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RESUMEN

América Latina es una región con elevada inequidad, en la que los aspectos étnicos no son ajenos. En particular, existe una significativa brecha socioeconómica entre los descendientes de europeos y las poblaciones indígenas y afro-descendentes. Uruguay se ha usualmente considerado una excepción a este patrón, si bien la carencia de datos estadísticos sobre raza y etnicidad no permitió realizar análisis empíricos. En 2006, el Instituto Nacional de Estadística incluyó una pregunta sobre ascendencia racial en la Encuesta de Hogares. En este trabajo, se utiliza por primera vez esta base de microdatos para analizar las diferencias salariales entre la población blanca y los afro-descendentes. La razón del salario por hora es 0.72 para los hombres y 0.78 para las mujeres. Se realizan las siguientes estimaciones para cada sexo: regresiones MCO, descomposiciones salariales y regresiones quintílicas. Los resultados indican que la discriminación contribuye a explicar la mitad de la diferencia salarial media entre los hombres, y alrededor del 20% de la brecha entre las mujeres. Parte de esta discriminación se da a través de la inserción de la población de ascendencia afro en trabajos peor pagos. El factor más importante que explica el resto de la diferencia es el nivel educativo alcanzado. Finalmente, las regresiones cuantílicas muestran que la medida de discriminación cae con el percentil.

ABSTRACT

Latin America is a region of sharp inequalities that are far from ethnically blind. In particular, there exists a significant socioeconomic gap between Latin Americans of European and the Afro-descendant and Indigenouos populations. Uruguay has usually been considered an exception to this pattern, although the lack of survey data about racial descent and ethnicity did not allow empirical analysis. In 2006, the National Institute of Statistics included a question on racial descent in the Household Survey. In this paper we use these microdata (for the first time) to analyze the wage gap between afro-descendants and whites. The wage ratio is 0.72 for men and 0.78 for women. For each sex, we perform OLS estimations, wage decompositions and quantile regressions. The estimations indicate that discrimination contributes to explain half of the average wage gap of men and 20% of the gap among femles. Part of discrimination works through the placement of Afro-descendant workers into lower-paid occupations. The most important attribute that explains the rest of the gap is education. Finally, quantile regressions show that discrimination declines with percentile.

JEL: J71

Palabras claves: raza, discriminación, desigualdad salarial, Uruguay

Keywords: race, discrimination, wage inequality, Uruguay

1. Introduction

Latin America is a region of sharp inequalities. These inequalities are far from ethnically blind. In particular, there exists a significant socioeconomic gap between Latin Americans of European descent (usually called "whites") and the Afro-descendant and Indigenous populations. (Busso, Cicowiez and Gasparini 2005; Rangel 2005; World Bank, 2003).

Uruguay –a South American country comprised of somewhat more than 3.3 million people– has usually been considered an exception to this pattern. According to the predominant view, Uruguay has managed to escape to the predominant high levels of class and ethnic inequality, in accordance with its traditionally robust welfare state, its higher rates of urbanization and its relatively homogeneous population in ethnic terms.

However, according to the Household Survey of 2006 (*Encuesta de Hogares Ampliada - ENHA*) carried out by the National Institute of Statistics (*Instituto Nacional de Estadística - INE*), which included for the second time in the country's history a question on race based on self-classification, there are clear signs of significant inequalities between Afro-descendants (the main national ethnic minority) and the rest of the Uruguayan population (which is mainly composed of Spanish and Italian descendants who self-classify as "white")[1]. Among other things, Afro-Uruguayans have lower levels of schooling at all age cohorts, are much more likely to be poor and perform clearly worse in the majority of labor market indicators (Bucheli and Cabella, 2007).

This paper deals precisely with this last dimension of racial inequality (labor market differences). Specifically, we focus on the wage differentials that exist between Afro-descendant and white workers, bearing in mind that labor income is one of most important sources of socio-economic welfare. Again based on the ENHA, the ratio of Afro-descendant and white mean hourly

[1] In contrast to other Latin American countries, Uruguay does not have a significant indigenous population with its own language, cultural traits and organizational apparatus. Before the Spanish conquest, demographically small indigenous groups such as the Charruas, Chanas and Guaranies populated the Uruguayan territory. These indigenous groups gradually disappeared as a consequence of a variety of diseases, wars and extermination campaigns (Bracco, 2004). Interestingly, however, in 2006 4.5% of the Uruguayan population declared to have Indigenous descent. This trend probably reflects the effects of "neo-indigenismo", a recent ideological trend through which Uruguayans have tried to connect the Uruguayan history and culture with that of the Indigenous tribes that lived in the country before the conquest (Porzecanski, 2005). In contrast to Afro-Uruguayans, however, it is safe to affirm that Indigenous identity in Uruguay is mainly an expression of symbolic ethnicity (Gans, 1979) that has no significant structural consequences.

wages is .72 and .78 respectively.[2] This difference is statistically significant at the .001 level. Although this gap is lower than that of other Latin American countries with substantial proportions of Afro-descendants (such as Brazil or Colombia as reported by Busso, Cicowiez and Gasparini 2005), it merits to be explained.

In the next (second) section we summarize the main characteristics of the race relations system in Uruguay. In the third section we describe the status of research on racial inequality in Uruguay. In the fourth section we present the methodology used to explain the racial wage gap: OLS estimations that use a dummy for race, wage decompositions of the average gap following Oaxaca's proposal and quantile regressions. In the fifth section, we provide a full description of the data used for analysis. In the sixth section we present the main findings and, finally, we conclude with a discussion and suggesting future lines of research.

2. Racial Relations in Uruguay

The Uruguayan population is mainly composed of European descendants from Spain and Italy. In 1860 the national population barely exceeded 200,000 persons and the proportion of foreign-born residents was 34% (mainly Spanish settlers). During the last decades of the XIX century, Uruguay became an important destiny of overseas migration and that process was reflected in the 1908 census, which counted more than one million people. The arrival of large numbers of Europeans continued until the 1940s. Since then, Uruguay has not received significant numbers of immigrants and, in contrast, thousands of Uruguayans have left the country in search of better economic opportunities. Although the majority of Uruguayans are European descendants, there is a significant percentage of the population who has African descent. According to the ENHA, in 2006 9.1% of the population declared having African descent.

The origins of the Afro-Uruguayan population date back to the first decades of the 17th century when the first waves of slave labor were introduced to the country (by then called "Banda

[2] A recent report of the International Labor Organization (OIT, 2007) shows that the wage ratio between whites and non-whites is smaller than that obtained through our estimations. We believe that the main reason that explains this difference is that ILO treats Uruguayans who self-classified as Afro-descendants and Indigenous as a single group ("non-whites"), while we computed the wage ratio between Afro-descendants and whites, excluding the Indigenous population from the analysis. Collapsing the Indigenous and Afro-descendantgroups decreases the wage gap because the labor market performance of self-classified Indigenous individuals is very similar to that of self-classified whites. In future studies, then, we suggest treating Indigenous and Afro-descendantworkers separately to avoid misleading conclusions.

Oriental") through contraband[3]. Most of the African population, however, was imported legally between 1742 and 1810 under Spanish rule (Rodriguez, 2006). During that period, recent historiography estimates that an average of four ships of slaves arrived to the port of Montevideo annually and that between 33,000 and 45,000 slaves entered the country (Montaño, 2001; Frega et al. 2005)[4]. In 1819, slaves constituted approximately 25% of the total population of Montevideo. The proportion of afro-descendants would diminish throughout the country's history as the combined result of large immigrant flows from Europe, wars, diseases and miscegenation. After the achievement of independence in 1828, slavery was gradually eliminated, first by decreeing the "freedom of wombs" and declaring slave traffic illegal, later by abolishing slavery and finally by eliminating the juridical figure of "patronato" in 1853[5]. Since then, all Uruguayan citizens have been considered equal under the law (voting rights, however, remained limited for a significant sector of the population, especially women, until the national elections of 1932). Like in the vast majority of Latin American countries, thus, in modern Uruguay race has not constituted a criterion for the distribution and allocation of state resources, rights and obligations among the population.

