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GENDER WAGE DIFFERENTIALS IN ITALY: A STRUCTURAL ESTIMATION APPROACH

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Gender Wage Differentials in Italy: A Structural Estimation Approach[1]

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Abstract

This paper studies gender wage differentials by providing a maximum likelihood structural estimation of the frictional parameters of an equilibrium search model with on-the-job search and firm heterogeneity. In a second step, I also consider the role of discrimination. Results indicate higher level of search frictions for women, this result is confirmed by various robustness checks, and by different specification and estimation strategies. I also find that the resulting mapping from productivity to wages for men is highly non linear, while for women it is almost linear. Search, productivity and discrimination play different roles in shaping the gender differential depending on the specification and estimation of the model.

Keywords: Gender Differentials, Equilibrium Search, Discrimination.

JEL Classification: J31, J41.

1 Introduction

What is the role of search frictions in shaping the gender wage differential? Are there important differences in wage policies of firms towards men and women when posting wage offers? Do firms explicitly discriminate against women? Is it possible to separately identify the role of each of these components to the overall gender wage gap? This paper tries to answer above questions by using an equilibrium search model as a reference framework and estimating its structural parameters with Italian data.

The empirical labor literature has paid particular attention to gender wage differentials, as these have been frequently associated with discrimination (see Altonji and Blank, 1999). However, identification of discrimination as source of such differentials with standard econometric tools is not a simple task; if one wants to empirically identify a measure of discrimination, it is difficult to rely on the estimated coefficient of the gender dummy in wage regressions. The problem is that discrimination is only one possible explanation for the observed gender wage gap, other possibilities being unobserved productivity differentials and different search behaviour of men and women.[1]

It is no surprise that human capital and search models are two of the candidate theories to explain gender differences, as both have predictions regarding the relation between wages, productivity and discrimination. By estimating the structural parameters of an equilibrium search model, all three sources of wage differentials are possible explanations for wage dispersion. What is more, estimation of structural behavioural parameters guarantees exact identification and equilibrium conditions can then be used to analyze the effects of policy experiments. Finally, the relative importance of each component on observed wage offers and earnings differentials can be identified.

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, few contributions look at gender (or racial) wage differentials in this specific framework; what is more, most of them refer to the US labor market.[2] Bowlus (1997) studies gender wage differentials using NLSY data: she estimates transition parameters and decomposes 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. Although the paper looks at different participation patterns for men and women, she 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 (2010a). Both estimate the share of prejudiced employers and their disutility factor upon hiring a worker from the minority group by using different methods: Bowlus and Eckstein (2002) look at racial differences by matching first moments in the data, while Flabbi (2010a) estimates differences in gender structural parameters using

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

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

maximum likelihood methods.[3]

This paper contributes to the equilibrium search literature by trying to estimate search, productivity and discrimination parameters in one single framework. It combines methodological contributions from the previous literature to disentangle the role of above components in different environments, and shows how different estimation methods and identification strategies affect the parameters of interest. The proposed estimation procedure is in two steps. Firstly, I explicitly look at the importance of upward mobility of men and women at different stages of their careers, explicitly considering the effect of search frictions both on wage offers and earnings distributions in a model with on-the-job search and productivity differentials. In fact, Flabbi (2010a) doesn't consider on-the-job search and looks at the role of productivity and discrimination on gender differentials. Secondly, conditional on first-stage estimates, I determine the residual role of discrimination in shaping the gender wage differential. Finally, I compare these estimates for discrimination parameters to those obtained in a model without productivity or search differences. In fact, Bowlus and Eckstein (2002) focus on race differentials explicitly considering discrimination but they don't assume any heterogeneity in firms' productivity and don't have any predictions regarding wage policies of heterogeneous firms. Hence, in this paper I show how on-the-job search, productivity and discrimination affect the gender differential in different environments.

This paper is also one of the first applications of equilibrium search models to study gender differentials in European labor markets; in fact, using different empirical approaches, some dynamics of the gender wage differential are substantially left unexplained.[4] For example, in a recent paper, Del Bono and Vuri (2010) focus their attention on wage growth at the beginning of the career for men and women in Italy. In particular, they show that most of the gender pay gap emerges in the years following labor market entry, and that throughout this period women experience significantly lower wage growth than men. Interestingly, they show that the gap increases as experience accumulates and that there are no significant differences in labor market attachment. However, since there are no important differences in within-firm wage growth, most of the gap is explained by different rates of job-to-job wage growth. Hence, a precise estimate of this transition probabilities turns out to be an essential component to understand gender differences.

To accomplish this task, I provide a maximum likelihood structural estimation of the relevant parameters of the equilibrium search model with frictions and heterogeneous productivity in the spirit of Bontemps et al. (2000). Having obtained gender specific transition parameters and an estimate of average productivity for

[3] Flabbi (2010b) 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. Flabbi and Moro (2010) and Usui (2007) explicitly consider the importance of preferences towards more flexible jobs in shaping different labour market outcomes for men and women.

[4] Bowlus and Grogan (2009) estimate an equilibrium search model on UK data, while Bartolucci (2009) uses data on productivity for German firms to disentangle more adequately the role of productivity and discrimination. His paper is the only example I found of structural estimation of search models to analyse gender or racial differences in continental Europe. See Sulis (2007) for comparison between structural and reduced form methods to analyze gender differentials.

both men and women, I derive the role of discrimination by matching means of the wage offer and earnings for women, as proposed by Bowlus and Eckstein (2002). In fact, the mean of the wage distribution is composed of two terms: the mean wage calculated at the average level of the productivity distribution and an additional term that depends on the search frictions parameters and the productivity distribution itself. In an environment in which productivity is estimated from duration and wage data, the mean of the earnings and offer distributions can be used to identify discrimination parameters.[5]

The empirical application is performed on Italian administrative data from INPS. I provide evidence of important differences in the speed of climbing the wage ladder between men and women: the search frictions index estimated with maximum likelihood techniques is much smaller for men than for women. Interestingly, this parameter varies differently with age for the two groups: I show women suffer much lower arrival rates of offers at the beginning of their careers and constantly higher job destruction shocks. The resulting 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, by matching first moments in the data, I estimate that the proportion of discriminating firms in the market is higher than 60%, while the disutility of firms upon hiring women is more than 40% of men's productivity; I also find that firms search less intensively for women when recruiting. After conducting a series of robustness checks, I show how search, productivity and discrimination parameters can be estimated in different environments, giving similar results. Finally, a wage decomposition exercise shows productivity and search differences are the most important components in explaining the gender differential. This result is partially confirmed when considering some thought experiments and the effects of the introduction of an equal pay law.

The rest of the paper is organised as follows: in Section 2, I briefly discuss the theoretical equilibrium search model with productivity dispersion across firms and on-the-job search, I also discuss how to consider taste discrimination in such a framework. Section 3 is dedicated to the empirical application: after describing the data, the identification strategy and the estimation procedure, I present the main results of the paper jointly with the fit of the model and a battery of robustness checks. In this Section I also analyze the effect of some policy experiments and of the wage decomposition exercise. In the last Section, I conclude and discuss further research ideas. Technical details regarding estimation methods are contained in the Appendix.

[5]Although this has not been done explicitly before, this intuition was already discussed by Bowlus and Eckstein (2002, footnote 32 on page 1327). In fact, they claim that mean earnings can identify the average of the productivity distribution in a model of heterogeneous firm productivity. In my model, average productivity is already estimated in the previous step, hence first moments of the offer and earnings distributions are jointly used with differences in transition rates to estimate discrimination parameters.

2 Theoretical Framework

The nature of gender wage differentials is analyzed using the theoretical structure of equilibrium search models with on-the-job search as originally proposed by Burdett and Mortensen (1998), and further developed by Bontemps et al. (2000) including firms' heterogeneity, and by Bowlus and Eckstein (2002) to account for discrimination. Both extensions are used in the empirical section of this paper to study gender wage differentials.[6]

In what follows, I present the equilibrium search model with search on-the-job and heterogeneity in productivity; then, I discuss its main implications for the study of gender wage differentials and the inclusion of discrimination. In the economy there are both workers and firms, workers maximise utility, while firms maximise profits. In the baseline version of the model, firms and workers are identical, i.e., no heterogeneity is considered. Both unemployed and employed workers search for a job, while firms post wages in the support of the wage offer distribution. Unemployed workers receive an offer with probability λ_u each period; similarly, employed workers search for better wage opportunities and face an arrival rate of offers while employed equal to λ_e. Exogenous productivity shocks destroy jobs with arrival rate δ. All arrival rates are modelled as a Poisson processes. Identical firms post wages in the support of the wage distribution and take into account both the strategies of other firms and the reservation strategy of workers.

The search strategy of workers has the reservation value property, where R is the reservation wage when unemployed, and the wage w is the reservation wage when employed. When 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. When employed, workers earn their wage w and P is the flow revenue generated per employed worker. 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), it represents the average number of offers received during an employment spell. The reservation wage of unemployed workers, with zero discounting, is given by

$$R = b + [k_u - k_e] \int_R^\infty \frac{1 - F(x)}{1 + k_e[1 - F(x)]} dx, \tag{1}$$

the equation above says that the reservation wage depends on the value of leisure, the transition parameters and the expected gains from search, which are determined by the probability of getting an offer higher than the actual wage $1 - F(w)$, discounted by the probability that the job is terminated (both for exogenous destruction or because of a better opportunity). $F(w)$ represents the distribution of wages offered by firms: as workers move from low to high paying firms, the distribution of wages actually paid differs from the wage offer distribution. Let $G(w)$ denote the distribution of wages actually paid to employed workers, i.e., the earnings distribution. As workers move from unemployment to employment and climb the wage ladder,

[6] To the best of my knowledge, no attempt has been made to jointly model firms' heterogeneity, discrimination and on-the-job search. Bowlus (1997) estimates a model with discrete productive heterogeneity and on-the-job search but no discrimination.

in the steady state, the model features a structural relationship between the two distributions regulated by the search frictions parameters that reads as

$$G(w) = \frac{F(w)}{1 + k_e[1 - F(w)]}. \tag{2}$$

The above equation says that 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 structural relationship that I use in the empirical application.[7]

Firms maximise profits offering wages 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. In this model, firms can offer higher wages and make less profits per worker but increase $L(w)$; viceversa, offering lower wages, they make more profits per worker but have higher turnover and lower recruitment rates. Formally, firms solve the following problem:

$$\pi(w|R, F) = \max_w (P - w)L(w|R, F). \tag{3}$$

Following Bontemps et al. (2000), assume now that firms are heterogeneous with respect to their labor productivity parameter P. Let $\Gamma(P)$ denote the (continuous) distribution of productivity with support $[\underline{P}, \overline{P}]$. Under this assumption, the optimal strategy for the firm is to post a unique wage in the set of profit maximising wages. Let the function $w(P)$ denote the mapping from the support of the productivity distribution to the support of the wage offer distribution for a firm of productivity P, the latter reads as

$$w(P) = P - [1 + k_e(1 - \Gamma(P)]^2 \int_R^P \frac{dx}{[1 + k_e(1 - \Gamma(x)]^2}. \tag{4}$$

The optimal wage policy of a firm depends on the productivity parameter, the transition rates and the distribution of productivity itself.[8] As search frictions vanish, the parameter k_e increases, and the gap between wages and productivity disappears. It is important to stress that the distribution of productivity is assumed to be exogenous and there is no other production factor in the model. Most importantly, firm heterogeneity is essential to get a good empirical fit of the wage distribution.

