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Abstract

This paper studies gender wage differentials in Italy by providing a structural estimation of the frictional parameters of two different theoretical specifications of an equilibrium search model. I alternatively allow for firm heterogeneity and discrimination empirically using maximum likelihood and matching first moments in the data. Results indicate substantial differences in transition parameters with higher level of search frictions for women. The mapping from productivity to wages for men is highly non linear, with high productivity firms offering proportionally higher wages; for women, the relationships is almost linear. Including discrimination, I find that productivity accounts for 61% of the wage offer differential, search for 28% and 11% is the part of discrimination.

Keywords: Gender Wage Differentials, Equilibrium Search, Discrimination, Structural Estimation, Italy.

JEL Classification: J31, J41.

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1 Introduction

The empirical labour literature has paid particular attention to gender wage differentials, as these have been frequently associated with discrimination in labour markets (see Altonji and Blank, 1999). However, identification of discrimination as source of such differentials with standard econometric tools is not a simple task. The problem is that discrimination is only one possible explanation for observed gender wage differentials; other possibilities being productivity differentials and different search behaviour of men and women.¹

As a consequence, if one wants to identify a measure of discrimination, it is difficult to rely on the estimated coefficient of the gender dummy in wage regressions. One possibility for analysing these issues is that of using and estimating an equilibrium search model. In that context, all three sources of wage differentials are present as an explanation for wage dispersion. What is more, estimation of structural behavioural parameters, both with maximum likelihood techniques and matching first moments in the data, guarantees exact identification. Equilibrium conditions can then be used to decompose observed wage differentials due to search frictions, productivity differentials and discrimination. Productivity and transition probabilities differentials are the two main determinants of wage differentials across workers in equilibrium search models, both are assumed exogenous. However, some recent contributions in the literature explicitly include another determinant of wage differentials: taste discrimination as studied in Becker (1971) is a further ingredient to explain race and gender wage differentials.²

The literature dealing with structural estimation of search models is now rapidly increasing and well established (see Eckstein and Van den Berg, 2007). Despite this fact, quite a few contributions look at gender wage differentials in this specific framework. Bowlus (1997) studies gender wage differentials using US data. The paper estimates an equilibrium model decomposing the wage differential into productivity and search components finding that productivity differentials explain about 70% of the wage gap, and the rest is search frictions. However, the paper explicitly doesn't take discrimination into account. Two papers that try to disentangle the role of unobserved productivity differentials, search frictions and discrimination are Bowlus and Eckstein (2002) and Flabbi (2005). The former deals with race differentials while the second explicitly looks at gender differentials. However this is not the only difference between the two studies. Although the papers share the same basic aim of disentangling differentials in productiv-

¹Standard wage regression control for most observable characteristics that can account for productivity differentials, i.e., human capital, experience, industry, occupation, and unobserved heterogeneity.

²Black (1995), Sasaki (1999) and Rosen (2003) are examples of theoretical search models in which discrimination persists in equilibrium.

ity, search and discrimination components, they basically differ in the theoretical structure and estimation approach. Both look at the share of prejudiced employers and their disutility factor upon hiring a worker from the minority group, however, the former uses a wage posting mechanism for wage offers and doesn't have any source of spillover effect from prejudiced to unprejudiced employers; the second, using a search-matching-bargaining framework, is able to reproduce the spillover effect. As a result, women's outside options are reduced at any employer, determining wage discrimination. Finally the two papers are estimated by using different methods. While Bowlus and Eckstein (2002) match first moments in the data, Flabbi (2005) estimates structural parameters by maximum likelihood. The latter methodology is able to fit the wage distribution quite satisfactorily, while the former identifies parameters assuming increasing densities for wage offers and earnings distributions.³

This paper provides a structural estimation of the relevant parameters of the equilibrium search model with frictions by using two different theoretical structures. First a model with firm heterogeneity in productivity without discrimination is estimated, then a model with no dispersion in productivity and discrimination is considered. The former approach assumes men and women are in separate labour markets and firms with different productivity offer different wages to workers; the latter analyses a labour market in which all men and women have the same productivity but there are gender differences and discrimination. The empirical application is performed on Italian administrative data from INPS.

In the first part of the paper, after a non-parametric estimation of the distribution of earnings; I recover a structural estimate of frictional parameters of the equilibrium model using maximum likelihood techniques as proposed by Bontemps et al. (2000). Conditional on previous steps, I look at the relationship between productivity and wages separately for men and women. The second part of the paper is devoted to estimate structural parameters matching first moments in the data by using again structural equilibrium relationships as proposed by Bowlus and Eckstein (2002). In this context, I assume men and women can have different productivity, but the distribution of productivity is not dispersed. Using their identification strategy, a measure of the number of discriminating firms and their disutility parameter upon employing women are estimated.

The main findings of the paper can be summarised as follows. The job finding rate is much higher for unemployed workers than for employed ones, both for men and women. The former is estimated ten times higher than the latter. As a consequence the frictions parameter, expressed as the ratio between the arrival rates of

³Flabbi (2007) explicitly addresses the issue of stable gender wage differentials over time by considering the role of discrimination. He concludes that the proportion of prejudiced employers in the US drops from 70% in 1985 to 32% in 2005.

offers while employed and the job destruction rate, is very low. Important differences in the speed of climbing the wage ladder between men and women are found. This quantity measure of search frictions is equal to 0.5 for men and 0.2 for women when using maximum likelihood techniques. The mapping from productivity to wages indicates again interesting differences across workers. For men, the relation is highly non linear, with high productivity firms offering proportionally higher wages, while for women, the relationship is almost linear. This suggest firms have quite different wage policies in recruitment and retention for men and women. Finally, explicitly taking into account discrimination, by matching moments in the data, results indicate the relative contribution of the search, productivity and discrimination is different for the wage offer and earnings distribution. In the first case, productivity accounts for 61% of wage differentials, while the part of search is 28% and 11% is the component of discrimination. The earnings distribution is differently affected: the relative contributions are 48%, 24% and 28% respectively. Interestingly, productivity differences are more relevant for wage offers than for earnings distribution, while discrimination is much more important to explain the earnings gap. The role of search behaviour is very similar in both cases.

The rest of the paper is organised as follows: in section two I briefly discuss the theoretical equilibrium search model with productivity dispersion across firms and the model with taste discrimination. Then, in section three I describe the data and the selection of the sample. The estimation method, results and comparison with those in the literature are also provided. In the last section, I conclude and discuss some policy issues.

2 Theory

In this section, I provide a brief description of the equilibrium search model of Burdett and Mortensen (1998). The model is also separately extended to include firms' heterogeneity (Bontemps et al., 2000) and discrimination (Bowlus and Eckstein, 2002). Both extensions are used for empirical estimation. It is important to stress from the onset, these are quite different representation of the labour market, however both of them have search frictions as essential component of the model.⁴

Heterogeneity in productivity is essential to obtain a reasonable fit of the wage distribution and allows to analyze the relation between wages and productivity. Men and women belong to separate labour markets in this setup. On the other hand, including discrimination and assuming there is a fraction of firms that have a disutility taste parameter towards women, helps to better explain the gender wage differential. However, in this case, although the model is identified, it has

⁴A more detailed description of models is also contained in Sulis (2007).

the counterfactual implication of increasing densities for wage offer and earnings distribution.⁵

2.1 Productivity Dispersion

The labour market is populated by workers and firms, the large number of identical firms is measure 1; m is the large number of workers in the market. They are all identical; however, some of them are employed and some others are unemployed. Let u denote the number of unemployed. Job search can occur in both states; the probability of receiving an offer is distributed according to a standard Poisson process where λ_u is the arrival rate of job offers while unemployed and λ_e when employed. The search strategy has the reservation property, R is the reservation wage when unemployed, and the wage w is the reservation wage when employed. If unemployed a worker has utility flow given by b , the latter has the standard interpretation as the value of leisure or the level of unemployment benefit per period. No heterogeneity in the value of leisure is assumed. When employed, workers earn their wage w and p is the flow revenue generated per employed worker, total surplus from matching is $p - b$, a firm earns $p - w$ when the job is filled, while a worker gets $w - b$. Exogenous productivity shocks destroy jobs with arrival rate δ . It is useful to define $k_u = \lambda_u/\delta$ and $k_e = \lambda_e/\delta$. The latter is the key parameter of the model and is a quantity measure of the level of search frictions in the market (Ridder and Van den Berg, 2003).

