	(0.04)
Central	-0.1012***	-0.1833***	0.0328	-0.1906***
	(0.04)	(0.04)	(0.06)	(0.07)
Self-employed	0.0509	0.2334***	0.1167**	0.1688***
	(0.05)	(0.05)	(0.05)	(0.05)
Employer	0.7303***	0.9057***	0.5894**	0.5788***
	(0.08)	(0.13)	(0.24)	(0.16)
Professional, Technical and Managerial	0.3430***	0.5358***	0.3581***	0.3410***
	(0.07)	(0.09)	(0.07)	(0.09)
Sales and Clerical	-0.0722	-0.0927	-0.0118	-0.1663**
	(0.05)	(0.08)	(0.06)	(0.08)
Non-Skill	-0.1965***	0.0774	-0.1830***	-0.2300***
	(0.03)	(0.08)	(0.04)	(0.09)
Commerce	0.0476	0.0288	0.0851*	0.0666
	(0.04)	(0.07)	(0.05)	(0.06)
Service	0.1098***	-0.0987	0.0866*	0.0627
	(0.04)	(0.07)	(0.05)	(0.06)
Constant	1.8993***	1.7761***	2.1162***	1.9963***
	(0.05)	(0.07)	(0.06)	(0.07)
R-squared	0.321	0.299	0.203	0.248
Sample size	3437	2551	4421	3545

Notes: Dependent variable is the natural logarithm of real hourly wages.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level. Robust standard errors are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

6.3 Mean Wage Decomposition

In this section we discuss the results of the Oaxaca-Blinder decomposition at the mean. Table 4 reports the aggregate decomposition of the mean wage gap uncorrected and corrected for selectivity (using definition 1). As was mentioned in section 5, the dummy variables are interpreted as the effect of a category relative to the base group. Taking into account that there is evidence of negative selection for males in 2005, we only present this adjusted decomposition. By comparing the unadjusted (columns 1-2) and adjusted (columns 5-6) results for 2005, we can observe that the mean wage gap increases by 0.046 log points, as the offered wage rate is higher than the wage of the working men. Nevertheless, the results of the decomposition do not change considerably. Therefore, we focus on the unadjusted decomposition (columns 1-4).

Overall, the estimates show that all the wage gap is accounted by the wage structure effect. This implies the presence of an "upper bound to discrimination", as unobserved characteristics like ability and non-cognitive factors could also play a role. The negative sign of the composition effect shows that women have advantage in observed characteristics compared to men. This is consistent with the graphical inspection in section 3.1.1. The decompositions are similar using males as the reference group or the coefficients from a pooled model.[40] Moreover, these results confirm previous evidence on the explanations of the mean wage gap for the case of Nicaragua.

The estimated mean wage is reduced by 0.0501 log points between 2005-2009. This result is driven by a reduction in the wage structure effect of 0.035-0.016 log points. Looking at the detailed decomposition in tables 9 and 10 in appendix is possible to analyze which factor has more influence in the reduction of the wage gap during the period of study. The composition effect (see table 9 in appendix) reflects a reduction in the wage gap due to higher women's endowments in terms of education (especially in complete tertiary and technical education) and experience. Also, the effect of women's endowment in educational attainment slightly increases for 2009. Meanwhile, there are no apparent differences in wages related to regional concentration of workers. Regarding job-related characteristics, the differences in endowment of self-employed, professional, technical and managerial occupations, and commerce and service activities have slightly contributed to narrowing the gender wage gap, although this effect fell during 2005-2009.

[40]This result is also found in Fortin, Firpo and Lemieux (2010).

Furthermore, the wage structure effect (see table 10 in appendix) is mainly driven by higher returns to experience to men. In fact, the reduction in the mean wage gap in the period of study has been due to a reduction in the returns to this characteristic. However, the wage structure also provides interesting evidence of other effects. It is observed that in 2005 self-employed women and those women working in professional, technical, managerial, sales, clerical and non-skill occupations faced less discrimination compared to the reference group (those with secondary complete, tertiary or technical incomplete education, living in the Pacific or Atlantic regions, working as employee in operational and services occupations in the industrial sector). However, for 2009 this situation has changed, as those women working in sales, clerical and non-skill occupations face slightly greater discrimination than the base group. Meanwhile, the wage gap attributed to different educational categories (in comparison with the reference group) has reduced over time. Moreover, the constant term, which captures other factors that influenced the wage gap that are not accounted by the explanatory variables (the change of the base group), remains positive and practically does not vary over 2005-2009.

From these results we can draw several considerations. Firstly, although the increase in women's human capital endowments contributes to narrowing the gender wage gap as predicted by the human capital model, the effects are low. Secondly, we do not find strong evidence of a wage gap due to gender occupational segregation. An exception could be in the service sector for 2005, in which women have higher representation than men (see table 7 in appendix) and the returns are greater for men. Nevertheless, this effect is very low for 2009. Finally, higher returns to experience for men accounts for a large share of the wage gap.

As mentioned in section 3.2, the literature has stressed that it is difficult to differentiate if this effect is driven by statistical or taste-base discrimination. Regarding the former, Tenjo, Ribero and Bernat (2005) argue that if human capital variables represent average productivity indicators for employers, we would expect that greater endowments are associated with lower differences in wages. However, in the data we observe that the returns to experience and schooling are larger on average for men, although the latter effect is marginal for 2009 (see figures 4 and 5). Moreover, these authors suggest that evidence of statistical discrimination in the results of the decomposition might be shown by a positive constant term and negative coefficient for the human capital variables. In this regard, we observe the opposite for the case of experience. However, it is difficult to make this assertion for educational attainment, as the dummy variables capture the effect of a given category compared to the based group (which is represented by the intercept). However, as we mentioned in the previous section the returns to education are greater for men in both years. Therefore, the wage structure effects are in the same vein of the theory of taste-based discrimination. As Becker's (1971) model predicts, there is a reduction in the wage gap during the period of study and also in the discrimination in the returns to experience and education, however we should interpret this result with cautious as our time span is short (four years). These considerations constitute the baseline to analyze how this picture has changed across the distribution.

Table 4: Gender Wage Gap: Oaxaca-Blinder Decomposition, 2005-2009

	OLS				**Corrected for selectivity**	
	2005		**2009**		**2005**	
Using:	Male coef.	Pooled coef.	Male coef.	Pooled coef.	Male coef.	Pooled coef.
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Mean log wage gap:						
$E[ln(w_m)] - E[ln(w_f)]$	0.1889	0.1889	0.1388	0.1388	0.2354	0.2354
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)
Composition effect	-0.0656	-0.0635	-0.0806	-0.0618	-0.0617	-0.0618
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
%	*-34.7%*	*-33.6%*	*-58.1%*	*-44.5%*	*-26.2%*	*-26.3%*
Wage structure effect	0.2545	0.2523	0.2194	0.2007	0.2970	0.2971
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)
%	*134.7%*	*133.6%*	*158.1%*	*144.5%*	*126.2%*	*126.3%*

Notes: Dependent variable is the natural logarithm of real hourly wages.
Standard errors computed using the Delta method are reported in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

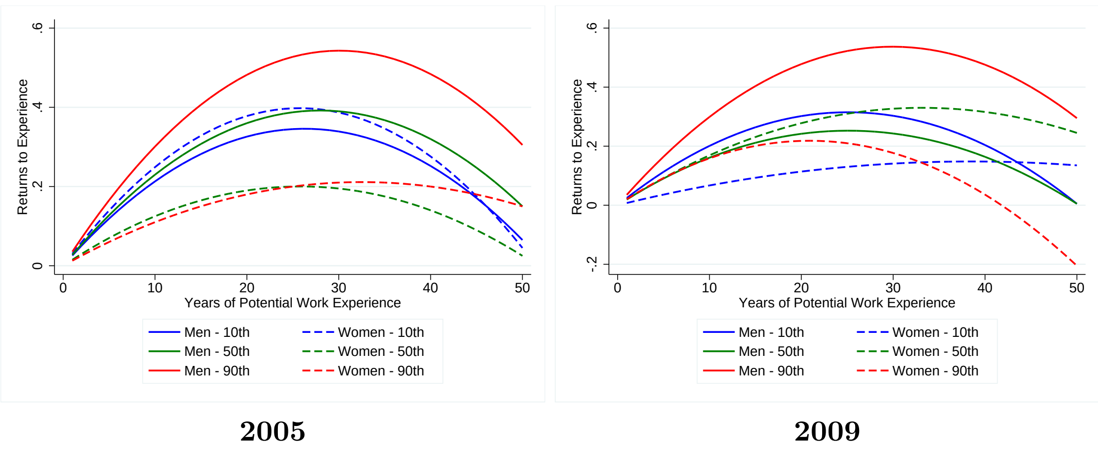
6.4 The Gender Wage Gap Across the Distribution

6.4.1 RIF Regressions

We now analyze the determining factors of the gender wage gap at the 10th, 50th and 90th percentiles using the RIF regression method. The results for the unconditional quantile regression for 2005 and 2009 are reported in tables 11 and 12 respectively. The sign and statistical significance of almost all coefficients are quite similar to the regressions for the mean wages. Therefore, in this section we focus on discussing how the returns to the factors analyzed differ across the distribution and during the period of study.