In this model, gender wage differentials emerge for two separate reasons. On the one hand, men and women can have different transition patterns in the labor market because of different family concerns, different monopsony power of firms, and different speed in climbing the wage ladder. Hence estimates of search frictions

[7] Similarly, the equilibrium unemployment rate is obtained by equating flows into and out of this state and reads as $\frac{\delta}{\delta + \lambda_0}$.

[8] This function is continuous and monotone. See Bontemps et al. (2000) for proofs regarding uniqueness and existence of the function. Notice that, given continuity of this function, the mapping from productivity to offered wages determines a continuous distribution for $F(w)$.

parameters account for differences in labor mobility. On the other hand, heterogeneous firms can have different pay policies and offer different wages to men and women, generating an additional source of gender differentials. However, the model discussed above doesn't take into account another important determinant of gender wage differentials, i.e., taste discrimination in the spirit of Becker (1971). The latter is incorporated in a Burdett and Mortensen (1998) equilibrium framework by Bowlus and Eckstein (2002). In their model, firm productivity is assumed to be homogeneous across firms, but different between men and women. Equilibrium wage distributions are identical to those derived in the baseline Burdett and Mortensen (1998) model for men, while for women the resulting wage distributions are non degenerate mixtures of two distinct distributions, in which discriminating firms offer lower wages, and non-discriminating firms offer higher wages to women. The shape of the two wage distributions under different scenarios is used for the identification of the model in the empirical application. Although this model doesn't explicitly incorporate firm heterogeneity, Bowlus and Eckstein (2002) suggest that, for empirical purposes, their model can be interpreted as one with productive heterogeneity when evaluated at the average level of productivity, hence relevant equations for average earnings and offers are also valid in the environment discussed above.

3 Empirical Analysis

The theoretical model presented in the previous section is able to explain patterns of labor market histories in terms of upward mobility and entry into unemployment. Moreover, it provides a simple measure of marginal productivity of labor at each firm. As long as these structural parameters differ between men and women, search theory can be used to explore some aspects of gender differentials. If discrimination is explicitly considered, Bowlus and Eckstein (2002) show that identification of the structural parameters is still possible, but the model has the same counterfactual implication of the standard Burdett and Mortensen (1998) model, in which 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: to fit the real wage distribution some heterogeneity in firm productivity is needed. This should allow me to obtain a reasonable fit.[9] Before discussing in detail the estimation method and identification issues, in the next subsection, I briefly present the data.

3.1 Data

The data is a 1:90 random sample of workers obtained from the Italian Social Security Institute (INPS), the national institute provides administrative archives for studying labor market dynamics. It is representative of the population of employed workers in the private sector observed from 1985 to 1996. In this data, as in other matched employer-employee data sets, each worker and each firm are identified by a

[9] Note also that assuming ex-ante heterogeneity in ability across workers guarantees that the resulting distribution of wages has the correct shape.

specific code during their permanence in the administrative files. For every match, a new code, generated as a string from the firm and worker's codes, is created. As the match is destroyed, the worker and the firm still continue maintaining their previous codes. For workers, information on gender, age, job duration and different measures of wages is available. On the firm side, it is possible to have information on the size of the workforce, average earnings of those workers, location, and industry.[10]

Although the dataset is well suited to study labor force dynamics and estimating an equilibrium search model, some clarifications regarding the characteristics of the data have to be provided in advance. First, the definition of unemployment deserves some discussion. When the worker-firm match is interrupted, workers can exit to unemployment, to work in the public sector, to work as self-employed, to retirement or to non-participation.[11] As a consequence, 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." Second, identification of job-to-job transitions versus layoffs is based on the duration of subsequent periods of unemployment and not on reported reasons for separation. Third, in the data there is no possibility of identifying transitions to non-participation against transition to unemployment; the latter is certainly an important limitation when studying gender differences in transition rates.[12]

As differences in search behaviour emerge at different stages of labor market career, I separately consider three age groups, and drop from the sample workers older than 50 to avoid confusing unemployment with retirement. To obtain a measure of monthly wages directly comparable across workers, as proposed by Contini (2002), yearly wages are first rescaled with the consumer price index provided by the Italian National Statistical Institute (base year 1996), then divided by number of days worked during the year and multiplied by 26, which is the estimated average number of days worked during the month. Having controlled for the number of days worked, I also drop apprentices and part time workers, the latter being less than 3% of the overall initial sample. Finally I trim the bottom 1% and top 99% of men's and women's tails of the monthly wage distribution.[13]

In Tables 1 and 2, descriptive statistics for the sample of men and women used in the estimation are presented. Some remarkable differences emerge confronting men and women. Firstly, the proportion of unemployed is higher for the latter,

[10] See Casavola et al. (1999) and Contini (2002) for a more accurate description of the dataset. Postel-Vinay and Robin (2002) estimate their equilibrium search model using the French Administrative DADS panel. The two datasets share the same advantages and disadvantages.

[11] I offer some evidence on these issues using Italian Labour Force data, which does not have any information on wages, but it has standard information regarding labour mobility. Available data for a sample of the population aged 15-50 for the period 1993-1994 shows that for men, the probability of staying in the same macro-sector is equal to 97% for private sector employees, and 90% for public sector ones. For women, corresponding figures are 96% and 94% respectively. Possible transitions to other states are discussed next.

[12] I further discuss this important point when commenting on the results obtained for structural transition parameters.

[13] The overall sample selection procedure is available upon request. Note that in the empirical section of the paper I present various sensitivity checks to control the robustness of my estimates to different definitions of the main variables of interest as unemployment, job-to-job transitions and reservation wages.

being about 19% against 16%; secondly, the duration of unemployment is slightly higher for women. Average wages of women are about 80% of those of men, while dispersion is higher for men with the percentile ratio equal to 2.35 against 2.09. I now turn to discuss identification of the model and then present the estimation method.

[Insert Tables 1 and 2 here]

3.2 Identification

Identification of the parameters of the equilibrium search model $(\lambda_u, \lambda_e, \delta, b, \Gamma)$ with heterogeneous productivity and on-the-job search is demonstrated by Bontemps et al (2000). The arrival rate of offers λ_u is identified from unemployment durations, while δ and λ_e are identified from job durations terminating in transitions to unemployment and to another job respectively. The value of leisure b is identified only if the reservation wage is higher than the minimum wage; as there is no institutional minimum wage in Italy, the reservation wage is identified and estimated. Finally, given an estimate of $k_e = \lambda_e/\delta$, the productivity distribution is identified from the empirical distribution of cross-sectional wages $G(w)$; no parametric assumption on the productivity distribution is needed, as wages and durations are sufficient to recover the distribution.[14]

Bowlus and Eckstein (2002) show that transition parameters can be also identified from different data: the arrival rate λ_u is still identified from unemployment durations, λ_e is identified from the proportion of transitions into unemployment, and the job destruction rate δ is identified from the unemployment rate. In the baseline specification, when no discrimination is considered, average mean earnings identify average productivity P. When discrimination is considered, identification of parameters of interest is based on the following idea. In the case of pure productivity differentials, distributions for men and women 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 wage distribution for men is identical to the previous case, while the wage distribution for women is a mixture of two distributions, one generated by discriminating and the other by non-discriminating firms. In this case, the distance is determined by the number of prejudiced firms γ_d, by the disutility parameter d, and by the difference in recruitment activity of firms for men and women z. In fact, the first and second parameters have a direct effect on the highest wage paid by discriminating firms; the disutility parameter d affects the reservation wage and the bottom of the earnings distribution; while the third parameter z affects the arrival rate of offers and the bottom part of the wage distribution. Hence, identification is reached by considering as the wage differential evolves at different parts of the distribution.

When firm heterogeneity is considered, productivity is identified from duration data and from the empirical distribution of earnings, hence discrimination parameters can be identified from duration data and from mean wage offers and earnings

[14] Flabbi (2010a) identifies the distribution of match-specific values of productivity using parametric assumptions on the observed wage distribution.

for women.[15] In particular, the proportion of discriminating firms γ_d is estimated from the mean of the wage offer distribution, the disutility parameter d is estimated from the mean of the earnings distribution and the search intensity parameter z is recovered from the differential duration of unemployment spells between men and women. This identification strategy for discrimination parameters is proposed by Bowlus and Eckstein (2002) in a model with no differences in search and productivity parameters. Hence, by comparing estimates of discrimination parameters in an environment in which such differences are present to those obtained in an environment in which search and productivity parameters are the same for men and women, I can disentangle the role of search and productivity on the one hand and the role of discrimination on the other hand.

