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The Impact of Employers' Prejudice

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Abstract[1]

This paper makes three contributions to the existing literature. First, it provides descriptive evidence on gender differentials by education level in the US labor market over the last twenty years. Second, it uses the structural estimation of a search model of the labor market to identify and quantify the impact of employers' prejudice on labor market gender differentials. Third, it connects both the descriptive and the analytical findings to recent policy interventions in the US labor market and presents some policy experiments. The results show that prejudice may still have a role in explaining the evidence on gender differentials and there is at least one scenario where the possibility of the presence of prejudiced employers in the labor market has substantial effects. In particular, it is responsible for the reversal of the returns to schooling ranking in recent years and it may explain up to 44% of the gender wage gap of the top education group (Master and PhD) in 2005. Since prejudice is still important, policy interventions may be effective in attaining both efficiency and welfare gains. The paper is in favor of implementing an affirmative action policy because it is frequently able to close the gender gap without reducing overall welfare and because it is effective in targeting the group that should take center stage in the future debate about gender differentials: high-skilled, high-earners workers, who also have family responsibilities.

JEL Classification: C51, J7, J64

Keywords: Gender differentials, discrimination, search models, maximum likelihood estimation, structural estimation, affirmative action.

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1 Introduction

This paper proposes three contributions. First, it provides descriptive evidence on gender differentials by education in the US labor market over the last twenty years. Second, it uses the structural estimation of a search model of the labor market to identify and quantify the impact of employers' prejudice on labor market gender differentials. Third, it connects both the descriptive and analytical findings to recent policy interventions in the US labor market and performs some policy experiments. For all the analysis in the paper, we use the *Annual Social and Economic Supplement* (ASES or March supplement) of the Current Population Survey (CPS)[2].

1.1 Descriptive evidence

We organize the descriptive evidence following the decision process of an individual deciding to supply labor in the market. First, we look at the outcomes of education decisions. Education decisions constitute the most important component of pre-labor market human capital and they influence not only future performance in the labor market but also the decision to participate in the labor market itself. It is also a choice and process where gender asymmetries are present but evolving quickly. We provide evidence on the overall quantity of education acquired and on one aspect of the "quality" of education acquired: the field of study. All the evidence on labor market outcomes will be correlated to these previous education decisions. The main result on pre-labor market characteristics is that women acquire more college education than men, reinforcing a trend started with the generation born in 1959. A lot of asymmetry by gender persists in the choice of field of study.

Second, we look at the decision to supply labor in the market both with respect to the extensive margin (the participation decision) and to the intensive margin (the hours supply decision). We correlate this evidence with education and we look at the evolution over-time. We present evolution over time by using the full cross-sectional information of each survey year but we restrain from presenting life-cycle evidence. We do this in preparation of the second part of the paper where we compare two labor market equilibria ten years apart (1995 and 2005) and where the equilibrium search model utilized abstract from life-cycle heterogeneity. The main result from this section is that women supply less labor than man both on the extensive and on the intensive margins. The result shows that part-time usage is a crucial determinant of gender differences in the labor market. We also find that the gender gap is not alleviated by education: the gender gap in the hours worked per week is actually exacerbated by education since it is larger on the College graduates sample than on the overall sample.

Third, we look at gender earnings differentials in the labor market. We compute both the raw differential and the differential conditional on standard human capital characteristics. We also

[2] A detailed description of the data and the estimation sample is contained in the Appendix.

provide evidence on the gender gap at different percentile of the earnings distribution and on very high-skilled occupations (CEOs and General Managers) to assess the magnitude of the so-called glass-ceiling effect. Results show that women earn about 20% less on average than men. The gap has been fairly stable in the last 10/15 years, after a period of significant reduction in the 1970s and 1980s. One reason for the persistent gender gap in recent years, in particular among skilled workers, is the large differential at the top of the earnings distribution, a possible indication of glass-ceiling effects.

1.2 The Impact of Employers' Prejudice

In the second part of the paper, we want to investigate the source of the observed gender differentials. We give priority to gender differentials in the labor market - both in terms of wage differentials and of labor market dynamic - but we draw some inference also on gender differentials in pre-labor market characteristics by proposing a novel measure of returns to education that takes into account the entire welfare effect of the labor market dynamic. We will be able to make distributional considerations and evaluate some determinants of the glass-ceiling but we will abstain from an analysis of labor supply determinants.

We will focus our analysis on three main determinants of gender differentials: productivity differences; employers' prejudice; and search frictions. These three determinants constitute a quite exhaustive list of the possible explanations proposed in the literature to account for the observed gender gap[3]. The difficulty, from a quantitative point of view, is to separately identify the contribution of these three components on the observed differential. The methodology we have chosen to use exploits the structure of a specific model - a search-matching-bargaining model with employers taste discrimination - to separately identify and then estimate these three components.

We estimate the model over two time periods (1995 and 2005); three education levels (Master and PhD; College; and High School); and three samples (full sample, married; married with children). Results suggest that the gender gap in wage offers is smaller than the gender gap in accepted wages on the high education samples but larger on the low education samples. The gender gap in productivity is estimated to be relatively small on the College and High School sample but it is increasing over time. The productivity gap for Master and PhD holders is quite large and increasing over time. The gender gap between workers employed at prejudiced employers and workers employed at unprejudiced employers is larger the higher the education level. The gender gaps in unemployment rates are relatively small in all years and education groups.

[3]Two main determinants are left out: gender asymmetries in household production and differential preferences with respect to job amenities. For a review of the first issue see Waldfogel (1998). The second issue focus on the relationship between education choices and occupation choices. For an example within the search and matching literature, see Flabbi and Moro (2012).

We use the separate identification and estimation of the three main determinants of gender differentials to decompose their impact on the gender wage gap. We find that prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time and it becomes smaller than the impact of productivity on all education groups in 2005. Master and PhD graduates are the exception to the trend: they experience a stronger impact of prejudice in 2005 than in 1995. Thanks to a decomposition of the gender wage gap at different points of the distribution, we also estimate that the Master and PhD sample shows some evidence of glass-ceiling effects. This evidence is marginally tempered when we take into account marital status and the presence of children, in particular on 2005.

1.3 Policy Experiments and Policy Implications

The descriptive section of the paper shows that gender differentials are by no means limited to average wage differentials, the variable often used in the literature to summarize the "gender gap" in the labor market. Gender differences concerns the shape of the entire wage distribution, the labor market dynamics across labor market states and the schooling choice preceding the entrance in the labor market. To really judge the overall welfare of labor market participants and to compare welfare across schooling groups and time periods, it is necessary to build an indicator able to take into account all these different elements. Thanks to the estimates of the structural model, we are able to propose and compute such indicator.

First, we use the indicator to compute a "welfare return" to schooling, i.e. the welfare differentials enjoyed by labor market participants at different level of schooling. We find that in 1995 female returns were higher than male returns, providing a possible explanation for the higher level of education acquired by women. However, the returns are estimated to be lower in 2005, a result mainly due to the presence of prejudiced employers in the labor market.

Second, we perform policy experiments that mimic the major policy interventions implemented in the US labor market: Equal Pay policies and Affirmative Actions policies. In the equal pay policy, we impose that wage schedules cannot be set conditioning on gender. In the affirmative action policy, we implement an employer subsidy to hire women. The Equal Pay policy is effective in redistributing welfare from men to women but it is never enough to completely close the gender gap. It is more effective for lower education levels than for higher ones and it has larger impacts in 1995 than in 2005. The affirmative action policy has a modest but positive impact on closing the gender gap in welfare. Despite the modest impact, the policy is promising because it is frequently able to close the gap without reducing overall welfare and it targets better the group that is not showing a positive evolution in closing the gap over time: the Master and PhD graduates sample.

2 Descriptive Evidence

2.1 Gender Differentials in Pre-Labor Market Characteristics

Figure 1 shows the gender gap (women - men) in the percentage of college graduates and Master and Ph.D. graduates. To look at the evolution over-time, we report the cohort evidence obtained by pooling the survey years data together, limiting the sample to individuals born between 1940 and 1980.

The most important result is that the gender gap has been shrinking over the last twenty years and it has actually become positive starting with the generation born in 1959 for College and with the generation born in 1971 for Master and Ph.D. A positive gap means that women acquire more education than men. This is a well-established empirical fact, which is becoming increasingly common among OECD countries [OECD (2008); Flabbi (2011)]. It is also evidence that has prompted an increasing literature trying to explain why the gap in education is positive while the gender gap in earnings remains negative[4].

In Figure 2 we look at one dimension of the quality of education: field of study. One possible explanation for the puzzle of a positive education gap together with a negative gender wage gap is that women may choose fields of study correlated with lower wages. While evidence on this correlation may have different sources, Figure 2 shows that the asymmetries on fields of study choices are substantial. If the favorite field for both men and women is "Business and Law", almost 20% of men choose "Engineering" while less than 5% of women do. At the same time, almost 15% of women choose "Humanities" compared with less than 8% of men. As a result, many fields see an imbalance in terms of gender distribution: looking at Figure 2, we see that the proportion of women in the "Education" and "Medical" fields is much higher than the proportion of women in the population (the red horizontal line). The opposite is true for "Science" and "Engineering". The red horizontal line reports the overall proportion of women in the population giving an immediate pictures of which field of study see an over- or an under-representation of women. This gender imbalance in the choice of College major is found on most OECD countries. Most proportions are strikingly similar (the two extremes, "Education" and "Engineering", are almost identical) while a few see a better gender balance in the US sample than in the Italian sample ("Business and Law").

We borrow the terminology of Flabbi and Moro (2012) to propose just one possible correlation between field of study choice, occupational choice and job characteristics[5]. Figure 3 reports

[4]The most complete explanations proposed so far focus on the return to education on the marriage market [Chiappori, Iyigun, and Weiss (2009) and GE (2011)]. For a different explanation based on job amenities, see Flabbi and Moro (2012). For international comparisons, see Becker, Hubbard and Murphy (2010).

[5]For some recent country-specific evidence on this correlation in European Countries, see Beffy, Fougère and Maurel (2009) and Chevalier (2011).

the correlation between the occupational choice of women and the degree of "flexibility" in the job by field of study choice. (In this Table flexibility simply means the possibility of working less than 30 hours a week.) What we find is that the field of study least favored by women ("Engineering") is characterized by the lowest degree of flexibility while the two relative most favored fields ("Education" and "Medical" professions) are characterized by the highest degree of flexibility.