In congruence with the historical absence of overt forms of official segregation and discrimination, the evolution of the Afro-Uruguayan community is characterized by increasing degrees of integration or assimilation in multiple dimensions such as linguistic, residential and intermarriage patterns. However, Afro descendants still show remarkably low levels of socioeconomic assimilation and, unlike other immigrant minorities, they have been unable fully to exploit the opportunities offered by the Uruguayan modern economy. As stated in the introductory section, regardless of the indicator of socioeconomic achievement chosen –occupational distribution, labor earnings, poverty rates and schooling among others– Afro-Uruguayans do remarkably worse than the rest of the country's population.

[3] Although significant numbers of Afro-descendants were brought to the country as slaves during the XVII and XVIII centuries, the importation of slaves was less important than in countries such as Brazil, Colombia and Ecuador, where high numbers of labourers were required for large-scale plantations and mining.
[4] Not all these slaves, however, remained in the Uruguayan territory. Some of them were sent to other regional domains of the Spanish Empire.
[5] The patronato was a form of de facto slavery that placed minors and adults born under free-womb legislation under the tutelage of owners until they reached 25 years-old or for a period of three years respectively

3. Research Background

During most of the country's history, there has been a remarkable lack of social scientific research on Afro-Uruguayans and racial inequality. The historical dearth of social scientific analyses on Afro-Uruguayans is probably explained by three major factors. First, like other Latin American countries (Dulitzky, 2005), Uruguayans have largely accepted the myths of racial democracy, homogeneity and equality of opportunities. After the abolition of slavery, the belief that race was not a significant barrier for achieving social mobility was increasingly accepted among the population. Like Carlos Rama's essay on Afro-Uruguayans vividly illustrates, if racial inequalities existed, they were mainly explained by class differences and differential points of departure (Rama, 1969). In a similar vein, there is a quite extended self-portrait of Uruguay as a racially homogenous country, mainly composed of people of European descent (Rodriguez, 2006, Arocena and Aguiar, 2007). The absence of official racism and the high degrees of Afro-Uruguayan assimilation on a variety of dimensions probably helped to create the impression that Afro-descendants were not a distinguishable and meaningful social group or category that had its own specific problems and dynamics.

Second, national censuses or official surveys (which usually are one of the most important data sources for statistical analysis of racial inequality) did not ask questions on racial membership until 1996, when a few questions on race were included in a special module of the Household Survey. Up to then, those who tried to convince state authorities to include questions on race in official surveys usually encountered firm resistance, based on the argument that this would create high rejection rates or force the population to classify in socially meaningless and scientifically invalid categories (Rodriguez, 2006).

Finally, the number of Afro-Uruguayan social scientists (who one might think would be particularly inclined to study Afro-Uruguayan topics) has been very small in congruence with the small proportion of Afro-descendants in the university system.

During the last decade, academic interest in the situation of Afro-Uruguayans increased substantially. Probably, this is explained by the greater pressure exerted by Afro-Uruguayan organizations, the increasing concern on racial topics shown by international agencies and the consolidation of a small but significant elite of Afro-descendant intellectuals and activists. Still, knowledge of contemporary patterns of racial inequality in Uruguay remains clearly underdeveloped. It must be noted, in particular, that so far only three studies have addressed the topic based on statistically representative samples of the Afro-Uruguayan population. These studies are two reports based on the Household Surveys of 1996-97 and 2006 (Beltrami, 1998; Bucheli and Cabella, 2007) and one monograph in which the author provides a further analysis of the 1996-97 survey (Foster, 2001). Although these works have made a significant contribution by detecting and illustrating some of the most important inequalities between Afro-descendants and whites, they are based on relatively simple methodological procedures (in particular cross-tabular analyses) and their primary aim is descriptive. Econometric analyses of racial dynamics in the country are, therefore, still pending. In this paper, we intend to address this critical gap in the literature.

4. Methods

To analyze the racial wage gap in Uruguay we follow three different approaches. First, we fit a semi-log wage function that includes a dummy for race. This is the most conventional approach for the study of racial inequality (Blank et al, 2004). Second, we estimate separate regressions for each racial group and decompose the wage gap into differences due to coefficients, characteristics and selectivity. Finally, we fit quantile regressions to observe the effects of race at different points of the wage distribution. This approach is much less frequently used than the first two but has been applied with success to the study of ethnic and racial inequality in other contexts (see for example Arias, Yamanda and Tejerina, 2002; Pendakur and Pendakur, 2007; Levanon and Raviv, 2007). In all approaches we treat male and female workers separately.

Regarding the first approach, the traditional semi-log wage function can be expressed as:

$$(1) \qquad \ln W_{s,j} = \beta_s X_{s,j} + \alpha_s D_{s,j} + u_{s,j}$$

where s is the sex of individual j, W his/her wage, X a set of observable variables that affect wages; β a vector of coefficients on the variables X, D a dummy or set of dummies for race, α a coefficient (or set of coefficients) that captures the difference between races and u a stochastic disturbance with zero mean that is not correlated with observed characteristics. We estimate this function using OLS.

The coefficient α_s is a first approach to measure discrimination. We fit four models. In model 1, we include race as the only covariate. Model 2 is a standard Mincerian equation whose covariates are human capital variables (education and potential experience) and region. A quoted problem of standard Mincerian equations is that the estimation of the returns of education may be biased because individuals with higher "ability" (innate attributes and background variables such as labor market connections, family human capital or school quality) perceive higher earnings and acquire more education. Thus, the introduction in the wage equation of covariates related to unobserved abilities may improve the estimation of schooling returns. In addition, if these unobservables are differently distributed among races and their correlation with education is stronger for one of the groups, the introduction of such variables will also improve the estimation of the "controlled" racial wage gap.

In this paper, we tackle this problem by introducing a dummy variable that distinguishes between individuals who mostly attended public or private elementary schools (Model 3). Taken into account that the interpretation of this variable is particularly elusive (it might may be an indicator of quality of education but also of family background), in this paper we use it principally to improve the estimation of schooling returns and the race coefficient.

Finally, in Model 4 we add various job characteristics as covariates (occupation, industry, full time status and firm size). Thus, a reduction of the wage gap (measured by the absolute value of α_s) due to these new covariates would indicate that at least part of discrimination stems from some type of occupational segregation.

In the second approach, we allow the coefficients of the independent variables to vary between races. We estimate two functions for each sex group:

$$\ln W_{a,s,j} = X'_{a,s,j}\,\beta_{a,s} + u_{a,s,j} \qquad (2)$$

$$\ln W_{w,s,j} = X'_{w,s,j}\,\beta_{w,s} + u_{w,s,j} \qquad (3)$$

where a and w are two sub-indexes for the Afro-descendant and white populations respectively. Denoting the mean of the variables with a bar and after a simple algebra, we follow Oaxaca (1973) and Blinder (1973) and decompose the average raw wage gap between racial groups as the sum of two components:

$$\left(\ln \overline{W}_{w,s} - \ln \overline{W}_{a,s}\right) = \left(\overline{X}_{w,s} - \overline{X}_{a,s}\right)'\,\hat{\beta}_{w,s} + \overline{X}_{a,s}{}'\left(\hat{\beta}_{w,s} - \hat{\beta}_{a,s}\right) \qquad (4)$$

The first term on the right is the part explained by differences in characteristics between the groups and the second one is the part explained by differences in coefficients. This last component is usually interpreted as a measure of discrimination that indicates the wage gain that an Afro-descendant worker with average characteristics would obtain if he had the same returns than a white worker.

Notice that the decomposition performed in (4) assumes that in the absence of discrimination, the returns for both groups would be equal to β_w. However, the choice of the non-discriminating structure bears discussion and the results are sometimes sensitive to it. Oaxaca (1973) suggests that the "true" non-discriminatory pay structure would lie in between that of the majority and minority group structures. Following this idea, Oaxaca & Ramson (1994) assume that the non-discriminatory wage structure β^* is a weighted average of β_a and β_w that results from an OLS estimation of the pool sample. The decomposition of the gap is now:

$$(5) \qquad \left(\ln \overline{W}_{w,s} - \ln \overline{W}_{a,s}\right) = \left(\overline{X}_{w,s} - \overline{X}_{a,s}\right)' \beta_s^* + \overline{X}_{w,s}{}' \left(\hat{\beta}_{w,s} - \beta_s^*\right) + \overline{X}_{a,s}{}' \left(\beta_s^* - \hat{\beta}_{a,s}\right)$$

Once again, the first term is the difference between characteristics and the sum of the other two reflects the amount of the wage gap due to differences in coefficients. The second term is usually interpreted as the wage advantage (overpayment) of white workers over what they would earn in the absence of discrimination. Inversely, the third term measures the Afro-descendant wage disadvantage (underpayment).