3.3 Likelihood Function and Estimation Procedure

3.3.1 Likelihood Function

The estimation of equilibrium search models is mainly based on workers' data, aggregate survey data can also be used to estimate relevant frictional parameters. Necessary information for empirical analysis is the observed duration in the state of unemployment or employment, the wage earned when employed, the wage accepted when exiting unemployment, and the exit destination after an employment spell. This data allows me to identify structural behavioural parameters, i.e., the two arrival rates of job offers in unemployment and employment and the job destruction rate. Usually, the reservation wage is estimated as the lowest wage observed in the sample, while marginal productivity of firms is estimated by using duration and wage data.[16]

To estimate such a model, I consider workers who were unemployed or employed in February 1991, where a subscript $i = 0, 1$ denotes their status; let t denote the duration of their spell. Hence, for each worker in the sample I observe either the average wage paid in 1991 w_1, or the accepted wage upon exiting unemployment w_0. As Eckstein and Van den Berg (2007) claim, the former is a random draw from G, the earnings distribution, while the latter is a random draw from F, the wage offer distribution. Workers employed in February 1991 can subsequently exit to another job (job-to-job transition) or to unemployment. As mentioned above, 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.[17]

The likelihood function is derived by multiplying the density of being in each state. The probabilities of being unemployed and being employed are

$$\begin{aligned} \Pr(u) &= \delta/(\delta + \lambda_u), \\ \Pr(e) &= \lambda_u/(\delta + \lambda_u). \end{aligned} \tag{5}$$

[15] When productivity is homogeneous but differs between men and women, it is also possible to identify productivity parameters using the minimum and the maximum wage observed in the sample jointly with estimated transition parameters (see Van den Berg, 1999).

[16] In Sulis (2008), I use this estimation procedure to analyse regional labour market differentials. Results for transition parameters for men are also reported in that paper.

[17] See also Postel-Vinay and Robin (2002) for similar choice on French data. In the next subsections, I conduct some robustness analysis on the definition of job-to-job transitions.

Unemployment durations have exponential distributions with parameter λ_u, hence their contribution to the likelihood is given by

$$f(t_0) = f(w_0)\lambda_u \exp\left[-\lambda_u(t_0)\right], \tag{6}$$

where it is assumed that the wage accepted is a draw from the wage offer distribution $F(w)$.

The distribution of job spells, conditional on wages, is

$$f(t_1|w_1) = g(w_1)\left[\delta + \lambda_e(1 - F(w_1))\right]\exp\left\{-\left[\delta + \lambda_e(1 - F(w_1))\right](t_1)\right\}, \tag{7}$$

where observed wages are draws from the earnings distribution $G(w)$. Finally, transition probabilities from employment to other states, conditional on the wage, read as follows

$$\begin{aligned}\Pr(jtu|w) &= \frac{\delta}{\delta + \lambda_e\left[1 - F(w_1)\right]}, \\ \Pr(jtj|w) &= \frac{\lambda_e\left[1 - F(w_1)\right]}{\delta + \lambda_e\left[1 - F(w_1)\right]}.\end{aligned} \tag{8}$$

After appropriately dealing with right and left censoring, the likelihood can be written as the multiplication of above terms

$$\begin{aligned}L(\theta) = f(w_0)\lambda_u \exp\left[-\lambda_u(t_0)\right] g(w_1)\left[\delta + \lambda_e(1 - F(w_1))\right] \\ \times \exp\left\{-\left[\delta + \lambda_e(1 - F(w_1))\right](t_1)\right\}\delta^v\left[\lambda_e(1 - F(w))\right]^{1-v}\end{aligned} \tag{9}$$

where v is equal to 0 if the employment terminates in a voluntary quit and 1 if there is an involuntary layoff.[18]

3.3.2 Estimation Procedure

The nonparametric estimation procedure proposed by Bontemps et al. (2000) that I follow in this paper can be summarised in three steps. First I estimate $G(w)$ and $g(w)$ using a nonparametric Gaussian kernel estimator for the density and the empirical cumulative distribution for $G(w)$. Let $\widehat{G}$ and $\widehat{g}$ denote such estimates. Conditional on k_e, consistent estimates of $1 - F(w)$ and $f(w)$ are

$$1 - F(w) = \frac{1 - \widehat{G}(w)}{1 + k_e\widehat{G}(w)} \tag{10}$$

and

$$f(w) = \frac{1 + k_e}{\left[1 + k_e\widehat{G}(w)\right]^2}\widehat{g}(w). \tag{11}$$

Second, I replace $1 - F(w)$ and $f(w)$ in the likelihood function by the preceding expressions, and maximize the likelihood with respect to λ_u, λ_e, and δ. Finally, estimate P using the equation below

$$P = w + \frac{1 + k_e G(w)}{2k_e g(w)}, \tag{12}$$

[18] I consider both left and right censored observations for those spells in progress in January 1985 and December 1996, which are the two bounds of the observation period.

where P represents a firm-specific constant value of productivity and $k_e = \lambda_e/\delta$.[19]

After estimating transition and productivity parameters with maximum likelihood, discrimination parameters can be estimated by using the estimated gap in arrival rates, average offers and average earnings for women by matching first moments in the data. There are three parameters to be estimated: the share of discriminating firms γ_d, the disutility parameter d, and the difference in recruitment activity of firms for men and women z.[20] The latter parameter constitutes the link between the two models. In fact, Bowlus and Eckstein (2002) show that women's arrival rates can be written as $\lambda_W = \lambda_M(1 - \gamma_d + z\gamma_d)$. Thus having obtained an estimate of λ for both men and women with maximum likelihood methods, their ratio can be used to estimate z. The two remaining parameters to be estimated are the proportion of discriminating firms γ_d and the disutility parameter d. They can be estimated using the average offers and earnings of women respectively: estimates of these parameters can be obtained matching first moments in the data, i.e., by simultaneously solving a system of three equations.[21]

Finally, to disentangle the role of search and productivity on the one hand, and the role of discrimination on the other hand, I estimate a model in which there are no differences in the arrival rate of offers when employed, in the job destruction rates and in productivity between men and women. Then, I use these estimates in a model in which only differences in arrival rates of offers *in unemployment* and discrimination are present as sources of gender differences: transition differences when unemployed are used to estimate z, while γ_d and the disutility parameter d are estimated using the average offers and earnings of women.

3.4 Results

3.4.1 Search Parameters and Productivity

In this subsection, I analyze 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.

Descriptive statistics show clear differences in average wages for men and women. In Figure 1, I consider different aspects of the gender differential by plotting the kernel density estimates of the wage offer and the earnings distributions. The former is approximated by wages accepted by workers upon exiting unemployment and it is clearly more concentrated at lower wages. The distance between the two distributions is given by the employment effect: as workers can search on-the-job and

[19] Bontemps et al. (2000) also derive a closed form solution for the density of the productivity of firms that are active in the market equilibrium. See next sections for further details about the recoverability of the density of the productivity distribution.

[20] This parameter suggests the possibility that arrival rates are influenced by preferences of employers towards workers' types. This proportional factor $0 \leq z \leq 1$ is added to the model. If $z = 0$, prejudiced firms do not search for women, while if $z = 1$ ($d = 0$ and $\gamma_d = 0$) arrival rates are not influenced by discrimination.

[21] See Appendix A for a detailed description of the estimation procedure.

can climb the wage ladder, high paying firms will attract more workers. This is represented by the structural relation between $G(w)$ and $F(w)$ reported in previous equation (2), in which the former dominates the latter.[22] This prediction turns to be true for both men and women, interestingly, the distribution of wages for women shows a little evidence of a bimodal shape, with a group of them earning very low wages. Heterogeneity in reservation wages, probably related to homework and transitions in and out of the labor market, can result in such a shape for the wage offer distribution.[23]

[Insert Figure 1 here]

In Tables 3 and 4, maximum likelihood estimates of structural behavioural parameters are reported. In this case, the probability of receiving an offer is distributed according to an exponential distribution where λ_u is the arrival rate of job offers while unemployed and λ_e is the one when employed; δ is the arrival rate of destruction shocks. Interpretation of these parameters suggests that the inverse is the expected duration of unemployment and jobs. The parameter $k_e = \lambda_e/\delta$ is a measure of search frictions describing the speed at which workers climb the job and wage ladder and equals the average number of job offers in a given spell of employment. As Ridder and Van den Berg (2003) suggest, 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, the quantity k_e is the index of search frictions that determines the distribution of wage offers. As labor market behaviour is different, this fundamental parameter can vary between men and women, determining equilibrium gender wage differentials.

[Insert Tables 3 and 4 here]

As expected, the job destruction rate is higher for women than for men, δ is estimated close to 0.012 for male workers and 0.015 for female ones, resulting in a differential job duration of 18 months. On the other hand, the arrival rate of offers when employed is much higher for men than for women: during a month, a man has twice as much probability of quitting the job for a better wage than a women. As a consequence, the summary index of search frictions, the ratio $k_e = \lambda_e/\delta$, is equal to 0.5 for a random male worker in this sample and to 0.2 for a representative women. This is a large difference in terms of speed of climbing the job ladder and it is mirrored in equilibrium wage offers and earnings differentials.

A careful inspection of Tables 3 and 4 also reveals interesting results regarding the relationship between age and labor mobility. The average number of offers received during an employment spell k_e varies with age in a different way for men and women. For men, the latter parameter shows an inverted u-shape in relation to age: it is equal to 0.31 for workers aged 15-25, then increases to 0.47 for men younger than 40, and eventually slightly decreases to 0.41 for workers in their forties.

[22] As adequate data on wage offers are not available, this Figure is a first necessary step to check the relationship between offers and earnings and before estimating frictional parameters.

[23] However, increasing the bandwidth of the kernel estimator the bimodality tends to disappear. Given a baseline value of 80, the second mode disappears at 200.

Interestingly, for women, the pattern is quite different, with very low values of k_e at the beginning of the career and a subsequent constant increase in later stage: the search frictions index is equal to 0.13, 0.23 and 0.34 respectively for the three age groups. Looking in more detail at these estimates, again, important differences in transition patterns are revealed. While the pattern for the job destruction rate is quite similar for men and women, being constantly decreasing as they get older, on the other hand, the estimated arrival rate of offers when employed is almost constant across age groups for women (about 0.003 per month) while for men it is reduced as workers get older.