To summarize, the evidence on pre-labor market characteristics shows that women acquire more college education than men, reinforcing a trend started with the generation born in 1959. Women acquire less graduate education than men but the differential is shrinking. Where a lot of asymmetry by gender persists is in the choice of field of study, choice that may be correlated to desirable future job characteristics.

2.2 Gender Differentials in Labor Supply

We look at the labor supply evidence by presenting results by education levels. To reduce clutter, we present only tow education levels (College completed or more and less than College completed). We will discuss in the text a few statistics for the very highly educated (Master and PhD) and we will focus on three educations groups in the following two sections of the paper.

Figures 4 report evidence on the first labor supply decision: supply labor in the market or not. This extensive margin reports a negative gender gap: men systematically participate in the labor market more than women both on the low education sample and on the high education sample but the differential has been shrinking over time. Education makes a difference: the differential is smaller on the College sample and it has uniformly been smaller over the entire twenty years period under consideration.

Age is also a relevant determinant of participation rates since it is strongly correlated with fertility. We have divided the sample in three age groups roughly describing a period before children (younger than 30); with young children (30-45 years old) and with older children (older than 45). What we find is that participation decisions are very sensitive to age but the education differential remains significant. Evidence by cohorts confirms this view because it seems to reflect more life-cycle patterns than major breaks across different generations.

Employment rates are reported in Figure 5 following the same structure used in Figure 4. Figures 5 reports no gender gap in employment rates among college graduates while a small positive gap exists on the low education sample. Notice the big drop in employment rates during the "Great Recession" of the last three years. By computing statistics by age and cohort, we find that employment rates are systematically lower for younger workers and for individuals without a College degree. Interestingly, the lack of a gender gap in employment for the College graduates is a quite old phenomenon, involving cohorts going as far back as 1940.

We look at labor force dynamic by computing Kaplan-Meier estimates of the hazard rate out of unemployment. We just discuss the main results of the exercise. A first striking result is how much more difficult it is to find a job during the recent recession: 2010 is clearly an outlier when compared with the other years. A second interesting result is that the impact of the recession is pretty homogenous on all four education/gender groups, in particular a College degree does not seem to cushion the severity of the crisis. Differences among the other years are smaller and the fact that College graduates systematically take more time to find a job suggests that a lower hazard rates also reflect "pickier" workers, i.e. workers waiting in unemployment for better job opportunities to come along. Differences between men and women are larger on the College sample than on the overall sample but they do not exhibit a strong trend over time.

We also look at the intensive margin of the labor supply. Figure 6 reports an indicator extremely relevant to asses gender differentials in the labor market: the incidence of part-time work. Results show a very large gender gap: women are more than twice more likely to work part-time than men. The gap is not significantly reduced when focusing on College graduates because the incidence of part-time is smaller both on men and women with College.

Our CPS data also report weekly hours worked but only starting with survey year 1985. As expected, we find a big concentration at 40 hours per weeks: About 50% of the sample declares to work that much. What is interesting is that most of the remaining population of male workers declares to work more than 40 hours per week while most of the remaining population of female workers declares to work less than that. This gender difference is not alleviated by education, it is actually exacerbated by education because male college graduates are more likely to work more than 40 hours per week than no college graduates. It is also a gender differential fairly stable over time.

To summarize, the evidence on labor supply shows that women participate less than men in the labor market but when they do they obtain similar employment rates. The intensive margin of the labor supply shows a large gender gap, mainly due to the much larger incidence of part-time among female workers than among male workers. This gender gap is not alleviated but actually exacerbated by education since it is larger on the college sample than no college graduates.

2.3 Gender Differentials in the Labor Market

Figure 7 reports estimates of the gender earnings gap from 1981 to 2011. We estimate the gap as the coefficient of a dummy =1 if the individual is a woman in an OLS regression of log hourly earnings. The top panel (Figure 7a) reports results from a specification including simply a constant and the dummy woman: it is therefore an estimate of the raw differential at the mean, unconditional on any observables. The bottom panel (Figure 7b) reports results from a specification including a constant, the dummy woman, three educational dummies, age linear and squared, two race dummies, a dummy for marital status and a dummy for presence of children younger than 18: it is therefore an estimate of the differential conditional on standard human capital and demographic characteristics. Dotted lines describe the 95% confidence interval.

As it is well documented, the gender gap in wage and earnings is persistent in the US labor market[6]. Figure 7a shows a significant convergence for all the 1980s, following a trend started in the previous decade (not shown). In the following decade, instead, the convergence slows down and then stops completely in the mid-1990s. The trend in the last ten years is less clear, with periods of minor convergence followed by period of small divergence. The most recent year available (2011) reports the smallest gender earnings gap ever, breaking the 20% mark on the unconditional differential for the first time ever. Figure 7b shows a very similar evolution over time but usually at a slighter lower level, implying that human capital differences do not explain the gender gap in earnings (at least under the very simple mincerian specification we use).

In Figure 7, we also report periods of recession to show how the gender gap is reacting to the business cycle, following a literature correlating the cycle, the change in inequality and the gender gap [Fortin and Lemieux (2000); Biddle and Hamermesh (2012)]. We find that recent recessions had a very different impact than earlier recessions: in the 1981 and 1990 recessions the gap decreased while in both the last two recessions the gap increased.

There is a large literature pointing out that the crucial sources of the gender gap in high-income economies may be concentrated at the top of the earnings distribution[7] and the top of the hierarchical ladder at the firm[8] (the so called glass-ceiling hypothesis). Figure 8 looks at the gender gap at different points of the unconditional earnings distribution. Results do not support the presence of a glass ceiling in the 1990s but they are consistent with the presence of a glass ceiling in the last 10/15 years, with a particularly large spike in 2000. Figure 9 reports some evidence on the gender asymmetries in the top hierarchical ladder at the firm. If we look at the CPS data we have used so far, the differentials are large: among CEOs and General Managers, only 20% are women, compared with a presence of women in the labor force which is very close to 50% (Figure 9). Overall, the proportion of men in Management Occupations is about 13% compared with about 8% for women. These differentials are essentially constant over-time, even if the time span we are forced to consider is much smaller than in previous figures because a change in the CPS definition of occupations does not make the values comparable over the entire three decades we are considering in this study. The data studied by Gayle, Golan and Miller (2011) looks at the top executives in the Standard and Poor's Execucomp dataset[9]. Thanks to their data, they are able to look deeper in the still relative large category of "CEOs and General Managers" reported by the CPS. Based on job titles and transitions across occupations, they build seven rankings within the

[6] For over-time evidence in the US, see Eckstein and Nagypal (2004); Blau and Kahn (2006), and Flabbi (2010).

[7] See Albrecht, Björklund, and Vroman (2003); Blau and Kahn (2006) and Bertrand, Goldin and Katz (2009).

[8] See Bertrand and Hallock (2001); Albanesi and Olivetti (2008); Bertrand, Goldin and Katz (2010); and Gayle, Golan and Miller (2011).

[9] Execucomp contains information on at least the top 5 executives in the S&P 500, S&P MidCap 400, S&P SmallCap 600 firms.

top executives (7th is the lowest and 1st the highest). What we see in Figure 10 confirms the very low presence of women at the top of the firm (no more than 6/7%), with their presence decreasing as the ranking is increasing.

To summarize, the evidence on gender earnings differential shows that women earn about 20% less on average than men, even when controlling for standard human capital and demographics characteristics. The gap shows a significant reduction from the 35% levels of the early 1980s but has remained fairly stable in the last 10/15 years. One reason for the persistent gender gap in recent years, in particular among skilled workers, is the large differential at the top of the earnings distribution.

3 The Impact of Employers' Prejudice

3.1 *The Search-Matching-Bargaining Model*

If explicit prejudice has been a part of economic theory for a long time[10], it is still very difficult to directly observe and measure. One possible way to gauge its presence and impact is to infer explicit prejudice from differential behaviors of labor market agents, conditioning on a parsimonious model of the labor market. A good candidate for such a model is a search-matching-bargaining model.

The model is a good candidate both for theoretical and empirical reasons. From a theoretical point of view, the presence of search frictions justifies the survival of prejudice employers in equilibrium, as suggested by Heckman (1998) and Altonji and Blank (1999.) From an empirical point of view, search models with matching and bargaining have been used in many empirical applications and have proved to have a good data fit (Eckstein and van den Berg (2007)). Most importantly, Flabbi (2010a) shows that when Becker's taste discrimination is added to the framework, the model is able to separately identify the impact of explicit prejudice, differential productivity and gender-specific search frictions on labor market outcomes.

3.1.1 Environment

The model's environment is as follows. The model is developed in continuous time and it is populated by four types of agents infinitely lived: two types of workers - Men (M) and Women (W) - and two types of employers - Prejudiced (P) and Unprejudiced (N). The employers' type is defined by a difference in preferences: prejudiced employers receive a disutility flow (d) from hiring women. Unemployed workers are looking for jobs and employers with unfilled vacancies are looking for workers to fill them. Search frictions are present in the market so that meetings may take time before they actually happen. There is random matching and there is not on-the-job search. Workers meet employers following a Poisson process with an instantaneous rate of arrival λ. Once an employer and a worker meet, they observe a match-specific productivity value

[10] A theory of explicit prejudice ("taste discrimination") was first proposed by Becker in 1957 (see Becker (1971)) and has been very influential on the discrimination literature ever since (see Altonji and Blank (1999)).

(x), which is drawn from an exogenous distribution denoted by the cdf $G(x)$. Upon observing the match-specific productivity value and their types, employers and workers engage in Nash-bargaining over the wage. Once a match is formed, it can be terminated following a Poisson process at an instantaneous rate η.

The technology used to produce the homogenous good produced in the economy is constant returns to scale with labor as the only factor of production. Therefore, the total output at a given employer is the sum of the productivity levels of all his/her matched employees. Workers' utility functions are linear in wages and there is no disutility from working. Employers' utility is linear in profit and in the intensity of discrimination. The intensity of discrimination is defined as the disutility from hiring women that affect prejudiced employers (Becker (1971)). While a vacancy is unfilled, employers sustain no cost and receive no benefit. While unemployed, workers receive an instantaneous utility (or disutility) flow b that takes into account search costs, unemployment benefits and other utility benefits and costs correlated with the state of unemployment. Time is discounted by a constant and common rate rho. All the model's parameters are common knowledge. Markets are fully segmented along gender-education-year cells. We denote gender with g, employer's type with t, year with y and education with e.