Let $F(w)$ represent the distribution of wages offered to workers and $G(w)$ the distribution of wages actually paid to employed workers, i.e., the earnings distribution. There is a structural relationship between the two regulated by search frictions parameters that reads as

$$G(w) = \frac{F(w)}{1 + k_e[1 - F(w)]}. \quad (1)$$

The fraction of workers receiving a wage less or equal to w is given by the fraction of firms offering that particular wage (or less) divided by the probability that the job is either destroyed for exogenous reasons or the worker quits for a better offer. This is the most important relationship that I use in the empirical application.

Firms post wage in the support of the wage offer distribution $F(w)$. Denote $l(w|R, F)$ as the measure of workers per firm earning a wage w given R and F . That specifies the steady state number of workers available to a firm offering a particular wage conditional on the wage offered by other firms, represented by F , and the workers' reservation wage R . Firms can offer higher wages and make less

⁵To the best of my knowledge, no attempt has been made to model both firms' heterogeneity and discrimination.

profits per workers but increase $l(w)$; viceversa, offering lower wages make more profits per worker but face more turnover.

Finally, following Bontemps et al. (2000), assume now that firms are heterogeneous with respect to their labour productivity parameter p . In this setting, firms maximise profit by choosing w , given productivity. From the first order condition of the firm maximisation problem, it is then possible to determine the firm's value of the exogenous productivity parameter at each firm

$$p = w + \frac{1 + k_e G(w)}{2k_e g(w)}. \quad (2)$$

The parameter p is an important measure of the marginal product of a worker in a competitive equilibrium. As search frictions vanish, the parameter k_e increases, and the gap between wages and productivity disappears. It is important to stress, the distribution of productivity is assumed to be exogenous and there is no other production factor in the model. Firm heterogeneity is essential to get a good fit of the wage distribution.

2.2 Discrimination

In what follows, I discuss in more detail the model when discrimination is explicitly taken into account as proposed by Bowlus and Eckstein (2002). In this case, there are two types of workers, M and W . There is a proportion θ of the latter and $1 - \theta$ of the former. Workers differ by gender and productivity with $P_M \geq P_W$ as type M workers can have higher skill level.⁶ Firms maximise utility that depends on profits and preferences over type of workers. There is a fraction γ_d of firms having a disutility d upon hiring a type W worker, while the remaining proportion is unprejudiced firms. Both θ and γ_d are exogenously given. In this setting arrival rates are influenced by preferences of employers towards workers' types. To model this, a proportional factor $0 \leq x \leq 1$ is added to the model. If $x = 0$, prejudiced firms do not search for W type workers, while if $x = 1$ ($d = 0$ and $\gamma_d = 0$) arrival rates are the same across workers. In general, arrival rates differ by x . Exogenous job destruction rates differ by assumption $\delta_W \geq \delta_M$.

In this context, firms can post different wages for each type of worker. What is more, since firms' profits are additive in workers' types, it is possible to solve separately for flows and wage offer distributions for each worker's type. In particular, for workers of type M , both prejudiced and unprejudiced firms post the same wage offer distribution; the latter is equal as the one in Burdett and Mortensen (1998), with increasing offer and earnings densities. Bowlus and Eckstein (2002) show that

⁶Productivity is denoted by capital letters to stress the fact all workers of the same gender have the same productivity.

wage distributions for type W workers is a (non degenerate) mixture of two distinct distributions, in which prejudiced firms offer lower wages, and unprejudiced firms offer higher wages. In this context, productivity differentials influence the conditional mean of the distribution, while discrimination determines the bottom of the wage distribution.

The identification strategy is based on the following idea. In the case of pure productivity differentials, distributions are identical, but the one for men is shifted to the right, so that the distance is determined by the difference between productivities; in the case of discrimination, the distance is determined by the number of prejudiced firms, by the disutility parameter, and by the difference in recruitment activity of firms for men and women. Predictions regarding the evolution of the differential as one moves to the top of the distributions are different in the pure productivity case and the pure discrimination case. The model is able to characterise wage, job duration and unemployment differentials across men and women.

3 Empirical Analysis

The empirical estimation of equilibrium search models as Burdett and Mortensen (1998) is mainly based on worker's data. Necessary information for empirical analysis is observed duration in unemployment and employment, accepted and earned wages, and exit state after employment. The relevant unknown parameters to be estimated are: b , the workers' common value of leisure or non market time; p , the firms' common value of productivity; the two ratios k_u and k_e (or λ_u and λ_e alternatively); and the job separation (or destruction) rate δ . If b is unobserved then, R is the fifth parameter.

However, the model in its simple version has the well-known counterfactual implication that theoretical densities for wage offer and earnings distribution are increasing and left skewed. The predicted shape is different from the expected cross sectional earnings distribution observed in the data, characterised by a very long right tail. As discussed in section 2.1, to fit the real wage distribution some heterogeneity in firm productivity is needed. This allows to obtain a reasonable fit and also, exploiting structural equilibrium relations, obtain a measure of productivity at each firm.

If discrimination is considered, identification is still possible, but the model has the same counterfactual implication of the standard Burdett and Mortensen (1998) model. In this case, men and women can have different search parameters and different productivity. Before discussing in detail the estimation methods and identification issues, in the next subsection, I briefly present the data.

3.1 Data

In this study, I use a matched employer-employee data base from Italian Administrative Archives representative of the population of employed workers in the private non-farm sector. The source of information is the National Social Security Institute (INPS).⁷ In this data, as in other matched employer-employee data sets, each worker and each firm are identified by a specific code during their permanence in the administrative files. For every match, a new code, composed of the union of the firm and worker codes, is created. As the match is destroyed, the worker and the firm still continue maintaining their previous code. This data contains all the relevant information I need to estimate an equilibrium search model.⁸ For workers, information on sex, age, tenure, number of weeks paid and wages earned is available. On the firm side, it is possible to have information on the size of the workforce (average number of employees during the year), the (mean) earnings of those workers, the geographical location, and the sector of activity.⁹

No information regarding education is available. However, the main difficulty with this data set is related to the definition of the status of a worker and his/her classification. While the position while employed is illuminating about the actual position in the labour market, on the other hand, if the worker exits the market, it is impossible to know if the subsequent period of absence from the records is due to unemployment, work in the public sector, self-employment or retirement. Although in the paper I refer to unemployment for exposition reasons, it is important to remember that this state has to be interpreted as “out of sample.” Finally, as is common in most administrative datasets, no information is provided about the nature of job separation, i.e., it is not possible knowing exactly if the worker has been laid off or the end of the job has been determined by a voluntary separation. In what follows I carefully explain how these problems are overcome in the empirical application.

To estimate the relevant parameters of the equilibrium search model I use a sub-sample of workers observed during a the period 1985-1996. I look at the current status of all workers in the sample in February 1991. Workers are then classified as employed or unemployed. For each worker I observe elapsed and residual duration in the state (employment or unemployment), the wage actually earned or accepted when exiting unemployment and, for those employed, the next transition to another job or unemployment (or censoring).

In Tables 1 and 2 I report descriptive statistics for the sample used in the

⁷See Casavola et al. (1999) and Contini (2002) for a description of the dataset.

⁸Postel-Vinay and Robin (2002) estimate their equilibrium search model using the French Administrative DADS panel. The two datasets share the same advantages and disadvantages.