Without further data, it is difficult to interpret these results as being driven by different labor market participation patterns, child rearing agreement in the couple or discrimination. Certainly, women have more constraints at the beginning of their career, with much higher destruction shocks and a constant arrival rate of offers afterwards, indicating their moves can be less related to money reasons. Note this result can be also attributed to the assumption that search intensity doesn't vary with the wage, determining a constant arrival rate of offers at any wage level, this effect being stronger for women.[24]

Previous results indicate important differences in transition parameters between men and women; as expected, job change behaviour seems to be influenced by gender specific factors.[25] Equilibrium search models incorporate these structural estimates to predict wage distributions and marginal productivity at each firm, which can be estimated using equation (12). Hence, in Figure 2, I plot the relationship between the latter and empirical wages. Inspection of the Figure reveals interesting differences in wage policies of firms for men and women. While the relationship for men is not linear, but is best approximated by a cubic, for women the relationship is close to a linear one. This evidence can have important implications for understanding of the gender wage differential.

[Insert Figure 2 here]

As there are search frictions in the market, different firms can offer dispersed wages to similar workers. What is more, with firm heterogeneity, more productive firms can offer higher wages to all workers, generating further differences in wage policies. In this case, different recruitment and retention activities of firms emerge between men and women. For men, lower levels of search frictions indicates their

[24] Further information is also hardly available in Labour Force Survey data. However, it is interesting to compare my results to those obtained from raw transition probabilities for a sample of the population aged 15-50 for the period 1993-1994 extracted from that dataset. Expected differences between men and women in transition rates are detected. In a given year, about 5% of employed men lose their jobs, half of those go to unemployment, while the rest goes out of the labour force; 24% of the unemployed find a job, while a similar proportion goes out of the labour force; finally, about 10% of those that were out of the labour force transit directly to employment. For women, the destruction rate is equal to 8%, 3% goes to unemployment, the rest moves to non-participation. The probability of finding a job is much lower (17% of unemployed find a job), while the probability of moving out of the labour force is very high (34%). Finally, less than 5% of women out of the labour force begin working in a given year.

[25] Although the parameter estimates are reliable and make economic sense, the model can have difficulties in fitting the data and an admissible underlying distribution of productivity could not exist. See next subsections and Sulis (2008) for more discussion on this point.

labor supply elasticity (toward the firm) is higher, so that firms have to offer proportionally higher wages to attract or retain them. On the contrary, women have much lower chances in the labor market and high productivity firms do not need to offer the convex wage-productivity profile discussed above. Monopsonistic competition determines this outcome. However, this differential result can be also attributed to discrimination or to the fact that search intensity doesn't vary at different part of the wage distribution.[26]

Previous results indicate two important sources of gender differentials: search behaviour and different wage policies of heterogeneous firms towards men and women. Estimates of transition parameters indicate women suffer more at the beginning of their career with much higher job destruction rates and lower upward mobility than men, this fact results in higher monopsony power for firms in setting wages. These differences are reduced for more mature workers. However, at this stage, it is difficult to assess the relative importance of these components in shaping the gender differential. In what follows, I try to shed some light on these issues by using the above estimates of structural parameters to study an equilibrium search model with search and productivity differentials and adding pure discrimination as further explanation of earnings differentials.

3.4.2 Considering Discrimination and Estimation of Different Models

The estimated average productivity of women is about 65% of men's productivity, such difference is very high and it is determined by differences in wage offers and subsequent transition rates. However, differences in transition and productivity parameters are not the only source of gender gaps, the third being discrimination. All three components affect the wage differentials in a different way. Hence, in what follows I recover an estimate of the three discrimination parameters mentioned above: the share of discriminating firms γ_d, the disutility parameter d, and the difference in recruitment activity of firms for men and women z.

In panel A of Table 5, I report previously estimated transition and productivity parameters from the model with heterogeneous productivity and on-the-job search jointly with discrimination ones, where these ones have been estimated using average wage offers and earnings of women as described in subsections above.[27] Results indicate that about 67% of firms discriminate against women, and that the disutility parameter is about 50% of estimated productivity of men. Finally, firms also discriminate against women by searching less intensively for this group of workers, estimated z is equal to about 0.55. For comparison purposes, in the third row of the panel, I report estimates of the model with pure discrimination where k_e and P are assumed to be equal between men and women. In this environment the share of discriminating firms increases to 0.92 and the taste disutility parameter is slightly reduced but still equal to more than 40% of productivity. Finally, the search intensity parameter is close to 1, which indicates firms search with the same intensity for men and women, at least when they are unemployed.

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

[27] Further details regarding the estimation procedure are in Appendix A.

[Insert Table 5 here]

The above estimates indicate the gender differential is jointly determined by discrimination and by relevant differences in transition rates and productivity. However, it is important to check if these results are sensitive to different estimation methodologies or different specifications of the model. In what follows, I report estimates of two different models to account for different specifications and/or different identification/estimation methods on equilibrium outcomes.

In panel B, I report estimates of transition and productivity parameters in an environment in which productivity is homogeneous across firms, but is different between men and women.[28] In this case, transition parameters are estimated using duration and wage data, while productivity is estimated as a weighted average of the highest and lowest wage observed in the sample.[29] Estimates of transition parameters are slightly different but perfectly in line with those obtained in the model with heterogeneous productivity. The job destruction rate is estimated higher than the one in panel A, for both men and women, while arrival rates of offers when employed are estimated quite similar (around 0.006 for men). As a result, the summary measure of frictions would be around 0.46 for men against 0.22 for women, very similar to the one found in the model with productive heterogeneity. In this case, productivity of women is estimated about 80% of men's productivity, such ratio is higher than the one estimated when considering heterogeneity in productivity, indicating that considering the entire earnings distribution helps to identify gender differentials at different parts of the distribution. Not surprisingly, estimates of discrimination parameters are higher, as search and productivity differences are smaller. Results indicate again the disutility parameter is about 50% of men's productivity, while the proportion of discriminating firms increases to 80%. Finally, when only discrimination is considered, the proportion of discriminating firms approaches 0.95 but no important differences in search intensity for firms are detected.

In the last panel of Table 5, I analyze the effect of a different identification and estimation strategy on equilibrium outcomes. I report estimates of transition parameters obtained by matching means in the data as proposed by Bowlus and Eckstein (2002).[30] The arrival rate λ_u is estimated from mean unemployment duration, the job destruction rate δ is estimated from the unemployment rate; while the arrival rate of offers when employed λ_e is estimated from the proportion of jobs terminating into unemployment. In the baseline model, productivity is estimated from the mean earnings of men and women respectively. However mean earnings of women are used in next step to identify discrimination parameters; hence, as in the previous model, productivity is estimated as a weighted average of the highest and lowest wage observed in the sample.[31] In Table 6 I report means for variables of interest.

[28] Technical details concerning the likelihood function and a brief summary of the identification strategy are in Appendix B.

[29] Using the highest and lowest wages observed in the sample is sensitive to data cleaning and trimming. After some sensitivity checks, I decide to use the minimum wage and the 99th percentile of the distribution of earnings. Estimates are not very different from the ones obtained using the average of the earnings distribution discussed above.

[30] See Appendix C for details regarding the methodology.

[31] Note that estimates of productivity obtained using average earnings of men and women are

[Insert Table 6 here]

Results indicate that maximum likelihood estimates are always higher than the ones obtained with the method of moments; in particular, while arrival rates of offers when unemployed are very similar across estimation methods, the arrival rate λ_e and the job destruction rate δ take quite different values. This is not surprising, as λ_u is estimated from average duration of unemployment in both cases. On the other hand, identification comes from different data for the two remaining parameters. The job destruction rate estimated using maximum likelihood methods is twice as high as the one estimated with matching techniques. The latter method uses the unemployment rate for identification, while the former is derived from the duration of jobs terminating into unemployment. The difference between the two estimates can give a very raw estimate of transition probabilities to non-participation: in fact, the ratio between destruction shocks of women and men is 2% higher when considering the first identification strategy. Likewise, the arrival rate λ_e estimated with maximum likelihood method explicitly considers the wage distribution and the duration of employment spells terminated by a quit, while the method of moments identifies this parameters from proportion of jobs terminating into unemployment.

As noted in previous sections, the preferred measure of search frictions is the ratio between the arrival rate of offers and the job destruction rate $k_e = \lambda_e/\delta$. In this case, the maximum likelihood method returns very large differences for men and women, i.e., 0.5 against 0.2. This difference is slightly reduced when estimating a model with homogeneous productivity, while it is substantially reduced when matching first moments in the data, resulting in estimates of 0.33 for men and 0.26 for women. Although estimates with nonparametric methods indicate larger differences in the speed of climbing the wage ladder than with matching moments, both methods show there are sizeable differences in transition rates.[32] Note also that the productivity differential varies from 0.65 in the model with heterogeneous productivity to 0.82 in the model estimated with the method of moments. Finally, observe discrimination parameters estimated with this method are quite high, but smaller than the ones obtained in a model with pure discrimination.[33]

Estimates of discrimination parameters obtained within different models deserve some discussion. The disutility factor varies from about 40% to more than 50% of men's productivity; similarly, the search intensity parameter varies between 0.6 and 0.7 depending on the model. Finally, the proportion of discriminating firms varies between 67% and 83%. It is interesting to compare these results with those obtained by Bowlus and Eckstein (2002) and Flabbi (2010a) for racial and gender differentials in the US labor market respectively. The first 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% while the search intensity parameter is equal to about 0.57. The paper by Flabbi (2010a) estimates that about half of employers

$P_M = 11110$ and $P_W = 10191$ respectively, resulting in a differential of 0.9 against 0.8 obtained using the minimum and maximum wage observed in the sample.

[32] See Sulis (2008) for comparison of estimates of these parameters to other results obtained in the literature; see also Jolivet et al. (2006) with ECHP data for Italy.

[33] Note these estimates still respect the condition $P > d + R$.

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.

3.5 Fit of the Model and Robustness

3.5.1 Fit of the Model

In this part of the paper, I provide different tests of fit for the model with heterogeneous productivity and on-the-job search. The first consists in comparing predicted and empirical wage distributions. In Figure 3, I report for both men and women empirical and predicted earnings distribution, where the latter is obtained by using equation (2) and previously estimated transition parameters. In this case, $F(w)$ is estimated non parametrically from the wages of those exiting unemployment. Inspection of the Figure reveals the fit of the model is not perfect, and that the predicted earnings distribution is shifted to the left with respect to the empirical one, while for women the fit is slightly better. To further investigate possible reasons for the model not fitting the data, in the bottom panels of the same Figure, I report the earnings distribution of employed workers dividing between those who quit they job and those that transit directly to unemployment. Theoretically, the two distribution should not be very close, as the model predicts that mostly low wage workers should make job-to-job transitions. A visual inspection shows this is not the case, especially for women, this could partially explain the difficulties of the model in fitting the data.