As expected, returns to education increase as we move up in the wage distribution, especially for those individuals with complete tertiary or technical education. As in the case of the mean, the gaps in returns to schooling have diminished for 2009, especially at the upper and lower part of the distribution. Meanwhile, returns to experience are heterogeneous across the wage distribution and during the period of study (see figure 8). In 2005, returns to experience are greater for men at the 50th and 90th percentiles, while is higher for women at the 10th percentile. In contrast, in 2009 men have greater returns to experience at the extreme points of the distribution, while women are better remunerated at the median. In both years, it is remarkable to notice the large difference in returns by gender at the 90th percentile. This picture suggests that experience might not have the same importance in the decomposition of the wage gap along the wage distribution.

Figure 8: Cumulative Returns to Experience Across the Wage Distribution



Source: Author's calculation based on EMNV 2005 and 2009.

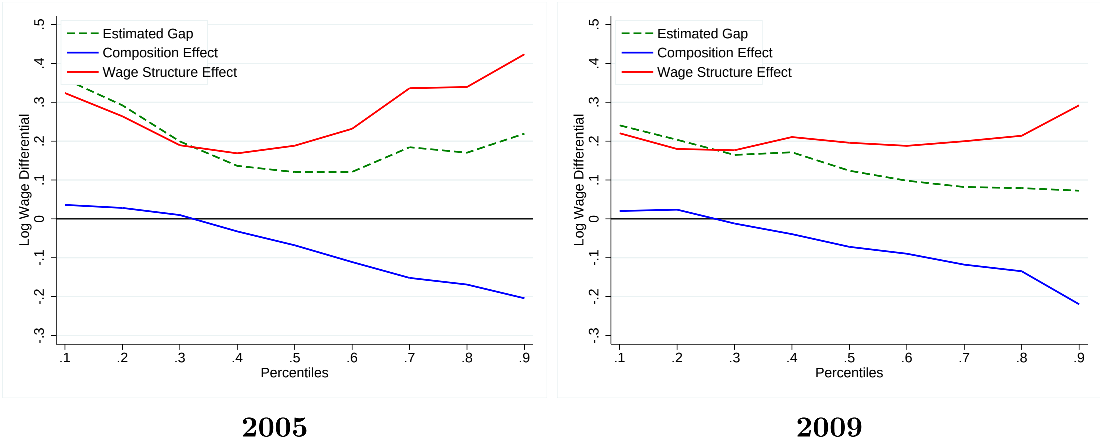
In relation to job-related characteristics, being self-employed and an employer increases wages compared to employee (reference group). This pattern is the same across the wage distribution, except for self-employed at the 10th percentile and female's employers at the lower part. Professionals, technicians and managers received higher wages than operators and services workers (reference group), except at the bottom of the distribution. Among non-skill workers there is no a clear pattern in their returns compared to the base group in both years and across the distribution. Furthermore, the wage rate among workers in commercial and service activities does not differ from industrial workers (reference group) across the distribution, except at the median (50th percentile), in which the returns of workers in service activities are higher. It is worth noticing that the returns in all the categories analyzed are higher as we move up in the distribution. Finally, at regional level the picture is not so different at the different percentiles from the results for the mean wages.

6.4.2 Which Factors are Driving the Gap Across the Distribution?

In this section we explore which factors determine the gender wage gap across the wage distribution using the estimates from the unconditional quantile regression. As we mentioned in the introduction of this study one of the advantages of the RIF method is that it is possible to compute a detailed decomposition of the gender wage gap across the distribution. Table 13 in appendix reports the aggregate decomposition at different percentiles. As was mentioned in section 5, the dummy variables are interpreted as the effect of a category relative to the base group. It is interesting to notice that for 2005 the wage gap along the distribution is driven by the wage structure effect, while for 2009 is driven by the composition effect (see figure 9).

The decompositions show that for 2005 (see figure 9) the wage structure accounts for almost all the wage gap in the lower part of the distribution (10th-30th percentiles), as the differences in observed characteristics between groups are marginal. Moreover, the wage structure is greater above the 30th percentile, but the greater endowments of women offsets to some extent the effect of the wage structure. Therefore, although the sticky floor effect might be accounted by discrimination, there might be higher level of discrimination at the upper half of the distribution.

Figure 9: Decomposition of the Gender Wage Gap at Different Percentiles



Source: Author's calculation based on EMNV 2005 and 2009.

In contrast, for 2009 (see figure 9) the gaps are reduced at the lower and upper part of the distribution in comparison to 2005. This effect is mainly driven by a reduction in the wage structure effect. In fact the wage structure is quite similar along the distribution, except at the 90th percentile in which this effect is higher. Furthermore, the pattern of the wage gap as we move up in the percentiles (30th-90th percentiles) is driven by a reduction in the wage differential due to greater women's endowments. In fact, at the 90th percentile, the large difference in endowments favoring women offset a higher effect of the wage structure. These results suggest that while the wage gap is small at the upper part of the distribution, the sticky floor effect is still determined by discrimination.

By looking at the contribution of each covariate, it is possible to provide a better understanding of the gender wage differential at the different percentiles analyzed. In order to simplify the report of the results, we focus on the variables that show the larger effects at the 10th, 50th and 90th percentile. The complete results of the decompositions are presented in tables 14 and 15 in appendix.

The composition effect appears to contribute to a greater reduction in the wage differences for 2005 and 2009 as we move up in the distribution. At the 10th percentile, the low wage gap due to differences in observed characteristics is mainly accounted by higher men's endowments among self-employed and in sales and clerical occupations. At the median (50th percentile), the difference in wages is reduced by higher women's endowments in terms of human capital (education and experience) and in self-employed, professional, technical and managerial occupations, and service workers. Despite women's advantages in these characteristics, the composition effect reduced the wage gap by 0.06-0.07 log points only in both years. However, at the top of the distribution (90th percentile), the composition effect contributes to reducing the wage gap in 0.20-0.22 log points in the period of study and in 2009 this effect almost offsets the wage structure. This is because women have greater endowments than men in terms of complete tertiary and technical education, self-employed and among professional, technical and managerial and sales and clerical occupations.

The wage structure effects show that the difference in returns to the covariates vary across the distribution in 2005 and 2009. At the bottom part, those women working in commercial and service activities seem to face greater discrimination compared to the base group (those with secondary complete, tertiary or technical incomplete education, living in the Pacific or Atlantic regions, working as employee in operational and services occupations in the industrial sector). However, the reduction in discrimination towards those women holding none or primary incomplete education, primary complete or secondary incomplete education and those who work in sales and clerical occupations have contributed to decreasing the wage structure at the 10th percentile during the period of study.

At the median, despite a considerable reduction in the returns to experience favoring men and a drop in the discriminatory levels of those women holding primary complete or secondary incomplete, the wage structure slightly increases over time. To some extent this is due to a greater discrimination for those women living in the central region, working in sales and clerical occupations and higher men's returns for the base group. At the top of the distribution, discrimination in the returns to experience accounts for a large share of the wage structure in both years. Nevertheless, there is an increase in discrimination for those women working in professional, technical and managerial, and sales and clerical occupations relative to the base group. In contrast, a reduction in discrimination is observed for those women working in the service sector and at the different educational categories.

In overall, the detailed decompositions show that women advantages in terms of human capital and in some job-related characteristics contributed to reduce the wage gap at the upper half of the distribution, especially at the top. At the lower part, discrimination accounted for a large share of the wage differential, being those women working in commerce and service activities more discriminated compared to the base group. Also, while discrimination in returns to experience is marginal at the median, it is still present at the top of the distribution. Moreover, there is a positive change in the constant term at the lower half of the distribution. This implies that there are other factors influencing the wage structure that cannot be attributed to the explanatory variables.

From these results we can observe that the picture at different percentiles vary among themselves as well as from the mean, as other country-case studies have shown. Firstly, we now observe the presence of occupational segregation due to discrimination at the 10th percentile. This is evidenced by the fact that women have higher representation than men in the commerce and service activities (see table 16 in appendix) but face a greater discrimination in their returns to these characteristics compared to the base group in 2005 and 2009. This situation is similar among professional, technical and managerial, and sales and clerical occupations at the 90th percentile, especially for 2009 (see table 16 in appendix).

Meanwhile, as in the case of the mean, we also find evidence of taste-based discrimination in the way described by Becker (1971). Men have greater returns to human capital compared to women. Also, the higher returns to experience and to other unobserved characteristics favoring men drive the effect of the wage structure at the upper half of the distribution. Moreover, there is a reduction in the wage gap over time, along the distribution and in the discrimination in the returns to experience and education. These results are in line with Becker's (1971) predictions. Nevertheless, as in the case of the mean, we should be cautious with this interpretation due to the short time span analyzed (four years).

As we mentioned in subsection 5.4, we might understate the level of discrimination if women are concentrated in certain sectors due to discriminatory practices. We argue that this might be our case. Although it is difficult to test this issue in the data, we can provide an intuitive idea about it. In table 16 in appendix, it is observed that women tend to be concentrated in commercial and service activities and in sales and clerical occupations. Agurto *et al.* (2008) states that women tend to be concentrated in this type of activities due to the role of "stereotypes" in the Nicaraguan society. Therefore, the actual effect of discrimination might be greater. However, we do not believe that this is the case for professional, technical and managerial occupations, as this category is the best remunerated in the labor market (see table 1) and usually individuals with greater human capital are hired. In this case, it is difficult to assert whether such effect is related to segregation due to discrimination or if other forms of discrimination are driving this result.

