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JOSÉ GUILHERME XAVIER DE BASTO TÓPICOS PARA UMA REFORMA FISCAL IMPOSSÍVEL

ORLANDO GOMES DECISÕES DE LOCALIZAÇÃO E CRESCIMENTO ECONÓMICO NA ERA DIGITAL

AMÉLIA BASTOS / GRACA LEÃO FERNANDES / JOSÉ PASSOS ESTIMATION OF GENDER WAGE DISCRIMINATION

IN THE PORTUGUESE LABOUR MARKET

JUDITE VIEIRA

FÁTIMA BARREIROS / MANUEL P. FERREIRA SENTIMENTOS E COMPORTAMENTOS EM MATÉRIA AMBIENTAL: DETECÇÃO DE DIFERENÇAS ENTRE GÉNERO E GRUPOS PROFISSIONAIS

Estimation of Gender Wage Discrimination in the Portuguese Labour Market

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resumo

résumé / abstract

A discriminação salarial por género é uma realidade no mercado de trabalho português. Todavia, existem poucos trabalhos que avaliem a sua dimensão. O conhecimento preciso e detalhado deste fenómeno constitui, com certeza, um importante elemento de suporte à definição de medidas de política económica que visem debelar o problema.

Neste artigo é estudado o problema da discriminação salarial no mercado de trabalho português, procedendo-se para o efeito à sua mensuração e análise nas regiões de Lisboa e Porto. O trabalho realizado tem como suporte estatístico as técnicas de *bootstrap*.

Os resultados obtidos sugerem que a discriminação salarial é mais intensa em Lisboa apresentando, todavia, uma maior variabilidade no Porto. La discrimination des salaires par genre est une réalité dans le marché du travail portugais. Cependant, son étude est réduite. La connaissance de ce phénomène donnera des éléments indicatifs des mesures de politique économique pour réduire le problème.

Dans cet article on analyse la discrimination des salaires dans le marché du travail portugais, détaillé pour les régions de Lisboa e Porto. Le soutenu statistique de l'étude est la technique de *bootstrap*.

Les résultats obtenus montrent que la discrimination des salaires est plus forte à Lisboa mais elle présente une variabilité plus grande à Porto.

Gender wage discrimination is a reality in the Portuguese labour market although little research has, so far, been carried out to measure its dimension. We think that economists should contribute to the knowledge of the dimension and significance of this phenomenon, by giving guidelines for the definition of political measures to help reduce it.

In this paper we measure the size of gender wage discrimination in the Portuguese labour market. Furthermore, we evaluate this measure for Portugal's two main cities, Lisboa and Porto, using bootstrap techniques.

The results suggest that in Porto gender wage discrimination would be expected to be lower than in Lisboa but with greater dispersion. The estimated values for discrimination range between numbers commonly found in studies of this kind.



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1. Introduction

Economists say that we are in presence of discrimination in the labour market if there is a gap between the wages of two groups that cannot be explained by individual characteristics.

The analysis of discrimination that has been done so far, basically uses five approaches to decompose the overall wage differential between two groups – Oaxaca (1973), Reimers (1983), Neumark (1988) and Oaxaca and Ranson (1994). Silber and Weber (1999) found that there were no significant differences among these decomposition procedures.

Recent analysis of discrimination considers the problem of sample selection bias (Christofides *et al.*, 2003), using selected – corrected wage equations.

From descriptive statistics as simple as the ratio between average male/female wages (0.30 in our data) it is clear that gender wage discrimination is a reality in the Portuguese labour market. However, little is known about how widespread this phenomenon is in the Portuguese labour market. As long as we keep in mind its limitations, this analysis helps the recognition of gender wage discrimination and provides elements to help define political measures for reducing it.

The problem of wage discrimination by gender in Portugal has not been studied in depth. Research has aimed to estimate the dimension of the phenomenon and to determine its underlying factors. There are also some studies, which, although related to other subjects (such as income inequality), also contribute to the knowledge about discrimination.