[Insert Figure 3 here]

Results above indicate the model has some problems in fitting the wage distribution. To further inspect the reason for this bad fit, a formal test of the model proposed by Bontemps et al (2000) could also be used. In fact, the equilibrium search model provides a closed form solution for the productivity parameter P and for the density of the productivity distribution. However, derivation of the density is feasible only if the model is well specified with respect to the equilibrium productivity distribution. Sometimes, the latter does not necessarily exist, hence the model is not able to fit the data. In practice, the estimate of the density expression can be negative, resulting in implausible values. This is the case when the earnings density is not monotonically decreasing and some groups of workers earning very high wages are observed in the right tail of the wage distribution. In fact, it turns out this is also the case for both men and women in the sample, confirming the difficulties of the model of fitting the wage distribution.[34]

Finally, note the model has also difficulties to match some other moments in the data. In fact, using estimated transition parameters, the model predicts an unemployment rate equal to 23% and 27% for men and women respectively, much higher than the observed in the data and reported in Table 6. The predicted job-to-job transition rate is also different than the observed one, being 18% for men and

[34]See Bontemps et al (2000) for analytical expressions and Sulis (2008) for further details on this test for the sample of men.

around 9% for women. Thus the model overestimates the job-to-job transition rate for men, while, in this case, doesn't do a bad job for women.

3.5.2 Robustness

Although the model has documented objective difficulties in fitting the data, estimates of transition parameters can reveal interesting differences between men and women that are not necessarily unreliable. To further check the quality of estimates, it is useful to provide a battery of robustness checks. As mentioned in the section dedicated to the data, it is very important to define precisely the state of workers and reasons for transitions between states to avoid identifying spurious transitions.

The first thing I do is to consider job-to-jobs transitions with an intervening period of unemployment less than or equal to three months instead of one month, results are reported in panel A of Table 7. Using this definition for job-to-job transitions, the parameter λ_e is clearly estimated higher for both men and women, however, as the job destruction rate is quite similar to that estimated before, the resulting k_e measure reflects the same relative differential between men and women. Similar results are obtained when considering as unemployed only those workers that have been previously displaced: panel B of the same Table confirms that the number of offers obtained during an employment spell is equal to 0.55 for men and 0.23 for women. Finally, in panel C I check if the trimming of the wage distribution has a significant impact on estimates of transition parameters, as it has a direct influence on the estimate of the reservation wage. Interestingly, results indicate that a different trimming of the wage distribution affects women relatively more, by increasing their estimate of k_e, while for men, the latter is very close to the one estimated in the two other panels in the same Table. This suggests that part of the gender differential could be attributed to the fact that women are much more concentrated in the bottom part of the wage distribution.

[Insert Table 7 here]

Finally, I also consider the possibility that the number of days worked during the month is equal to 22 instead of 26, and re-estimate the model accordingly: in this case, results indicate that k_e is equal to 0.62 for men and to 0.42 for women.

3.6 Policy Experiments and Wage Decomposition

3.6.1 Thought Experiments

An important advantage of the structural estimation approach is the possibility of conducting policy experiments and evaluate equilibrium effects on labor market outcomes. To exploit this possibility, in this subsection I conduct two policy experiments. The first is a set of thought experiments in the spirit of Bowlus (1997), while the second is the introduction of an equal pay policy in the spirit of Bowlus and Eckstein (2002). The former set of experiments uses the equilibrium search model with productive heterogeneity as a benchmark, while the second uses the model with homogeneous productivity and discrimination.

Figure 4 shows the results of the first experiment, where I predict the women's earning distribution $G(w)$ using men's parameters.[35] In the top-left panel, I just report the earnings distributions of men and women, then in the top-right panel I predict $G(w)$ for women using equation (2) with men's k_e. A visual inspection of the distributions shows men's higher arrival rates help to shift the distribution function of women to the right, although such a shift is not very prominent.

[Insert Figure 4 here]

In the bottom-left panel, I predict earnings distribution of women by using the wage offer distribution $F(w)$ of men, in this case, the shift is much more important, confirming women could be discriminated when entering the labor market and when returning after unemployment (or non participation) periods. Finally, in the bottom-right panel, I predict the earnings distribution of women by using an estimate of men's productivity, where the latter is obtained by using equation (12). Again, in this case, the shift is significant: interestingly, it doesn't have a uniform effect on the distribution, as it shifts more the bottom part of it. To sum up, it looks that in this model the most important component of the shift in the earnings distribution are the wage offer and the productivity components, while search parameters are less important. As in this model discrimination is absent, the residual effect could be attributed to discrimination.

3.6.2 Equal Pay Act

To further check the possibility that discrimination plays a substantial role in shaping the gender differential, in what follows, I conduct a different type of experiment. It consists of introducing an equal pay law in a context in which productivity is homogeneous, search frictions are at the same level but there is discrimination. Bowlus and Eckstein (2002) show that two different scenarios can be considered: the former is one in which firms do not search less intensively for women ($z = 1$), while in the other $z < 1$ and this additional source of discrimination could be included in the model.[36] When the search intensity factor is equal to 1, Bowlus and Eckstein (2002) that men and women face the same wage offer distribution, the same arrival rates of offers, the same reservation wage and the same average earnings, hence the wage differential should disappear. The only difference between firm types is the expected utility per worker.

To show this, I estimate a model in which there are no differences in transition parameters or productivity between men and women. I solve the system of equations (28) to (31) reported in Appendix C using means for the whole sample, obtaining the following estimates: $P = 10866$ and $k_e = 0.29$. Having obtained these estimates, I impose $z = 1$ and estimate the two remaining discrimination parameters from the mean wage offers and earnings distribution of women (equations (14) and (15) in Appendix A). The estimated fraction of discriminating firms equals $\gamma_d = 0.83$, while

[35] It is important to note that these exercises do not take into account the equilibrium change in the reservation wage of workers.

[36] Flabbi (2010a) shows that implementation of equal pay policies may not be possible in contexts in which the match-specific value of productivity is unknown to the policy maker.

disutility parameter is $d = 2541$.[37] After obtaining these estimates, I impose equal pay for firms: the resulting average earnings is equal to 3209, which is lower than the observed earnings for men equal to 3490, but higher than the observed average earning for women 2815. Hence the equal pay law increases the wage of women, but decreases the wage of men.[38]

3.6.3 Wage Decomposition

Previous results indicate search, productivity and discrimination have important roles in shaping the gender wage differential, and that these effects partially depend on the specification and estimation methods. Hence, it is important to provide a measure of their relative contributions to the overall gender gap. 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 by using previous parameters estimates, I predict mean earnings for women and men using equations (15) and (17) reported in the Appendix A. First note that the raw earnings gap between men and women is about 20%. In the first row of Table 8 I report the predicted earnings differential resulting from a model in which all three components are included: results obtained with maximum likelihood with

[37] Note the disutility parameter is estimated lower than in previous contexts, while the proportion of discriminating firms is higher. This could be due to the fact that here the parameter z is not considered. Note also these are not directly comparable to estimates reported in panel C of Table 5 as productivity is estimated in a different way.

[38] Equations used to estimate these effects are taken from Bowlus and Eckstein (2002), and read as follows:

$$F(w) = \begin{cases} \frac{1+k_e}{k_e} - \left(\frac{1+k_e}{k_e}\right)\left(\frac{P-(\theta * d)-w}{P-(\theta * d)-R}\right)^{0.5} & \text{if } R \leq w \leq w_{hd} \\ \frac{1+k_e}{k_e} - \left(\frac{1+k_e*(1-\gamma_d)}{k_e}\right)\left(\frac{P-w}{P-w_{hd}}\right)^{0.5} & \text{if } w_{hd} \leq w \leq w_h \end{cases}$$

where

$$\begin{aligned} w_{hd} &= P - (\theta d) - \left(\frac{1 + k_e * (1-\gamma_d)}{1+k_e}\right)^2 (P - (\theta d) - R) \\ w_h &= P - \left(\frac{1}{1+k_e(1-\gamma_d)}\right)^2 (P - w_{hd}), \end{aligned}$$

and $\theta = 0.36$ is the proportion of women in the sample. It is important to stress that, in this setting, I don't consider the equilibrium effects of these policy changes on the reservation wage. To calculate those effects, an estimate of the value of leisure is needed. However, such estimates returned implausibly high negative values and are not reported. Hence, it is important to stress the fact that not considering these changes can miss an important channel of transmission, that are left for future research.

heterogeneous productivity, with homogeneous productivity and with the method of moments are reported. It is important to note from the onset that all models overestimate the gender wage differential, in fact, the predicted earnings differential would be as high as 37% in the model estimated with maximum likelihood and heterogeneous productivity. The model estimated with the method of moments would predict a differential of 25%, which is closer to 20% observed in the data.

[Insert Table 8 here]

In what follows, I analyze the different contribution of discrimination, search and productivity to this differential. For example, the row labelled "Discrimination" indicates the latter is assumed to be the only source of differential between men and women. In fact, predicted earnings are estimated imposing the restriction that men and women have identical transition and productivity parameters, where men's parameters are always assumed as benchmark. The interpretation of the cells is that the predicted ratio of women/men earnings differential would be 0.93 in a model with on-the-job search and heterogeneous productivity in which men and women are identical and only discrimination as a source of differential is considered. The role of discrimination turns higher when not considering heterogeneity in productivity across firms in the second column, in fact the earnings differential would be around 19%. Similarly, considering a different identification and estimation method, the role of discrimination turns out to be very important. In fact, when considering the method of moments in the third column of the Table, discrimination alone explains a large part of the differential, resulting in a gap of 17%.

The role of search is identified in the third row of the Table. Maximum likelihood techniques indicate search accounts for a large part of the differential: a model with the same productivity for men and women and no discrimination would result in a wage differential of about 30% and 21% in an environment with heterogeneous and homogeneous productivity respectively, while the method of moments suggests the latter would be around 13%. The last row analyzes the role of productivity. Interestingly, the model with heterogeneous productivity is the one that attributes the greatest importance of this source to explain gender wage differentials. In fact, the predicted wage differential would be 26%, definitely higher than the value obtained in a model with homogeneous productivity, which would be equal to 18%. Productivity differences are also quite important to explain the gender differential in a model estimated with the method of moments.