Finally, it is likely that potential experience overstates actual experience, especially for women (Arends, 1992; Scott, 1992). Therefore, in order to explore to which extent the effect of potential experience is overstated in our results, we estimate the decompositions at the 10th, 50th and 90th percentiles using occupational tenure instead of potential experience. We do so only for 2005 due to data availability on occupational tenure only in this survey. As mentioned before, it is important to highlight that this variable does not necessarily reflect the returns to experience over the life-cycle. The results of the decompositions are presented in table 17 in appendix. As we can observe, we reach the same conclusions than before, as the results does not vary considerably. Therefore, we focus on the effect captured by occupational tenure. It is found that an increase in the wage gap due to a higher tenure in occupations for men compared to women, as was reflected in the graphical inspection in subsection 3.1.1 (see figure 3). Furthermore, the difference in returns to experience is higher for men, but the effect is lower compared to the one found with potential experience. Thus potential experience is likely to understate the endowment effect and overstate the wage structure effect.

7 Conclusions

Women in urban Nicaragua have lower wages on average than men for 2005 and 2009. This situation is also observed across the wage distribution. The gap is larger at the bottom part, which provides evidence of a "sticky floor effect" during the period analyzed. In this study we explore in detail which factors influence these differences, the effect of labor market participation and is updated the wage differential for 2009. For this task, using data from the National Household Living Standards Survey (EMNV), we applied an Oaxaca-Blinder (1973) decomposition (standard and correcting for potential selection bias) of the mean wage and the novel Recentered Influence Function (RIF) regression method introduced by Firpo, Fortin, and Lemieux (2009) for the wage distribution.

The results for 2005 and 2009 suggest that age and education have strong impact in the decision of participation in the labor market of both groups, while the need for income seems to be more important for women's decision. The latter finding points to an evidence of substitution in household work, in which children (especially girls) perform most of the home tasks (Agurto *et al.*, 2008). These results are robust to different definitions of labor market participation. Nevertheless, we do not find a clear evidence of selection bias, therefore it is likely that the observed characteristics of the working individuals are not very different from those who are out of the labor market (voluntary and non-voluntary unemployed).

Looking at the decomposition of the mean wages, it is observed that discrimination accounted for a large share of the differences in wages in urban areas, confirming previous evidence for the country. We argue that the wage gap is driven by taste-based discrimination in the way stated by Becker (1971) and we do not find support to a mean wage gap due to gender occupational segregation. Moreover, the discriminatory levels in average wages have been reduced over the period of study.

Meanwhile, looking at the decomposition across the wage distribution the picture is different from the mean, as other country-case studies have shown. In 2005, discrimination appears to have a different effect on the wage gap across the distribution. In contrast, for 2009 the level of discrimination has been reduced at the lower and upper part and now the wage structure is similar along the distribution, except at the top. The wage structure (including the effect of discrimination) captures almost all the sticky floor effect in both years, but discrimination tend to be higher at the upper half of the distribution. Nevertheless, higher women endowments in human capital and some job-related characteristics contribute to offset the effect of discrimination in both years as we move up in the distribution.

We argue that discrimination takes different forms along the distribution. We found evidence of occupational segregation due to discrimination at the bottom part. In contrast, at the upper half there appears to be taste-based discrimination outlined in Becker's (1971) view, although there is a discriminatory effect for those women working in professional, technical and managerial occupations that is somewhat puzzling. In fact, the effect of discrimination is difficult to measure with exact precision. Firstly, potential experience is likely to overstate actual experience and thus understate the endowment effect and overstate the wage structure effect. Secondly, the inclusion of occupational categories is likely to understate discrimination as women are concentrated in commercial and services activities due to the role of "stereotypes" in the Nicaraguan society (Agurto *et al.* 2008). Moreover, The results should be treated with caution as decomposition methods provide descriptive results of the differences in the labor market but not structural relations and causal estimations. This is because unobserved characteristics, potential sample selection and endogeneity could also influence the results (Fortin, Lemieux and Firpo, 2010).

The results highlight the importance of designing policies that narrow the gender wage gap. For example, for women with lower wages, policies should be oriented towards reducing discrimination in commercial and services activities. Meanwhile, for women with higher wages, policies should be focused on promoting the reduction of employer's discrimination based on taste among professional, technical and managerial occupations. In addition, discrimination in sales and clerical occupations should be tackled. In this regard, the reduction in discrimination during the period of study suggests that the policy shift during Ortega's administration could be contributing to the wage convergence.

Future research should be oriented as follows. Firstly, it should explore the selection into job-categories between men and women and test if this has an effect on labor market participation and on the decomposition of the wage gap. Secondly, our results from the RIF regression method should be confirmed by applying a reweighting approach combined with the RIF method in the way suggested by Fortin, Lemieux and Firpo (2010). Finally, when a new survey becomes available, the determinants of the gender wage gap should be tested in order to make a better evaluation of Ortega's policies focused on gender equity.

8 References

Adireksombat, K., Zheng, F., and Sakellariou, C. (2010). The Evolution of Gender Wage Differentials and Discrimination in Thailand: 1991-2007 An Application of Unconditional Quantile Regression, *Economic Growth Centre Working Paper Series 1005*, Nanyang Technological University, School of Humanities and Social Sciences, Economic Growth Centre.

Agurto, S., Guido, A., Alanz, E, Sandino, A., Acevedo, I., and Michell, N. (2008). Mujeres Nicaraguenses, Cimiento Económico Familiar: Estadísticas e Investigaciones de FIDEG, 1st edn, Managua: FIDEG.

Ahmed, S. and Maitra, P. (2010). Gender Wage Discrimination in Rural and Urban labor Markets of Bangladesh, *Oxford Development Studies*, vol. 38, no. 1, pp. 83-112.

Aigner, D. J. and Cain, G. G. (1977). Statistical Theories of Discrimination in Labor Markets, *Industrial and Labor Relations Review*, vol. 30, no. 2, pp. 175-187.

Albrecht, J., Björklund, A., and Vroman, S. (2003). Is There a Glass Ceiling in Sweden?, *Journal of Labor Economics*, vol. 21, no. 1, pp. 145-177.

Altonji, J. G. and Blank, R. (1999). Race and Gender in the Labor Market, in O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, vol. 3 C, Amsterdam: Elsevier Science, pp. 3143-3259.

Anker, R. (1997). Theories of Occupational Segregation by Sex: An Overview, *International labor Review*, vol. 136, no. 3, pp. 315-339.

Antecol, H. and Cobb-Clark, D. A. (2010). Do Non-Cognitive Skills Help Explain the Occupational Segregation of Young People?, *IZA Discussion Papers 5093*, Institute for the Study of Labor (IZA).

Arends, M. (1992). Female Labor Force Participation and Earnings in Guatemala, in G. Psacharopoulos and Z. Tzannatos (eds), *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank, pp. 273-298.

Arrow, K. J. (1971). Models of Job Discrimination, in A. H. Pascal (ed), *Racial Discrimination and Economic Life*, Lexington Books.

Arulampalam, W., Booth, A. L., and Bryan, M. L. (2007). Is There a Glass Ceiling Over Europe? Exploring the Gender Pay Gap Across the Wage Distribution, *Industrial and Labor Relations Review*, vol. 60, no. 2, pp. 163-186.

Atal, J. P., Ñopo, H., and Winder, N. (2010). New Century, Old Disparities: Gender and Ethnic Wage Gaps in Latin America, *IZA Discussion Papers 5085*, Institute for the Study of Labor (IZA).

Beblo, M., Beninger, D., Heinze, A., and Laisney, F. (2003). Measuring Selectivity-Corrected Gender Wage Gaps in the EU, *ZEW Discussion Paper 03-74*, Centre for European Economic Research (ZEW), Mannheim.

Becker, G. (1971). *The Economics of Discrimination*, 2nd edn, Chicago: The University of Chicago Press.

Bergmann, B. (1974). Occupational Segregation, Wages, and Profits When Employers Discriminate by Race or Sex, *Eastern Economic Journal*, vol. 1, no. 2, pp. 103-110.

Black, D. A. (1995). Discrimination in an Equilibrium Search Model. *Journal of Labor Economics*, vol. 13, no. 2, pp. 309-334.

Blau, F. D. and Kahn, L. M. (2000). Gender Differences in Pay, *Journal of Economic Perspectives*, vol. 14, no, 4, pp. 75-99.

Blinder, A. (1973). Wage Discrimination: Reduced Form and Structural Estimates, *Journal of Human Resources*, vol. 8, no. 4, pp. 436-455.

Bourguignon, F. and Ferreira, F. H. G. (2005). Decomposing Changes in the Distribution of Household Incomes: Methodological Aspects, in F. Bourguignon, F. H. G. Ferreira, and N. Lustig (eds), *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America*, Washington, D.C: World Bank, pp. 17-46.

Bourguignon, F., Ferreira, F. H. G., and Leite, P. G. (2008). Beyond Oaxaca-Blinder: Accounting for Differences in Household Income Distributions. *Journal of Economic Inequality* vol. 6, pp. 117-148.

Cain, G. G. (1986). The Economic Analysis of Labor Market Discrimination: A Survey, in O. C. Ashenfelter and R. Layard (eds), *Handbook of Labor Economics*, vol, 1, Elsevier, pp. 693-785.

Central Bank of Nicaragua -BCN- (2012). Informe Anual 2011 [pdf] Available at: `http://www.bcn.gob.ni/publicaciones/anual/memoria/2011/Informe_anual_2011.pdf` [Accessed 28 May 2013]

Chernozhukov, V., Fernandez-Val, Ivan, Melly, B. (2009). Inference on Counterfactual Distributions, *CeMMAP working paper CWP09/09*.

Chi, W. and Li, B. (2008). Glass Ceiling or Sticky Floor? Examining the Gender Earnings Differential Across the Earnings Distribution in Urban China, 1987-2004, *Journal of Comparative Economics*, vol. 36, pp. 243-263.