⁹It is possible to have information on wages earned on a yearly and weekly base. Using other information regarding days worked it is straightforward to have also monthly and daily wages.

estimation. I restrict my attention to workers aged 15-50 and divide them in three age groups. Apprentices are excluded as are part time workers. Finally I trim the lowest 1% and highest 99% of men's and women's tails of the overall monthly wage distribution.¹⁰ Some remarkable differences emerge confronting men and women. First, the proportion of unemployed is higher for the latter, about 19% against 16%; second, the duration of unemployment is slightly higher, one month on average. Average wages are about 22% higher for men, and dispersion is also higher with the percentile ratio equal to 2.35 against 2.09. I now turn to describe the estimation method used for structural parameters and productivity distributions.¹¹

3.2 Likelihood Function

The estimation method used in this section is based on Bontemps et al. (2000). I refer to this method as a nonparametric one. Workers can be employed or unemployed. To denote their status in February 1991, I use a binary variable $i = 0, 1$. Employment and unemployment durations are defined by t_i , the subscripts b and f stand for backward and forward respectively, to denote durations before and after February 1991. Then, t_{ib} and t_{if} represent durations with $i = 0, 1$. Define left and right censored observations for those spells in progress in January 1985 and December 1996. Let d_{ib} and d_{if} denote those indicators. For each worker in the sample I observe either the wage paid in February 1991 w_1 , or accepted wage upon exiting unemployment w_0 . As Eckstein and Van den Berg (2007) claim, the former is a random draw from G while the latter is a random draw from F . Workers employed in February 1991 can subsequently exit to another job (job-to-job transition) or to unemployment. Following Contini (2002), I arbitrarily define as job-to-job transitions those moves with an intervening period of unemployment less or equal to one month.¹²

The likelihood function is derived by strictly following the theoretical model and multiplying individual observations. In this model, unemployment duration has exponential distribution with parameter λ_u ; the probability of a draw for unemployed workers is $u/m = 1/(1 + k_u)$. Finally, when the worker leaves unemployment, he/she draws from the wage offer distribution $F(w)$. For this group of

¹⁰Following Contini (2002), yearly wages are deflated with the CPI at 1996 prices. Then, to make them comparable across workers with different number of days worked during the year, the following adjustment is adopted: $\text{realwage} = (\text{yearly wage}/\text{days paid}) * 26$ where 26 is the average number of days worked during the month. The overall sample selection procedure is available upon request.

¹¹In Sulis (2004), I use this estimation procedure to analyse regional labour market differentials. Results for men are also reported in that paper.

¹²See also Postel-Vinay and Robin (2002) for French data.

Table 1: Descriptive Statistics, Men

	All Sample	Blue Collars	White Collars	Managers	15-25	26-40	41-50
<u>Number of Workers</u>	60,506	41,223	18,819	464	12,904	31,042	16,523
Unemployed	16.48%	19.37%	10.40%	5.60%	34.10%	14.41%	6.42%
Employed	83.52%	80.63%	89.60%	94.40%	65.90%	85.59%	93.58%
Age: mean (std dev)	33.75 (8.75)	32.94 (8.91)	35.32 (8.11)	41.69 (5.97)	22.51 (2.07)	32.34 (4.31)	45.20 (2.80)
<u>Unemployed</u>							
left censored	36%	34%	44%	23%	43%	31%	23%
right censored	15%	15%	13%	15%	14%	16%	14%
<u>Duration (not censored)</u>							
mean (std dev)	24.37 (21.42)	24.18 (25.30)	25.30 (21.96)	24.41 (21.22)	23.44 (20.57)	25.19 (22.15)	24.22 (21.25)
<u>Employed</u>							
Transitions $e \rightarrow e$	13%	13%	12%	12%	15%	14%	10%
Transitions $e \rightarrow u$	87%	87%	88%	88%	85%	86%	90%
left censored	25%	23%	27%	28%	1%	24%	40%
right censored	41%	39%	46%	43%	29%	43%	45%
<u>Duration (not censored)</u>							
mean (std dev) - total	47.10 (32.01)	44.40 (31.46)	53.03 (32.41)	62.33 (31.16)	35.01 (25.44)	47.75 (31.55)	58.82 (34.72)
if transition $e \rightarrow e$	25.67 (20.18)	24.39 (19.37)	28.55 (20.90)	34.75 (20.40)	26.09 (15.07)	26.75 (20.69)	30.68 (23.13)
if transition $e \rightarrow u$	50.44 (32.22)	47.55 (31.80)	56.78 (32.23)	65.63 (30.62)	37.62 (25.98)	51.14 (31.69)	61.99 (34.36)
<u>Wage Distribution</u>							
minimum	974	975	974	1166	978	974	977
p10	2139	2068	2455	6407	1972	2176	2426
median	3032	2807	3856	9017	2527	3053	3542
p90	5030	3974	6477	11164	3480	4913	6083
p90/p10	2.35	1.92	2.63	1.74	1.76	2.25	2.50
mean (std dev)	3386 (1440)	2941 (891)	4227 (1726)	8749 (2059)	2468 (762)	3372 (1341)	3992 (1723)

Durations are expressed in months. Monetary values are in 000s of Italian Lira.

Table 2: Descriptive Statistics, Women

	All Sample	Blue Collars	White Collars	15-25	26-40	41-50
<u>Number of Workers</u>	34,514	15,110	19,404	10065	18228	6203
Unemployed	18.69%	21.28%	16.67%	28.96%	16.09%	9.45%
Employed	81.31%	78.72%	83.33%	71.04%	83.91%	90.55%
Age: mean (std dev)	31.41 (8.30)	31.73 (9.04)	31.16 (7.67)	22.44 (2.00)	31.75 (4.26)	45.00 (2.83)
<u>Unemployed</u>						
left censored	42%	40%	45%	54%	33%	34%
right censored	19%	21%	16%	15%	20%	30%
<u>Duration (not censored)</u>						
mean (std dev)	25.40 (21.45)	25.86 (20.83)	24.93 (22.06)	23.76 (20.67)	26.64 (22.13)	25.40 (20.30)
<u>Employed</u>						
Transitions $e \rightarrow e$	11%	9%	12%	13%	11%	8%
Transitions $e \rightarrow u$	89%	91%	88%	87%	89%	92%
left censored	22%	24%	21%	3%	25%	40%
right censored	36%	35%	37%	30%	37%	42%
<u>Duration (not censored)</u>						
mean (std dev) - total	46.13 (31.39)	46.19 (31.21)	46.08 (31.53)	40.56 (27.95)	46.30 (31.79)	58.39 (33.84)
if transition $e \rightarrow e$	24.90 (20.35)	26.45 (20.69)	24.04 (20.12)	22.65 (17.98)	25.25 (21.08)	30.60 (22.85)
if transition $e \rightarrow u$	48.79 (31.52)	48.25 (31.41)	49.21 (31.61)	43.06 (28.19)	48.95 (31.92)	61.02 (33.53)
<u>Wage Distribution</u>						
minimum	835	835	835	835	835	838
p10	1877	1750	1999	1832	1887	1986
median	2573	2313	2840	2362	2659	2804
p90	3936	3164	4322	3343	4034	4391
p90/p10	2.09	1.80	2.16	1.82	2.13	2.21
mean (std dev)	2760 (945)	2399 (694)	3042 (1015)	2479 (711)	2829 (973)	3017 (1073)

Durations are expressed in months. Monetary values are in 000s of Italian Lira.

workers, the likelihood is

$$\frac{\lambda_u^{2-d_{0b}-d_{0f}}}{(1+k_u)} \exp[-\lambda_u(t_{0b}+t_{0f})] f(w_0)^{1-d_{0f}}. \quad (3)$$

The probability of sampling an employed individual is $1 - u/m = k_u/(1+k_u)$. The job duration, given the wage w_1 , is exponentially distributed with parameter δ , while the employment relationship has exponential duration with parameter $\delta + \lambda_e \bar{F}(w_1)$, where $\bar{F}(w_1) = 1 - F(w)$. The likelihood for employed workers reads as

$$\frac{k_u}{(1+k_u)} g(w) [\delta + \lambda_e \bar{F}(w_1)]^{1-d_{1b}} \exp\{-[\delta + \lambda_e \bar{F}(w_1)](t_{1b} + t_{1f})\} \left\{ \delta^v [\lambda_e \bar{F}(w_1)]^{1-v} \right\}^{1-d_{1f}}, \quad (4)$$

where v is equal to 0 if the employment relationship is voluntarily terminated with a quit and 1 if there is a layoff.