In this paper we perform the decompositions using both β_w and β^* as the non-discriminatory wage structure.

The third approach that we use in this paper is the estimation of quantile regressions. The average wage differential between races may hide large variations across the wage distribution. In order to look at the effects of race and other covariates at different points of the conditional log-wage distribution, we estimate quantile regressions. Assuming that the log wage has a linear relationship with X and omitting the sub indexes that denote sex and race, we specify the θ quantile regression for each group as:

$$(6) \qquad Q_\theta \ln W_j = \beta_\theta X_j + u_{\theta,j}$$

In the quantile regression framework, the distribution of the error u_θ is left unspecified and the restriction is that $Q_\theta\ (u_\theta\ /X) = 0$. The estimated parameters are obtained by minimizing the absolute distance of the weighted residuals:

$$(7) \quad \hat{\beta}_\theta = \arg\min_{\beta_\theta} \left(\sum_{j:\ln W_j \geq \beta_\theta X_j} \theta \, |\ln W_j - \beta_\theta X_j| + \sum_{j:\ln W_j < \beta_\theta X_j} (1-\theta) \, |\ln W_j - \beta_\theta X_j| \right)$$

For a positive residual, the weight is θ and for a negative residual, it is $1-\theta$. The estimated parameters may be interpreted as the returns of X at the θth quantile of the conditional wage distribution. Thus, the coefficients for race may be interpreted as the effect of discrimination on wage at different parts of its distribution. We fit the model for every 5th percentile (5, 10, 15…, 95).

In order to interpret the coefficients at different percentiles, we may depict workers at different conditional quantiles as individuals with different unobservable characteristics. Indeed, workers at the bottom receive lower wages than expected in accordance with their human capital levels and other wage determinants. On the contrary, workers at the top receive higher wages than expected. Thus, the coefficients at the bottom of the conditional wage distribution measure the covariates effects for low-ability workers while coefficients at the top indicate the covariates effects for high-ability workers.

Glass ceiling is a well-known concept that depicts that minorities face limits to their career prospects because of invisible barriers to reach the upper end positions. A wider racial gap at the top of the wage distribution, or more generally an increasing gap, would indicate that high ability workers –i.e. those who compete for top positions- are the most discriminated. On the other hand, a decreasing wage gap would indicate higher discrimination levels for low-ability workers; this phenomenon has recently been called "floor pattern" (de la Rica et al, 2008). Note that a U-shape profile (higher gaps in the middle of the distribution) would not be surprising either. We may think that low-performance workers do not add enough production value to justify large pay differences. Meanwhile, the benefit associated to high-performance workers may justify a stronger ability-based selection. Thus, the racial gap would narrow at the tails of the conditional wage distribution.

We are aware that the estimation of the wage functions requires dealing with the self-selection issue stemmed from being employed. We estimate a selection term following the proposal by Heckman (1979) and developed by Buchinsky (1996). In a first step we estimate the likelihood of being employed for each racial/sex group. Thus, we fit a *probit* model $P = \Phi\ (\gamma\ Z),$ where Φ is the accumulated density function of a normal distribution, Z a vector of independent variables that includes the variables that affect wages (and hence the choice of being in the labor force) and other variables that have a direct effect on being employed, and γ the parameters to be estimated[6]. We use the predicted probability to estimate the inverse of the Mills ratio as $\lambda = \psi\ (.)\ /\ \Phi\ (.)$ where ψ denotes the density function of a normal distribution. Then, we fit another probit model in which the independent variables are a constant and the predicted value of *P*. The selectivity correction term is $SCT = \lambda(\mu + \sigma P)$ where μ and σ are the coefficients of the constant and *P*, respectively.

The correction for selectivity bias requires to introduce a new term in the decompositions presented in equations 4 and 5, equal to the difference of the mean values of *SCT* between groups, weighted by their estimated coefficients. It is not obvious how this term should be treated and interpreted (for a good discussion on this topic see Neuman and Oaxaca, 2003). In this paper we follow the traditional strategy of considering the effects of differences in selectivity separately from those of differences in endowments and coefficients.

5. Data

We use the data of the ENHA 2006. The Household Survey has been implemented since 1981 and has traditionally collected information on socio-demographic, work and income variables of the Uruguayan urban population. The data are collected through face to face interviews with one household member aged 18 or older who gives information on himself and all the other household members.

In 2006, INE implemented a special version of the Household Survey, covering rural areas, expanding the sample size and adding new items to the questionnaire. As part of these changes, INE decided for the second time in the country's history to include a set of questions on racial descent. Specifically, for each household member the survey inquires *"Do you believe you have…(black, Asian, white, native, other) descent?"* in five separate questions. For each question on descent the subject had to respond "yes" or "no" (it is possible, thus, to declare multiple kinds of descent). Using this information we built three groups. The *black* group includes persons who reported having black descent only. We call *mixed* those who reported having black descent but declared

[6] The coviariates in the *probit* model are: sex, age, education, region, civil status, household role, attendance at educational organizations, residence in cities of 5,000 or more inhabitants, presence of children in the household (between 0 and 2 years, 3 and 6 years and 7 and 13 years), type of household, unemployment rate among the other household members, household per capita income excluding the labor income of the person and retiree (yes or no).

having other types of descent too. Finally, we label *whites* all subjects who declared having white descent only.

We restrict our analysis to individuals aged between 18 and 59 years. We excluded from the analysis all subjects who are not afro-descendants or whites (4,485 cases in total) and 187 cases that correspond to domestic employees that resided in the household where they worked. Thus, we use information corresponding to 61,726 men and 66,014 women (table 1).

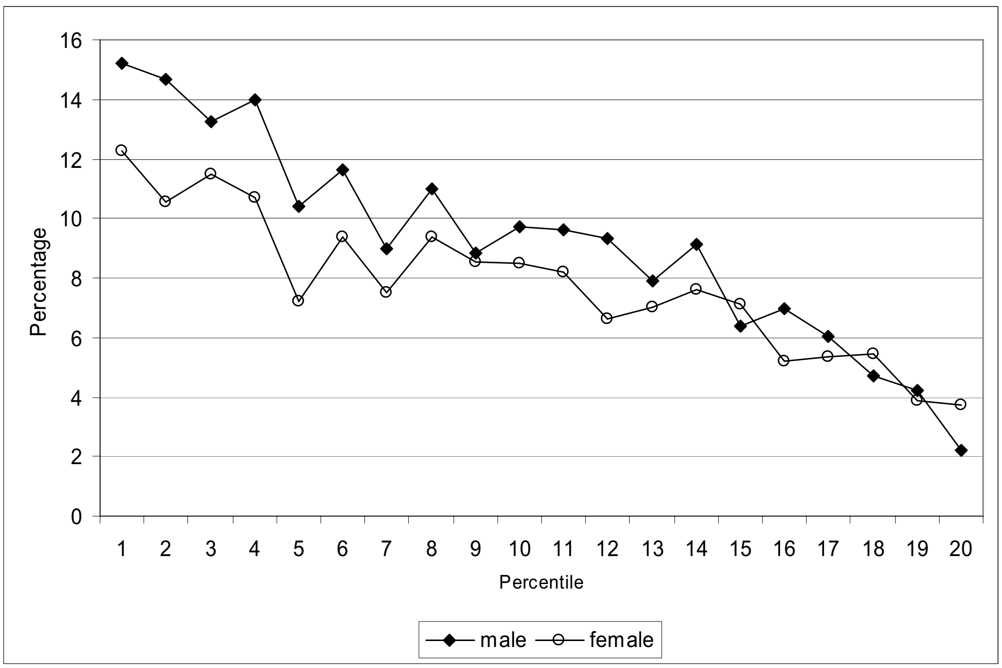
Table 1. Number of cases

	Men				**Women**			
	White	Mixed	Black	Total	White	Mixed	Black	Total
All Persons Aged 18-59	55,728	4,448	1,550	61,726	60,090	4,562	1,362	66,014
Employed	47,958	3,781	1,315	53,054	35,112	2,449	735	38,296
Dependent Workers (Income>0)	32,014	2,675	963	35,652	24,588	1,715	545	26,848
Dep. Workers Except Agric. Workers	25,543	2,016	724	28,283	23,913	1,669	537	26,119
Valid Cases for Regressions	25,473	2,006	719	28,198	23,847	1,661	536	26,044