Cotton, J. (1988). On the Decomposition of Wage Differentials, *The Review of Economics and Statistics*, vol. 70, no. 2, pp. 236-243.

Das Gupta, M. (1987). Selective Discrimination Against Female Children in Rural Punjab, India, *Population and Development Review*, vol. 13, no. 1, pp. 77-100.

Deutsch, R., Morrison, A., Ñopo, H., and Piras, C. (2005). Working Within Confines: Occupational Segregation by Gender for Three Latin American Countries, *The ICFAI Journal of Applied Economics*, ICFAI Press, Vol. 0, no. 3.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-parametric Approach, *Econometrica*, vol. 64, no. 5, pp. 1001-1044.

Dolton, P. J. and Makepeace, G. H. (1986). Sample Selection and Male-Female Earnings Differentials in the Graduate labor Market, *Oxford Economic Papers*, vol. 38, no. 2, pp. 317-341.

Duryea, S., Galiani, S., Ñopo, H., and Piras, C. (2007). The Educational Gender Gap in Latin America and the Caribbean, *Research Department Working Paper 600*, Washington, DC, United States: Inter-American Development Bank.

Economic Comission for Latin America and the Caribbean -ECLAC- (2012). Social Panorama of Latin America 2012 [e-book] Santiago: United Nations, Economic Commission for Latin America and the Caribbean. Available through: `http://www.eclac.org/publicaciones/xml/8/49398/2012-960-PSI_WEB.pdf` [Accessed 29 May 2013]

Enamorado, T., Izaguirre, A. C., and Ñopo, H. (2009). Gender Wage Gaps in Central American Countries: Evidence from a Non-Parametric Approach, *Research Department Publications 4639*, Inter-American Development Bank, Research Department.

Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional Quantile Regressions, *Econometrica*, vol. 77, no. 3, pp. 953-973.

Fortin, N. M. (2008). The Gender Wage Gap Among Young Adults in the United States: The Importance of Money versus People, *Journal of Human Resources*, vol. 43, no. 4, pp. 886-920.

Fortin, N. M., Lemieux, T., and Firpo, S. (2010). Decomposition Methods in Economics, in O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, vol. 4 A, Elsevier B.V., pp. 1-102.

Gobierno de Reconciliación y Unidad Nacional -GRUN- (2012). Plan Nacional de Desarrollo Humano 2012-2012 [pdf] Available at: `http://www.pndh.gob.ni/documentos/pndhActualizado/pndh.pdf` [Accessed 29 May 2013]

Gutierrez, C., Paci, P., and Ranzani, M. (2008). *Making Work Pay in Nicaragua: Employment, Growth, and Poverty Reduction*, [e-book] Washington, D.C: World Bank. Available through: `https://openknowledge.worldbank.org/handle/10986/6472` [Accessed 08 May 2013]

Heckman, J. (1979). Sample Selection Bias as a Specification Error, *Econometrica*, vol. 47, no. 1, pp. 153-161.

Jann, B. (2008). The Oaxaca-Blinder Decomposition for Linear Regression Models, *Stata Journal*, vol. 8, pp. 435-479.

Juhn, C., Murphy, K. M., and Pierce, B. (1993). Wage Inequality and the Rise in Returns to Skill, *Journal of Political Economy*, vol. 101, no. 3, pp. 410-442.

Lauer, C. and Steiner, V. (2000). Returns to Education in West Germany - An Empirical Assessment, *ZEW Discussion Paper 00-04*, Mannheim.

Law No. 287: Código de la Niñez y la Adolescencia. Managua: National Assembly.

Lewbel, A. (2007). Endogenous Selection Or Treatment Model Estimation, *Journal of Econometrics*, vol. 141, no. 2, pp. 777-806.

Machado, J. A. F. and Mata, J. (2005). Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression, *Journal of Applied Econometrics*, vol. 20, no. 4, pp. 445-465.

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution, *Journal of Political Economy*, vol. 66, no. 4, pp. 281-302.

Ministerial Agreement JCHG-010-06-07 approved on May 23, 2007 by the Minister of Labor of Nicaragua.

Monroy, E. (2008). Equidad de Género en el Mercado Laboral para Nicaragua, *Serie de Cuadernos de Género para Nicaragua 1*, Washington, D.C: World Bank and Inter-American Development Bank.

Neumark, D. (1988). Employers' Discriminatory Behaviour and the Estimation of Wage Discrimination, *Journal of Human Resources*, vol. 23, no. 3, pp. 279-295.

Neuman, S. and Oaxaca, R. (2004). Wage Decompositions with Selectivity-Corrected Wage Equations: A Methodological Note, *Journal of Economic Inequality*, vol. 2, no. 1, pp. 3-10.

Ng, Y. C. (1992). Female Labor Force Participation and Gender Earnings Differentials in Argentina, in G. Psacharopoulos and Z. Tzannatos (eds), *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank, pp. 1-20.

Ñopo, H. and Hoyos, A. (2010). Evolution of Gender Wage Gaps in Latin America at the Turn of the Twentieth Century: An Addendum to "New Century, Old Disparities", *IZA Discussion Papers 5086*, Institute for the Study of Labor (IZA).

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets, *International Economic Review*, vol. 14, no. 3, pp. 693-709.

Oaxaca, R. and Ransom, M. R. (1994). On Discrimination and the Decomposition of Wage Differentials, *Journal of Econometrics*, vol. 61, no. 1, pp. 5-21.

Phelps, E. S. (1972). The Statistical Theory of Racism and Sexism, *American Economic Review*, vol. 62, no. 4, pp. 659-661.

Polachek, S. (1985). Occupation Segregation: A Defense of Human Capital Predictions, *Journal of Human Resources*, University of Wisconsin Press, vol. 20, no.3, pages 437-440.

Polachek, S. (2004). How the Human Capital Model Explains Why the Gender Wage Gap Narrowed, *IZA Discussion Papers 1102*, Institute for the Study of Labor (IZA).

Psacharpoulos, G. and Tzannatos, Z. (eds) (1992). *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank.

Puhani, P. (2000). The Heckman Correction for Sample Selection and its Critique, *Journal of Economic Surveys*, vol. 14, no. 1, pp. 53-68.

Reimers, C. W. (1983). Labor Market Discrimination Against Hispanic and Black Men, *The Review of Economics and Statistics*, vol. 65, no. 4, pp. 570-579.

Salardi, P. (2013). An Analysis of Pay and Occupational Differences by Gender and Race in Brazil - 1987 to 2006, Unpublished, PhD Thesis, University of Sussex, U.K.

Scott, K. (1992). Women in the Labor Force in Bolivia: Participation and Earnings, in G. Psacharopoulos and Z. Tzannatos (eds), *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank, pp. 21-38.

Stelcner, M., Smith, J. B., Breslaw, J. A., and Monette, G. (1992). Labor Force Behavior and Earnings of Brazilian Women and Men, 1980, in G. Psacharopoulos and Z. Tzannatos (eds), *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank, pp. 39-88.

Tenjo, J., Ribero, R., and Bernat, L.F. (2005). Evolución de las Diferencias Salariales por Sexo en Seis Países de América Latina: Un Intento de Interpretación, *Document CEDE 2656*, Bogota, Colombia: Universidad de los Andes, Centro de Estudios sobre Desarrollo Económico (CEDE).

The World Bank (2013). World Development Indicators. Available Online: `http://databank.worldbank.org/data/views/reports/tableview.aspx` [Accessed 27 May 2013]

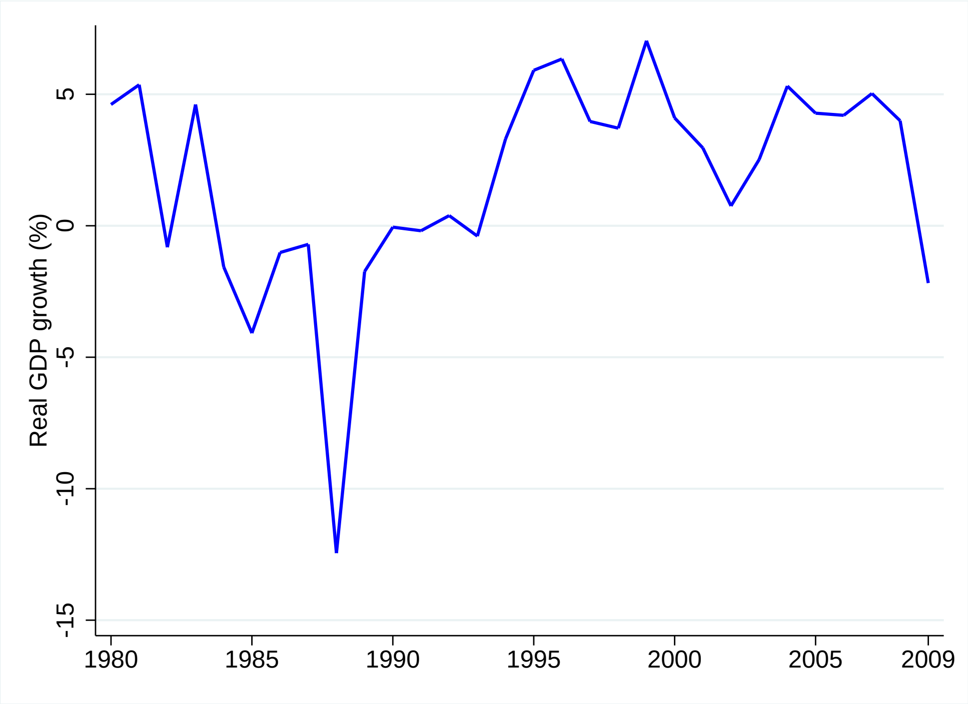
Tinoco, G. and Agurto, S. (2003). Diagnóstico Género y Mercado Laboral en Nicaragua, Informe Final. Oficina Internacional del Trabajo-Managua.