When heterogeneity in productivity is considered, the model is identified as follows. Frictional parameters λ_u , λ_e , and δ are identified from unemployment durations, employment durations terminating into another job and those terminating to unemployment respectively. The reservation wage R is identified as the lowest wage observed in the sample. Finally, the distribution of productivity can be identified by using wage data and estimated frictional parameters (see Eckstein and Van den Berg, 2007).

The nonparametric estimation procedure proposed by Bontemps et al. (2000) can be summarised in three steps. First I estimate $G(w)$ and $g(w)$ using a non-parametric procedure. I use a standard Gaussian kernel estimator for the density and the empirical cumulative distribution for $G(w)$. Let \hat{G} and \hat{g} denote such estimates. Conditional on k_e , consistent estimates of \bar{F} and f are

$$\hat{\bar{F}}(w) = \frac{1 - \hat{G}(w)}{1 + k_e \hat{G}(w)} \quad (5)$$

and

$$\hat{f}(w) = \frac{1 + k_e}{[1 + k_e \hat{G}(w)]^2} \hat{g}(w). \quad (6)$$

Second, replace \bar{F} and f in the likelihood function by the preceding expressions, and maximize the likelihood with respect to k_u , k_e , and δ . Finally, estimate p using the equation below

$$p = w + \frac{1 + k_e G(w)}{2k_e g(w)}, \quad (7)$$

where p represents a firm-specific constant value of productivity.

The estimation routine has two parts. In the first one, transition parameters are estimated by looking at workers and their states in the market. In the second part, conditional on previous steps, a measure of productivity is estimated for each firm. Note the procedure doesn't need any assumption regarding the distribution of productivity.

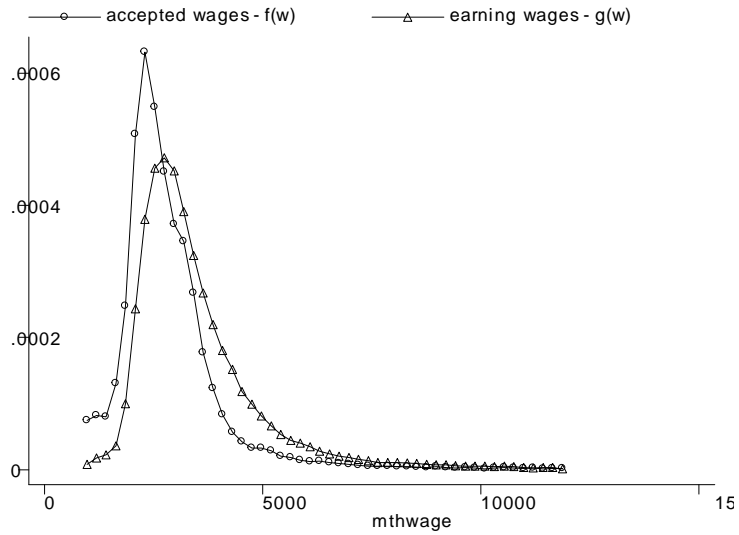
3.3 Results

In this subsection, I analyse results obtained by estimating the equilibrium model with firm heterogeneity using the nonparametric procedure discussed above. In this case, search frictions parameters and the relationship between wages paid and productivity are the most important results I look at. I also consider the different role of search frictions at various experience levels for men and women.

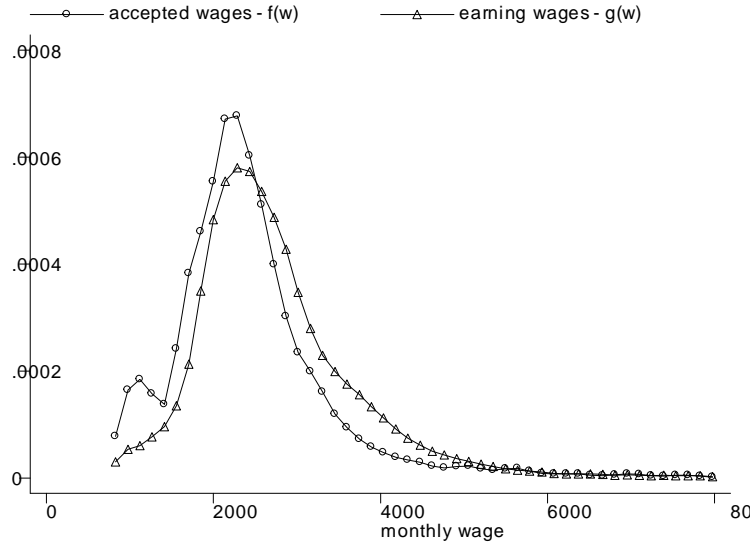
The first empirical test of the equilibrium search model has a theoretical motivation. Equation (1) has a clear prediction about the shape of earnings and wage offer distributions: the earnings distribution has to first order stochastically dominate the wage offer distribution. This is because there is on-the-job search and workers can move to better paying jobs. In Figure 1 this prediction is verified with an eyeball-test using standard kernel estimations of the two densities. For both men and women, the earnings distribution is shifted to the right, indicating that higher wages are more likely to be earned for those employed in February 1991 (see Christensen et al., 2005). The distribution of accepted wages after unemployment is instead more concentrated at lower wages. Interestingly, the women's offer distribution is bimodal, with a small group of women earning very low wages. One plausible explanation for this is heterogeneity in reservation wages, probably related to homework and transitions in the labour market. This nonparametric estimation is a first necessary step before estimating frictional parameters; it shows interesting differences between men and women.

In Tables 3 and 4 estimation results for transition parameters are presented. Arrival rates define transition parameters and represent probabilities of an event. In this case, the probability of receiving an offer is distributed according to a standard Poisson process where λ_u is the arrival rate of job offers while unemployed and λ_e when employed; δ is the arrival rate of destruction rates. Interpretation of these parameters suggests that the inverse of these is the expected duration of unemployment and jobs. The parameter $k_e = \lambda_e/\delta$ is a quantity and it is a measure of search frictions describing the speed at which workers climb the job and wage ladder. As Ridder and Van den Berg (2003) suggest, k_e equals the average number of job offers in a given spell of employment, since the average duration of a spell of employment is $1/\delta$, and job offers arrive according to a Poisson process with parameter λ_e , this quantity is the index of search frictions that enters the distribution of wage offers.

Figure 1: Kernel Density Estimates of Earnings and Wage Offer Distributions



Men



Women

Table 3: Transition Parameters, Men

	δ	λ_u	λ_e	k_e
All Sample	0.0128 [0.0127, 0.0128]	0.0431 [0.0427, 0.0436]	0.0064 [0.0063, 0.0068]	0.5039 [0.4925, 0.5218]
Blue Collars	0.0139 [0.0138, 0.0140]	0.0421 [0.0415, 0.0427]	0.0053 [0.0051, 0.0055]	0.383 [0.3742, 0.3920]
White Collars	0.0109 [0.0107, 0.0111]	0.0466 [0.0450, 0.0484]	0.0103 [0.0097, 0.0108]	0.9472 [0.8802, 0.9953]
Managers	0.0122 [0.0115, 0.0132]	0.0786 [0.0630, 0.1070]	0.0655 [0.0408, 0.1373]	5.3561 [3.3168, 10.892]
15-25	0.0251 [0.0247, 0.0254]	0.0350 [0.0339, 0.0359]	0.0079 [0.0073, 0.0085]	0.3154 [0.2926, 0.3429]
26-40	0.0126 [0.0124, 0.0128]	0.0475 [0.0465, 0.0483]	0.0060 [0.0057, 0.0063]	0.4762 [0.4525, 0.5114]
41-50	0.0098 [0.0097, 0.0099]	0.0709 [0.0677, 0.0737]	0.0040 [0.0039, 0.0042]	0.4111 [0.4005, 0.4288]

Time period is month. 5% and 95% percentiles of the bootstrap distribution in square brackets.