Portuguese studies on this topic, generally use the Oaxaca methodology to estimate a gender wage discrimination measure. Kiker and Santos (1991) found that in 1985, 67% of the gender wage gap was due to discrimination. Ribeiro and Hill (1996) analysed the gender wage differential for the Restaurant and Hotel sector in Lisboa, in 1992, and concluded that 76% of the gender wage gap was related to discrimination. Vieira and Pereira (1992) state that, for the Azores, in 1989, the gender wage gap ranged between 58 and 81%.

Other studies, such as Lopes (1996) and Cardoso (1997, 1999) also provide an insight into this topic, by analysing gender differences in wages and income. These investigations also conclude for the existence of a quite significant gender wage differential in the Portuguese labour market.

These studies, however, were based on smaller samples concerning a more restricted set of economic sectors. Furthermore, although some of them used the Oaxaca decomposition to measure gender wage discrimination none of them determines the statistical distribution of the gender wage gap in a way that allows inference analysis.

We use the Oaxaca, Ranson (1994) decomposition to measure gender wage discrimination in Lisboa and Porto, the two biggest regional labour markets in Portugal. Furthermore, we use bootstrap techniques to find the distribution of the wage gender gap due to discrimination in each region. This distribution enables us to use statistical techniques to infer the results. This is something new in gender wage discrimination studies for the Portuguese labour market.

The paper is divided in four sections. This first section introduces the problem of gender wage discrimination in Portugal. In section II we briefly review the Oaxaca, Ranson (1994) decomposition. Section III describes the data used for the wage equation estimation and the methodology employed. Section IV introduces the results and presents the relevant conclusions.

2. The gender wage gap decomposition

The Oaxaca (1973) decomposition to estimate a measure of wage discrimination decomposes the average wage gap between two groups of workers in two components, one explained by productive differences due to workers' skill differentials and the other, not explained by individual characteristics, and thus considered discrimination.

Mincerian wage equations¹ are estimated for each of the groups (male and female). Let $\ln \overline{W}_m$ and $\ln \overline{W}_f$ refer to the mean of the actual log wage received by men (group m) and women (group f). The average wage gap is calculated from:



(1)

where: b

represents the non-discriminatory wage structure;

 $\hat{\beta}_i$ (*i* = *m*, *f*) the estimated coefficients of the wage equations;

 \overline{X}_i (*i* = *m*, *f*) vectors of average individual skill endowments.

The first term in the RHS of equation 1 measures the discrimination in favour of male, the second refers to the discrimination against female and the third is the gap due to differences in individual skills endowment.

Several authors² discuss the non-discriminatory wage structure definition that leads to different algorithms to estimate *b*. In this paper we follow the Oaxaca, Ranson (1994) approach where *b* are the coefficients from the pooled (male/female) regression.

3. Methodology and data

The wage equation used for estimation in this paper is not a typical Mincerian one since it includes variables characterising the location, sector and business volume or plant size, where the individuals are employed.

Our wage equation is then specified as:

$$\ln W = \alpha + \beta X + \gamma Z + \mu$$

(2)

- where: *W* hourly wage rate before tax including base wage plus all regularly paid allowances;
 - X vector of workers characteristics (educational level, experience, skill, level, time in current job);
 - Z-vector of firm characteristics (business volume, plant size, sector).

The most common human capital variables in Mincerian wage equations were included. Educational level is the last formal school year passed. Experience was calculated as potential experience in the usual way (experience = age - years of schooling – 6). We took skill levels instead of occupational status for two main reasons:

 Skill level codification in Portuguese labour market statistics encompasses a mix of actual qualification levels and hierarchical and management grades. It is thus, basically, an occupational control variable;

¹ Mincer (1974).

² Reimers (1983), Neumark (1988), Cotton (1988), Oaxaca, Ranson (1994).



- The number of missing in our database is much higher for the second than for the first variable for the same level of aggregation. So, the number of observations for estimation would be considerably reduced if we took occupational status rather than skill levels.