Vella, F. (1998). Estimating Models with Sample Selection Bias, *Journal of Human Resources*, vol. 33, no. 1, pp. 129-169.

Yang, H. (1992). Female Labor Force Participation and Earnings Differentials in Costa Rica, in G. Psacharopoulos and Z. Tzannatos (eds), *Case Studies on Women's Employment and Pay in Latin America*, Washington, D.C: World Bank, pp. 209-222.

Appendices

Figure 10: Real GDP growth (%) in Nicaragua, 1980-2009



Source: Central Bank of Nicaragua (BCN).

Table 5: Urban labor Market Characteristics by Gender, 2005

Variable	Working		Unemployed: Voluntary		Unemployed: Non voluntary	
	Male	Female	Male	Female	Male	Female
Age	34.66	36.62	19.24	30.00	27.80	27.82
Age group (%)						
Age 14 to 24	28.20%	18.96%	92.14%	51.74%	58.44%	51.91%
Age 25 to 29	14.39%	15.00%	1.95%	9.04%	11.93%	16.44%
Age 30 to 34	12.84%	12.34%	0.19%	7.34%	4.94%	7.97%
Age 35 to 39	10.15%	13.99%	0.74%	5.00%	5.46%	7.74%
Age 40 to 44	9.48%	11.75%	0.48%	5.23%	4.86%	3.87%
Age 45 to 49	9.37%	11.71%	0.51%	4.98%	3.82%	4.21%
Age 50 to 54	5.61%	7.70%	0.09%	5.79%	2.52%	3.05%
Age 55 to 59	5.50%	5.02%	0.51%	4.47%	4.49%	3.18%
Age 60 to 65	4.46%	3.53%	3.39%	6.41%	3.55%	1.63%
Years of education	8.61	9.16	9.40	8.03	8.33	9.79
Education levels (%)						
None or Primary Incomplete	26.38%	25.60%	12.62%	27.46%	27.69%	18.16%
Primary Complete or Secondary Incomplete	44.11%	34.04%	64.24%	50.30%	46.02%	40.41%
Secondary Complete, Tertiary or Technical Incomp.	17.36%	23.78%	19.90%	17.56%	17.11%	29.58%
Tertiary and Technical Complete	12.15%	16.58%	3.24%	4.67%	9.17%	11.85%
Region (%)						
Managua	41.95%	40.74%	37.13%	37.28%	38.88%	50.73%
Pacific	30.53%	31.18%	34.14%	30.79%	32.41%	24.41%
Central	20.58%	21.22%	20.30%	23.36%	22.35%	18.78%
Atlantic	6.94%	6.86%	8.43%	8.56%	6.36%	6.08%
Household characteristics						
Household size (#)	5.95	5.84	6.21	6.19	6.40	6.21
Married (%)	63.53%	47.58%	6.31%	45.66%	29.09%	37.58%
# employed persons in HH	1.57	1.63	1.07	0.97	0.95	1.01
# children $<$ 14 years old in HH	1.66	1.68	1.37	1.77	1.66	1.76
Number of observations	3,437	2,551	718	2,662	763	576

Notes: Sample includes individuals between 14 and 65 years old. 69.89% of the men and 44.07% the women in the sample were classified as working, as they reported positive hours and earnings in the primary occupation. Outliers and missing values were eliminated from the sample.
Source: Author's calculations based on EMNV 2005.

Table 6: Urban labor Market Characteristics by Gender, 2009

Variable	Working		Unemployed			
			Voluntary		Non voluntary	
	Male	Female	Male	Female	Male	Female
Age	35.34	36.81	21.03	29.99	29.07	29.60
Age group (%)						
Age 14 to 24	23.05%	16.94%	88.70%	51.06%	49.60%	44.00%
Age 25 to 29	17.14%	15.04%	1.32%	10.61%	14.25%	17.19%
Age 30 to 34	12.43%	13.86%	0.12%	6.87%	8.35%	9.21%
Age 35 to 39	11.89%	15.02%	0.35%	5.18%	6.07%	10.07%
Age 40 to 44	9.63%	11.77%	0.47%	5.28%	5.40%	5.39%
Age 45 to 49	9.80%	10.20%	0.36%	5.60%	4.66%	4.92%
Age 50 to 54	6.88%	8.38%	1.31%	4.26%	4.87%	3.43%
Age 55 to 59	5.61%	5.36%	1.03%	4.84%	4.12%	3.22%
Age 60 to 65	3.59%	3.43%	6.35%	6.29%	2.69%	2.57%
Years of education	8.96	9.48	9.56	8.63	8.49	9.37
Education levels (%)						
None or Primary Incomplete	25.17%	24.58%	11.70%	23.09%	25.30%	22.64%
Primary Complete or Secondary Incomplete	41.32%	32.23%	61.27%	49.50%	47.99%	38.08%
Secondary Complete, Tertiary or Technical Incomp.	20.21%	23.46%	23.30%	21.73%	18.02%	25.59%
Tertiary and Technical Complete	13.30%	19.74%	3.73%	5.67%	8.70%	13.69%
Region (%)						
Managua	38.74%	41.03%	40.63%	36.71%	40.41%	42.90%
Pacific	31.06%	31.38%	30.51%	30.96%	32.95%	26.46%
Central	21.39%	20.09%	21.09%	23.17%	20.97%	23.37%
Atlantic	8.80%	7.50%	7.77%	9.17%	5.68%	7.28%
Household characteristics						
Household size (#)	5.25	5.13	5.45	5.46	5.92	6.25
Married (%)	66.27%	49.92%	8.06%	46.09%	35.61%	39.15%
# employed persons in HH	1.32	1.38	0.74	0.75	0.79	0.71
# children < 14 years old in HH	1.39	1.44	1.09	1.43	1.38	1.78
Number of observations	4,421	3,545	1,089	3,299	1,104	737

Notes: Sample includes individuals between 14 and 65 years old. 66.84% of the men and 46.76% the women in the sample were classified as working, as they reported positive hours and earnings in the primary occupation. Outliers and missing values were eliminated from the sample.
Source: Author's calculations based on EMNV 2009.

Table 7: **Job-related Characteristics by Gender, 2005-2009**

Variable	2005 Male	2005 Female	2009 Male	2009 Female
Hours worked	50.58	44.75	49.59	44.18
Potential experience	20.05	21.45	20.38	21.33
Occupational tenure	6.82	6.14	-	-
Occupational category (%)				
Employee	71.03%	58.33%	64.53%	57.03%
Self-employed	22.14%	37.86%	34.04%	42.40%
Employer	6.83%	3.81%	1.43%	0.57%
Economic sector (%)				
Industry	44.69%	21.40%	41.12%	16.77%
Commerce	24.83%	33.80%	25.16%	35.89%
Service	30.48%	44.80%	33.73%	47.34%
Occupation classes (%)				
Non-skill workers	28.75%	28.45%	28.99%	30.73%
Professional, Technical and Managerial	14.21%	21.01%	16.84%	20.39%
Sales and Clerical	14.67%	36.82%	12.58%	38.24%
Operational and Services Workers	42.37%	13.72%	41.59%	10.64%
Number of observations	3,437	2,551	4,421	3,545

Source: Author's calculations based on EMNV 2005 and 2009.

Table 8: Wage Equations Corrected for Selectivity, 2005-2009

	2005				2009			
Variable	**Males (1)**	**Females (2)**	**Males (3)**	**Females (4)**	**Males (5)**	**Females (6)**	**Males (7)**	**Females (8)**
None or Primary Incomplete	-0.3546***	-0.4423***	-0.3543***	-0.4375***	-0.4129***	-0.3148***	-0.4161***	-0.3157***
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Primary Complete or Secondary Incomplete	-0.1294***	-0.2812***	-0.1340***	-0.2752***	-0.2492***	-0.2136***	-0.2505***	-0.2138***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
Tertiary and Technical Complete	0.5076***	0.4545***	0.5132***	0.4537***	0.2768***	0.4464***	0.2753***	0.4467***
	(0.08)	(0.06)	(0.08)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
Experience	0.0270***	0.0206***	0.0286***	0.0203***	0.0280***	0.0178***	0.0280***	0.0179***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Experience^2	-0.0005***	-0.0003***	-0.0005***	-0.0003***	-0.0005***	-0.0003***	-0.0005***	-0.0003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Managua	0.2001***	0.2082***	0.2002***	0.2080***	0.0718**	0.1000***	0.0718**	0.1002***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Central	-0.1018***	-0.1836***	-0.1014***	-0.1834***	0.0333	-0.1903***	0.0329	-0.1902***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.06)	(0.07)
Self-employed	0.0521	0.2316***	0.0519	0.2320***	0.1152**	0.1687***	0.1145**	0.1688***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Employer	0.7333***	0.9063***	0.7319***	0.9062***	0.5775**	0.5807***	0.5807**	0.5815***
	(0.08)	(0.13)	(0.08)	(0.13)	(0.23)	(0.16)	(0.23)	(0.16)
Professional, Technical and Managerial	0.3469***	0.5334***	0.3448***	0.5323***	0.3520***	0.3406***	0.3522***	0.3404***
	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)
Sales and Clerical	-0.0679	-0.0981	-0.0697	-0.0984	-0.0137	-0.1665**	-0.0132	-0.1666**
	(0.05)	(0.08)	(0.05)	(0.08)	(0.06)	(0.08)	(0.06)	(0.08)
Non-Skill	-0.1944***	0.0745	-0.1951***	0.0736	-0.1864***	-0.2300***	-0.1867***	-0.2302***
	(0.03)	(0.08)	(0.03)	(0.08)	(0.04)	(0.09)	(0.04)	(0.09)
Commerce	0.0464	0.0323	0.0468	0.0324	0.0847*	0.0665	0.0852*	0.0667
	(0.04)	(0.07)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.06)
Service	0.1060***	-0.0968	0.1077***	-0.0966	0.0891*	0.0633	0.0895*	0.0636
	(0.04)	(0.07)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.06)
λ_m^{def1}	-0.1576*				0.1280			
	(0.09)				(0.11)			
λ_f^{def1}		0.0966				0.0172		
		(0.07)				(0.08)		
λ_m^{def2}			-0.0745				0.1026	
			(0.06)				(0.08)	
λ_f^{def2}				0.0652				0.0171
				(0.05)				(0.05)
Constant	1.9557***	1.7144***	1.9331***	1.7226***	2.0698***	1.9830***	2.0697***	1.9809***
	(0.06)	(0.09)	(0.06)	(0.08)	(0.08)	(0.10)	(0.07)	(0.09)
R-squared	0.322	0.300	0.321	0.300	0.204	0.248	0.204	0.248
Sample size	3437.00	2551.00	3437.00	2551.00	4421.00	3545.00	4421.00	3545.00