4 Conclusions

This paper analyzes gender wage differentials by estimating structural parameters of an equilibrium search model. In particular, it provides estimates of transition and productivity parameters using maximum likelihood methods, then uses these estimates to obtain different measures of discrimination in the labor market, which are obtained by matching first moments in the data. The paper represents a first attempt of considering on-the-job search, heterogeneity in firm productivity and discrimination in one single framework.

Results indicate that search frictions are an 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. In particular, while the pattern for job destruction rates is very similar, women have a constant arrival rate of offers at different stages of their career. This can indicate that labor market transitions of women can be influenced by many factors, including family organization and child rearing. For both groups, wages are increasing function of productivity levels, however, while for men the relationship is not linear, for women it 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. Although the model doesn't pass a formal test of fit, these results are robust to a series of sensitivity checks as different definitions of transitions, different specifications and different identification methods. When considering taste discrimination, results indicate the relative contribution of search, productivity and discrimination on the earnings gap depends on the model specification and estimation method: interestingly, search and productivity are more important when considering the model with heterogeneous productivity and on-the-job search, while discrimination is much more important when considering the method of moments.

This paper contributes to the literature dealing with the structural estimation of equilibrium search models with an application of such models to study gender labor market differentials in Italy. It offers some quantitative results and provides explanations for the basic stylized facts. However, a few interesting extensions to this paper are worth mentioning. Firstly, it would be very interesting to include different search efforts of workers in job search; secondly, analysing joint labor supply and fertility decisions of couples in such a context can shed some light on pre-market factors that can eventually lead to discrimination in the labor market.

Appendix

A. Estimating Discrimination Parameters

In this Appendix, I briefly present the method used to estimate discrimination parameters and report equations used to predict average earnings as proposed by Bowlus and Eckstein (2002). After estimating transition and productivity parameters in the first step, the ratio between estimated arrival rates for women λ_W and men λ_M can be used to estimate z.[39] The two remaining parameters are estimated from mean wage offers and earnings respectively. As in the rest of the paper, M is for men, W is for women, $G(w)$ denotes the earnings distribution, $F(w)$ is the wage offer distribution, E denotes expectations, P is productivity, R is the reservation wage, d is the disutility parameter, γ_d is the proportion of discriminating firms, while z is the search intensity parameter. Discrimination parameters are obtained by solving

[39] The ratio of arrival rates is calculated as an average between the arrival rate of offers when unemployed and the one when employed.

the system of three equations below to match moments in the data:

$$\frac{\lambda_W}{\lambda_M} = (1 - \gamma_d + z\gamma_d), \tag{13}$$

$$\begin{aligned} E^W_{F(w)} = &\left(\frac{(k_{eW})^z(3 + 2(k_{eW})^z)P_W + (3 + 3(k_{eW})^z + ((k_{eW})^z)^2)R_W}{3(1 + (k_{eW})^z)^2} \right) \\ &+ \left(\frac{z(k_{eW})\gamma_d d(2(1 + (k_{eW})(1 - \gamma_d)) + (zk_{eW}\gamma_d)}{3(k_{eW})^z(1 + k_{eW}(1 - \gamma_d))^2(1 + (k_{eW})^z)^2} \right. \\ &\left. - \frac{2(1 + k_{eW}(1 - \gamma_d))^2(1 + (k_{eW})^z)^2}{3(k_{eW})^z(1 + k_{eW}(1 - \gamma_d))^2(1 + (k_{eW})^z)^2} \right), \end{aligned} \tag{14}$$

$$\begin{aligned} E^W_{G(w)} = &(1 - \gamma_d)\frac{(1 + (k_{eW})^z)}{(1 - \gamma_d + z\gamma_d)} \left(\frac{k_{eW}(1 - \gamma_d)P_W}{(1 + k_{eW}(1 - \gamma_d))^2} + \frac{R_W}{(1 + (k_{eW})^z)^2} \right) \\ &+ \left(\frac{\gamma_d z}{(1 - \gamma_d + z\gamma_d)(1 + (k_{eW})^z)} \right) \left(\frac{(zk_{eW}\gamma_d)(P_W - d)}{(1 + k_{eW}(1 - \gamma_d))} + R_W \right) \\ &+ \left(\frac{(\gamma_d)(1 - \gamma_d)zk_{eW}(1 + (k_{eW})^z)(2 + 2k_{eW}(1 - \gamma_d) + zk_{eW}\gamma_d)(P_W - d)}{(1 - \gamma_d + z\gamma_d)(1 + (k_{eW})^z)^2(1 + k_{eW}(1 - \gamma_d))^2} \right). \end{aligned} \tag{15}$$

The two other relevant equations used to predict averages of the earnings and offer distribution for men in the wage decomposition exercise read as

$$E^M_{F(w)} = \frac{k_{eM}(3 + 2k_{eM})P_M + (3 + 3k_{eM} + (k_{eM})^2)R_M}{3(1 + k_{eM})^2} \tag{16}$$

$$E^M_{G(w)} = \frac{k_{eM}P_M + R_M}{(1 + k_{eM})} \tag{17}$$

Note that the estimates of discrimination parameters are obtained by numerically solving the system of equations (13), (14) and (15) reported above, hence they can be very sensitive to the choice of previously estimated transition and productivity parameters, as little variations in starting values could result in implausible results or non existence of a solution. What is more, no standard errors for these estimates are available.

B. Likelihood Function with Homogeneous Productivity

In what follows, I briefly present the method used to estimate the transition and productivity parameters in the Burdett and Mortensen (1998) model with homogeneous workers and firms. The model is estimated using duration and wage data, however it is not based on the nonparametric estimation of the wage distribution used in the estimation of the model with productive heterogeneity and it has the counterfactual implication of increasing wage densities. Data requirement is very similar to that needed for the model with heterogeneous productivity: the duration of the spell of unemployment or employment, the wage earned in each state, and the destination after the employment spell.[40] The likelihood is obtained by multiplication of the probability distributions of the observables.

The probabilities of being in each state are

$$\begin{aligned} \Pr(u) &= \delta/(\delta+\lambda_u), \\ \Pr(e) &= \lambda_u/(\delta+\lambda_u). \end{aligned} \tag{18}$$

The duration of unemployment has an exponential distribution with parameter λ_u, the marginal distribution of t_0 is

$$f(t_0) = \lambda_u \exp(-\lambda_u t_0). \tag{19}$$

The marginal distribution of wages of the re-employed is a drawing from the equilibrium wage distribution, and the density function is

$$f(w) = \left[\frac{\delta+\lambda_u}{2\lambda_e}\right]\left[(P-w)(P-R)\right]^{-\frac{1}{2}}. \tag{20}$$

The conditional distribution of the job length, conditional on the wage received, is

$$f(t_1|w) = \{\delta + \lambda_e[1-F(w)]\}\exp\{-(\delta+\lambda_e[1-F(w)]\,t_1)\}, \tag{21}$$

where

$$F(w) = \frac{\delta+\lambda_e}{\lambda_e}\left[1-\left(\frac{P-w}{P-R}\right)^{\frac{1}{2}}\right]. \tag{22}$$

The marginal distribution of wages of the employed is a drawing from the equilibrium earnings distribution, and the density function is

$$g(w) = \frac{\delta(P-R)^{\frac{1}{2}}}{2\lambda_e}(P-w)^{-\frac{3}{2}}. \tag{23}$$

Transition probabilities from employment to other states, conditional on the wage, read as follows

$$\begin{aligned} \Pr(jtu|w) &= \frac{\delta}{\delta+\lambda_e[1-F(w)]}, \\ \Pr(jtj|w) &= \frac{\lambda_e[1-F(w)]}{\delta+\lambda_e[1-F(w)]}. \end{aligned} \tag{24}$$

After appropriately dealing with right and left censoring, the likelihood can be written as the multiplication of above terms

$$\begin{aligned} L(\theta) = {} & f(w)\lambda_u \exp[-\lambda_u(t_0)]\, g(w)\,[\delta+\lambda_e(1-F(w))] \\ & \times \exp\{-[\delta+\lambda_e(1-F(w_1))]\,(t_1)\}\,\delta^v\,[\lambda_e(1-F(w))]^{1-v} \end{aligned} \tag{25}$$

where v is equal to 0 if the employment terminates in a voluntary quit and 1 if there is an involuntary layoff.

[40] To ease exposition, censoring is not considered, but information on it was used in the estimation routines.

In this setting, the reservation wage and the productivity parameter are estimated as follows:

$$\widehat{R} = \min(w), \tag{26}$$

$$\widehat{P} = \left[\frac{(1+k_e)^2}{(1+k_e)^2-1}\right]\max(w) - \left[\frac{1}{(1+k_e)^2-1}\right]\min(w). \tag{27}$$

To simplify notation, $k_e = \lambda_e/\delta$ has been used to estimate the productivity parameter, where the latter is estimated using wage and transition data without using nonparametric estimates of earnings. However, note that using the minimum and the maximum observed wage is sensitive to data manipulation and trimming, hence estimates of the productivity parameters have been conducted using the 99th percentile of the wage distribution after some sensitivity tests.

C. Method of Moments

In this last part of the Appendix, I follow computation procedures proposed by Bowlus and Eckstein (2002) to estimate δ, λ_u, λ_e, and P by matching first moments observed in the data.[41] The reservation wage R is assumed to be gender specific and it is estimated as the lowest wage observed in the sample for men and women. The basic system of equations, based on the standard Burdett and Mortensen (1998) theoretical model is described below.