The industry variables in the wage equation are plant size, measured by the number of employees in a plant, and business volume, measured as the total yearly income earned by the firm from selling products or services.

We include sectoral dummies, given the evidence that women are concentrated in certain sectors, which points to the fact that the distribution of male/female across sectors could itself be a result of discrimination.

On the basis of the estimated earning functions and the data set, we use bootstrap techniques for statistical inference purposes relative to discrimination, in the Portuguese labour market.

The bootstrap was introduced by Efron (1979) as a computer-based method for estimating the variance of an estimator. Freedman (1981) extended this method to the regression framework.

Basically, the bootstrap treats the data as if they were the population for the purpose of evaluating the quantity of interest. The method has been shown to be very useful in situations where the asymptotic distribution of an estimator is difficult to derive. Moreover, it is often more accurate in finite samples than first-order asymptotic approximations.

Our purpose in this paper is twofold: i) testing the null hypothesis of non-discrimination, which requires computing the standard deviation of the male-female wage differential due to discrimination and ii) testing the equality of this wage discrimination between the two major cities of Portugal (Lisboa and Porto). Due to the mathematical difficulty of obtaining the exact distribution of the wage discrimination estimator the bootstrap methodology has been adopted.

In general, bootstrapping regression models can be used in two different ways: i) through resampling errors or ii) resampling cases. The main difference between these two approaches is related to the hypothesis underlying the regression model. With resampling cases the regression model still applies with no assumption on the random error other than independence, being robust to departures from the homoskedasticity assumption, which is a typical problem in cross-sectional models.

In the following, resampling cases is applied to derive the distribution of the estimator defined as the proportion of male-female wage differential due to discrimination,

(3)

$$D = \frac{(\hat{\beta}_{m} - \beta^{*}) \,\overline{X}_{m} + (\beta^{*} - \hat{\beta}_{f}) \,\overline{X}_{f}}{\Delta \overline{W}}$$

Considering the wage models for Lisboa and Porto, we have drawn 1000 bootstrap samples. From each bootstrap sample and for each city the least squares regression is applied, given estimates, β_{m}^{*} , β_{f}^{*} and D^{*} by (3). Table 1 summarizes the main results.

To estimate the wage equations we have used *Quadros de Pessoal* (establishment) data gathered by the Department of Statistics of the Ministry of Employment and Social Security for 1997.

These data are the most extensive, complete and reliable micro data set available for the study of the Portuguese labour market. It is collected annually through a compulsory survey of firms employing salaried workers³.

Our data has 2 267 717 workers (1 334 687 male and 933 030 female), individual characteristics (age, educational levels, skill levels) as well as their firms' location, sector, business volume and size.

3 This database does not include public administration and non-market services. The agriculture sector is poorly covered.

From this data we selected all full time salaried workers⁴ in firms located in mainland Portugal for whom there are no missing values for the variables included in the wage equation. So the working data included 1 884 843 individuals (1 090 844 male and 793 999 female).

As the bootstrap methodology is so demanding and time consuming in computational effort it was difficult to apply it to the whole working data. Having to select a smaller sub-sample to work with, we chose to analyse only the data for Lisboa and Porto⁵. These are the two biggest Portuguese regional labour markets. In addition, these markets are quite distinct in several features that might affect the gender wage discrimination, such as: proportion of highly skilled workers, percentage of women with high educational level, size and gender distribution of firms. So it seemed interesting to compare the gender wage discrimination in these two cities.

We therefore took 157 271 male and 112 223 female workers in firms located Lisboa and, 59 281 male and 37 667 female workers in firms located in Porto, to estimate the wage equations.

4. Results and main conclusions

Table A_1 (in the Appendix) gives the means of some of the variables included in the earning functions, separately for men and for women and for Lisboa and Porto. In these two cities men are, on average, older than women, have more experience and show higher skill levels. Nevertheless, they had lower educational attainments, compared with women.