After estimating the selectivity coefficients for each racial group and before estimating the wage functions, we proceeded to eliminate further cases. First, we excluded all persons who do not have a positive work income (unemployed subjects and unpaid workers mostly). Second, we excluded self-employed workers. We made this decision because labor market discrimination is strictly applicable to wage earners and because it is difficult to estimate a comparable wage for self-employed workers. We also excluded dependent agricultural workers. The exclusion of this group of workers is based on problems arising from wage mis-reporting. First, it is difficult to estimate the net income of agricultural workers because of the relevance of some non-pecuniary earnings, such as the possibility of cultivating the land for own consumption or eating with the family for whom they work. Second, the reported timing of work is dubious because farm workers do not have limitations on working hours. Finally, we dropped some cases because of data unavailability. Our final sub-sample of analysis consists of 28,198 males and 26,044 females. Among males, 2,725 are Afro-descendants and 25,473 are whites; among women, 2,197 are Afro-descendants and 23,847 are whites. Self-employed workers are the largest excluded category among males while individuals out of the labor force or unemployed constitute the largest excluded category among females.

White men and Afro-descendant women report the highest and lowest mean hourly wages respectively[7]. For men, the mean log wage racial gap is 0.280 and for women it is 0.222. In figure 1 we depict the percentage of afro men at different percentiles of the male wage distribution and the percentage of afro women along the female wage distribution. For both women and men, the share of Afro-descendants decreases throughout the distribution.

Figure 1. Percentage of Afro-descendant Workers across the Wage Distribution by Gender



In Tables 2 and 3 we summarize the main characteristics of Afro-descendant and white workers included in our analysis. Table 2 reports the mean values of traditional human capital variables. In each sex group, whites have more years of schooling and firm experience than afros and within each sex, women are more educated than men but report fewer years of experience in the firm. The potential experience, measured as the difference between age and years of schooling less six, is quite similar for the four groups.

[7] The hourly wage is calculated as the ratio between the earnings received in the month preceding the interview and 4.3 times the hours worked the week before the interview. The monthly earnings include pecuniary and in-kind earnings in the main occupation.

We also report the percentage of workers who have attended elementary private schools. As depicted by the data, attendance to private schools during childhood is more common among whites than among Afro-descendants (there is a difference of around 9 percentage points). Finally, the distribution of workers by region reflects the relative important size of the country's capital city (Montevideo), the highest female activity rate in Montevideo and the stronger presence of Afro-descendants in the North-Eastearn provinces.

Table 2. Individual Characteristics by Race and Gender

	Males			Females			All
	Whites	**Afros**	**Diff.**	**Whites**	**Afros**	**Diff.**	
Years of Schooling	9.9	8.4	1.5***	11.0	9.2	1.8***	10.3
Potential Experience	21.8	21.6	0.2	21.5	22.1	0.6	21.5
Experience in Firm	8.9	7.5	1.4***	8.1	6.5	1.6***	8.4
Private School (Yes=1; No=0)	15.6	6.6	9.0***	19.2	8.3	10.9***	16.5
Region (Yes=1; No=0)							
Montevideo	45.3	43.8		48.8	51.1		47.0
South	21.8	18.9		19.5	16.1		20.5
South-West	7.0	2.6		6.7	2.0		6.5
West	9.4	13.4		9.1	8.7		9.4
Center	7.8	6.1		7.6	5.3		7.5
North-East	8.6	15.2		8.3	16.8		9.1
Share of groups	46.9	4.8		44.6	3.8		1.00

Weights were used to compute means and calculate distributions; *** p<0.001

In table 3 we present the distribution of workers according to various job characteristics. The percentage of full time workers is higher for men than for women. Females are more likely to work in small firms than males, especially Afro-descendant women. Gender differences in occupations and industries are well known: female participation in blue-collar occupations and in construction and transport industries is very small. Inversely, females are over-represented among domestic service workers and other personal service categories as well. The proportion of Afro-descendant women who are domestic employees is particularly remarkable (35.6%) and it almost doubles up that corresponding to white females (19.9%).

Table 3. Job Characteristics by Race and Gender

	Males		Females		All
	Whites	Afros	Whites	Afros	
Full time Status (Yes=1; No=0)	85.8	86.9	60.0	57.2	73.3
Type of Firm					
Public	24.2	25.0	24.8	16.2	24.2
Private (1-9 workers)	30.1	31.8	40.0	54.2	35.5
Private (10+ workers)	45.8	43.2	35.2	29.7	40.3
Occupation					
Managers	1.7	0.3	0.7	0.3	1.1
Professionals	7.2	2.4	16.5	6.8	11.1
Technicians	7.4	4.4	6.4	4.6	6.7
Armed Forces (Officials)	0.4	0.5	0.0	0.0	0.2
Clerks	11.9	5.6	19.4	9.4	14.8
Customer service clerks	2.6	1.4	5.6	4.6	4.0
Personal & Protective Services	7.8	9.8	8.1	10.5	8.1
Sales	5.7	4.2	8.7	7.4	7.0
Construction Workers	8.2	13.3	0.1	0.0	4.5
Metallurgic Workers	7.2	7	0.1	0.2	3.7
Craftsmen	0.9	1.2	0.3	0.1	0.6
Other Workers	5.1	5.8	2.3	2.9	3.8
Machinists	4.4	4.3	2.2	2.8	3.3
Transport Workers	11.0	9.4	0.1	0.1	5.6
Unskilled Service Workers	8.5	12.9	8.1	13	8.7
Unskilled Manual Workers	8.1	12.9	1.6	1.7	5.2
Domestic Service	0.2	0.3	19.9	35.6	10.3
Armed Forces (Soldiers)	1.8	4.3	0.1	0.1	1.1
Industry					
Agriculture	3.7	4.2	1.8	2	2.8
Manufacturing	22.3	20.5	10.8	10.8	16.6
Construction	8.5	13	0.3	0.2	4.7
Commerce	21	20.4	16.4	15.1	18.7
Transport	9.9	8.2	3.1	2.3	6.5
Finance	6.6	3.4	6.9	3.4	6.4
Public Administration	14.3	17.8	8	5.7	11.3
Health and Education	7.7	5.6	28	20.4	17.2
Personal Services	6.0	7.0	24.7	40.2	15.7

Weights were used to compute means and calculate distributions

Within each sex, Afro-descendants are less likely to work in occupations that require high levels of education, such as managers, professionals and technicians. On the other side, they are more concentrated in unskilled occupations. Finally, we observe that female workers are less likely to work at medium and large private firms than their male counterparts and that Afro-descendant females are much more likely to work at small sized firms than the other groups.

6. Findings

6.1. Wage equations

As mentioned in section 4, our first approach to measure discrimination consists in fitting wage equations that use a dummy for race, separately for men and women. The results are presented in Annexes I and II.[8] For both sexes, the findings are consistent with the usual patterns of the human capital model. Indeed, in all models wage increases with education and the linear and quadratic terms for potential experience have the expected positive and negative signs respectively. Adding attendance to public/private elementary school to the standard Mincerian model rises slightly the explanatory power of the equation and decreases a little the returns of education. As we expected, wages are higher for workers who attended private schools. Finally, introducing job characteristics in the equations increases the explanatory power of the model and reduces the returns of education and the effects of type of school attended. Once again, we obtain the expected signs. We find higher wages for workers at medium and big firms of the private sector, for occupations related to managerial and professional tasks and for workers at financial activities.

In table 4 we present the estimated coefficients of the race variable. The first rows (panel A) present the results obtained when considering two racial groups (Afro-descendants and whites). The second panel (B) reports the estimated coefficients when considering three groups (blacks, mixed and whites). In columns, we show the estimations obtained with different models. "Model 1" reports the race effects estimated through an OLS regression in which race is the only covariate. The rest of the columns include other covariates that are specified in the rows of panel C.

[8] We performed several estimations in which we addressed the selectivity issue differently. Specifcally, we fitted equations: i) without any selection term; ii) based on the traditional inverse Mill's ratio and iii) based on *SCT*. The results are similar in all cases. For brevity, we only report the estimations using *SCT*. The results of the other estimations are available upon request.