Notes: Dependent variable is the natural logarithm of real hourly wages.
*** significant at 1% level, ** significant at 5% level, * significant at 10% level. Robust standard errors are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
λ_m^{def1} and λ_f^{def1} correspond to the λ coefficients using definition 1 for males and females, respectively. λ_m^{def2} and λ_f^{def2} are the λ coefficients using definition 2 for males and females, respectively.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 9: Oaxaca-Blinder Decomposition, 2005-2009 (Composition Effect)

	2005		2009	
	Male coef.	Pooled coef.	Male coef.	Pooled coef.
Mean log wage gap:				
$E[ln(w_m)] - E[ln(w_f)]$	**0.1889**	**0.1889**	**0.1388**	**0.1388**
	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**
Composition effect	**-0.0656**	**-0.0635**	**-0.0806**	**-0.0618**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**
Contribution of X to the composition effect:				
None or Primary Incomplete	-0.0028	-0.0029	-0.0024	-0.0022
	(0.01)	(0.01)	(0.01)	(0.01)
Primary Complete or Secondary Incomplete	-0.0142	-0.0184	-0.0218	-0.02
	(0.01)	(0.00)	(0.01)	(0.00)
Tertiary and Technical Complete	-0.0229	-0.021	-0.0175	-0.0232
	(0.01)	(0.01)	(0.01)	(0.01)
Experience	-0.0436	-0.0354	-0.023	-0.0195
	(0.02)	(0.01)	(0.01)	(0.01)
Experience^2	0.0286	0.0233	0.0175	0.0144
	(0.01)	(0.01)	(0.01)	(0.01)
Managua	0.0024	0.0025	-0.0016	-0.0020
	(0.00)	(0.00)	(0.00)	(0.00)
Central	0.0006	0.0009	0.0004	-0.0008
	(0.00)	(0.00)	(0.00)	(0.00)
Self-employed	-0.0080	-0.0229	-0.0097	-0.0109
	(0.01)	(0.01)	(0.00)	(0.00)
Employer	0.0221	0.0242	0.0051	0.0051
	(0.01)	(0.01)	(0.00)	(0.00)
Professional, Technical and Managerial	-0.0233	-0.0261	-0.0127	-0.0127
	(0.01)	(0.01)	(0.01)	(0.01)
Sales and Clerical	0.0160	0.0286	0.0030	0.0248
	(0.01)	(0.01)	(0.01)	(0.01)
Non-Skill	-0.0006	-0.0004	0.0032	0.0032
	(0.00)	(0.00)	(0.00)	(0.00)
Commerce	-0.0043	-0.0068	-0.0091	-0.0084
	(0.00)	(0.00)	(0.01)	(0.00)
Service	-0.0157	-0.0089	-0.0118	-0.0097
	(0.01)	(0.00)	(0.01)	(0.01)

Notes: Dependent variable is the natural logarithm of real hourly wages.
Standard errors computed using the Delta method are reported in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 10: Oaxaca-Blinder Decomposition, 2005-2009 (Wage Structure Effect)

	2005		2009	
	Male coef.	Pooled coef.	Male coef.	Pooled coef.
Mean log wage gap:				
$E[ln(w_m)] - E[ln(w_f)]$	**0.1889**	**0.1889**	**0.1388**	**0.1388**
	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**
Wage structure effect	**0.2545**	**0.2523**	**0.2194**	**0.2007**
	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**
Contribution of X to the wage structure effect:				
None or Primary Incomplete	0.0153	0.0155	-0.0243	-0.0246
	(0.02)	(0.02)	(0.02)	(0.02)
Primary Complete or Secondary Incomplete	0.0397	0.0439	-0.0095	-0.0113
	(0.02)	(0.03)	(0.02)	(0.03)
Tertiary and Technical Complete	0.0121	0.0103	-0.0339	-0.0282
	(0.02)	(0.01)	(0.02)	(0.02)
Experience	0.291	0.2829	0.1467	0.1432
	(0.13)	(0.13)	(0.14)	(0.14)
Experience^2 Squared	-0.155	-0.1496	-0.0861	-0.0830
	(0.08)	(0.08)	(0.08)	(0.08)
Managua	-0.0025	-0.0026	-0.0114	-0.0110
	(0.02)	(0.02)	(0.02)	(0.02)
Central	0.0174	0.0172	0.0449	0.0462
	(0.01)	(0.01)	(0.02)	(0.02)
Self-employed	-0.0691	-0.0542	-0.0221	-0.0210
	(0.03)	(0.02)	(0.03)	(0.03)
Employer	-0.0067	-0.0088	0.0001	0.0000
	(0.01)	(0.01)	(0.00)	(0.00)
Professional, Technical and Managerial	-0.0405	-0.0377	0.0035	0.0035
	(0.02)	(0.02)	(0.02)	(0.02)
Sales and Clerical	0.0076	-0.0050	0.0591	0.0373
	(0.03)	(0.03)	(0.04)	(0.03)
Non-Skill	-0.0779	-0.0781	0.0145	0.0144
	(0.03)	(0.03)	(0.03)	(0.03)
Commerce	0.0064	0.0089	0.0066	0.0059
	(0.03)	(0.03)	(0.03)	(0.03)
Service	0.0934	0.0865	0.0113	0.0093
	(0.04)	(0.03)	(0.04)	(0.03)
Constant	0.1232	0.1232	0.1200	0.1200
	(0.09)	(0.09)	(0.09)	(0.09)

Notes: Dependent variable is the natural logarithm of real hourly wages.
Standard errors computed using the Delta method are reported in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 11: Unconditional Quantile Wage Regressions, 2005

	10th		50th		90th	
Variables	**Males (1)**	**Females (2)**	**Males (3)**	**Females (4)**	**Males (5)**	**Females (6)**
None or Primary Incomplete	-0.3548***	-0.5072***	-0.3913***	-0.5117***	-0.2248*	-0.0688
	(0.08)	(0.12)	(0.07)	(0.08)	(0.12)	(0.13)
Primary Complete or Secondary Incomplete	-0.1914***	-0.4266***	-0.1331**	-0.3633***	-0.0247	0.1236
	(0.06)	(0.10)	(0.06)	(0.07)	(0.11)	(0.11)
Tertiary and Technical Complete	0.0776	0.1059*	0.3504***	0.3379***	1.3159***	1.0735***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.23)	(0.19)
Experience	0.0268***	0.0315***	0.0285***	0.0158***	0.0367***	0.0132
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Experience^2	-0.0005***	-0.0006***	-0.0005***	-0.0003**	-0.0006***	-0.0002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Managua	0.1712***	0.1217	0.2003***	0.2242***	0.1678*	0.2333**
	(0.05)	(0.08)	(0.05)	(0.05)	(0.09)	(0.10)
Central	-0.1349**	-0.3724***	-0.0660*	-0.1592***	-0.0254	-0.0511
	(0.06)	(0.09)	(0.04)	(0.04)	(0.07)	(0.08)
Self-employed	-0.2778***	-0.0536	0.1589***	0.3037***	0.3366***	0.2947***
	(0.07)	(0.09)	(0.05)	(0.06)	(0.10)	(0.10)
Employer	0.1853***	0.2311**	0.5507***	0.7668***	1.3320***	1.6614***
	(0.05)	(0.12)	(0.07)	(0.10)	(0.23)	(0.41)
Professional, Technical and Managerial	-0.0233	0.1985	0.2021***	0.4296***	1.0597***	1.0446***
	(0.07)	(0.12)	(0.07)	(0.12)	(0.21)	(0.23)
Sales and Clerical	-0.1227	-0.2567*	-0.1026	-0.0613	0.1967	0.0461
	(0.08)	(0.13)	(0.07)	(0.10)	(0.13)	(0.16)
Non-Skill	-0.1947***	-0.0124	-0.3644***	0.0524	-0.0141	0.3264*
	(0.06)	(0.13)	(0.05)	(0.11)	(0.07)	(0.18)
Commerce	0.0139	-0.0343	0.0492	0.0221	-0.0411	0.1416
	(0.06)	(0.13)	(0.06)	(0.09)	(0.10)	(0.17)
Service	0.0544	-0.3415***	0.1418***	-0.0368	-0.0039	-0.2545
	(0.06)	(0.12)	(0.05)	(0.09)	(0.11)	(0.18)
Constant	1.3412***	1.2179***	1.9060***	1.8010***	2.5034***	2.2779***
	(0.08)	(0.12)	(0.07)	(0.10)	(0.11)	(0.14)