The value of employment for a worker of type g working at an employer of type t, producing x, in year y, with an education e is:

$$(\rho + \eta_{gye})V_{gye}[w_{gtye}(x)] = w_{gtye}(x) + \eta_{gye}U_{gye} \tag{1}$$

where $w(x)$ denotes the wage, which is determined by Nash-bargaining. The value of unemployment conditioning on type, education and year is:

$$\begin{aligned} \rho U_{gye} \;&=\; b_{gye} + \lambda_{gye}\Big\{(p_{ye}\int \max[V_{gye}[w_{gPye}(x)] - U_{gye}, 0]dG_{gye}(x) \\ &\quad +(1-p_{ye})\int \max[V_{gye}[w_{gNye}(x)] - U_{gye}, 0]dG_{gye}(x)\Big\} \end{aligned} \tag{2}$$

3.1.2 Equilibrium

Given this environment, workers have a very simple decision to make: accept or reject the match with a given employer. They make this decision by balancing the flow benefit of receiving a wage higher than the current utility of unemployment with the expected benefit of receiving a potentially better offer in the future. Since the present discounted value of being unemployed does not depend on a given wage but only on the entire expected wage offers distribution while the present discounted value of being employed at a given employer is increasing in the wage received, there will exist a wage at which the worker is indifferent between accepting the job or remaining unemployed. We call this value the *reservation wage*. A similar argument holds for the employer. The reservation value is determined as the value at which the agents are indifferent between accepting or rejecting the match.

By adding the optimal decision rules to the value functions, we obtain an equation that implicitly defines the only necessary equilibrium object, the value of unemployment U:

$$\begin{aligned}\rho U_{gye} \quad = \quad & b_{gye} + \lambda_{gye} \left\{ p_{ye} \int_{\rho U_{gye}+d1_{(g=W)}}^{\infty} [x - d_{ye}1_{(g=W)} - \rho U_{gye}] dG_{gye}(x) \right. \\ & \left. +(1-p_{ye}) \int_{\rho U_{gye}}^{\infty} [x - \rho U_{gye}] dG_{gye}(x) \right\} \end{aligned} \tag{3}$$

We are now ready to propose the following:

Definition 1. *In each market defined by year and education group, given the vector of parameters* $\{\lambda_{gye}, \eta_{gye}, \rho, b_{gye}, \alpha, d_{ye}, p_{ye}\}$ *and the cdf of match-specific productivity values* $G_{gye}(x)$*, the equilibrium is defined by the vectors of values of unemployment* U^*_{gye} *that solves equation (3), which in turn determine the reservation values characterizing the optimal decision rules.*

We assume the axiomatic Nash-bargaining solution to the bargaining problem faced by workers and employers bargaining over the wage, given the match-specific productivity x and their types. The solution corresponds to maximizing the product of the worker's and employer's surpluses, weighted by their bargaining power α:

$$w_{gtye}(x) = argmax_w \left\{ V_{gye}[w] - U_{gye} \right\}^{\alpha} \left\{ \frac{x - d_{ye}1_{(g=W)} - w}{\rho + \eta_{gye}} \right\}^{(1-\alpha)} \tag{4}$$

Nash-Bargaining solution has the property that the worker and the employer will always agree to a match when the match is producing a surplus and they agree to share the surplus according to their respective bargaining weight and their outside options. The analytical expressions of the resulting wage schedules makes this concept clear.

First, look at the wage of a man working for a prejudiced or unprejudiced employer (the employer's type has no impact on male workers) with a match-specific productivity equal to x:

$$w_M(x) = \rho U_M + \alpha(x - \rho U_M) \tag{5}$$

The expression states that the wage guarantees the worker his outside option (ρU_M) plus a portion of the surplus ($x - \rho U_M$) equal to the bargaining weight (α). The bargaining weight capture factors related to the bargaining strength of workers with respect to employers: the higher the weight, the higher the wage at given productivity. The outside option of the worker is the present discounted value of being unemployed: We denote this value with ρU_M and we formally characterized this expression in equation (3). The higher the outside option's utility, the higher the wage at given productivity because the worker will have a better state to go back to if the match is not realized. Finally, $(x - \rho U_M)$ is the surplus generated by the match because is the difference between what is produced in the match (x) and what is lost if the match is realized (ρU_M). Notice that the employer does not loose anything if the match is realized because the cost of keeping a vacancy open is zero.

Second, look at the wage of a woman working for an unprejudiced employer with a match-specific productivity equal to x:

$$w_{WN}(x) = \rho U_W + \alpha(x - \rho U_W) \tag{6}$$

The expression is exactly equal to equation (5) with the difference that the outside option is allowed to be different. We use subscript M to denote men and subscript W to denote women. Notice also that the wage equation has two subscripts: W to denote women and N to denote unprejudiced employers. This is necessary because the female wage schedules are employer's type-specific in equilibrium.

Third, look at the wage of a woman working for a prejudiced employer with a match-specific productivity equal to x:

$$w_{WP}(x) = \rho U_W + \alpha(x - d - \rho U_W) \tag{7}$$

The expression is different from (6) because the surplus is reduced by the disutility that the prejudiced employers receive when hiring women (d). The expression makes clear that, as a result of the bargaining process, the cost of prejudice is shared by both the employer and the worker: The higher the discrimination intensity d, the lower the wage at same productivity.

We are now ready to state the equilibrium decision rules resulting from the model:

1. The optimal decision rules are *reservation values rules* and both workers and employers agree on what these reservation values are. The reservation value rule in this case means that the match will be realized (i.e. both workers and employers agree to enter a job relationship governed by wage equations (5)-(7)) if the match-specific productivity is higher than the *reservation productivity value*. The wages corresponding to these reservation productivity values are the *reservation wages*.

2. The reservation productivities are different between men and women and they are different between women accepting to work for a prejudiced employer and women accepting to work

for an unprejudiced employer. We denote them with x^* and they are defined as follows:

$$x^*_M = \rho U_M \tag{8}$$
$$x^*_{WN} = \rho U_W \tag{9}$$
$$x^*_{WP} = \rho U_W + d \tag{10}$$

3. The reservation wages are worker's type-specific but not employer's type-specific. We denote them with w* and they are defined as follows:

$$w^*_M = \rho U_M \tag{11}$$
$$w^*_W = \rho U_W \tag{12}$$

The structure of the equilibrium has some interesting *implications* about the impact of prejudice on labor market outcomes:

1. Everything else equal, the presence of prejudiced employers makes the present discounted value of participating in the market (U) lower for women than men (See Proposition 1 in Flabbi 2010a).

2. Wage discrimination is present at prejudiced employers: Women working at prejudiced employers receive lower wages than men working at prejudiced with the *same* level of productivity. This is easy to see by comparing wage equation (7) with wage equation (5): For given x, women earn lower wages because of the negative impact of d (the direct effect of prejudice) and because the women's outside option is lower than the men's outside option (the equilibrium or "spillover"[11] effect of prejudice).

3. Wage discrimination is also present at unprejudiced employers: Women working at unprejudiced employers are also receiving lower wages for same productivity. The effect results from comparing equation (5) and (6): if women outside option are lower (as stated in the first equilibrium) implication then unprejudiced employers wage discriminate due to the spillover effects even if they do not have any prejudice against women. This is an interesting result that allows to make a clear distinction between explicit prejudice and wage discrimination.

4. Partial segregation arises in equilibrium, that is women are overrepresented at unprejudiced employers and underrepresented at prejudiced employers. This is an important result to explain, or at least be consistent with, the segregation observed in labor market data. We emphasize that we obtain "partial" segregation as opposed to complete segregation. Complete segregation is a starker result which is at odds with the recent empirical evidence since

[11] For a formal definition of this spillover effect, see Definition 4 in Flabbi 2010a.

it implies that prejudiced employers never hire women. This is the setting of the previous, and still most influential, model merging search frictions with taste discrimination: Black (1995).

3.2 Estimation and Identification

Search and matching models have been extensively studied and implemented. The identification theory is laid out by Flinn and Heckman (1982): they show that under an appropriate parametric assumption the crucial structural parameters of the model are identified from data on unemployment durations and accepted wages.

To the Flinn and Heckman's result, we have to add the identification of the prejudiced parameters. Flabbi (2010a) shows that, under the same parametric assumptions imposed by Flinn and Heckman (1982)[12], the proportion of prejudiced employers and the disutility they receive from hiring women are identified. This is a useful result because it allows for the separate identification of the prejudiced parameters, the gender-specific productivity parameters, and the gender-specific search frictions parameters. One parameter that is difficult to identify is the Nash-bargaining weight (Flinn (2006)). We do not attempt to identify it and we simply impose a standard assumption in the literature: symmetric Nash bargaining, i.e. workers and employers have the same Nash-bargaining weight which is therefore set to be equal to 1/2.

Estimation is performed by maximum likelihood: after a first stage in which an order statistic (the minimum observed wage) is used to obtain a strongly consistent estimator of the reservations wages (w^*_M, w^*_W), the maximization of the resulting concentrated likelihood delivers estimates of all the remaining structural parameters. The analytical expression for the maximum likelihood estimator is provided in Flabbi (2010b).

3.3 Results

3.3.1 Estimation Results

The Maximum Likelihood estimates of the structural parameters are reported in Tables 2 to 4. The model estimation is performed assuming that productivity, for both males and females, follows a log-normal distribution or $\ln(x) \sim N(\mu, \sigma^2)$. Under this assumption the average productivity and its variance are: $\exp(\mu + 0.5\sigma^2)$ and $(\exp(\sigma^2) - 1)\exp(2\mu + \sigma^2)$. Therefore, μ and σ reported in Table 2 to 4 refer to the location and scale parameters of the lognormal gender-specific productivity distribution. λ refers to the exogenous arrival rate of job offers and η to the exogenous termination rate. p is the proportion of prejudiced employers in the economy while k is the ration between the disutility from hiring women suffered by prejudiced employers (d) and the expected value of

[12] On top of showing that a distributional assumption is essential to obtain identification, they also show that estimation results may be sensitive to the distributional assumption used. In the next subsection, we discuss some sensitivity analysis we performed in this respect.

productivity for male. We estimate k instead of d to better scale the comparison across years and samples.