Unemployment duration identifies the arrival rate of offers when unemployed λ_u:

$$u_{dur} = \frac{1}{\lambda_u}. \tag{28}$$

Having estimated λ_u, the unemployment rate identifies the job destruction rate δ:

$$u_{rate} = \frac{\delta}{\delta+\lambda_u}, \tag{29}$$

while the proportion of jobs terminating into unemployment identifies the arrival rate of offers when employment λ_e :

$$jtu = \frac{\lambda_e}{(\delta+\lambda_e)\ln(1+\frac{\lambda_e}{\delta})}. \tag{30}$$

Finally, the average wage of the cross section earnings distribution identifies average productivity:

$$E_{G(w)} = \frac{\lambda_e P + \delta R}{\lambda_e+\delta}. \tag{31}$$

The above model is separately estimated for men and women, hence all parameters are gender specific. Note that when discrimination is considered, the average of the earnings distribution $E_{G(w)}$ is used to estimate discrimination parameters, hence productivity can be estimated as in the model with homogeneous productivity discussed in Appendix B using equation (27).

[41] As for discrimination parameters, I solve the systems below using numerical methods with Maple. As mentioned above, it should 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.

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Table 1: Descriptive Statistics, Men

	All Sample	15-25	26-40	41-50
Number of Workers	60,506	12,904	31,042	16,523
Unemployed	16.48%	34.10%	14.41%	6.42%
Employed	83.52%	65.90%	85.59%	93.58%
Age: mean (std dev)	33.75 (8.75)	22.51 (2.07)	32.34 (4.31)	45.20 (2.80)
Unemployed				
left censored	36%	43%	31%	23%
right censored	15%	14%	16%	14%
Duration (not censored)				
mean (std dev)	24.37 (21.42)	23.44 (20.57)	25.19 (22.15)	24.22 (21.25)
Employed				
Transitions to another job	13%	15%	14%	10%
Transitions to unemployment	87%	85%	86%	90%
left censored	25%	1%	24%	40%
right censored	41%	29%	43%	45%
Duration (not censored)				
mean (std dev) - total	47.10 (32.01)	35.01 (25.44)	47.75 (31.55)	58.82 (34.72)
if transition to another job	25.67 (20.18)	26.09 (15.07)	26.75 (20.69)	30.68 (23.13)
if transition to unemployment	50.44 (32.22)	37.62 (25.98)	51.14 (31.69)	61.99 (34.36)
Wage Distribution				
minimum	974	978	974	977
p10	2139	1972	2176	2426
median	3032	2527	3053	3542
p90	5030	3480	4913	6083
p90/p10	2.35	1.76	2.25	2.50
mean (std dev)	3386 (1440)	2468 (762)	3372 (1341)	3992 (1723)

[a] Durations are expressed in months; monetary values are in 000s of 1996 Italian Lira.

Table 2: Descriptive Statistics, Women

	All Sample	15-25	26-40	41-50
Number of Workers	34,514	10,065	18,228	6,203
Unemployed	18.69%	28.96%	16.09%	9.45%
Employed	81.31%	71.04%	83.91%	90.55%
Age: mean (std dev)	31.41 (8.30)	22.44 (2.00)	31.75 (4.26)	45.00 (2.83)
Unemployed				
left censored	42%	54%	33%	34%
right censored	19%	15%	20%	30%
Duration (not censored)				
mean (std dev)	25.40 (21.45)	23.76 (20.67)	26.64 (22.13)	25.40 (20.30)
Employed				
Transitions to another job	11%	13%	11%	8%
Transitions to unemployment	89%	87%	89%	92%
left censored	22%	3%	25%	40%
right censored	36%	30%	37%	42%
Duration (not censored)				
mean (std dev) - total	46.13 (31.39)	40.56 (27.95)	46.30 (31.79)	58.39 (33.84)
if transition to another job	24.90 (20.35)	22.65 (17.98)	25.25 (21.08)	30.60 (22.85)
if transition to unemployment	48.79 (31.52)	43.06 (28.19)	48.95 (31.92)	61.02 (33.53)
Wage Distribution				
minimum	835	835	835	838
p10	1877	1832	1887	1986
median	2573	2362	2659	2804
p90	3936	3343	4034	4391
p90/p10	2.09	1.82	2.13	2.21
mean (std dev)	2760 (945)	2479 (711)	2829 (973)	3017 (1073)

[a] Durations are expressed in months; monetary values are in 000s of 1996 Italian Lira.

Table 3: Structural Parameters, Men

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

[a] The 5% and 95% percentiles of the bootstrap distribution in square brackets.
[b] Time period is month.

Table 4: Structural 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]

[a] The 5% and 95% percentiles of the bootstrap distribution in square brackets.
[b] Time period is month.

Table 5: Search, Productivity and Discrimination: Alternative Models

	δ	λ_u	λ_e	k_e	P	R	d	γ_d	z
A: Maximum Likelihood, Heterogeneous Productivity									
Men	0.0128	0.0431	0.0064	0.50	13490	974			
Women	0.0154	0.0398	0.0032	0.21	8781	835	6617	0.67	0.55
All	0.0138	0.0418	0.0051	0.37	11809	835	5164	0.92	0.91
B: Maximum Likelihood, Homogeneous Productivity									
Men	0.0149	0.0412	0.0069	0.46	12544	974			
Women	0.0192	0.0403	0.0043	0.22	10285	835	6939	0.83	0.64
All	0.0164	0.0409	0.0060	0.36	11557	835	3966	0.95	0.98
C: Method of Moments, Homogeneous Productivity									
Men	0.0078	0.0410	0.0026	0.33	13248	974			
Women	0.0092	0.0393	0.0024	0.26	10738	835	8562	0.64	0.69
All	0.0083	0.0405	0.0025	0.30	11827	835	3593	0.96	0.96

[a] Time period is month; monetary values are expressed in 000s of Italian Lira.

Table 6: Means Used for the Method of Moments

	All	Men	Women
Unemployment Rate u_{rate}	0.17	0.16	0.19
Unemployment Duration u_{dur}	24.7	24.4	25.4
Jobs to Unemployment jtu	0.88	0.87	0.89
Average Earnings $E_{G(w)}$	3249	3490	2815
Average Offers $E_{F(w)}$	2727	2857	2524
Median $G(w)$	2833	3032	2573
Reservation Wage R	835	974	835

[a] Monetary values are expressed in 000s of 1996 Italian Lira.
[b] Time period is month.

Table 7: Structural Parameters, Robustness

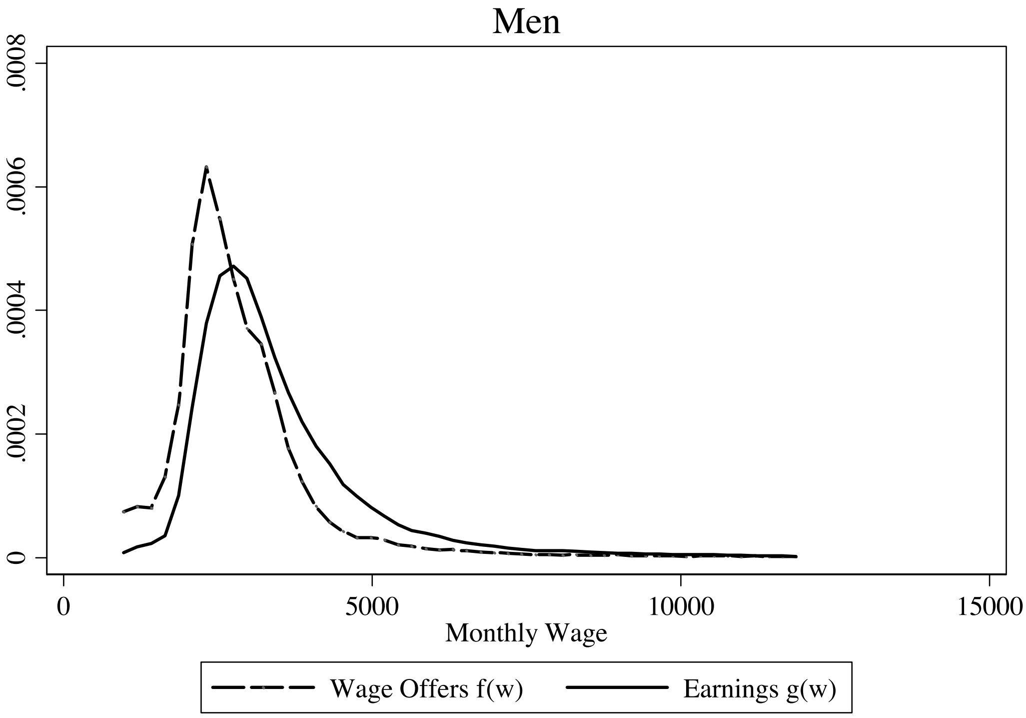
	δ	λ_u	λ_e	k_e
A: job-to-job equals 3 months				
Men	0.0124	0.0427	0.0078	0.6273
	[0.0123, 0.0125]	[0.0422, 0.0433]	[0.0076, 0.0080]	[0.6102, 0.6451]
Women	0.0151	0.0396	0.0043	0.2831
	[0.0150, 0.0152]	[0.0391, 0.0399]	[0.0041, 0.0044]	[0.2712, 0.2956]
B: job to unemployment, only displaced workers				
Men	0.0127	0.0429	0.0070	0.5519
	[0.0126, 0.0128]	[0.0425, 0.0434]	[0.0068, 0.0072]	[0.5329, 0.5678]
Women	0.0153	0.0398	0.0036	0.2357
	[0.0152, 0.0155]	[0.0393, 0.0404]	[0.0035, 0.0038]	[0.2248, 0.2489]
C: trimming 5% and 95% of earnings distribution				
Men	0.0125	0.0448	0.0072	0.5742
	[0.0124, 0.0126]	[0.0442, 0.0456]	[0.0070, 0.0074]	[0.5567, 0.5957]
Women	0.0148	0.0403	0.0057	0.3839
	[0.0147, 0.0148]	[0.0396, 0.0408]	[0.0055, 0.0060]	[0.3705, 0.4055]