Notes: Dependent variable is the RIF at 10th, 50th and 90th percentiles.
Robust standard errors are in parentheses.
The number of observations is 3,437 for males and 2,551 for females.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 12: Unconditional Quantile Wage Regressions, 2009

	10th		50th		90th	
Variables	**Males (1)**	**Females (2)**	**Males (3)**	**Females (4)**	**Males (5)**	**Females (6)**
None or Primary Incomplete	-0.5127***	-0.3835**	-0.4255***	-0.4772***	-0.3758***	-0.0173
	(0.12)	(0.16)	(0.06)	(0.08)	(0.13)	(0.12)
Primary Complete or Secondary Incomplete	-0.2411***	-0.1147	-0.2624***	-0.3549***	-0.2334**	-0.0359
	(0.08)	(0.12)	(0.05)	(0.06)	(0.11)	(0.09)
Tertiary and Technical Complete	0.0733	0.1661**	0.1173**	0.2767***	0.8847***	1.0429***
	(0.10)	(0.08)	(0.06)	(0.06)	(0.21)	(0.16)
Experience	0.0256***	0.0078	0.0205***	0.0202***	0.0365***	0.0214**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Experience^2	-0.0005**	-0.0001	-0.0004***	-0.0003***	-0.0006***	-0.0005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Managua	0.1423**	0.2037***	0.0605*	0.0713*	-0.0033	0.1093
	(0.06)	(0.07)	(0.03)	(0.04)	(0.08)	(0.08)
Central	-0.0491	-0.1213	0.0260	-0.1795**	0.0608	-0.0754
	(0.13)	(0.13)	(0.06)	(0.07)	(0.13)	(0.13)
Self-employed	-0.2199**	-0.0539	0.1834***	0.1608***	0.5620***	0.5176***
	(0.09)	(0.09)	(0.04)	(0.05)	(0.09)	(0.09)
Employer	0.3474***	-0.1710	0.2812**	0.2272*	1.2923**	2.5033***
	(0.08)	(0.19)	(0.14)	(0.14)	(0.65)	(0.51)
Professional, Technical and Managerial	-0.0155	0.1952	0.3010***	0.3043***	0.9410***	0.6275***
	(0.11)	(0.15)	(0.06)	(0.11)	(0.17)	(0.18)
Sales and Clerical	-0.1646	-0.0595	-0.0360	-0.1977**	0.1968	-0.1285
	(0.12)	(0.15)	(0.06)	(0.10)	(0.14)	(0.12)
Non-Skill	-0.1272	-0.2272	-0.3010***	-0.2907***	-0.1259*	-0.0642
	(0.09)	(0.16)	(0.04)	(0.11)	(0.07)	(0.14)
Commerce	0.0627	-0.1292	0.0485	0.1243	0.1010	0.1448
	(0.09)	(0.13)	(0.05)	(0.08)	(0.09)	(0.10)
Service	0.0305	-0.1917	0.1317***	0.1453*	0.0032	0.0838
	(0.09)	(0.12)	(0.04)	(0.08)	(0.10)	(0.12)
Constant	1.4841***	1.3042***	2.1586***	2.0184***	2.6203***	2.5089***
	(0.12)	(0.13)	(0.06)	(0.10)	(0.12)	(0.13)

Notes: Dependent variable is the RIF at 10th, 50th and 90th percentiles.
Robust standard errors are in parentheses.
The number of observations is 4,421 for males and 3,545 for females.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 13: Decomposition of the Gender Wage Gap at Different Percentiles, 2005-2009

	10th	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
2005									
Estimated raw gap	0.360	0.292	0.199	0.136	0.120	0.121	0.184	0.170	0.219
(Bootstrapped std. error)	*(0.04)*	*(0.04)*	*(0.03)*	*(0.03)*	*(0.04)*	*(0.04)*	*(0.05)*	*(0.05)*	*(0.07)*
Composition effect	0.036	0.028	0.010	-0.032	-0.068	-0.111	-0.152	-0.169	-0.204
(Bootstrapped std. error)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.03)*	*(0.04)*	*(0.03)*	*(0.04)*
Wage structure effect	0.324	0.264	0.189	0.169	0.188	0.232	0.336	0.339	0.423
(Bootstrapped std. error)	*(0.05)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.05)*	*(0.05)*	*(0.07)*
2009									
Estimated raw gap	0.241	0.204	0.165	0.171	0.124	0.098	0.082	0.079	0.073
(Bootstrapped std. error)	*(0.05)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.03)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.06)*
Composition effect	0.020	0.024	-0.012	-0.039	-0.072	-0.090	-0.118	-0.135	-0.220
(Bootstrapped std. error)	*(0.03)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.03)*	*(0.03)*	*(0.05)*
Wage structure effect	0.220	0.180	0.177	0.211	0.196	0.188	0.200	0.214	0.292
(Bootstrapped std. error)	*(0.06)*	*(0.04)*	*(0.04)*	*(0.03)*	*(0.03)*	*(0.04)*	*(0.04)*	*(0.05)*	*(0.08)*

Notes: Dependent variable is the RIF at the *th* percentile.
Bootstrapped standard errors with 100 replications are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 14: Detailed Decomposition at Different Percentiles, 2005

	Composition effect			Wage structure effect		
	10th	**50th**	**90th**	**10th**	**50th**	**90th**
Total effect:	**0.036**	**-0.0679**	**-0.2042**	**0.3237**	**0.1883**	**0.4234**
	(0.0249)	(0.0244)	(0.0418)	(0.0491)	(0.0417)	(0.0741)
None or Primary Incomplete	-0.0028	-0.0030	-0.0017	0.0390	0.0308	-0.0399
	(0.0056)	*(0.0060)*	*(0.0034)*	*(0.0406)*	*(0.0288)*	*(0.0451)*
Primary Complete or Secondary Incomplete	-0.0193	-0.0134	-0.0025	0.0801	0.0784	-0.0505
	(0.0071)	*(0.0062)*	*(0.0112)*	*(0.0431)*	*(0.0335)*	*(0.0562)*
Tertiary and Technical Complete	-0.0034	-0.0155	-0.0583	-0.0047	0.0021	0.0402
	(0.0027)	*(0.0052)*	*(0.0193)*	*(0.0139)*	*(0.0179)*	*(0.0624)*
Experience	-0.0375	-0.0399	-0.0514	-0.1009	0.2721	0.5039
	(0.0206)	*(0.0168)*	*(0.0237)*	*(0.2753)*	*(0.1350)*	*(0.3118)*
Experience^2	0.0276	0.0263	0.0316	0.0583	-0.1546	-0.2500
	(0.0193)	*(0.0139)*	*(0.0191)*	*(0.1766)*	*(0.0812)*	*(0.1643)*
Managua	0.0021	0.0024	0.0020	0.0202	-0.0097	-0.0267
	(0.0034)	*(0.0036)*	*(0.0032)*	*(0.0411)*	*(0.0284)*	*(0.0621)*
Central	0.0009	0.0004	0.0002	0.0504	0.0198	0.0055
	(0.0017)	*(0.0009)*	*(0.0009)*	*(0.0247)*	*(0.0121)*	*(0.0201)*
Self-employed	0.0437	-0.0250	-0.0529	-0.0849	-0.0548	0.0159
	(0.0125)	*(0.0102)*	*(0.0164)*	*(0.0517)*	*(0.0308)*	*(0.0473)*
Employer	0.0056	0.0166	0.0402	-0.0017	-0.0082	-0.0126
	(0.0021)	*(0.0043)*	*(0.0117)*	*(0.0050)*	*(0.0055)*	*(0.0200)*
Professional, Technical and Managerial	0.0016	-0.0137	-0.0720	-0.0466	-0.0478	0.0032
	(0.0046)	*(0.0058)*	*(0.0207)*	*(0.0279)*	*(0.0294)*	*(0.0778)*
Sales and Clerical	0.0272	0.0227	-0.0436	0.0494	-0.0152	0.0555
	(0.0188)	*(0.0141)*	*(0.0280)*	*(0.0549)*	*(0.0487)*	*(0.0752)*
Non-Skill	-0.0006	-0.0011	-0.0000	-0.0519	-0.1186	-0.0969
	(0.0034)	*(0.0060)*	*(0.0012)*	*(0.0423)*	*(0.0363)*	*(0.0564)*
Commerce	-0.0013	-0.0044	0.0037	0.0163	0.0092	-0.0618
	(0.0063)	*(0.0048)*	*(0.0092)*	*(0.0439)*	*(0.0344)*	*(0.0622)*
Service	-0.0078	-0.0203	0.0006	0.1774	0.0800	0.1122
	(0.0086)	*(0.0072)*	*(0.0131)*	*(0.0615)*	*(0.0471)*	*(0.0881)*
Constant				0.1233	0.1050	0.2255
				(0.1542)	*(0.1286)*	*(0.2226)*

Notes: Dependent variable is the RIF at the *th* percentile.
Bootstrapped standard errors with 100 replications are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 15: Detailed Decomposition at Different Percentiles, 2009