The first interesting result that holds for both groups is that of an arrival rate of acceptable wage offers when employed much lower than the one when unemployed; λ_u 's estimate for the all sample is almost ten times larger than λ_e . According to these figures, the estimated average duration of unemployment is equal to about 24 months, with a slight higher duration for women.¹³ On the other hand, the average duration of an employment relationship terminated by the worker with a quit is equal to 156 months for men and more than 310 months for women. This indicates that on-the-job search activity is very low and that job search reveals much more profitable when unemployed. On the other hand, the job destruction rate is estimated close to 0.012 for men and 0.015 for women, with an average duration of the job of 83 months for males. Finally, $k_e = \lambda_e/\delta$ gives a measure of the speed at which workers climb the wage and job ladder. It can be also interpreted as the average number of offers received in a given spell of employment. The search frictions index is equal to 0.5 for a random male worker in this sample and to 0.2 for a representative women. Results for the overall sample highlight important differences in transition parameters between men and women. As expected, job change behaviour seems to be influenced by gender specific factors.

Until now, workers have been treated as homogeneous, however they certainly

¹³This result should be considered with a grain of salt. Remember that I refer to unemployment for simplicity, but this state refers to out of sample condition with work in public sector, self-employment, inactivity, and unemployment.

Table 4: Transition Parameters, Women

	δ	λ_u	λ_e	k_e
All Sample	0.0154	0.0398	0.0032	0.2099
	[0.0153, 0.0154]	[0.0378, 0.0405]	[0.0021, 0.0053]	[0.1998, 0.2101]
Blue Collars	0.0158	0.0381	0.0017	0.1133
	[0.0156, 0.0160]	[0.0379, 0.0392]	[0.0012, 0.0021]	[0.1101, 0.1145]
White Collars	0.0151	0.0414	0.0056	0.3749
	[0.0149, 0.0152]	[0.0410, 0.0431]	[0.0053, 0.0059]	[0.3654, 0.3956]
15-25	0.0236	0.0332	0.0032	0.1369
	[0.0233, 0.0240]	[0.0329, 0.0341]	[0.0022, 0.0040]	[0.1298, 0.1403]
26-40	0.0148	0.0465	0.0034	0.2321
	[0.0138, 0.0051]	[0.0455, 0.0475]	[0.0024, 0.0045]	[0.2301, 0.2405]
41-50	0.0095	0.0488	0.0033	0.3466
	[0.0090, 0.0099]	[0.0480, 0.0497]	[0.0027, 0.0040]	[0.3376, 0.3501]

Time period is month. 5% and 95% percentiles of the bootstrap distribution in square brackets.

differ according to some observable and unobservable characteristics that affect their labour market outcomes. Stratification of the sample according to worker characteristics can give some indication of the difference in the degree of search frictions that workers face when looking for a job. Results in Tables 3 and 4 indicate interesting differences among different occupations and age groups. Apprentices are excluded from the sample, as are managers for women, as they are too few. As expected, managers (only men) rank very high in the probability of getting outside offers, their estimated arrival rate of job opportunities is equal to 0.06 per month with an average value of the search friction parameter greater than 5. On the other hand, job destruction rates are almost constant across different groups with a somewhat higher rate for blue collars.

Stratification by different age groups gives interesting results with higher job destruction rate for young workers and higher probability of move for them. For men, results in the last column of the Table also confirm well known findings about the concave relationship between wage and experience in the labour market, with an increasing profile in early stages of the career and with a flattening in later stages. For women instead, the relationship is increasing with age. Looking more in detail at estimates, note that the job destruction rate is quite similar for men and women. On the other hand, the estimated arrival rate of offers is almost constant across age groups for women while for men is reduced as workers get older. This result can have an interesting interpretation regarding different job search behaviour of the two groups. While for men the career path is a standard one with diminishing arrival rates when older; for women, the arrival rate is constant

indicating their move can be less related to money reasons. This result can be also attributed to the fact that, in this model, search intensity doesn't vary with the wage, determining a constant arrival rate of offers at any wage level; this effect is stronger for women.

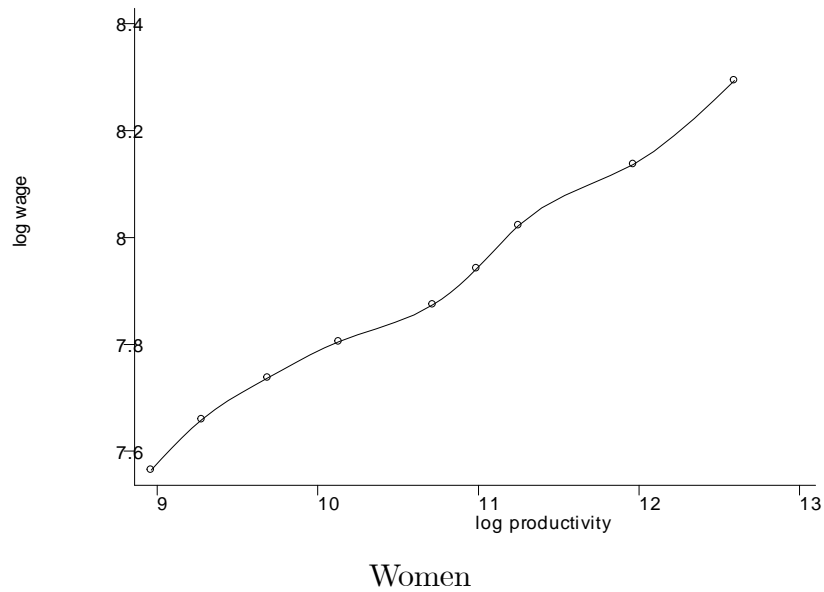
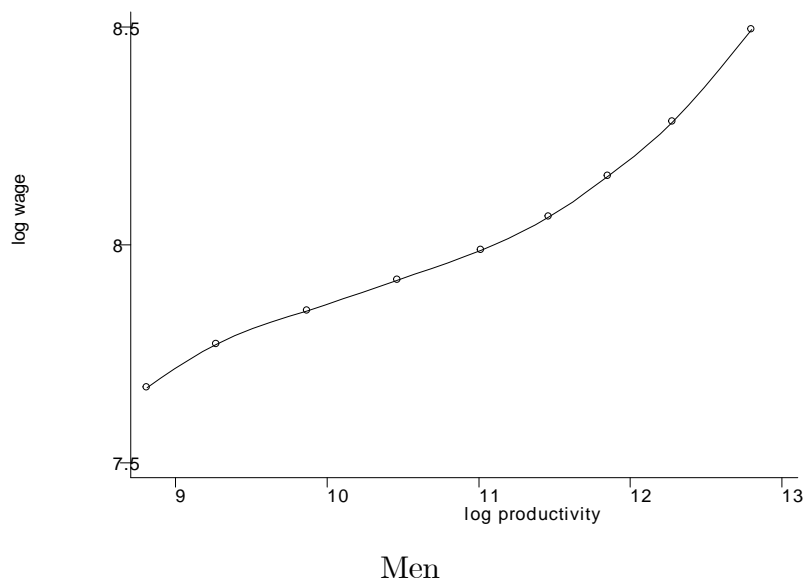
Figure 2 looks at the estimated mapping between productivity and offered wages. The estimated relationship is increasing at all levels of productivity as predicted by the model. However, this Figure reveals interesting differences among men and women. While the relationship for men is not linear, but is best approximated by a cubic with an inflection point at median productivity levels, for women the relationship is close to a linear one. This can have important implications for our understanding of the gender wage differential.

In fact, previous results presented above confirm that men and women exhibit important different transition patterns. This is reflected in the wage offer and earnings distributions. However, this influences also the mapping from productivity to wages for men and women. Given there are imperfections in the market, and women face higher level of search frictions, firms can offer different wages. However, firms also offer different wages to workers with different productivity. For men, lower level of search frictions indicates their labour supply elasticity is higher, so that firms have to offer proportionally higher wages to attract or retain them; on the contrary, women have much lower chances and even high productivity firms do not need to offer the convex wage-productivity profile discussed above. Again, this differential result can be also attributed to the fact that here search intensity doesn't vary at different part of the wage distribution.¹⁴

In general, above results indicate firms do exert a strong monopsony power when posting wages. The latter is defined as the percentage difference between the wage and productivity and gives a direct measure of the degree of exploitation of labour market frictions by firms when setting wages. The monopsony condition can be theoretically identified as one of very low mobility and almost no search while on-the-job. The model gives also a measure of the proportion of the rents that accrue to workers when starting an employment relationship, or how far are workers from being paid their marginal product p . Results indicate that firms are able to extract almost all the surplus from their workers, in particular from women. This can be easily interpreted in the theoretical framework proposed in this paper. Given very low levels of on-the-job search and a few opportunities to move to better paying jobs, firms are able to extract all the surplus from their workers paying them wages just above their value of leisure. However, the pattern is somewhat different for low productivity and high productivity firms. The mapping from productivity to wages in Figure 2 indicates that high productivity firms offer to

¹⁴Allowing for different search intensities can have interesting implications for the shape of the wage-productivity profile. This is left for future research.