However, the similar pattern of these variables in Lisboa and Porto has some differences. In Porto, workers seem to be youngest, on average, which may be why their educational levels were lower than those from Lisboa; women register a greater divergence in skills and education, compared with men and are less qualified than men, in spite of averaging the highest educational levels.

The results of the empirical estimation⁶ of the earning functions are presented in Tables A_2 and A_3 , in the appendix. All estimates are roughly significant to a 0.001 significance level and have the expected magnitude and signals. Standard errors are robust to heterokedasticity using White (1980) type estimation. The estimated models are all robust to alternative specifications. A comparative analysis between men and women, first, and then between the two cities studied, permits the following conclusions:

• The rates of return on education do not vary with gender or regional localization;

· An extra year of experience benefits more men than women, in both cities;

• Gains from skill up-grading are greater the higher the skill level, for both men and women. This impact seems to be stronger for women, in terms of gender, and in Porto, in terms of regional localization;

• A firm's turnover has a positive and increasing impact on wages. Men benefit from this effect more than women, except for the firms with the highest turnover in Lisboa;

There are differences between men and women concerning the impact of job sector.
Manufacturing and services have a higher negative impact on women's wages, especially in Porto;

• Finally, the tenure variable introduced in the model affects wages positively, particularly for women, but at a decreasing rate.

Let us now analyze the decomposition of the wage difference between men and women, according to the regions considered.



⁴ We focus on full time workers so that the estimated gender wage gap is not affected by any hourly wage penalty of part time work.

⁵ By Lisboa and Porto we mean the main cities and respective neighborhoods (Municipalities of Lisboa and Porto).

⁶ Results for the best fitted estimated equation only are presented.



The log wage differential is similar in Lisboa and Porto. On average, in Porto, the gender wage differential due to productivity is higher and pure discrimination is lower, than in Lisboa (Tables A_4 and A_5 in the Appendix).

The application of the bootstrap technique makes it possible to construct the discrimination factor distribution. Table 1 summarizes the main results of the proportion of male-female wage differential due to discrimination (D).

Table 1 – Bootstrap Estimates of D						
	Min	1 st Quart	Mean	3 rd Quart	Max	Stdv
Lisboa	0.571	0.586	0.589	0.593	0.607	0.00545
Porto	0.532	0.555	0.560	0.565	0.593	0.00828

The standard deviation of the bootstrap estimator of is very low compared with the mean and therefore the null hypothesis of non-discrimination is easily rejected for both Lisboa and Porto. Moreover, Lisboa and Porto exhibit different patterns of discrimination with Porto having a larger variance and a lower mean value of discrimination [see Figure 1].

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Figure 1 – Distribution of male-female wage discrimination



Proportion of wage differencial due to discrimination



Proportion of wage differencial due to discrimination

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From the bootstrap estimates of for Lisboa and Porto the distribution of the difference is also computed [see Figure 2] and the main results presented in Table 2. The null hypothesis of equal discrimination between these two cities is easily rejected.

Table 2 – Bootstrap Estimates of the difference between proportions in Lisboa and Porto					
Min	1 st Quart	Mean	3 rd Quart	Max	Stdv
-0.002	0.023	0.030	0.036	0.061	0.00993



Difference between proportions in Lisboa and Porto



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According to Figures 1 and 2, Lisboa seems to register higher pure gender wage discrimination and a lower dispersion than Porto.

These results are robust to other wage discrimination decomposition procedures, as Silber and Weber (1999) also pointed out.

One possible explanation for these pattern differences in discrimination between Lisboa and Porto may be the existence of a different cultural environment. In addition, there is an unequal distribution of men and women by sector in the two cities. In Porto there is a higher proportion of women in manufacturing, where the proportion of men is low, while in Lisboa, women are concentrated in the service sector, where the proportion of men is also significant [see tables A_1 and A_6 in the appendix]. This evidence, itself the result of discrimination, influences the gender wage gap through a crowding effect⁷ as defined by Sorensen (1989). So, it is only natural that it also affects the value assumed by the discrimination coefficient, contributing to the variability of the discrimination factor in Porto and favoring the intensity of discrimination in Lisboa. These hypothetical explanations need further research.