The estimation is performed jointly for 1995 and 2005 but separately by education level. The joint estimation is done to constrain the relative prejudiced preferences to be the same over the 10 years period. Following Flabbi (2010b), we assume that the proportion of prejudiced employers is quicker to adjust than preferences, therefore we leave the first one free to change over time while we constrain the second to be the same over the two periods. In estimation, we reparametrize the model and we estimate the disutility of prejudiced employers relative to the average male productivity. This ratio is the parameter k reported in Table 2.

The estimates of the structural parameters are in line with previous literature (Flabbi (2010a,b); Flinn (2006); Bowlus and Eckstein (2002)): women usually have higher arrival rates of offers and lower average productivity. The proportion of prejudiced employers and the relative disutility of discrimination are consistent with the result of Flabbi (2010b): the labor market for College graduates see a decrease in the proportion of prejudiced employers and a disutility value equal to about 30% of average male productivity. If High School also experience a decrease in the proportion of prejudiced employers, this is not the case on the sample of Master and PhD. However, the estimates of the prejudiced parameters are much more imprecise on this sample, probably due to the smaller sample size.

Table 5 and 6 shows some relevant predicted values obtained from our estimation results. Table 5 focuses on the cross-sectional distribution of productivity and wages. The Accepted Wages distribution corresponds to the observed wage data and it is the measure conventionally used to compute the gender wage gap. The wage offers distribution is not directly observed and we are able to predict it thanks to the model structure: It indicates the wage offers actually received by men and women before they decide if accepting them or not. In many respects, the wage offers distribution represents a better measure to gauge the actual disadvantage or wage gap experienced by women because it avoids the selection bias due to gender differences in reservation wages[13]. The productivity distribution is also unobserved and it is the true primitive distribution in the model. Finally, another unobserved component that we are able to recover thanks to the structural estimates is the assignment of women to prejudiced and unprejudiced employers.

The gender gap in accepted wages is in line with the descriptive evidence, ranging from 26% to 20% overall. The gap is decreasing on the High School sample, stable on the College sample and actually increasing on the Master and PhD sample. The evidence of the gender wage gap over time - for example Eckstein and Nagypal (2004), Blau and Kahn (2006) and Flabbi (2010b)

[13] This is one of the advantage of obtaining structural parameters estimates. The first paper estimating a search-matching-bargaining model (Eckstein and Wolpin (1995)) makes a similar argument in the context of returns to schooling estimation.

- report a stable or decreasing gap but they do not focus on schooling level as high as Master and PhD. This relative disadvantage of very high skilled women is a robust finding throughout the paper.

The gender gap in wage offers is smaller than the gender gap in accepted wages at high education levels and larger at low education levels. This is evidence consistent with high skilled women being relative more choosy than similarly educated men. Two possible sources of this behavior are: 1) gender and education-specific preferences for job amenities and 2) gender asymmetries in household-level decisions. An example of the first is the result in Flabbi and Moro (2012): women with a College degree value the job amenity "work flexibility" more than women with an High School degree. An example of the first is the result in Flabbi and Mabli (2012): once we take into account that labor market decisions are taken at the household level, gender differentials in wage offers are estimated to be smaller than in an individual search model. Both elements are ignored in the version of the model we estimate. However, in line with the second approach, we also estimate the model conditioning on two crucial elements related to household behavior: marital status and the presence of young children in the household. We will comment on the results starting from the earnings decomposition in Tables 7 and 8.

The gender gap in productivity is relatively small in the College and High School sample but it is increasing over time. The productivity gap for Master and PhD holders is quite large and increasing over time. As a result, and as we will see in the next section, differential in productivity are responsible for most of the gap we observe on the highest education group. However, since we ignore important factors such as preferences for job amenities and gender asymmetries in household-level decisions, we should regard this result with caution. Productivity is introduced in the model in a very reduced form way and it may well be the residual component that absorbs dynamic not explicitly modeled in our framework.

The gender gap between workers employed at prejudiced employers and workers employed at unprejudiced employers is larger the higher the education level. For example, the gender gap in wage offers at prejudiced employers on the Master and PhD sample in 2005 is equal to 55% while at unprejudiced employers is equal to 80%. This 25 percentage points difference decreases to about 2 percentage points on lower education levels. This result shows that even if the overall impact of prejudice on the high skilled sample is smaller than the impact of gender-specific productivity, it still has major impact in generating wage discrimination.

Table 6 shows some evidence on labor market dynamics: the hazard rates out of a given labor market state and the proportion of workers in each labor market states in equilibrium. The overall hazard rate out of unemployment is higher for women, a result explained both by higher arrival rates of offers and by lower reservation wages (see Table 2). The gender gaps in unemployment rates are relatively small. Larger but not big differences are observed in the distribution of men and women between prejudiced and unprejudiced employers. Notice that we report the overall employment by employer type so when the proportion of prejudiced employers is extremely high (as in High School sample in 1995) most of employed workers must work for them. This only partial segregation result implies that policies imposing quotas by employer (as common in some Affirmative Action policies, see Section 4.3) would not be very effective in reducing wage discrimination and in alleviating the impact of prejudice on labor market outcomes.

Our results are potentially sensitive to the distributional assumptions. In order to analyze how sensitive the estimation results are to assuming a lognormal, we have estimated the model using two additional distributions. In the first exercise, we have assumed that productivity follows a gamma distribution, that is $x \sim \Gamma(\alpha, \theta)$ where α and θ are the shape and scale parameters and the average productivity and its variance are defined as $\alpha\theta$ and $\alpha\theta^2$, respectively. In the second exercise, we have assumed that productivity follows a normal distribution, that is $x \sim N(\mu_x, \sigma_x^2)$, where μ_x and σ_x^2 are directly the average productivity and its variance. It is important to mention that these three distributions satisfy the recoverability condition, which is crucial under the identification strategy of Flinn and Heckman (1982). The starting values used in the likelihood maximization procedure were the same for all the estimation exercises. The equivalence between the distributional parameters was found using the definitions for the average productivity and its variance.

The results of this sensitivity analysis indicate that some estimated parameters are indeed sensitive to the distributional assumptions. Comparing the estimates under the gamma distribution assumption with the benchmark estimates obtained using a log-normal distribution, we do not find large difference in the mobility parameters (for example the largest difference in job arrival rates is just 0.04) but we find large differences in the prejudice parameters (the largest differences for p and k are, respectively, 0.7 and 1.4). Comparing the estimates under the normal distribution assumption with the benchmark we find larger differences on the prejudiced parameters and we experience converge problems on some samples.

3.3.2 Gender Wage Gap Decomposition

Table 7 reports a decomposition of the gender wage gap at different points of the accepted wages distribution. The gap is decomposed in the three sources of gender differentials assumed in the model: productivity, search frictions and prejudice. We perform the decomposition by taking into account equilibrium effects, i.e. by taking into account that changing the labor market environment induces individual agents to adjust their behavior.

The procedure we implement is the following. To isolate the impact of productivity, we impose that all the other differences between men and women do not exist. In particular, we assume that there are not prejudiced employers in the economy and that men and women face the same search frictions. Given this new environment, we compute the new optimal decision rules and we obtain new accepted wages distributions. On this counterfactual accepted wages distributions, we compute average accepted wages for men and women and we take the ratio of women values over men values. These ratios are reported in the Table. For example, the first row of College graduates in Table 7 states that if the only difference between men and women was the differential productivity we estimate, then the observed wage differential at the mean of the entire distribution would be much smaller than the one observed in the data: 8.9% as opposed to 22.1%. To isolate the impact of prejudice, we follow the same procedure: we fix productivity and search frictions of women equal to those of men but we let the proportion of prejudiced employers and their disutility to be equal to the one we estimate. We recompute the equilibrium and we obtain the statistics on the counterfactual wage distribution. Same exercise is done to isolate the impact of search frictions: the only parameters allowed to be different are the arrival rate of offers and the job termination rate. The "all parameters" exercise is a sort of goodness of fit: we generate wage offers distributions from an environment with all the parameters set equal to the point estimates.

Differences in productivity are the most important factor in explaining the wage gap for the top education level in 1995: Productivity differentials alone will generate the entire differential we observe at the mean. This strong impact becomes smaller in 2005 and it is significantly smaller on the College sample but similar on the High School sample. The impact of search frictions always plays in favor of women: we would actually observe a reverse gender wage gap if the only differences between men and women in the labor market were due to search frictions[14]. Finally, the impact of prejudiced employers is very strong for College graduated in 1995: Prejudice is the most important factors in explaining the wage gap for this year and education group. The impact of prejudice becomes smaller over time, becoming less important than the impact of productivity in 2005. Instead, the top education group (Master and PhD) shows the opposite trend: smaller impact in 1995 and stronger impact in 2005.

The top education group also shows a different behavior in terms of wage gap at top percentiles. This evidence is important to link back to the glass-ceiling issue we mentioned in the descriptive section. Master and PhD graduates in 2005 are the only group exhibiting evidence of glass-ceiling, i.e. a wage gap increasing as we move toward the top of the accepted wages distribution. This increasing wage gap is captured by the model but with a much smaller magnitude than in the data.

Table 8 reports the wage gap decomposition conditioning on Marital Status and the presence of children. As we compare the overall sample with the sample of married individuals and the sample with married individuals with children, the decomposition changes but the magnitudes are similar. The most striking result is on the sample of Masters and PhDs in 2005: as we move

[14]The positive impact of search frictions is mainly driven by the higher arrival rate of job offers to women (see Table 2).

from the entire sample to the sample of married with kids, productivity becomes less important while prejudice becomes more important in explaining the wage gap. This result is present but less strong in 1995 and it is not present on the other education groups.