	Composition effect			Wage structure effect		
	10th	**50th**	**90th**	**10th**	**50th**	**90th**
Total effect:	**0.0203**	**-0.0719**	**-0.2196**	**0.2203**	**0.1958**	**0.2921**
	(0.0331)	*(0.0217)*	*(0.0491)*	*(0.0587)*	*(0.0330)*	*(0.0805)*
None or Primary Incomplete	-0.0030	-0.0025	-0.0022	-0.0318	0.0127	-0.0881
	(0.0068)	*(0.0059)*	*(0.0053)*	*(0.0560)*	*(0.0271)*	*(0.0489)*
Primary Complete or Secondary Incomplete	-0.0219	-0.0239	-0.0212	-0.0407	0.0298	-0.0637
	(0.0089)	*(0.0064)*	*(0.0089)*	*(0.0493)*	*(0.0262)*	*(0.0451)*
Tertiary and Technical Complete	-0.0047	-0.0076	-0.0569	-0.0183	-0.0314	-0.0312
	(0.0073)	*(0.0043)*	*(0.0187)*	*(0.0262)*	*(0.0191)*	*(0.0549)*
Experience	-0.0245	-0.0196	-0.0349	0.3802	0.0073	0.3230
	(0.0150)	*(0.0096)*	*(0.0206)*	*(0.2973)*	*(0.1588)*	*(0.2917)*
Experience^2	0.0228	0.0149	0.0236	-0.2924	-0.0338	-0.0680
	(0.0165)	*(0.0085)*	*(0.0170)*	*(0.1850)*	*(0.0896)*	*(0.1559)*
Managua	-0.0033	-0.0014	0.0001	-0.0252	-0.0044	-0.0462
	(0.0025)	*(0.0013)*	*(0.0023)*	*(0.0362)*	*(0.0246)*	*(0.0481)*
Central	-0.0006	0.0003	0.0008	0.0145	0.0413	0.0274
	(0.0029)	*(0.0012)*	*(0.0032)*	*(0.0351)*	*(0.0197)*	*(0.0423)*
Self-employed	0.0184	-0.0153	-0.0470	-0.0704	0.0095	0.0188
	(0.0099)	*(0.0047)*	*(0.0130)*	*(0.0604)*	*(0.0300)*	*(0.0617)*
Employer	0.0030	0.0024	0.0111	0.0029	0.0003	-0.0069
	(0.0015)	*(0.0019)*	*(0.0070)*	*(0.0013)*	*(0.0012)*	*(0.0066)*
Professional, Technical and Managerial	0.0006	-0.0107	-0.0334	-0.0430	-0.0007	0.0639
	(0.0036)	*(0.0040)*	*(0.0145)*	*(0.0390)*	*(0.0260)*	*(0.0559)*
Sales and Clerical	0.0422	0.0092	-0.0505	-0.0402	0.0618	0.1244
	(0.0277)	*(0.0148)*	*(0.0393)*	*(0.0689)*	*(0.0527)*	*(0.0828)*
Non-Skill	0.0022	0.0052	0.0022	0.0307	-0.0032	-0.0190
	(0.0033)	*(0.0053)*	*(0.0027)*	*(0.0633)*	*(0.0354)*	*(0.0559)*
Commerce	-0.0067	-0.0052	-0.0108	0.0689	-0.0272	-0.0157
	(0.0095)	*(0.0048)*	*(0.0098)*	*(0.0561)*	*(0.0381)*	*(0.0528)*
Service	-0.0041	-0.0179	-0.0004	0.1052	-0.0064	-0.0381
	(0.0125)	*(0.0071)*	*(0.0134)*	*(0.0767)*	*(0.0487)*	*(0.0822)*
Constant				0.1799	0.1402	0.1114
				(0.1765)	*(0.1347)*	*(0.1936)*

Notes: Dependent variable is the RIF at the *th* percentile.
Bootstrapped standard errors with 100 replications are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005 and 2009.

Table 16: Job-related Characteristics Across the Wage Distribution

	10th percentile				50th percentile				90th percentile			
	2005		2009		2005		2009		2005		2009	
Variable	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Occupational category (%)												
Employee	60.23%	55.10%	53.87%	36.30%	77.33%	58.08%	79.71%	62.60%	52.24%	54.96%	58.92%	64.99%
Self-employed	38.60%	43.95%	46.13%	62.99%	18.32%	39.62%	19.80%	37.14%	29.55%	39.26%	38.92%	34.75%
Employer	1.16%	0.96%	0.00%	0.71%	4.35%	2.31%	0.49%	0.26%	18.21%	5.79%	2.15%	0.27%
Economic Sector (%)												
Manufacture	63.72%	16.24%	36.74%	13.17%	54.97%	23.85%	44.50%	31.95%	37.91%	13.64%	31.40%	7.96%
Commerce	20.47%	33.44%	36.46%	49.82%	19.25%	35.00%	28.85%	34.55%	22.39%	28.93%	26.67%	28.12%
Service	15.81%	50.32%	26.80%	37.01%	25.78%	41.15%	26.65%	33.51%	39.70%	57.44%	41.94%	63.93%
Occupation classes (%)												
Non-skill workers	45.58%	45.54%	40.06%	38.79%	34.78%	27.31%	30.81%	35.84%	11.04%	15.70%	12.90%	15.12%
Professional, Technical and Managerial	1.40%	1.59%	6.91%	2.14%	8.39%	16.54%	8.07%	7.01%	28.06%	39.67%	31.40%	48.01%
Sales and Clerical	11.40%	42.99%	17.40%	51.96%	13.04%	42.31%	20.29%	34.03%	15.22%	37.60%	15.48%	33.42%
Operational and Services Workers	41.63%	9.87%	35.64%	7.12%	43.79%	13.85%	40.83%	23.12%	45.67%	7.02%	40.22%	3.45%

Source: Author's calculations based on EMNV 2005 and 2009.

Table 17: Detailed Decomposition at Different Percentiles, 2005 (Using Occupational Tenure)

	Composition effect			Wage structure effect		
	10th	50th	90th	10th	50th	90th
Total effect:	**0.0530**	**-0.0437**	**-0.1798**	**0.3067**	**0.1641**	**0.3991**
	(0.0236)	**(0.0240)**	**(0.0420)**	**(0.0485)**	**(0.0413)**	**(0.0752)**
None or Primary Incomplete	-0.0026	-0.0027	-0.0008	0.0517	0.0368	-0.0213
	(0.0052)	(0.0053)	(0.0021)	(0.0395)	(0.0282)	(0.0366)
Primary Complete or Secondary Incomplete	-0.0156	-0.0089	0.0048	0.0888	0.0909	-0.0339
	(0.0067)	(0.0062)	(0.0105)	(0.0403)	(0.0339)	(0.0538)
Tertiary and Technical Complete	-0.0044	-0.0166	-0.0598	0.0008	0.0078	0.0453
	(0.0028)	(0.0055)	(0.0197)	(0.0139)	(0.0180)	(0.0623)
Occupational tenure	0.0198	0.0263	0.0134	-0.0681	0.0671	0.1017
	(0.0103)	(0.0121)	(0.0102)	(0.0853)	(0.0611)	(0.1114)
Occupational tenure^2	-0.0206	-0.0219	-0.0127	-0.0003	-0.0455	-0.0561
	(0.0095)	(0.0095)	(0.0081)	(0.0434)	(0.0293)	(0.0542)
Managua	0.0023	0.0028	0.0023	0.0123	-0.0092	-0.0207
	(0.0038)	(0.0043)	(0.0035)	(0.0411)	(0.0285)	(0.0620)
Central	0.0008	0.0004	0.0001	0.0504	0.0190	0.0064
	(0.0016)	(0.0008)	(0.0009)	(0.0246)	(0.0122)	(0.0199)
Self-employed	0.0452	-0.0216	-0.0600	-0.0817	-0.0591	0.0265
	(0.0125)	(0.0100)	(0.0171)	(0.0496)	(0.0309)	(0.0471)
Employer	0.0059	0.0162	0.0432	-0.0007	-0.0082	-0.0099
	(0.0021)	(0.0042)	(0.0123)	(0.0048)	(0.0055)	(0.0204)
Professional, Technical and Managerial	0.0020	-0.0130	-0.0719	-0.0374	-0.0416	0.0044
	(0.0047)	(0.0058)	(0.0208)	(0.0271)	(0.0295)	(0.0790)
Sales and Clerical	0.0314	0.0251	-0.0371	0.0467	-0.0196	0.0469
	(0.0185)	(0.0142)	(0.0281)	(0.0551)	(0.0491)	(0.0756)
Non-Skill	-0.0006	-0.0010	-0.0000	-0.0546	-0.1154	-0.0944
	(0.0033)	(0.0056)	(0.0012)	(0.0431)	(0.0359)	(0.0560)
Commerce	-0.0014	-0.0053	0.0031	0.0080	0.0058	-0.0638
	(0.0064)	(0.0050)	(0.0092)	(0.0434)	(0.0347)	(0.0619)
Service	-0.0094	-0.0234	-0.0043	0.1772	0.0888	0.1213
	(0.0086)	(0.0075)	(0.0132)	(0.0593)	(0.0472)	(0.0899)
Constant				0.1137	0.1465	0.3468
				(0.1493)	(0.1191)	(0.2022)

Notes: Dependent variable is the RIF at the *th* percentile.
Bootstrapped standard errors with 100 replications are in parentheses.
The reference categories are: secondary complete, tertiary or technical incomplete; Pacific and Atlantic regions; employee; operational and services workers; and industrial sector.
Source: Author's calculations based on EMNV 2005.