Finally, it should be mentioned that the estimated value for discrimination takes values within the range found in similar studies for other countries, such as those of Silber and Weber (1999) and Neumark (1988).

The effect of a possible sample selection bias on the measuring of the gender wage discrimination, a problem that has raised much discussion⁸, has not been tackled in this paper, but it is a topic that will be developed in further research.

7 Ribeiro and Hill (1992) show evidence of such a crowding effect for a sector of the Portuguese labour market. 8 Christophides *et al.* (2003).

Appendix

Table A ₁ – Mean value of the variables					
Variable	Lisl	ooa	P	Porto	
	Men	Women	Men	Women	
Age	39.23	36.76	38.55	35.62	
Tenure	9.25	8.01	10.29	8.23	
Exper	24.57	21.46	24.98	21.3	
School	8.66	9.30	7.57	8.31	
SL1	.18	.12	.11	.08	
SL2	.17	.15	.14	.11	
SL3	.39	.38	.46	.40	
SL4	.08	.14	.09	.19	
BV1	.53	.47	.50	.50	
BV2	.42	.58	.42	.58	
BV3	.37	.63	.29	.71	
BV4	.34	.66	.27	.73	
Manufact.	.37	.63	.39	.61	
Constr.	.10	.90	.09	.91	
Serv.	.56	.44	.55	.45	
Transp.	.28	.72	.21	.79	
Prpty	.12	.88	.35	.65	

Exper - experience

School - highest level of education achieved

SL; (i=1,2,3,4,5) - skill level. From 1= White collars; 2= highly skilled; 3=skilled; 4= low skilled to 5=non skilled



Junho '04 / (35/48)





Table A_2 – Earning functions for men and women from Lisboa (dependent variable: logarithm of hourly wage)

Variable	Coefficients of the earning functions in Lisboa for			
	Me	n	Wo	men
С	5.37207	(686.718)	5.33265	(758.616)
BV2	.081548	(23.1189)	.094258	(30.4746)
BV3	.218683	(61.6843)	.224532	(68.9603)
BV4	.329691	(86.7804)	.269388	(69.1264)
Tenure	.011945	(28.9494)	.018723	(40.3758)
Ten2	169730E-03	(- 14.048)	279324E-03	(- 18.455)
School	.062123	(136.691)	.059934	(118.941)
Exper	.033623	(87.1858)	.023829	(61.6381)
Exper2	428525E-03	(- 68.109)	303558E-03	(- 45.611)
Manuf	.088389	(17.9524)	771063E-03	(15982)
Constr	024347	(- 5.4528)	026699	(- 3.2491)
Ser	.049974	(12.1175)	046696	(- 14.469)
Transp	.135479	(33.7649)	.151951	(34.3382)
Financ	.378605	(80.1573)	.427586	(92.4851)
Prpty	.076839	(15.2626)	.057136	(14.8820)
SL1	.541855	(102.962)	.549714	(91.8917)
SL2	.248974	(57.6662)	.351974	(74.7927)
SL3	492661E-02	(- 1.4434)	.074659	(22.7447)
SL4	083994	(- 20.155)	06596	(- 18.929)
$\overline{R}^2 = 0.608547$			$\overline{R}^2 = 0.653847$	

t - values in parenthesis

 BV_{i} (i = 2,3,4) turnover. Where :

- i = 1 if turnover < 100 000 000\$ (500 000 euros);
- i = 2 if 100 000 000\$ turnover< 1 000 000 000\$ (5 000 000 euros);

i = 3 if 1 000 000 000\$turnover< 10 000 000 000\$ (50 000 000 euros);

i = 4 if turnover 10 000 000 000\$ (50 000 000 euros).