Our overall conclusion on the decomposition analysis is that most of the results confirm Flabbi (2010b): Prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time, reaching a level smaller than the impact of differential productivity on all education groups in 2005. The disturbing exception to the trend, missed by Flabbi (2010b) since he considers only College graduates, is the top education group: Master and PhD graduates experience a stronger impact of prejudice in 2005 than 1995. By estimating the model conditioning on individuals married and with children, we observe that a good portion of this impact is driven by this specific sample. This result would imply that the impact of prejudice is one of the possible channels of the impact of fertility decisions on labor market outcomes. Master and PhD graduates is also the education group showing evidence of glass-ceiling in 2005, confirming the view that sees the glass-ceiling as the remaining obstacle to reach gender equality in the labor market. However, the model does not have strong prediction in terms of the sources of the glass ceiling because it is able to only qualitatively match the gap at different percentiles of the distributions but it is unable to provide a precise quantitative fit[15].

4 Policy Implications and Policy Experiments

It has long been recognized that the presence of discrimination and prejudiced behavior generates inefficiencies and negative externalities[16] therefore presenting an opportunity for policy interventions. The United States has a relative long tradition of anti-discriminatory laws targeting the labor market. They can be broadly separated between Equal Employment Opportunity policies and Affirmative Action policies, even if the difference between the two types of policies tends to be starker in theory than in practice (Holzer and Neumark (2006)). The results of the Descriptive Section of the paper confirm systematic differences in labor market outcomes for men and women. The results of the more quantitative section of the paper suggest the presence of explicit prejudice against women and of a significant amount of wage discrimination and segregation. The main policy implication is therefore that policy interventions could be justified. More specific policy implications can be drawn by simulating policy interventions exploiting the estimates of the labor market environment we generated in Section 3. This is the objective of this last section of the paper. Before articulating specific policies, though, we have to define the welfare measure we want

[15]One possible reason for this poor fit is the imprecise estimates of the prejudiced parameters: Probably due to the small sample size, the estimate of the disutility suffered by the prejudiced employers hiring Masters and PhDs is very imprecise. See Table 2. parameter k.

[16]An example of negative externality generated by the formal model presented in this paper is the spillover-effect inducing unprejudiced employers to wage discriminate.

to use to evaluate them. In doing so, we also want to say something about pre-labor market decisions, which - as shown in the descriptive section of the model - are also significantly influenced by gender.

4.1 Welfare Measure and Returns to Schooling

The overall welfare of labor market participants dependents on their current labor market state and, if employed, on their current wage. However, it also depends on the labor market dynamics related to the transitions between labor market states, the movements over the wage distributions and the durations in each state. A summary measure of overall workers' welfare should then go beyond the comparison of wage gaps that we presented in Section 3.3.2.

One relative straightforward way to proceed is assigning to each labor market states occupied by workers in steady state the corresponding utility value (i.e. the wage if the workers is employed and the flow utility of unemployment if the worker is unemployed) and then averaging out these utilities values according to the equilibrium steady state distribution. This summary measures takes into account both the cross-sectional and the dynamics components of the labor market: the first is captured by the utility values associated to the labor market states and the second by the distribution over them since the distribution is directly related to durations and transitions probabilities[17]

We first exploit this welfare measure to address some determinants of education decisions. We have seen that women acquire more education than men even if the usual returns to schooling do not seem to suggest higher returns for women than men in the labor market. We think we can contribute to the debate by computing the returns based on our welfare measure. We can also perform the counterfactual experiments of computing what the returns would be if there were no prejudiced employers in the labor market. The results are reported in Table 9 where we compute for each year the gender-specific return of each schooling level. The first column states that completing Master or PhD increase welfare on average by about 26.8% with respect to simply completing College. The returns increase to 92.5 with respect to completing only High School and they are about 51.8% when comparing College with High School.

The comparison of men and women leads to one of the most interesting result of our analysis. In 1995, female returns are higher than male returns. This result may provide an explanation for the empirical puzzle found in the descriptive section where we observe women with higher education levels but lower hourly wages than men. By simply looking at cross-sectional wages, we are ignoring that women may have more to gain in terms of the overall labor market dynamic by acquiring additional education. Women completing Masters and PhDs receive a 30.7% return with respect to College and a 100.7% return with respect to High School; men receive, respectively, a

[17] An in depth discussion of this and similar welfare measures is in Flinn 2002. For the analytical expression of the welfare measure we use here, see Flabbi (2010a), Appendix A.5, Definition 5.

21.5% return and a 82.4% return. However, in 2005 there is essentially no difference in the returns between men and women, implying that the incentives that have in the past induced women to acquire more education may be coming to an end. The counterfactual exercise in which we compute the same measures eliminating prejudiced employers (and taking into account equilibrium effects) implies the following results: If prejudice were to be eliminated in a market similar to the one we estimate in 2005, then the welfare returns to MA and PhD would be back to be higher for women than men. Both results are robust to estimate the model only on the sample of married individuals with children younger than 18 years old, as shown in the bottom panel of Table 9.

4.2 Equal Employment Opportunity Policies

Equal Employment Opportunity policy interventions date back at least to the *Civil Rights Act* of 1964 which made it unlawful for an employer to "fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual with respect to his compensation, terms, conditions or privileges or employment, because of such individual's race, color, religion, sex, or national origin." [Section 703 (a)] The Act also established a specific institutional body to implement the law: *The Equal Employment Opportunity Commission* (EEOC). The role of the EEOC have been progressively expanded by subsequent legislation and the Commission is now responsible to enforce all the federal statutes prohibiting discrimination.

Equal Pay policies - i.e. policy specifically aiming at eliminating pay discrimination - are an active part of the equal employment opportunity policy agenda. The first Act signed by President Obama into Law after his inauguration is an example of equal pay policy. *The Lilly Ledbetter Fair Pay Act* of 2009 is a federal statue amending the *Civil Rights Act* of 1964 and stating that the 180-day statute of limitation for filing an equal-pay lawsuit regarding pay discrimination resets with each new discriminatory paycheck. Another related policy initiative is the *Paycheck Fairness Act*, which updates and strengthens the *Equal Pay Act* of 1963 to ensure better protection against sex-based pay discrimination. The Act has the objective of preventing retaliation against workers who voluntarily discuss or disclose their wages and it allows women to receive the same protections for sex-based pay discrimination that are currently available to those subject to race or ethnicity-based discrimination[18] In the context of an economic model, an equal pay policy can defined as any policy that imposes restrictions on the wage determination with the objective of equalizing differentials among clearly identified groups. A simple implementation of such a policy within the Search-Matching-Bargaining model of the previous section would be to require each employer to pay the same wage to workers with identical productivity. Enforcement of such a policy can be guaranteed by assuming that the public authority responsible of enforcing (say, the EEOC) has the possibility of observing the match-specific value of productivity. Clearly, this is a very strong

[18] The *Paycheck Fairness Act* was recently reintroduced in the 112th Congress after having twice passed the U.S. House of Representatives but falling two votes short of a Senate vote on its merits in the 111th Congress.

assumptions since the measures used to proxy productivity are often quite limited. An alternative way to think this equal pay policy is requiring that gender cannot be observed when wages and hiring are decided. Very limited examples of such a policy have been implemented in practice. Blind auditions to hire musicians implemented by some of the major US orchestras are probably the most well known (Goldin and Rouse (2000)).

We impose the requirement that each employer has to pay the same wage to workers with identical productivity by interpreting the Nash bargaining wage schedules defined in equations (5)-(7) as a reduced form sharing rules. As a result, offered wages are the average between the wages that would have been offered without the policy, where the average is over the respective proportions of men (m) and women in the population. The new wage equations are:

$$w_N(x) = \rho U + \alpha[x - \rho U] \tag{13}$$
$$w_P(x) = \rho U + \alpha[x - (1-m)d + \rho U] \tag{14}$$

where:

$$\rho U = m\rho U_M + (1-m)\rho U_W \tag{15}$$

Notice that by definition the wage equations are not gender-specific. However, they remain employer-specific, as indicated by the subscript P and N.

Results of the policy are summarized in Table 10. For each year, the first column of Table 10 reports the Benchmark model, the second the Equal Pay policy experiment and the third the Affirmative Action policy experiment that we will discuss in the next section. The Benchmark model is the model simulated using the point estimated obtained by our estimation procedure. The table reports the average welfare values by gender, year and education normalized with respect to the men's average welfare value of the appropriate year-education cell. The top panel reports values obtained from the entire sample estimates; the bottom panel reports values obtained from the married with children sample estimates. For example, looking at the first column in 2005 we observe that the average welfare of MA and PhD women is 76% of the average welfare of MA and PhD men. The value increases as education decreases, reaching about 80% on the High School graduates sample.

The Equal Pay experiment is effective in redistributing welfare from men to women but it is never enough to completely close the gender gap. In general, the equal pay policy is more effective in reducing the gap at low education levels than at high education levels. Due to the equilibrium effects and the presence of spillover, the policy has the potential to generate average net gains, i.e. a situation where the average benefit received by women is higher than the average loss experienced by men. By looking at the Overall average welfare value, we observe that this is the case only for MAs and Ph.Ds in the married with children sample. It is also marginally true on the entire sample for College and High School graduates in 1995. In conclusion, the policy imposes a very strong requirement in terms of wage determination but it does not seem to generate very large effects, with the possible exception of very high skilled individuals who are married and have young children. On the overall sample, it is a policy more effective for lower education levels than for higher ones and it has larger impacts in 1995 than in 2005.

4.3 Affirmative Action Policies

Affirmative Action policies in the labor market officially starts in the US with the 1961 *Kennedy Executive Order #10925* that mandates "affirmative action" to avoid discrimination by race in the labor market. The 1967 *Johnson Executive Order #11375* extends its application to cover women. In the legislative and policy debate an Affirmative Action policy is any anti-discrimination policy that requires proactive steps (Holzer and Neumark 2000). In the economic literature, an Affirmative Action policy is frequently described as a "quota" policy, i.e. a system of exogenously imposed numerical yardsticks for minority in hiring, federal contracting or school enrollments. A quota system definition was not mentioned in the original Presidential Executive orders but, given its convenience in providing objective measures and targets, was introduced in the subsequent regulations governing the executive orders. For example, the 1968 Department of Labor Regulations governing the 1967 Johnson executive order requires explicitly to identify "underutilization" of women and minority. The quota system definition is also the definition most frequently enforced by the Equal Employment Opportunity Commission (EEOC).