As shown in panel A, when race is treated as a binary variable the race coefficient is significant in all models for both men and women and its sign is negative. Thus, the predicted hourly wages for afro-descendants are lower than those of whites, holding other variables constant. The comparison of the coefficients obtained with different models suggests that education, experience and key job characteristics play a major role in the explanation of the racial wage gap. For instance, model 1 reports that the wage gap for afro-descent males is –0.279. When we control for region and traditional human capital variables (model 2), the gap decreases to –0.143, and when we add a dummy for attendance at private elementary schools the gap is –.138 (model 3). Finally, when controlling for seniority, full time status, firm size, industry and occupation the racial gap falls to -0.094 (model 4).

We obtain similar results in the models in which afro-descendants are divided into blacks and mixed (Panel B). Again, the racial coefficients are negative for both sexes, although for females, "black" is not statistically different from zero. The main usefulness of these estimations is that they allow to analyze differences within afro-descendent workers. For men, the conditional expected wages for blacks are lower than those of mixed workers in all models. However, the difference between the coefficients for blacks and mixed afro-descendents is not statistically significant at standard levels in model 4. For women, we find that mixed Afro-descendant women have the lowest expected hourly wages (models 2 to 4). In turn, the coefficients for black females are not statistically different from those of mixed or whites, except in model 1.

Our results also show that the effects of race are higher for men, regardless of the way in which race is measured. Moreover, the difference in the race coefficients between females and males' models becomes stronger once controlling for education and experience. According to model 1, the racial gap is –0.279 for men and –0.194 for women, so the ratio of these coefficients is 1.4. In model 2, this ratio increases to 3.6. This suggests that human capital variables play a greater role in the explanation of the racial gap among females than males. When introducing job characteristics, the ratio falls to 3 suggesting that racial differences in job characteristics are more important for men than for women.

Table 4. Race Coefficients of Standard Regressions on Log Hourly Wages

	Model 1	Model 2	Model 3	Model 4
		Panel A: Race Two Groups		
Males (N=28,198)				
Afro-descendant	-0.279***	-0.143***	-0.138***	-0.091***
	(0.015)	(0.014)	(0.014)	(0.013)
R^2	0.039	0.258	0.262	0.399
Females (N=26,043)				
Afro-descendant	-0.194***	-0.040*	-0.038*	-0.031*
	(0.017)	(0.016)	(0.016)	(0.015)
R^2	0.130	0.284	0.285	0.413
		Panel B: Race Two Groups		
Males (N=28,198)				
Black	-0.338***	-0.195***	-0.189***	-0.125***
	(0.028)	(0.026)	(0.027)	(0.025)
Mixed	-0.258***	-0.125***	-0.120***	-0.079***
	(0.018)	(0.017)	(0.017)	(0.015)
R^2	0.039	0.258	0.262	0.399
Females (N=26,043)				
Black	-0.204***	-0.011	-0.008	-0.010
	(0.032)	(0.031)	(0.031)	(0.028)
Mixed	-0.191***	-0.050**	-0.047*	-0.037*
	(0.020)	(0.019)	(0.019)	(0.017)
R^2	0.130	0.284	0.285	0.413
		Panel C: Controls		
Region		x	x	x
Education & Experience		x	x	x
Type of Elem. School Attended			x	x
Job Characteristics				x

*** p<0.001, ** p<0.01, * p<0.05; Robust standard errors in parentheses

6.2. Decompositions

In table 5 we present the main results of the decompositions of the mean raw wage gap, based on the results of wage equations reported in Annexes III and IV.[9] We report the contribution of endowments, coefficients and selectivity to the racial wage gap for men and women separately. For each sex group, we assume that the non-discriminatory pay structure is alternatively that of white workers and that of the pooled sample. The decompositions are performed with the wage equations that control for human capital and regional variables (Model 2) and with the ones that also include job characteristics and attendance to private elementary school (Model 4).

The amount explained by endowments, coefficients and selectivity is similar for both pay structures. However, the patterns differ between models. For men, when using the estimates of Model 2, the proportion explained by differences due to coefficients and endowments is very similar while selectivity does not play a major role. However, when using Model 4, the contribution of the endowment term increases (from 0.14 to 0.19) and explains 68% of the raw gap. Inversely, the absolute contribution of differences in coefficients decreases from around 0.14 (50%) to less than 0.09 (30%). This is not surprising because job characteristics and type of school attended increase the explanatory power of the wage equation. Based on these results, we may interpret that one of the main ways through which racial discrimination in the labor market works, is by placing black male workers in low-paid jobs. Nevertheless, we should note that even in the model that controls for job characteristics, the explanatory power of differences in coefficients is still quite substantial (30%).

For women, the most remarkable finding is that differences in endowments account for the majority of the wage gap in both models (0.18 and 0.19, around 80%). However, differences in coefficients also contribute to broaden the racial wage gap. Selectivity differences, finally, only play a significant role in model 4 and contribute to narrow the gap. Unlike men, the contribution of differences in coefficients is more salient in model 4 than in model 2 (35% versus 20%). This finding, which is not consistent with occupational segregation, merits further analysis and is related to the problem of selectivity. Indeed, in decompositions that did not control for selectivity we found

[9] Once again, we only report the estimations addressing the selectivity issue using *SCT*. We also fitted equations using the inverse Mill's ratio and without any selection term. The results are similar in all cases for both sexes.

that the amount explained by coefficients is lower in model 4 than in model 2 (results available upon request).

In short, differences in endowments play a greater role in the explanation of the racial wage gap among females than among males. Inversely, racial differences in coefficients (which might be associated with discriminatory processes) are greater for men than for women. Selectivity issues, finally, are not important among males but they might play an important role in the explanation of the gap between afro and white females.

Table 5. Decomposition of Racial Log Hourly Wage Gap for each Sex Group

	Non.discriminatory pay structure:					
	White (β_w)			Pooled (β^*)		
	Endowments	Coefficients	Selectivity	Endowments	Coefficients	Selectivity
Males						
Log Wage Difference = .280						
Model 2	.138	.139	.003	.140	.137	.003
Model 4	.189	.089	.002	.192	.086	.002
Females						
Log Wage Difference = .222						
Model 2	.183	.039	- .001	.184	.039	- .001
Model 4	.188	.084	- .050	.190	.082	- .050

When performing detailed decompositions, we found that schooling is by far the endowment that contributes most to the explanation of the wage gap. This variable accounts for practically all the endowment term for both sexes (that is, 50% of the raw gap) in model 2, and for 40% and 50% in model 4 for men and women respectively (that is 27% and 42% of the raw gap).

Although less important than the effects of schooling, we also found that racial differences in firm experience broaden the racial wage gap. For males, differences in experience account for around 15% of differences in endowments and slightly less than 10% of the wage gap. For females, the effects are somewhat stronger: differences in firm experience represent 18% of the endowments' effects and 16% of the total wage gap.

Regarding the coefficients' effects, the most significant result is again related to schooling. Schooling has much higher returns for whites than for afro-descendants although this finding merits some qualifications for female workers. For men, decompositions based on Model 2 show that if schooling had the same returns among Afro-descendant and white workers, the racial wage gap would be reduced around 56% (.156 units). The effects of differences in the returns of schooling are much lower once we control for job characteristics, but they still explain 14% of the wage gap (0.038 in absolute units). For women, results based on Model 2 indicate that education has again greater returns for white workers. The schooling returns gap account for approximately 35% of the wage gap. In Model 4, however, we find that that the coefficient of education is greater for Afro-descendant women and that differences in education coefficients narrow the wage gap around 50%. This result might be due to the fact that the effects of education on occupation are more powerful for white than for Afro-descendant females.

6.3. Wage gap distribution

We analyze the effects of race at different percentiles through the estimation of quantile regressions for men and women separately, capturing racial differences through an afro-dummy variable. We perform the estimations of Model 2 and 4 at every fifth percentile point between percentiles 5 and 95, but for the sake of brevity, we only report the results obtained for the percentiles 10, 25, 50, 75 and 90 (see Annex V and VI).[10]

Overall, the results are in accordance with those obtained through the estimation of OLS equations: broadly speaking, the signs of the coefficients are the same but their value vary among percentiles**.** The returns of education are positive and the terms on experience have the expected signs for both sexes at all percentiles. The effects of job characteristics are also the expected: positive for seniority, negative for its square and negative for full time. In turn, the coefficient of attendance only to public schools is negative at all percentiles. Finally, the racial coefficient is negative and statistically significant at all positions except at the highest percentile of the female wage distribution, for which it is positive and non-different from zero at the usual confidence levels. As OLS estimations, quantile regressions indicate a greater racial gap for Model 2 than for Model 4 at all positions.