Figure 2: Mapping from Productivity to Wages, Percentiles



men proportionally higher wages compared to those paid by firms in the lower part of the distribution. For women that is not the case.

Previous results indicate that the degree of search frictions in Italian labour market is considerable and is a relevant source of gender wage differentials. Workers face difficulties in climbing the job ladder and firms are able to exploit the monopsony power that accrues to them because of the presence of information problems in the market. Women suffer more from this condition. Estimates of transition parameters indicate that segmentation of the labour market by observable characteristics of workers can help us to identify those groups that are more severely damaged in this context. Results found for different age groups and for different occupation categories confirm previous expectations and highlight important differences between men and women in their career paths.

3.4 The Relative Effect of Productivity, Search and Discrimination

In this subsection, instead I follow estimation procedures from Bowlus and Eckstein (2002). I solve the following system to estimate δ , λ_u , λ_e , and P to match moments observed in the data.¹⁵ The reservation wage R is assumed to be the lowest wage observed in the sample. The basic system, based on the theoretical model is described below

1. unemployment duration

$$u_{dur} = \frac{1}{\lambda_u}, \quad (8)$$

2. unemployment rate

$$u_{rate} = \frac{\delta}{\delta + \lambda_u}, \quad (9)$$

3. proportion from job to unemployment

$$jtu = \frac{\lambda_e}{(\delta + \lambda_e) \ln(1 + \frac{\lambda_e}{\delta})}, \quad (10)$$

4. average wage of cross section earnings distribution

$$E_{G(w)} = \frac{\lambda_e P + \delta R}{\lambda_e + \delta}. \quad (11)$$

¹⁵I solve numerically the systems below with Maple. Detailed computations are available upon request. As mentioned above, it should be made also clear that estimation methods used in this section do not take into account the counterfactual increasing density distributions generated by the model. However, as discussed in Bowlus and Eckstein (2002), the model is identified.

Table 5: Means for Matching Moments Estimation

	all	men	women
unemployment rate u_{rate}	0.17	0.16	0.18
unemployment duration u_{dur}	24.73	24.37	25.40
jobs to unemployment jtu	0.88	0.87	0.89
average earnings $E_{G(w)}$	3249.34	3490.47	2815.12
average offers $E_{F(w)}$	2727.01	2857.94	2524.66
median $G(w)$	2833.04	3032.11	2573.56
reservation wage R	835	974	835

Time period is month. Monetary values are expressed in 000s of Italian Lira.

In Table 5 I report means for variables of interest.¹⁶ Descriptive statistics show what women have somewhat higher non-employment rate and duration of it. Note also the difference between average earnings is higher than the difference between average offers, 23% against 13%, indicating different effects of transition parameters on the distribution across men and women at different stages of their careers.

General results deriving from the solution of the system above for the pooled sample of matching moments estimation are reported in columns (4) and (5) of Table 6. In columns (2) and (3), maximum likelihood nonparametric estimates obtained in previous section are reported for comparison purposes. Results indicate that maximum likelihood estimates are always higher. In particular, while arrival rates of offers are very similar across estimation methods, the destruction rate δ takes quite different values. Actually, using maximum likelihood methods it is twice as high as the one estimated with matching techniques. However, for the analysis of equilibrium wage differentials, what is really important is the ratio between the arrival rate of offers and the job destruction rate $k_e = \lambda_e/\delta$. In this case, for males results are $k_e = 0.5$ and $k_e = 0.32$ for nonparametric and matching methods respectively. For women, corresponding values are $k_e = 0.2$ and $k_e = 0.26$. Estimates with nonparametric methods indicate big differences in the speed of climbing the wage ladder, whereas these differences are substantially reduced when using matching moments.¹⁷ Finally, note that estimation of average productivity with nonparametric methods turned in implausible high results, due by difficulties in estimation of the earnings density. To analyse the differential effect of productivity, search and discrimination, in next steps, I continue using matching estimates.

¹⁶Data are from Tables 1 and 2.

¹⁷These estimates are not very different by those obtained by Jolivet et al. (2006) with ECHP data for Italy. See also Sulis (2007) for details and extensive comparison.

Table 6: Parameters' Comparison: Nonparametric and Matching Moments

	Nonparametric		Matching	
	Men	Women	Men	Women
	(2)	(3)	(4)	(5)
δ	0.0128	0.0154	0.0078	0.0086
λ_u	0.0431	0.0398	0.0410	0.0393
λ_e	0.0064	0.0032	0.0025	0.0023
P	102,583	87,819	10,691	9,964
k_e	0.5	0.2	0.32	0.26
R	974	835	974	835
u_{dur}	24.37	25.40	24.37	25.40
u_{rate}	0.16	0.18	0.16	0.18
jtu	0.87	0.89	0.87	0.89
$E_{G(w)}$	3386	2760	3386	2760

Previous exercise gives interesting insights, however, it doesn't provide any evidence on identification of the source of the gender wage differential as discussed in the preceding section. What I try to assess here is the extent to which different sources of the wage differentials contribute to the wage gender gap. I do this in the following way. Parameters are divided in productivity parameters P , transition parameters: λ_u , δ , λ_e , and discrimination parameters: x , d , γ_d . They are all defined in the theoretical section. Note I allow transition parameters and productivity to vary across men and women. The first discrimination parameter x indicates if firms search less intensively for women than for men. So, if firms search equally $x = 1$, otherwise $x < 1$; d is the firm disutility parameter, and finally γ_d is the proportion of firms that discriminate (not necessarily the proportion of those that do not hire women).

The detailed identification strategy for each computation is outlined below.¹⁸

1. In this case, there are no differences in transition parameters $\delta_M = \delta_W$, no differences in productivity $P_M = P_W$ and no discrimination $x = 1$, $d = 0$, $\gamma_d = 0$. It is relatively easy to solve the system of equations by referring to mean values for the whole sample. The arrival rate of offers while unemployed λ_u is identified from average unemployment duration u_{dur} in equation (8); the arrival rate of offers while unemployed λ_e is identified from the proportion of jobs terminating into unemployment jtu in equation (10). The (common) job destruction rate δ is identified from the unemployment rate u_{rate} in equation (9). Given a common reservation wage R , estimated as the smallest observed

¹⁸Means for variables are reported in Table 5.

wage in the sample, the value of the common productivity parameter P is identified by the mean of the earnings distribution $E_{G(w)}$ in equation (11).