The difference between "proactive steps" and "exogenously imposed quota" seems to inform a lot of the debate on affirmative action in the labor market and in education. Holzer and Neumark (2000) provide an extensive review of the economic and public policy literature and conclude that the difference is crucial both in terms of effectiveness and in terms of political viability of the policies. Their overall conclusion is that affirmative action in the US has offered "significant redistribution toward women and minorities, with relatively small efficiency consequences." Donohue and Heckman (1991) focus on the impact of the Civil Rights legislations on labor market outcomes of African-Americans. They also broaden the definition of affirmative action beyond a simple quota system and conclude that the policies had a significant role in improving labor market outcomes. The two most recent Supreme Court opinions about affirmative action - Grutter v. Bollinger and Gratz v. Bollinger - were delivered on June 24, 2003 and stress the unconstitutionality of explicit quota policies bit the admissibility of proactive policies. Discussing, respectively, the admission policy to the College and Law School of the University of Michigan, Justice O'Connor states in the majority opinion that "a race-conscious admission program cannot use a quota system" but a "narrowly tailored plan system" in which "race or ethnicity" may be considered "a 'plus' in a particular applicant's file" constitutes a legitimate affirmative action policy. In conclusion, the tendency of the legislation and the public policy debate has been to push affirmative action policies away from rigid and exogenous quota target toward other proactive steps that could endogenously generate similar outcomes.

In line with this debate, we propose an affirmative action policy which is not a quota policy but a proactive step in the form of a subsidy. The policy is defined as a flow subsidy received by an employer for each woman hired. The subsidy is paid by a lump-sum tax on workers. Defining with γ the subsidy and with t the endogenous tax rate necessary to finance it, the new wage equations become:

$$w_M(x,\gamma) = \rho U_M(\gamma) + t(\gamma) + \alpha[x - t(\gamma) - \rho U_M(\gamma)] \tag{16}$$

$$w_{WN}(x,\gamma) = \rho U_W(\gamma) + t(\gamma) + \alpha[x + \gamma - t(\gamma) - \rho U_W(\gamma)] \tag{17}$$

$$w_{WP}(x,\gamma) = \rho U_W(\gamma) + t(\gamma) + \alpha[x + \gamma - d - t(\gamma) - \rho U_W(\gamma)] \tag{18}$$

The first equation states that men receive a wage that should compensate for the tax they pay but takes into account the reduced surplus implied by the tax. The second equation states that women working at unprejudiced employers receive the same tax effects but at the same time see the surplus increased by the subsidy γ. Finally, the third equation states that women working at prejudiced employers receive similar impacts from the presence of the tax and the subsidy but still share the cost of the disutility implied by prejudice. We denote the tax rate and the value of unemployment as a function of γ to emphasize that they are endogenous objects changing with the subsidy.

A subsidy does not impose any predetermined quota but by being offered only for hiring women, definitely make gender a "a ’plus’ in" some "applicant’s file", as stated in the Supreme Court opinion. The impact of the policy is magnified by the spillover effects: not only the presence of a flow subsidy has a direct positive impact on women wages because firms receive additional revenue from hiring them but also has an indirect positive impact because it increases women’s outside option. We fix the subsidy to be equal to 5% of men’s average wage in the corresponding year and education group.

The results of the subsidy policy are reported in the third column of each year in Table 10. The policy is less effective in closing the gap than the equal pay policy is but at the same time it is generating more net gains. Net gains are realized in both 1995 and 2005 on the College sample and in 1995 on the Master and PHD sample. Another advantage of the policy is that it can be calibrated more precisely by increasing or decreasing the subsidy and its costs can be distributed in a variety of ways by changing the structure of the tax necessary to support it. In this respect, the lump-sum tax implemented here is the least distortionary for the economy but it is also the most costly for men. If even under this scheme, more than half of the education-year combinations generate positive gains then an affirmative action policy structured as a subsidy should be seen as the policy with the larger potential for success among the two policies considered here. It is also the policy that generates the largest impact on the group that the previous evidence has shown to be the most problematic: Women with top education skills, supplying labor in the most recent years.

In conclusion, an affirmative action policy structured as a relative modest subsidy provided to employers that hire women has a modest but positive impact in closing the gender gap in welfare. Despite the modest impact, the policy is promising because it is frequently able to close the gap without reducing overall welfare and it is effective in targeting the most problematic education and demographic group: Master and Ph.D. graduated who are married and with young children, observed in 2005.

5 Summary and Conclusions

5.1 Summary of Results

Three main results emerge from the descriptive evidence on gender differentials by education in the US labor market over the last twenty years.

1. Women acquire more college education than men, reinforcing a trend started with the generation born in 1959. The proportion of women with a Master or PhD degree is still smaller than the proportion of men but the differential is shrinking.

2. Women participate less than men in the labor market but when they do, they obtain similar employment rates. The intensive margin of the labor supply shows a large gender gap, mainly as a result of the larger incidence of part-time work among female workers. The gender gap in labor supply is not reduced but actually magnified by additional education.

3. The gender earnings gap is about 20%, even after controlling for standard human capital and demographics characteristics. The gap shows a significant reduction over time (it was about 35% in the early 1980s) but has remained fairly stable in the last 10/15 years. One reason for the persistent gender gap in recent years among highly-educated workers is the large differential at the top of the earnings distribution, an evidence often correlated with "glass-ceiling" effects.

We use a search-matching-bargaining model to investigate some of the sources of the observed gender differentials. We focus on gender differentials with the objective of isolating the impact of three determinants of gender gaps: productivity differences; employers' prejudice; and search frictions. Four main results emerge from the analysis.

1. Prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time and it becomes smaller than the impact of productivity on all education groups in 2005.

2. Search frictions actually favors women, thanks to the higher frequency with which they receive job offers.
3. Master and PhD graduates are an exception to the decreasing impact of prejudice over time: they experience a stronger impact of prejudice in explaining the wage gap in 2005 than in 1995. We find that a good portion of this result is due to sample of individuals married and with young children.
4. We also decompose the impact of the three sources of the gender wage gap at different point of the distribution: the data show evidence of glass-ceiling effects on the Master and PhD sample in 2005, a result that only the equilibrium effects of all three factors together is able to partially explain.

We use the structural estimates of the model to build a welfare measure to evaluate returns to education and two policy interventions. The first policy is an equal pay policy imposing one wage at same productivity, the second is an affirmative action policy providing incentives to hire women. Three main results emerge from the exercise:

1. In 1995, female returns to schooling estimated using our welfare measure are higher than male returns. This new result provides a rationale for the apparent empirical puzzle of women acquiring more education than men even if they are paid less for these skills in the labor market. In 2005, female returns are estimated to be lower than male returns, implying that women attitudes toward education could change, reversing the positive education gap.
2. The equal pay policy redistributes welfare from men to women but it is not able to fully close the gender gap. Given the strong requirement in terms of wage determination imposed by the policy, we judge it not very effective.
3. The Affirmative Action policy has a smaller impact on closing the gender gap than the equal pay policy but it is more likely to generate net welfare gains. The impact of the policy is increasing in the education level of the worker and it seems to target well the most problematic education and demographic group: Master and Ph.D. graduated who are married and with young children, observed in 2005.

5.2 Shortcomings of our Model

As any policy evaluations using the structure and the estimated parameters of a highly stylized model, our results depend on the assumptions we have made. We want to at least discuss a few of these simplifying assumptions, choosing the ones we think are more relevant for the policy implications we have obtained. First, we have assumed that workers do not search for new jobs while they are employed. Removing this assumption may give additional opportunities to women to leave prejudiced employers and potentially reduce the impact of discrimination on labor market outcomes. If this is actually the case crucially depends on the gender differential in the arrival rate of offers while working. Since a lot of the time use evidence shows strong gender asymmetries in the time devoted to household production, it is not clear if women will have enough time to search on the job. If they do not, then the results of an on-the-job search model should not be radically different from the results we have found with our model.

Second, we have assumed that the proportion of prejudiced employers is fixed and exogenous, even if we allow their impact on labor market outcomes to be endogenous. If we were able to let the proportion of prejudiced employers depends on the model parameters, then we could study the impact of our policy experiments on prejudiced employers who actually survive in equilibrium. For example, our affirmative action policy, by giving incentive to hire women, it is clearly favoring employers with lower costs in doing so, i.e. employers that do not receive any disutility from hiring women. In this respect, our policy experiments of Section 4 should be considered a lower bound of the possible impact of the policies considered.

Finally, we have assumed that a job is fully described by its wage, with no other job characteristics taken into consideration. This is a crucial limitation when comparing men and women since they have different preference over job characteristics. For example, Flabbi and Moro (2012) claim that job flexibility may be crucial in explaining not only gender differentials in the labor market but also gender differential in education. As a result, technology and legislation able to reduce the cost of part-time or tele-commuting may accommodate preferences for flexibility, increase the range of jobs available to women, and possibly decrease opportunities for prejudiced employers.

5.3 Conclusions

We think the evidence provided in this paper indicates that gender gaps in labor market outcomes are far from being settled issues. On top of the traditional issues of lower participation rates and gender gaps in wages, new issues that are likely to become more relevant in the future include:

1. Convergence in education levels is not enough to close gender gaps in the labor market.
2. Evidence of "glass-ceiling" effects. The evidence includes a marked underrepresentation of women in top positions at the firm and a larger gender wage gap at the top of the wage distribution.

The conclusion of our analytical contribution is that prejudice may still have a role in explaining the evidence. Even if the magnitudes of our effects are conditional on a highly stylized model, we characterize in some details at least one scenario were the possibility of the presence of prejudiced employers in the labor market has substantial effects. In particular, it is responsible for the reversal of the return to schooling ranking in recent years and it may explain up to 44% of the gender wage gap of the top education group (Master and PhD) in 2005.

If prejudice is still important, then policy interventions may be effective in attaining both efficiency and welfare gains. We use our model to evaluate an equal pay policy and an affirmative action policy. Among the policies we consider, we favor an affirmative action policy structured as a relative modest subsidy provided to employers for hiring women. We favor this policy because it is frequently able to close the gender gap without reducing overall welfare and because it is effective in targeting the group that should take center stage in the future debate about gender differentials: high-skilled, high-earners workers, who also have family responsibilities.

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Appendix: Data Sources and Definitions

Data used in the Descriptive Evidence section.