[10] Following Buchinsky (1998), we introduce the selection term using different polynomial forms: degree 1, 2 and 3. We report and analyse the results of the former. The other specifications lead to similar conclusions.

In figure 2 we present the estimated coefficients for the afro dummy variable for men at every fifth percentile between percentiles 5 and 95. Race has a decreasing effect over the distribution and the gap is considerably wider at the bottom than at the top, although it seems to increase once again at the highest percentiles. For example, according to Model 4 the coefficient is –0.15 at the 5^{th} percentile and declines to –0.11 at the 25^{th} percentile and to -0,08 at the median. The gap goes on reducing until reaching a value of -0.03 at the 85^{th} percentile and then presents a slightly increase, being -0.05 at the 95^{th} percentile.

The estimated race coefficient for women appears in figure 3. At the tails of the distribution, they are a bit more erratic than those of men. However, they have large standard errors that make them non-different from zero at the usual statistical levels. Once again, the coefficient decreases throughout the wage distribution. According to Model 4, its value is -.09 at the 5^{th} percentile, -0.04 at the median and close to 0 at the top of the wage distribution.

To sum up, labor market discrimination seems to be more important at the lowest percentiles, suggesting that the Uruguayan evidence is in accordance with the abovementioned floor pattern. In other words, our evidence supports the hypothesis that racial discrimination is higher among low-ability workers, defining abilities as genuine but unobserved factors that affect productivity. Note, however, that unobservables may also be related to barriers that do not affect individual productivity but impede the access to good jobs. For example, employers might use workers' appearance as proxies of labor habits and productivity. Following this interpretation, appearance could be an important source of racial inequality among workers at the bottom of the conditional wage distribution. Another important factor related to unobservables is labor connections. Indeed, labor intermediation in Uruguay is quite intensive in non-objective screening channels. Arim and Salas (2007) estimate that in 2006, 40% of workers found their job through a relative or friend's recommendation while only 20% were selected through universalistic channels (interviews, CVs, contests, etc). Thus, it might be the case that among low-paid workers Afro-descendants have fewer labor connections than their white counterparts.

Figure 2. Afro-descendant coefficient across percentiles (Men)

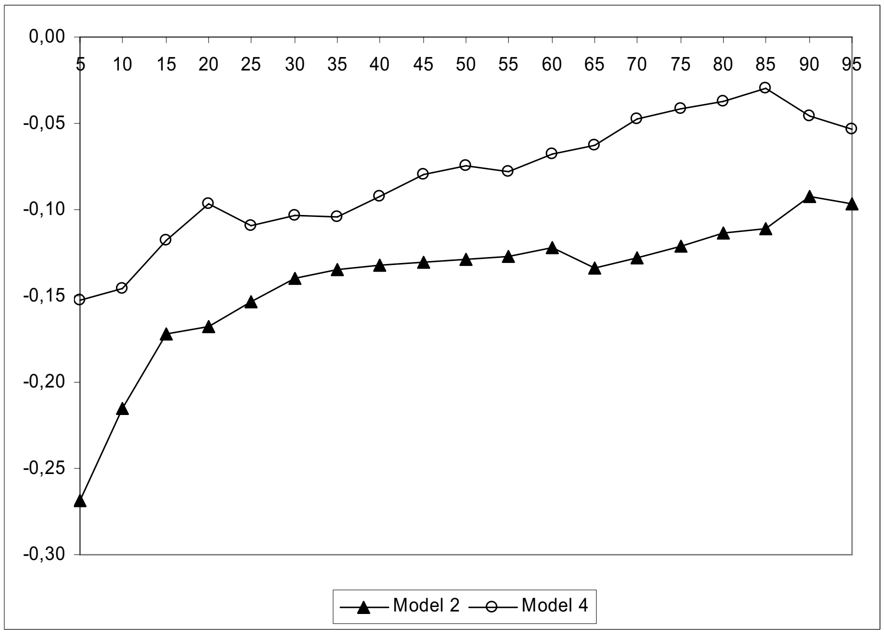
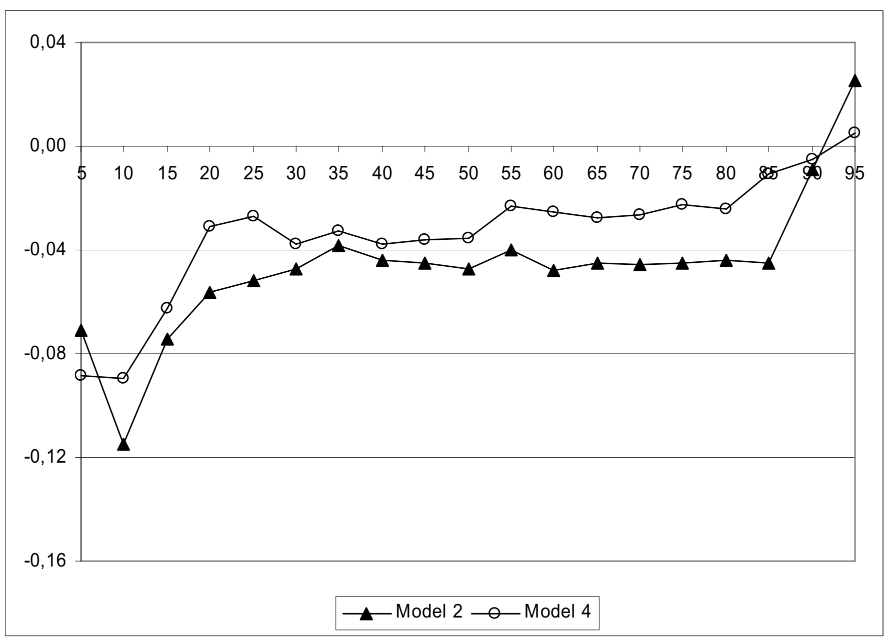


Figure 3. Afro-descendant coefficient across percentiles (Women)



7. Conclusions

Overall, our results lead us to six major conclusions. First, discrimination seems to play an important explanatory role of the racial wage gap in Uruguay**.** This conclusion is supported by two major patterns: a) in OLS wage equations based on pooled samples of white and Afro-descendant workers, the expected wage for afro-descendants is significantly lower than that of whites (i.e. the race coefficient is negative and statistically significant); b) in wage decompositions, differences in coefficients account for an important part of the wage gap, especially among male workers.

Second, the fact that the coefficient for race decreases substantially when controlling for job characteristics such as occupation and industry is in line with the hypothesis that at least part of labor market discrimination works through the placement of Afro-descendant workers into lower-paid occupations (i.e. occupational segregation).

Third, we conclude that racial discrimination is stronger among men than women. Indeed, the coefficient for race is lower among female workers when estimating wage equations separately for both sexes. Similarly, in decompositions we find that the proportion explained by differences in endowments is quite greater for females, regardless of the model chosen for performing the analysis.

Fourth, when treating race as a three-category variable, we find that the conditional expected wage for male workers who reported having African descent only ("blacks") is lower than that of "mixed" afro-descendants. A possible explanation of this trend is that the first group has a darker skin color and, consequently, suffers more from the effects of racial discrimination in the labor market. For females, however, the difference in coefficients between black and mixed is not statistically significant in any model.

Fifth, differences in education are the most important explanatory endowment of the racial gap. This evidence provides support to the idea that Uruguay needs to implement public policies that promote similar levels of access to the educational system and that guarantee a non-discriminatory treatment of Afro-descendant students. However, returns to schooling are lower for afro-descendants, which may explain their lower investment in education. Thus, to accomplish the goal of eliminating racial differences in education, it might be necessary not only to implement public policies in the educational system but also labor market policies that promote that education has the same returns for both racial groups.

Finally, quantile regressions indicate that Afro-descendants are more exposed to suffer from racial discrimination at the bottom of the wage distribution. We may interpret that unobserved factors in our estimations, such as abilities, labor connections or appearance, play an important role in the explanation of discrimination. Further analyses that compare the white and Afro-descendant conditional wage distributions would help to the interpretation of this result.