2. The second step allows productivity levels to differ across men and women $P_M \neq P_W$ while transition parameters $\delta_M = \delta_W$ are estimated exactly as in previous item (1). No discrimination is allowed at this stage, $x = 1$, $d = 0$, $\gamma_d = 0$. Given a common reservation wage R , different productivity levels are identified by different average earnings for men and women $E_{G(w)}^M$ and $E_{G(w)}^W$ respectively.
3. In a no discrimination scenario, $x = 1$, $d = 0$, $\gamma_d = 0$, in this item, different job destruction rates δ_M and δ_W are identified by using different unemployment rates for men and women after estimating a common arrival rate of offers while unemployed λ_u from average unemployment duration u_{dur} . Again, arrival rates of offers and productivity levels $P_M \neq P_W$, are estimated as in item (2) by using different mean earnings for men and women and (common) unemployment duration and the overall proportion of exits to unemployment respectively.
4. Arrival rates, job destruction rates and different productivity levels are identified exactly as in (3) with $P_M \neq P_W$, $\delta_M \neq \delta_W$. The search intensity for the two groups is the same by keeping $x = 1$. Discrimination is considered, whereas the two parameters d and γ_d , that represent the disutility parameter for discriminating firms and the proportion of them respectively, are identified. The parameter γ_d is identified by average value of the offer distribution for women $E_{F(w)}^W$ in equation (15) in the Appendix. The parameter d is identified by the the women/men median wage differential by using $G^W(w_{median})/G^M(w_{median})$ by using equations (13) and (12) in the Appendix.
5. By considering different search intensities, at this point, it is imposed $x = 0.85$ so that different search intensity is revealed in different durations of unemployment for men and women. In this case, γ_d and d are identified as in item (4). The arrival rates, different job destruction rates $\delta_M \neq \delta_W$, and different productivities $P_M \neq P_W$, are identified as in previous scenario.¹⁹
6. Finally, the pure discrimination case identifies transition parameters λ_u , λ_e and $\delta_M \neq \delta_W$ as in previous steps, and the common value of productivity

¹⁹The parameter x should be identified by different durations by using $u_{dur}^W = \lambda_0(1 - \gamma_d(1 - x))$. In this case I impose $x = 0.85$. For values of $x < 0.85$ the percentage of discriminating firms γ_d is very small. Actually for lower values of x , I do find a solution for γ_d , but no plausible solution for d , that should satisfy the restriction $d > p_B - R$.

Table 7: Productivity, Search and Discrimination: Alternative Models

	(1)	(2)	(3)	(4)	(5)	(6)
λ_u	0.04043	0.04043	0.04043	0.04043	0.04103	0.04103
λ_e	0.00247	0.00247	0.00254	0.00254	0.00258	0.00258
δ_M	0.00828	0.00828	0.00770	0.00770	0.00781	0.00781
δ_W	0.00828	0.00828	0.00887	0.00887	0.00864	0.00864
R	835	835	835	835	835	835
P_M	11332	12381	11533	11533	11533	11533
P_W	11332	9444	9726	9446	9446	11533
d	0	0	0	5503	5503	-15478
γ_d	0	0	0	0.1703	0.2703	0.2703
x	1	1	1	1	0.85	0.85

Monetary values are expressed in 000s of Italian Lira.

$P_M = P_W$, from average earnings for the whole sample. Discrimination parameters are identified as follows: the parameter γ_d is identified by average value of the offer distribution for women $E_{F(w)}^W$ in equation (15); d from mean earnings for females $E_{G(w)}^W$ using equation (17) in the Appendix, and $x = 0.85$ is imposed.

Results are summarised in Table 7 in different columns. First, comparison of results from column (1) and (2) indicates that not considering productivity differentials can miss important things. Infact, in the second step, introducing differences in productivity, women have much lower measures of productivity parameter to account for the observed wage differential. Allowing both productivity and job destruction rates to be different (in 3) indicates that productivity for women is not as lower as estimated before in column (2) and that their destruction rate is higher. In column (4), the role of discrimination is considered. Although the intensity of recruitment activity for both workers is the same, there is a proportion of prejudiced firms (17%) having a disutility parameter upon hiring women. Then, in column (5), I include discrimination as a possible explanation of wage differentials and different unemployment durations for the two groups. Note that the proportion of discriminating firm increases. The arrival rates differ between men and women, and results indicate that productivity of women is about 19% lower than productivity of men; about 27% of firms discriminate when hiring and their disutility parameter is equal to about 47% of males' productivity parameter. Finally, in column (6) the pure discrimination case is considered with equal productivity; however note results are not plausible, with a negative disutility parameter.

It is interesting to compare these results with those obtained by Bowlus and Eckstein (2002) and Flabbi (2005) for racial and gender differentials in the US labour market respectively. The former paper estimates black's productivity to be about 3.3% lower than the productivity of white workers with a disutility taste parameter equal to 31% of the productivity of whites. The proportion of discriminating firms is equal to 56%. The paper by Flabbi (2005) estimates that about half of employers are prejudiced and the productivity of women is 6.5% lower than the estimated parameter for men. The disutility factor is estimated to be about 36% of men's productivity.

Previous results indicate search, productivity and discrimination have important roles in shaping the gender wage differential. However, it is important to provide a measure of their relative contributions. This decomposition exercise is provided in some important studies in the equilibrium search literature. In a model of search with heterogeneity in productivity but no discrimination, Van den Berg and Ridder (1998) find that about 73% of wage variance is due to productivity variation, while the rest is due to search frictions. They suggest this is in line with the R^2 from standard wage regressions. On the other hand, Bowlus (1997) finds that behavioural differences, as reflected in different transition parameters, account for about 20–30% of the differential. More specifically, decomposition of wage offer means shows the search components account for around 20%, while this component is about 30% for the earnings distribution.

To calculate the relative contribution of search, productivity and discrimination, using equations from (14) to (17) in the Appendix, and previous parameters estimates, I calculate predicted mean wage offers and earnings for both men and women respectively. Different scenarios allowing for different components are presented. First note that the raw wage offer gap is equal to 0.88 against the earnings gap of 0.81. This is not surprising as the effect of the three components on the gender gap can be different after some experience accumulated in the labour market. In Table 8 I report results for simulations.²⁰

As I said before, interestingly, the gap is different for wage offers and earnings distributions. The procedure to calculate relative contributions is the following. I assume in absence of all forces, there is no gender differential. First, I look at earnings distribution. From row (1) I calculate 0.22 as the role of productivity by subtracting 1-0.78; then from (2) I obtain 0.11 as the contribution of search differences. The sum of discrimination and productivity is obtained by (5) as 0.35, then discrimination is calculated as difference 0.35-0.22, this gives 0.13, the latter is the contribution of discrimination. Then I compare results in (3) and (4) with predictions for the effect of search and productivity (0.33) and search

²⁰Note that numbering doesn't necessarily correspond to those in used to in Table 7 to calculate transition, productivity and discrimination parameters.

Table 8: Predicted Wage Offers and Earnings Gaps

Components	<i>wage offer gap</i> $\frac{E_{F(w)}^W}{E_{F(w)}^M}$	<i>earnings gap</i> $\frac{E_{G(w)}^W}{E_{G(w)}^M}$
1) no search	0.78	0.78
yes productivity		
no discrimination		
2) yes search	0.90	0.89
no productivity		
no discrimination		
3) yes search	0.73	0.72
yes productivity		
no discrimination		
4) yes search	0.88	0.78
no productivity		
yes discrimination		
5) no search	0.74	0.65
yes productivity		
yes discrimination		

and discrimination (0.23). It turns out that in (3) there is small difference and in (4) the fit is good. Finally I can calculate the relative contributions of search, productivity and discrimination in the two cases, both for wage offers and earnings distribution.

Results indicate differences for wage offers and earnings. In the first case the percentages are as follows: 61% for productivity, 28% for search and 11% for discrimination, in the second case these are 48%, 24% and 28%. Interestingly, productivity differences are more relevant for wage offers than for earnings, while discrimination is much more important to explain the earnings gap. The role of search behaviour is very similar in both cases.²¹

4 Conclusions

This paper provides estimates of the relevant frictional parameters of the equilibrium search model to analyse gender wage differentials. Two different versions of the model are estimated. The first is a model in which men and women are in

²¹Note these results are in line with those found by Van den Berg and Ridder (1998) and Bowlus (1997).

separate markets but firms are heterogeneous with respect to their productivity parameter. The second one, is a model without a distribution of productivity but where men and women can have different productivity levels and discrimination is explicitly taken into account.

The first model is estimated assuming an exogenous continuous distribution of firms' productivity to get a good fit of the wage distribution. First, the earnings distribution is estimated non-parametrically; then these estimates are used to recover frictional parameters using maximum likelihood methods. Conditional on previous steps, in the third stage, an estimate of the productivity distribution is provided. Results indicate that search frictions are important source of the gender wage differential. The quantitative measure of search frictions indicates that men climb the wage ladder much faster than women. Looking at different age groups, it turns out that this speed increases and then decreases with experience for men, while it is always increasing for women. This can indicate that labour market transitions of women can be influenced by many factors, including the family environment and child rearing. For both groups, wages are increasing function of productivity levels; however, while for men the relationship is not linear, for women is almost linear. In other words, firms with high productivity are able to offer proportionally higher wages to men to retain or attract them, they do not need to do it for women.