Ten2 - (Tenure)2

School - highest level of education achieved

Exper - experience

Esper2 - (Exper)2

Manuf - manufacturing Constr - construction

Ser - services

Transp - transport

Financ - finance

Prpty - property

SL_i (i = 1,2,3,4,5) - skill level. From 1 = White collar; 2 = highly skilled; 3 = skilled; 4 = low-skilled to 5 = unskilled

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Variable	Coe	fficients of the ea	rning functions in Po	ort for	
	Mei	n	Wo	/omen	
С	5.36375	(426.687)	5.37757	(485.622)	
BV2	.111779	(24.2211)	.102276	(25.0720)	
BV3	.275860	(56.0028)	.249387	(47.5109)	
BV4	.324904	(59.2414)	.308565	(43.2862)	
Tenure	.011103	(19.5148)	.016474	(24.8727)	
Ten2	156061E-03	(- 9.9368)	287227E-03	(13068)	
School	.056260	(78.6009)	.052734	(66.8344)	
Exper	.030145	(51.9779)	.019721	(32.6494)	
Exper2	387149E-03	(- 40.195)	238789E-03	(- 22.358)	
Manuf	045063	(- 6.6934)	120297	(- 22.964)	
Constr	09477	(- 13.095)	05179	(- 3.5869)	
Ser	01787	(- 2.7509)	06289	(- 12.965	
Transp	.109937	(16.8902)	.144711	(15.6932)	
Financ	.413139	(52.7856)	.467129	(54.5545)	
Prpty	05329	(- 6.4976)	02269	(- 3.5679)	
SL1	.560473	(64.8093)	.585272	(56.7227)	
SL2	.279327	(43.0500)	.371114	(46.7696)	
SL3	.055978	(11.0056)	.075562	(16.3008	
SL4	02139	(- 3.5673)	03719	(- 7.3537	
$\overline{R}^2 = 0.633266$			$\overline{R}^{2} = 0.678623$		

t-values in parenthesis

46 47

Table A_4 – Descriptive statistics for discrimination in Lisboa					
	Mean	Std Dev	Minimum	Maximum	
LWM	6.87840	0.0017005	6.87249	6.88308	
LWF	6.64326	0.0018893	6.63751	6.64928	
DW1	0.096579	0.0019346	0.090316	0.10227	
DW2	0.13857	0.0015205	0.13359	0.14352	
PDW2	0.58930	0.0054544	0.57110	0.60681	
	0		0		
C. State Barriel	Sum	Variance	Skewness	Kurtosis	
LWM	6878.40227	2.89167D-06	-0.0061559	-0.12789	
LWF	6643.25840	3.56951D-06	0.079905	-0.16702	
DW1	96.57887	3.74253D-06	-0.080842	0.012573	
DW2	138.56501	2.31201D-06	0.024278	0.0091486	
PDW2	589.30061	0.000029750	0.074536	0.0067597	

Table A_5 – Descriptive statistics for discrimination in Porto				
	Mean	Std Dev	Minimum	Maximum
LWM	6.65327	0.0025411	6.64492	6.66227
LWF	6.42250	0.0028049	6.41163	6.43130
DW1	0.10160	0.0029988	0.091029	0.11153
DW2	0.12917	0.0022720	0.12246	0.13735
PDW2	0.55980	0.0082830	0.53175	0.59254

	Sum	Variance	Skewness	Kurtosis
LWM	6653.26642	6.45715D-06	0.054233	0.18460
LWF	6422.49887	7.86719D-06	-0.080492	0.034687
DW1	101.59706	8.99271D-06	-0.0022146	0.12711
DW2	129.17049	5.16190D-06	0.091479	-0.022006
PDW2	559.79552	0.000068607	0.043958	0.25340

LWM - log wage for men

LWF – log wage for women DW1 – wage differentiation due to productivity

DW2 – discrimination

PW2 – proportion of the wage differentiation due to discrimination

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Table A ₆ – Women distribution by sector					
Variable	Lisboa	Porto			
	Women	Women			
Manufact.	.07	.16			
Constr.	.02	.02			
Serv.	.34	.30			
Transp.	.10	.05			
Prpty	.12	.10			

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