The data used in the descriptive evidence section are extracted from the Annual Social and Economics Supplement (ASES or March Supplement) and the School Enrollment Supplement (October Supplement) of the Current Population Survey (CPS). The first supplement contains data on family characteristics, household composition, marital status, education attainment, earnings, labor market status, work experience, job characteristics. The second focuses on school enrollment, college attendance, fields of study, major choices. Both supplements are conducted annually. We use the March yearly supplement from 1981 to 2011 and the October supplement in 2002. We use only the 2002 supplement because it is the only one reporting Field of Study choice.

Individual characteristics

The individual characteristics are obtained from the CPS questions on gender, race, age, marital status, and presence of kids under 18 years in the household. The year of birth, for the analysis by cohort, was inferred from the year of the survey and the age.

Education Level and Fields of Study

The education levels and fields of study choices are obtained from the set of questions related to education attainment in the March Supplement and with school enrolment in the October Supplement. We classify Education level in three groups according to the highest degree obtained: (1) Masters and Doctorate degree, (2) College degree and (3) High School degree. It is important to mention that this classification is used from 1992 onward, because in that year there was a major change in the coding of the CPS data to classify education attainment. For the survey years before 1992, we simply define college graduates as persons with 14 years or more of education.

The gap in Figures 1 and 2 is calculated as a percentage difference with respect to men, that is $\frac{(x_W - x_M)}{x_M}$ where x is percentage of college graduates.

The Field of Choice variable is only collected in the October supplement of 2002 and this is why Figures 4 and 5 reports the distribution only on 2002.

Labor Market Status

The labor market status (employment, unemployment and nonparticipation) is obtained by a set of questions organized by the CPS team in the monthly labor force recode variable which directly assigns each individual in the sample to employment, unemployment or not-in-the labor force status. Excluded from the universe are kids and individuals in the armed forces.

Earnings and Hours Worked

Hourly earnings are obtained either by using the value directly reported in the CPS survey or by computing the value dividing weekly earnings by the usual hours worked per week. Earnings are measured in real terms. We express Earnings in 2005 US dollars by deflating them by the Consumer Price Index for All Urban Consumers. For hours worked we use, as before, the usual hours worked per week directly reported in the survey.

Unemployment Durations

Unemployment durations are measured in months and they are obtained by rescaling the original weekly unemployment durations reported in the CPS.

Job Characteristics

The job characteristics are obtained from the set of questions related to full/part time job and occupational classification. The codes in this last variable are the 2002 NAICS equivalent. It is important to mention that all the descriptive analysis related with occupations is done from 2002 onward because in that year there was a major change in the coding used in the CPS to classify occupations.

Data used in the Impact of Employer's Prejudice Section

The data used in the structural estimation of the search-matching-bargaining model with employers taste discrimination are extracted from the March Supplement of the CPS for 1995 and 2005. These years were chosen because they satisfy two criteria. First, these are years neither boom nor recession years, and therefore they seem appropriate to describe a model under the steady state assumption. Second, they are equally spaced over-time and far away enough to potentially describe different steady-states.

An important assumption in the model is ex-ante agents' homogeneity. To obtain the estimation sample, we extract individuals homogenous sample with respect to the following characteristics: race (white), age (30 to 55 years old) and education (MA and PhD; College; High School).

The variables used in the estimation are: real hourly wages, unemployment duration in month, gender, education level, and labor market status. Wages are available only for individuals currently employed and unemployed duration only for individuals currently unemployed. As a result unemployment durations are not complete spells but on-going spells.

Table 1 presents number of observations and descriptive statistics, by education level and year, of the sample used in the Maximum Likelihood Estimation procedure.

Figure 1: Gender Gap in Percentage of Graduates by Cohort

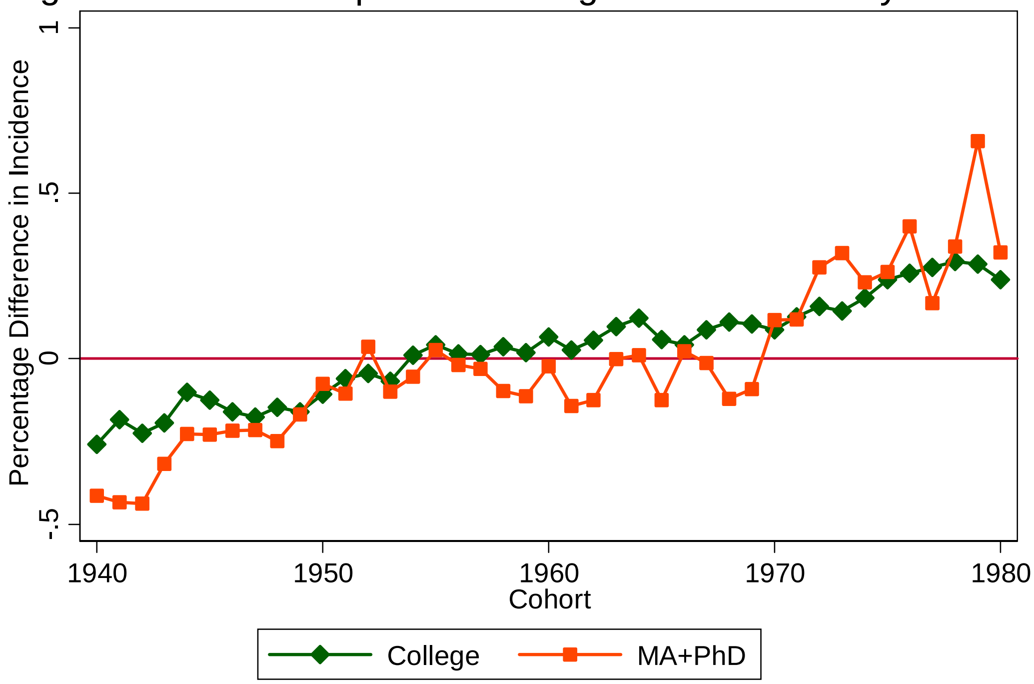
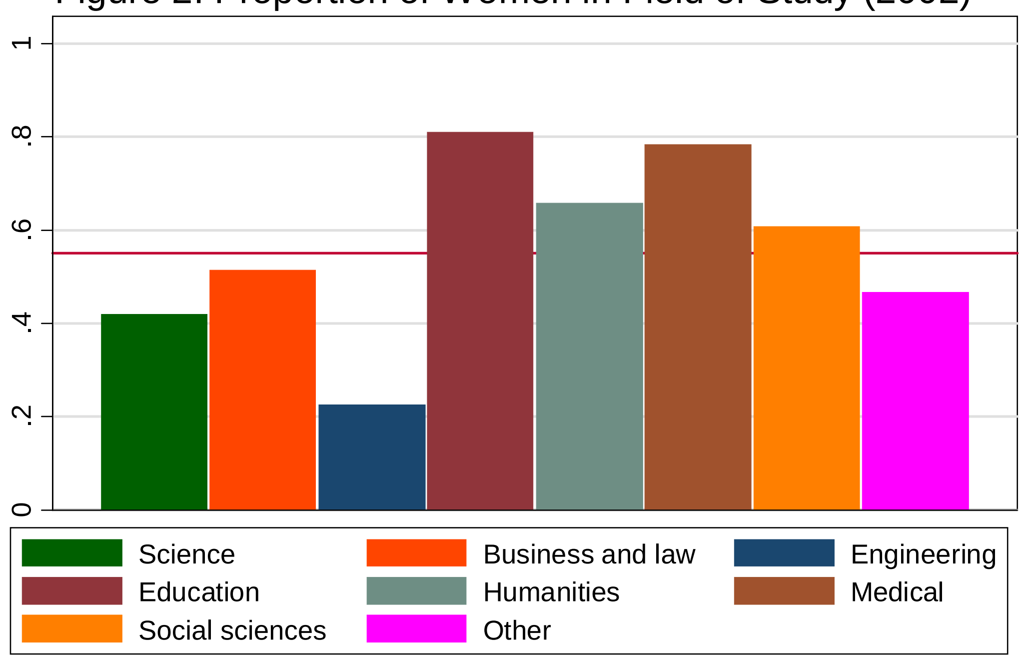


Figure 2: Proportion of Women in Field of Study (2002)



Note: 30-45 years old.

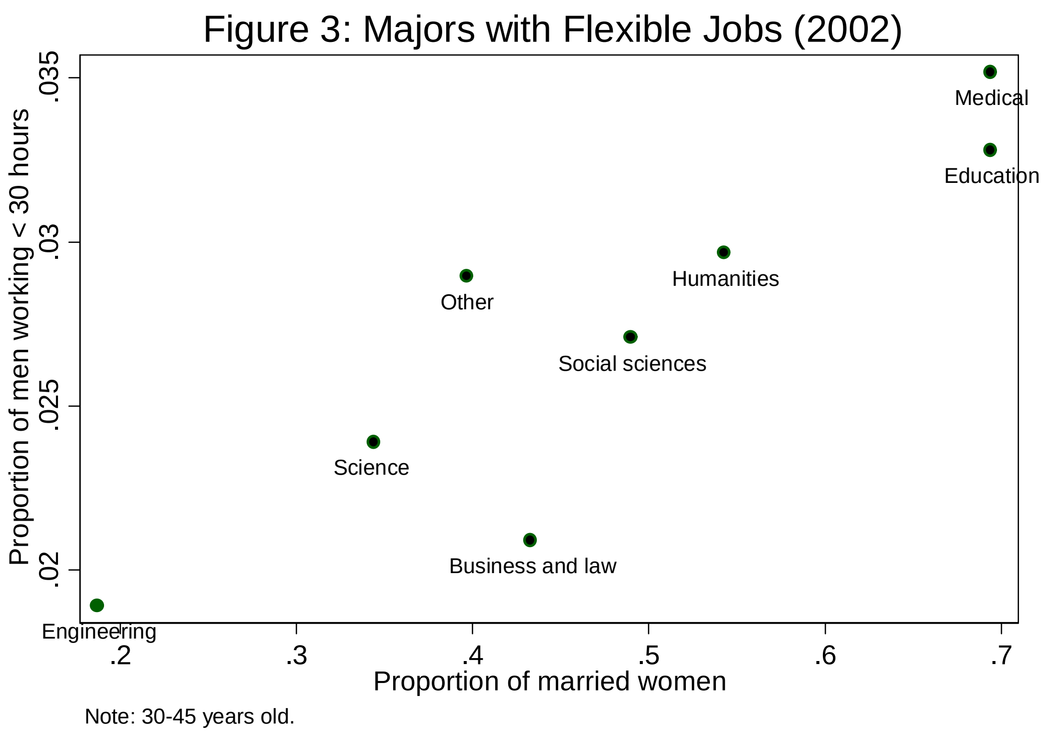


Figure 3: Majors with Flexible Jobs (2002)
Proportion of men working < 30 hours
.02
.025
.03
.035
Medical
Education
Humanities
Other
Social sciences
Science
Business and law
Engineering
.2
.3
.4
.5
.6
.7
Proportion of married women
Note: 30-45 years old.