When estimating the model with taste discrimination and no heterogeneity in the productivity distribution, results indicate the relative contribution of search, productivity and discrimination is different for the wage offer and earnings distribution. In the first case, productivity accounts for 61% of wage differentials, while the part of search is 28% and 11% is the component of discrimination. The earnings distribution is differently affected: the relative contributions are 48%, 24% and 28% respectively. Interestingly, productivity differences are more relevant for wage offers than for earnings distribution, while discrimination is much more important to explain the earnings gap. The role of search behaviour is very similar in both cases.

This paper contributes to the literature dealing with the structural estimation of equilibrium search models. It also proposes an application of such models to study gender labour market differentials in terms of wages and unemployment in Italy. To the extent that gender differentials are also widely recognised in all labour markets, studying the different sources of wage differentials (search, productivity and discrimination) is important to shed some light on possible policy interventions to reduce wage and unemployment inequalities. In particular, some policy experiments as equal pay policies or affirmative actions can be implemented in such an environment.

Appendix

Equations used for matching moments are from Bowlus and Eckstein (2002); I report them below. As in the rest of the paper, $G(w)$ denotes the earnings distribution, $F(w)$ is the wage offer distribution, E denotes expectations. Note that A stands for men M and B stands for women W . The parameter k is equal to x in the text, $\lambda_1 = \lambda_e$, $\lambda_0 = \lambda_u$; p is productivity and R is the reservation wage.

$$G^M(w_{median}) = \frac{1}{z_{1A}} \left(\left(\frac{p_A - R_A}{p_A - w_{median}} \right)^{0.5} - 1 \right) \quad (12)$$

$$G^W(w_{median}) = \frac{z_{0B}}{z_{1B} * w_{0B}} \left(\left(\frac{p_B - d - R_B}{p_B - d - w_{median}} \right)^{0.5} - 1 \right) \quad (13)$$

$$E_{F(w)}^M = \frac{z_{1A}(3 + 2z_{1A})p_A + (3 + 3z_{1A} + (z_{1A})^2)(R_A)}{3(1 + z_{1A})^2} \quad (14)$$

$$E_{F(w)}^W = \frac{(z_{1B})(3 + 2 * z_{1B})p_B + (3 + 3z_{1B} + (z_{1B})^2)(R_B)}{3(1 + z_{1B})^2} + \frac{(kz_{1B}\gamma_d d(2(1 + z_{1B}(1 - \gamma_d))) + (kz_{1B}\gamma_d) - (2(1 + z_{1B}(1 - \gamma_d))^2(1 + w_{1B})^2))}{3w_{1B}(1 + z_{1B}(1 - \gamma_d))^2(1 + w_{1B})^2} \quad (15)$$

$$E_{G(w)}^M = \frac{(z_{1A}p_A) + (R_A)}{(1 + z_{1A})} \quad (16)$$

$$E_{G(w)}^W = \left(\frac{(1 - \gamma_d)(1 + w_{1B})}{(1 - \gamma_d + k\gamma_d)} \right) \left(\frac{z_{1B}(1 - \gamma_d)p_B}{(1 + z_{1B}(1 - \gamma_d))^2} + \frac{R_B}{(1 + w_{1B})^2} \right) + \left(\frac{\gamma_d k}{(1 - \gamma_d + k\gamma_d)(1 + w_{1B})} \right) \left(\frac{(kz_{1B}\gamma_d)(p_B - d)}{(1 + z_{1B}(1 - \gamma_d))} + R_B \right) + \left(\frac{(\gamma_d)(1 - \gamma_d)kz_{1B}(1 + w_{1B})(2 + (2 * z_{1B}(1 - \gamma_d) + kz_{1B}\gamma_d))(p_B - d)}{(1 - \gamma_d + k\gamma_d)(1 + w_{1B})^2(1 + z_{1B}(1 - \gamma_d))^2} \right) \quad (17)$$

where $z_{1A} = \frac{\lambda_1}{\delta_A}$, $z_{1B} = \frac{\lambda_1}{\delta_B}$, $z_{0A} = \frac{\lambda_0}{\delta_A}$, $z_{0B} = \frac{\lambda_0}{\delta_B}$, $w_{1B} = (z_{1B})^k$, $w_{1A} = (z_{1A})^k$, $w_{0B} = (z_{0B})^k$, $w_{0A} = (z_{0A})^k$.

References

- [1] Altonji, J. and Blank, R. (1999), "Race and Gender in the Labor Market," in Ashenfelter, O. and Card, D. (eds) *Handbook of Labor Economics*, vol. 3C, 3143-3259; Elsevier North Holland, Amsterdam;
- [2] Becker, G. (1971), *The Economics of Discrimination*, University of Chicago Press, Chicago;
- [3] Black, D. (1995), "Discrimination in an Equilibrium Search Model," *Journal of Labor Economics*, **13** (2), 309-334;
- [4] Bontemps, C., Robin, J.-M. and Van den Berg, G. (2000), "Equilibrium Search with Continuous Productivity Dispersion: Theory and Non-Parametric Estimation," *International Economic Review*, **41** (2), 305-358;
- [5] Bowlus, A. (1997), "A Search Interpretation of Male-Female Wage Differentials," *Journal of Labor Economics*, **15** (4), 625-657;
- [6] Bowlus, A. and Eckstein, Z. (2002), "Discrimination and Skill Differences in an Equilibrium Search Model," *International Economic Review*, **43** (2), 1309-1345;
- [7] Burdett, K. and Mortensen, D. (1998), "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, **39** (2), 257-73;
- [8] Casavola, P., Cipollone, P. and Sestito, P. (1999), "Determinants of Pay in the Italian Labor Market: Jobs and Workers," in Haltiwanger et al. (eds), *The Creation and Analysis of Employer-Employee Matched Data*, Elsevier Science - North Holland, Amsterdam;
- [9] Christensen, B., Lentz, R., Mortensen, D., Neumann, G. and Werwatz, A. (2005). "On-the-Job Search and the Wage Distribution," *Journal of Labor Economics*, **23** (1), 31-58;
- [10] Contini, B. (ed) (2002), *Labour Mobility and Wage Dynamics in Italy*, Rosenberg & Sellier, Turin;
- [11] Eckstein, Z. and Van den Berg, G. (2007). "Empirical Labor Search: A Survey," *Journal of Econometrics*, 136 (2), 531-564 ;
- [12] Flabbi, L. (2005) "Gender Discrimination in a Search Model with Matching and Bargaining," *IZA Discussion Paper* 1764;

- [13] Flabbi, L. (2007) “Prejudice and Gender Differentials in the U.S. Labor Market in the Last Twenty Years,” *Carlo Alberto Notebooks* 57;
- [14] Jolivet, G., Postel-Vinay, F. and Robin, J.-M. (2006), “The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and the US,” *European Economic Review* **50**, 877-907;
- [15] Postel-Vinay, F. and Robin, J.-M., (2002), “Equilibrium Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, **70** (6), 2295-2350;
- [16] Ridder, G. and Van den Berg, G. (2003), “Measuring Labor Market Frictions: A Cross-Country Comparison,” *Journal of the European Economic Association*, **1**, 224-244;
- [17] Rosen, A. (2003), “Search, Bargaining, and Employer Discrimination,” *Journal of Labor Economics*, **21** (4), 807-829;
- [18] Sasaki, M. (1999), “An Equilibrium Search Model with Coworker Discrimination,” *Journal of Labor Economics*, **17** (2), 377-407;
- [19] Sulis, G. (2004) “Wage Dispersion and Equilibrium Search Models: Some Evidence from Italy,” *Working Paper CRENoS* 02/04;
- [20] Sulis, G. (2007) *Three Essays in Applied Labour Economics: Wages, Search and Gender*, PhD Dissertation, University of Essex;
- [21] Van den Berg, G. and Ridder, G. (1998), “An Empirical Equilibrium Search Model of the Labor Market,” *Econometrica*, **66** (5), 1183-1221;