In general, our standard regression and decomposition results are in accordance with most analyses of wage inequality between whites and non-whites in Latin America (Busso, Cicowiez and Gasparini, 2005; Hall and Patrinos 2006; World Bank 2003). In particular, these analyses suggest that differences in endowments (in particular schooling) explain most of the racial gap but that discrimination is also an important explanatory force. Like in our results, in these works the race variable remains significant in wage equations that treat white and non-white workers jointly. And, in decompositions, although differences in endowments between racial groups are greater than differences in coefficients, the latter nonetheless account for a substantial proportion of the wage gap.

It must be noted that many of these works compare whites and indigenous workers and that the causes and sources of white-indigenous and white-afro inequality might not be the same. For instance, differences in urbanization rates are much higher between indigenous and whites than between afros and whites (Busso, Cicowiez and Gasparini, 2005; Bello and Rangel 2000). It seems appropriate thus to compare our results with those that address the problem of wage inequality between whites and afro-descendants specifically. In this sense, our results are similar to the Brazilian case, the Latin American country for which there exists substantial research on the topic. In analyses that measure discrimination through the introduction of a dummy variable in wage equations, the conditional expected wage for Afro-Brazilians is always lower than that of whites and the race coefficient is always statistically significant (Guimaraes 2006, Busso, Cicowiez and Gasparini 2005; Valle do Silva, 1999; Lovell, 1994)[11]. Similarly, decompositions performed for Brazil are in line with our findings. For instance, using estimates of a model very similar to our model 4, Guimaraes finds that around 30% of the wage gap is explained by differences in coefficients while our results show that these differences explain 33% and 36% of the gap for men and women workers respectively.

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[11] However, the proportion of the wage gap explained by the race coefficient seems to be stronger in Brazil than in Uruguay.

In sum, an overall comparison of our OLS and decomposition results with those of other Latin American countries shows that, in terms racial inequality, Uruguay does not escape from the prevalent regional pattern. In particular, although the Uruguayan racial gap is mostly explained by differences in endowments (being differences in education particularly important), the country does not seem to be exempt from significant degrees of racial discrimination in the labor market.

In contrast, our quantile regression findings differ from those of Arias, Yamanda and Tejerina (2002) who examine the gap between Afro-descendants and whites in the Latin American context. This study analyzes the racial gap across the Brazilian wage distribution using three racial categories and finds that both for blacks (pretos) and mixed (pardos) the gap increases among higher-paid workers. Although the comparison of the Brazilian and Uruguayan results merits to be addressed in further studies, we should bear in mind that quantile regression results usually vary between countries and minority groups. For instance, Levanon and Raviv (2007) find that in Israel, the wage gap between Jews and Druses increases at the upper end of the distribution while for Muslims and Christians, the ethnic wage gap shape is U-shaped. Pendankur and Pendankur (2007) also find quite different patterns for different minorities in Canada. In the specific case of Aborigine, the wage gap is decreasing along the distribution, that is, the authors' results are in line with ours. However, the analysis of a sub-sample of older and more educated men suggests that the overall picture may hide a glass ceiling for this group. As the study points out, we may imagine that opportunities to reach a top position would affect only this kind of workers (educated and seniors). In Uruguay, the presence of a glass ceiling among workers with high levels of human capital is an open question.

Before concluding this paper, it is necessary to stress that our approach to the measurement of discrimination is indirect and tries to capture labor market discrimination. That is, we infer the existence of discriminatory barriers based on the magnitude and significance of the race coefficient and the extent to which differences in coefficients explain the racial wage gap. In principle, pre-labor market discrimination should not be captured by the results. However, unobservable forces might be captured by the race variable and by the "coefficients' effects". Parental human capital, quality of schooling, labor market connections are some of the most important forces that usually remain unobserved in wage inequality analyses and that could be biasing our estimates. In this paper, we tried to tackle this problem by introducing a dummy variable that distinguishes between those who mostly attended public or private elementary schools. Our results show a slight decrease of the education and race variables when adding this dummy. Still, more encompassing solutions to the problem of "unobservables" would be desirable.

Finally, we are also aware that the way through which the race variable is measured might affect racial inequality analyses. In this paper, we have used a question based on self-classification that asks about descent. One potential problem of this methodological strategy is that upper or middle-class Afro-descendants (i.e. workers at the middle and top of the wage distribution) could have a greater tendency to “whiten” themselves than their co-ethnics who are at the bottom of the social pyramid, in accordance with the trend observed for other Latin American countries (Harris, 1964; Wood, 1991; Wade, 1995). If this was the case, analysts might confound the true effects of racial membership on socioeconomic status with those of socioeconomic status on race (i.e. racial classification). Also, the fact that we do not have measures of race based on the interviewers' perceptions can be problematic. Following Telles and Lim, it might be more precise to analyze racial wage inequality through a race variable that reflects the interviewers' rather than the interviewees' classifications because the “perceptions of others about one's race weigh more heavily than self-classification in determining labor market outcomes” (1998: 473). In our opinion, due to the fluid, contextual and changing character of ethnic and racial identifications in Latin America, the safest methodological strategy to study racial inequalities would be to measure race through a variety of questions that collect both pollsters and interviewees' perceptions and then analyze the data based on these alternative measures. Unfortunately, this is a pending matter in Uruguay as well as in most Latin American countries.

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Annex I: Regression Results on Log Hourly Wages (Male Workers; N=28,898)

	Race: Two Groups				Race: Three Groups			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Afro-Descendant	-0.279***	-0.143***	-0.138***	-0.091***				
	(0.015)	(0.014)	(0.014)	(0.013)				
Black					-0.338***	-0.195***	-0.189***	-0.125***
					(0.028)	(0.026)	(0.027)	(0.025)
Mixed					-0.258***	-0.125***	-0.120***	-0.079***
					(0.018)	(0.017)	(0.017)	(0.015)
Education		0.102***	0.098***	0.058***		0.102***	0.098***	0.058***
		(0.001)	(0.001)	(0.002)		(0.001)	(0.001)	(0.002)
Experience		0.038***	0.038***	0.022***		0.038***	0.038***	0.022***
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
$Experience^2$		-0.000***	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Seniority				0.031***				0.031***
				(0.003)				(0.003)
$Seniority^2$				-0.000***				-0.000***
				(0.000)				(0.000)
Fulltime				-0.222***				-0.222***
				(0.014)				(0.014)
Big-Med. Private Firm				0.418***				0.418***
				(0.014)				(0.014)
Small Private Firm				0.026				0.026
				(0.015)				(0.015)
Public Elem. School			-0.162***	-0.101***			-0.162***	-0.101***
			(0.014)	(0.012)			(0.014)	(0.012)
Lambda	-0.853***	-0.350***	-0.371***	-0.390***	-0.854***	-0.350***	-0.371***	-0.390***
	(0.033)	(0.033)	(0.033)	(0.031)	(0.033)	(0.033)	(0.033)	(0.031)
Constant	4.018***	2.555***	2.730***	4.026***	4.019***	2.554***	2.729***	4.025***
	(0.006)	(0.025)	(0.028)	(0.058)	(0.006)	(0.025)	(0.028)	(0.058)
R-squared	0.039	0.258	0.262	0.399	0.039	0.258	0.262	0.399

*** $p<0.001$, ** $p<0.01$, * $p<0.05$; Robust standard errors in parentheses.
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.