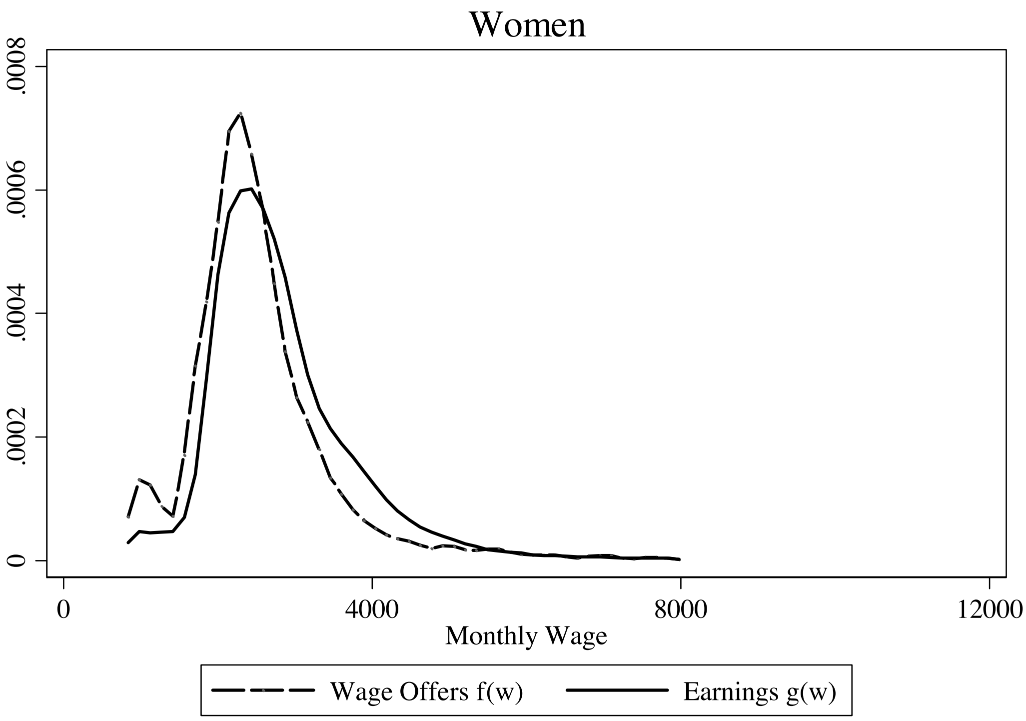
[a] The 5% and 95% percentiles of the bootstrap distribution in square brackets.
[b] Time period is month.

Table 8: Earnings Differential Decomposition

	Maximum Likelihood Heterogeneity	Maximum Likelihood Homogeneity	Method Moments Homogeneity
All Components	0.63	0.76	0.75
Discrimination	0.93	0.81	0.83
Search	0.70	0.79	0.87
Productivity	0.74	0.82	0.82

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





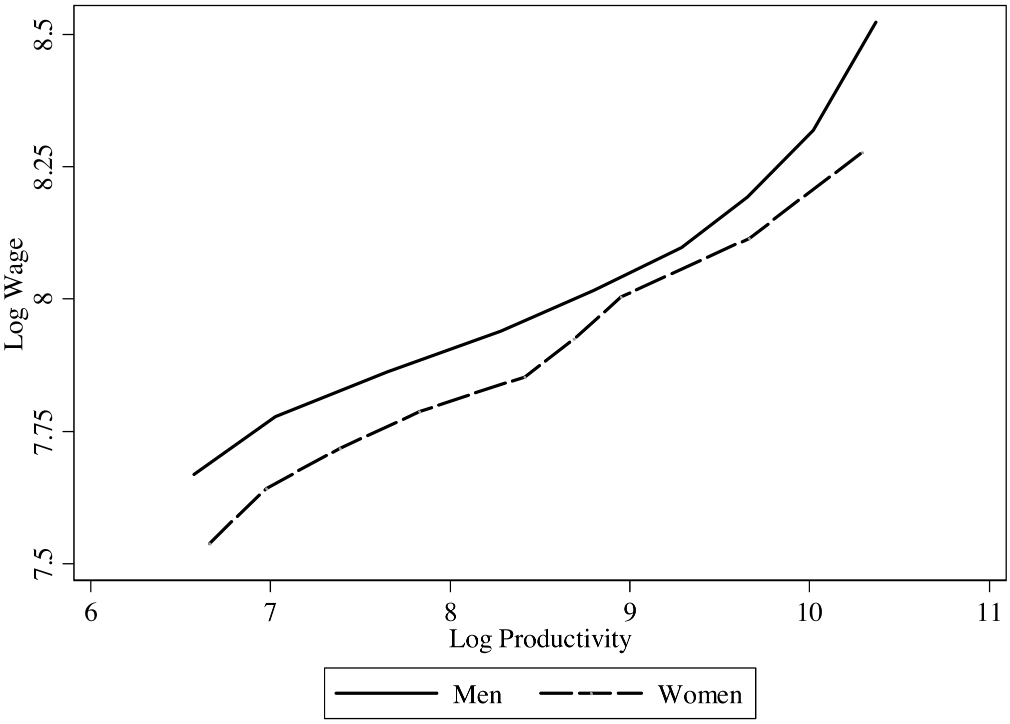


Figure 2: The Mapping from Productivity to Wages, Percentiles

Figure 3: Empirical and Predicted Earnings Distributions

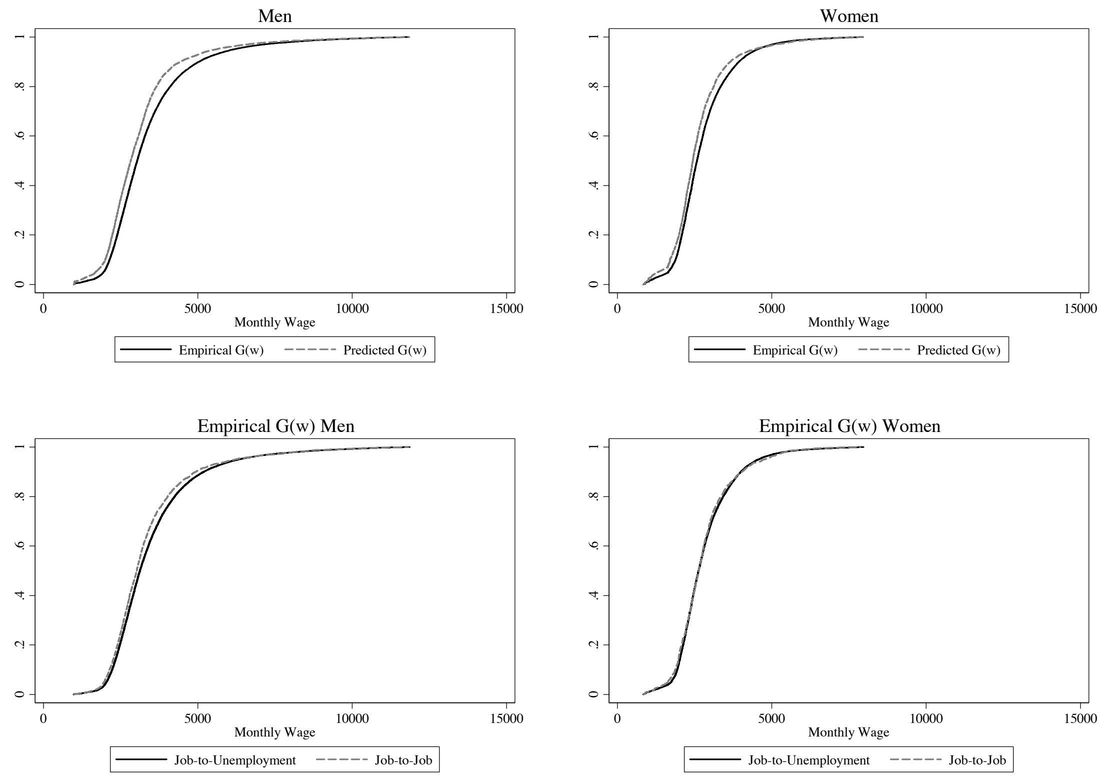
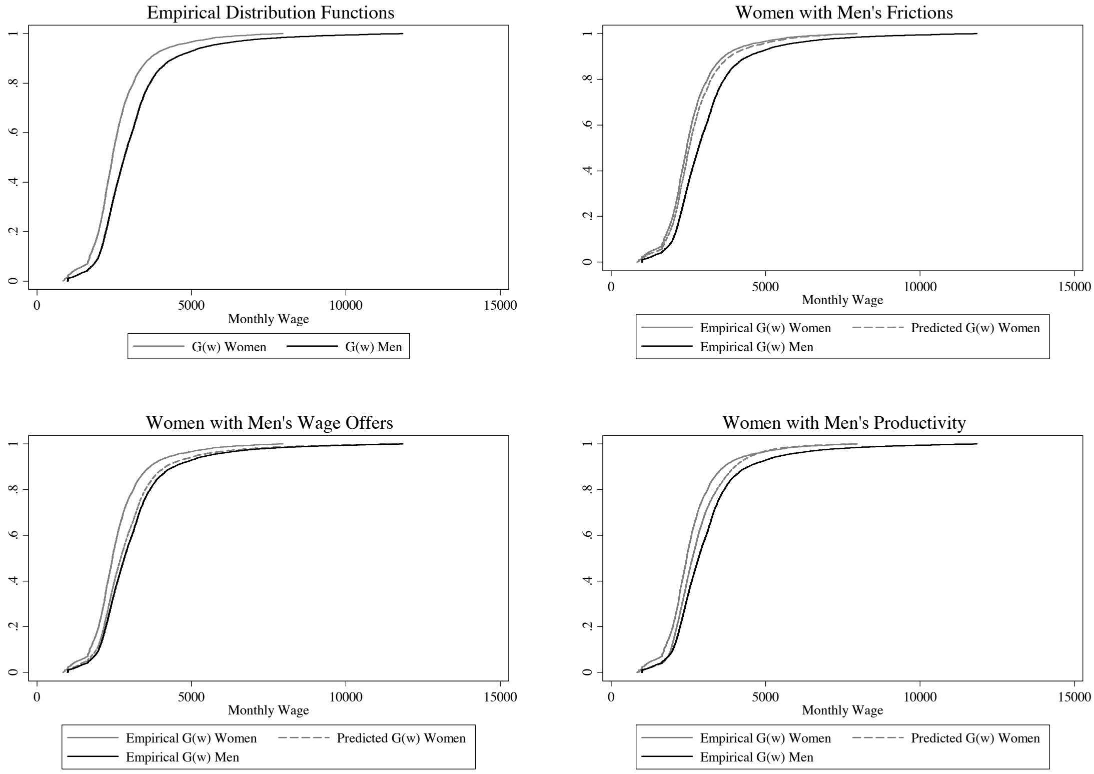


Figure 4: Thought Experiments



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