Annex II: Regression Results on Log Hourly Wages (Female Workers; N=26,043)

	Race: Two Groups				Race: Three Groups			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Afro-Descendant	-0.194***	-0.040*	-0.038*	-0.031*				
	(0.017)	(0.016)	(0.016)	(0.015)				
Black					-0.204***	-0.011	-0.008	-0.010
					(0.032)	(0.031)	(0.031)	(0.028)
Mixed					-0.191***	-0.050**	-0.047*	-0.037*
					(0.020)	(0.019)	(0.019)	(0.017)
Education		0.111***	0.110***	0.049***		0.111***	0.110***	0.049***
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
Experience		0.037***	0.037***	0.017***		0.037***	0.037***	0.017***
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
Experience 2		-0.000***	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Seniority				0.045***				0.045***
				(0.002)				(0.002)
Seniority 2				-0.001***				-0.001***
				(0.000)				(0.000)
Fulltime				-0.324***				-0.324***
				(0.009)				(0.009)
Big-Med. Private Firm				0.463***				0.463***
				(0.013)				(0.013)
Small Private Firm				0.166***				0.166***
				(0.016)				(0.016)
Public Elem. School			-0.055***	-0.017			-0.055***	-0.017
			(0.013)	(0.012)			(0.013)	(0.012)
Lambda	-1.258***	0.043	0.038	-0.105***	-1.258***	0.043	0.038	-0.105***
	(0.022)	(0.029)	(0.029)	(0.027)	(0.022)	(0.029)	(0.029)	(0.027)
Constant	4.348***	2.244***	2.305***	3.902***	4.348***	2.244***	2.305***	3.902***
	(0.010)	(0.039)	(0.042)	(0.091)	(0.010)	(0.039)	(0.042)	(0.091)
R-squared	0.130	0.284	0.285	0.413	0.130	0.284	0.285	0.413

*** p<0.001, ** p<0.01, * p<0.05; Robust standard errors in parentheses.
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.

Annex III: Regression Results on Log Hourly Wages (White and Afro Male Workers)

	Model 2		Model 4	
	Whites	Afros	Whites	Afros
Education	0.103***	0.084***	0.058***	0.053***
	(0.001)	(0.006)	(0.002)	(0.006)
Experience	0.038***	0.032***	0.023***	0.012*
	(0.002)	(0.005)	(0.002)	(0.005)
Experience 2	-0.000***	-0.000**	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Seniority			0.031***	0.042***
			(0.003)	(0.005)
Seniority 2			-0.000***	-0.001***
			(0.000)	(0.000)
Fulltime			-0.221***	-0.250***
			(0.014)	(0.044)
Big-Med. Private Firm			0.431***	0.251***
			(0.014)	(0.051)
Small Private Firm			0.040*	-0.151**
			(0.016)	(0.054)
Public Elem. School			-0.097***	-0.137*
			(0.013)	(0.054)
Lambda	-0.351***	-0.375**	-0.388***	-0.405***
	(0.034)	(0.118)	(0.032)	(0.118)
Constant	2.547***	2.573***	3.876***	3.524***
	(0.026)	(0.089)	(0.060)	(0.335)
R-squared	0.260	0.161	0.406	0.287
N	25,473	2,725	25,473	2,725

*** p<0.001, ** p<0.01, * p<0.05; Robust standard errors in parentheses;
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.

Annex IV: Regression Results on Log Hourly Wages (White and Afro Female Workers)

	Model 2		Model 4	
	Whites	Afros	Whites	Afros
Education	0.112***	0.103***	0.048***	0.061***
	(0.002)	(0.007)	(0.002)	(0.008)
Experience	0.037***	0.044***	0.016***	0.028***
	(0.002)	(0.006)	(0.002)	(0.006)
Experience 2	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Seniority			0.044***	0.055***
			(0.002)	(0.005)
Seniority 2			-0.001***	-0.001***
			(0.000)	(0.000)
Fulltime			-0.317***	-0.395***
Big-Med. Private Firm			0.474***	0.315***
			(0.014)	(0.053)
Small Private Firm			0.172***	0.080
			(0.017)	(0.064)
Public Elem. School			-0.024*	0.157**
			(0.012)	(0.058)
Lambda	0.047	0.046	-0.111***	0.006
	(0.031)	(0.095)	(0.028)	(0.090)
Constant	2.238***	2.190***	3.902***	3.156***
	(0.041)	(0.133)	(0.094)	(0.381)
R-squared	0.285	0.232	0.416	0.360
N	23,847	2,197	23,847	2,197

*** p<0.001, ** p<0.01, * p<0.05; Robust standard errors in parentheses;
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.

Annex V: Quantile Regression Results on Log Hourly Wages (Males; N=28,898)

	Model 2					Model 4				
	10	25	50	75	90	10	25	50	75	90
Afro-Descendant	-0.216***	-0.154***	-0.129***	-0.122***	-0.093***	-0.146***	-0.109***	-0.074***	-0.042***	-0.046**
	(0.035)	(0.027)	(0.013)	(0.013)	(0.019)	(0.029)	(0.016)	(0.008)	(0.013)	(0.018)
Education	0.101***	0.093***	0.091***	0.102***	0.115***	0.055***	0.054***	0.054***	0.056***	0.062***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Experience	0.032***	0.029***	0.034***	0.044***	0.049***	0.011***	0.013***	0.019***	0.026***	0.0329***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Experience 2	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.000*	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seniority						0.051***	0.041***	0.033***	0.026***	0.023***
						(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Seniority 2						-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fulltime						-0.102***	-0.135***	-0.163***	-0.275***	-0.414***
						(0.020)	(0.014)	(0.015)	(0.018)	(0.018)
Big-Med. Private Firm						0.291***	0.409***	0.449***	0.490***	0.536***
						(0.024)	(0.021)	(0.016)	(0.017)	(0.017)
Small Private Firm						-0.213***	-0.061***	0.066***	0.157***	0.201***
						(0.031)	(0.021)	(0.017)	(0.020)	(0.023)
Public Elem. School						-0.092***	-0.087***	-0.098***	-0.101***	-0.114***
						(0.022)	(0.011)	(0.012)	(0.015)	(0.020)
Lambda	-0.705***	-0.452***	-0.300***	-0.209***	-0.181***	-0.571***	-0.428***	-0.373***	-0.290***	-0.267***
	(0.107)	(0.039)	(0.039)	(0.032)	(0.400)	(0.080)	(0.034)	(0.032)	(0.027)	(0.030)
Constant	1.855***	2.374***	2.729***	2.889***	3.056***	3.234***	3.617***	4.096***	4.527***	4.838***
	(0.060)	(0.036)	(0.026)	(0.029)	(0.042)	(0.125)	(0.083)	(0.072)	(0.079)	(0.096)

*** $p<0.001$, ** $p<0.01$, * $p<0.05$; Robust standard errors in parentheses.
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.

Annex VI: Quantile Regression Results on Log Hourly Wages (Females; N=26,043)

	Model 2					Model 4				
	10	25	50	75	90	10	25	50	75	90
Afro-Descendant	-0.115***	-0.052***	-0.048***	-0.045***	-0.009	-0.090***	-0.027	-0.036**	-0.023*	-0.005
	(0.028)	(0.015)	(0.015)	(0.0173)	(0.022)	(0.033)	(0.022)	(0.017)	(0.014)	(0.022)
Education	0.122***	0.108***	0.105***	0.105***	0.113***	0.043***	0.042***	0.046***	0.052***	0.064***
	(0.003)	(0.003)	(0.002)	(0.0021)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Experience	0.049***	0.035***	0.030***	0.033***	0.038***	0.016***	0.010***	0.012***	0.016***	0.023***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Experience 2	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seniority						0.066***	0.050***	0.040***	0.034***	0.031***
						(0.004)	(0.003)	(0.001)	(0.001)	(0.003)
Seniority 2						-0.002***	-0.001***	-0.001***	-0.001***	-0.001***
						(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Fulltime						-0.2619***	-0.240***	-0.267***	-0.312***	-0.416***
						(0.018)	(0.015)	(0.011)	(0.009)	(0.013)
Big-Med. Private Firm						0.451***	0.448***	0.478***	0.531***	0.607***
						(0.0222)	(0.0152)	(0.012)	(0.014)	(0.021)
Small Private Firm						0.075**	0.100**	0.197***	0.264***	0.334***
						(0.035)	(0.025)	(0.014)	(0.016)	(0.024)
Public Elem. School						-0.230***	-0.181***	-0.082***	-0.051*	-0.007
						(0.050)	(0.029)	(0.026)	(0.027)	(0.025)
Lambda						0.0016	-0.0143*	-0.028***	-0.044***	-0.058***
						(0.012)	(0.009)	(0.010)	(0.009)	(0.018)
Constant						2.990***	3.488***	4.037***	4.359***	4.685***
						(0.1798)	(0.1031)	(0.059)	(0.073)	(0.154)

*** $p<0.001$, ** $p<0.01$, * $p<0.05$; Robust standard errors in parentheses.
Models 2-4 include dummies of region; Model 4 includes dummies of occupation and industry.