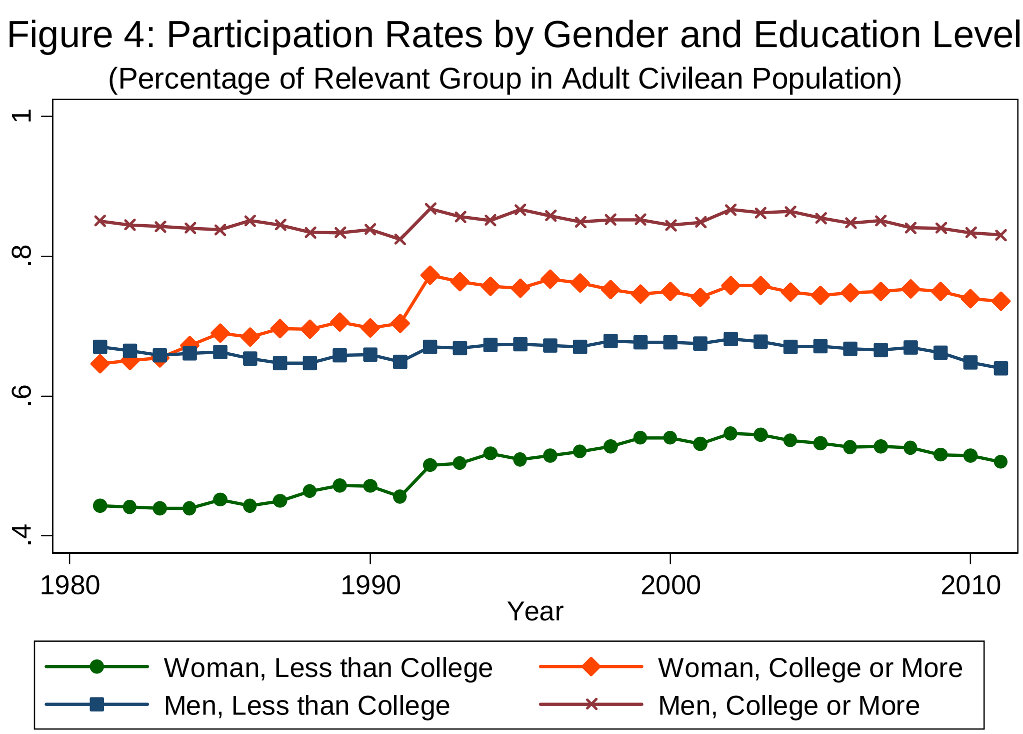


Figure 4: Participation Rates by Gender and Education Level
(Percentage of Relevant Group in Adult Civilean Population)
.4
.6
.8
1
1980
1990
2000
2010
Year
Woman, Less than College
Woman, College or More
Men, Less than College
Men, College or More

Figure 5: Employment Rates by Gender and Education Level

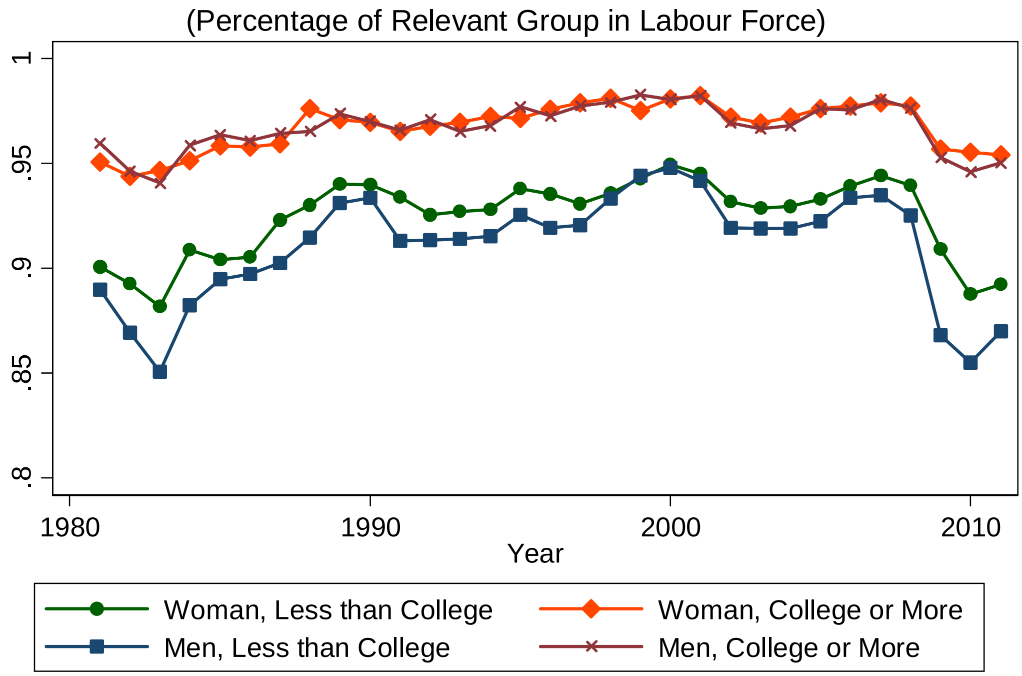


Figure 6: Gender Gaps in Part Time Occupations

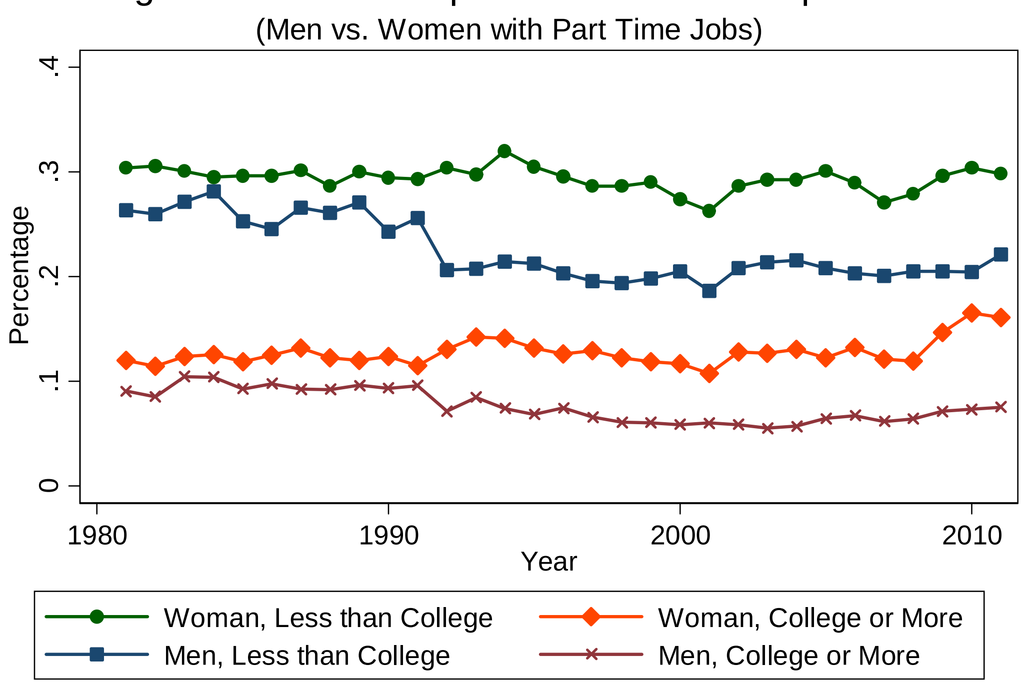
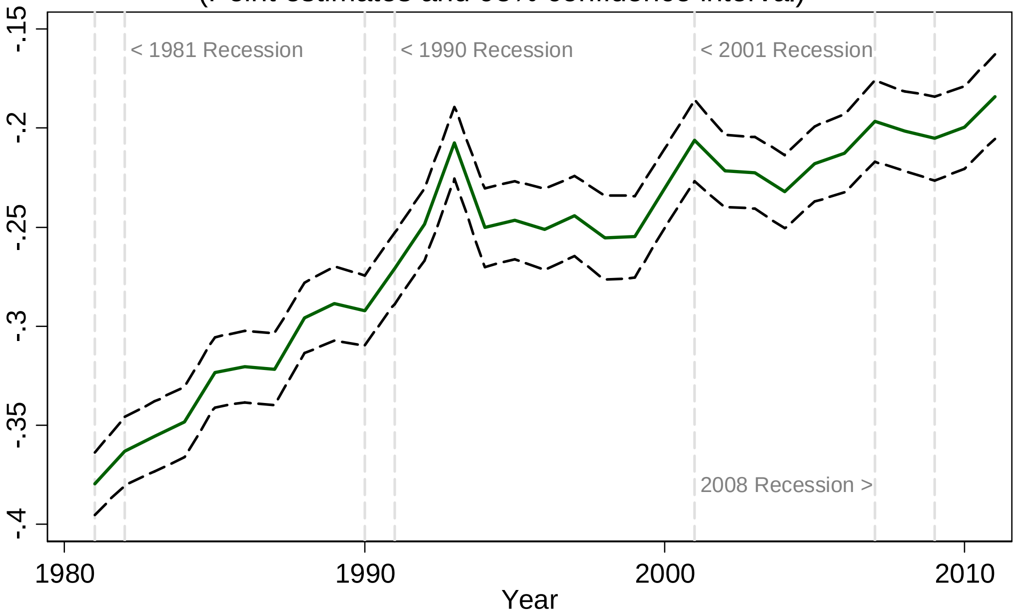


Figure 7a: Gender Earnings Differential Over Time, Unconditional Case

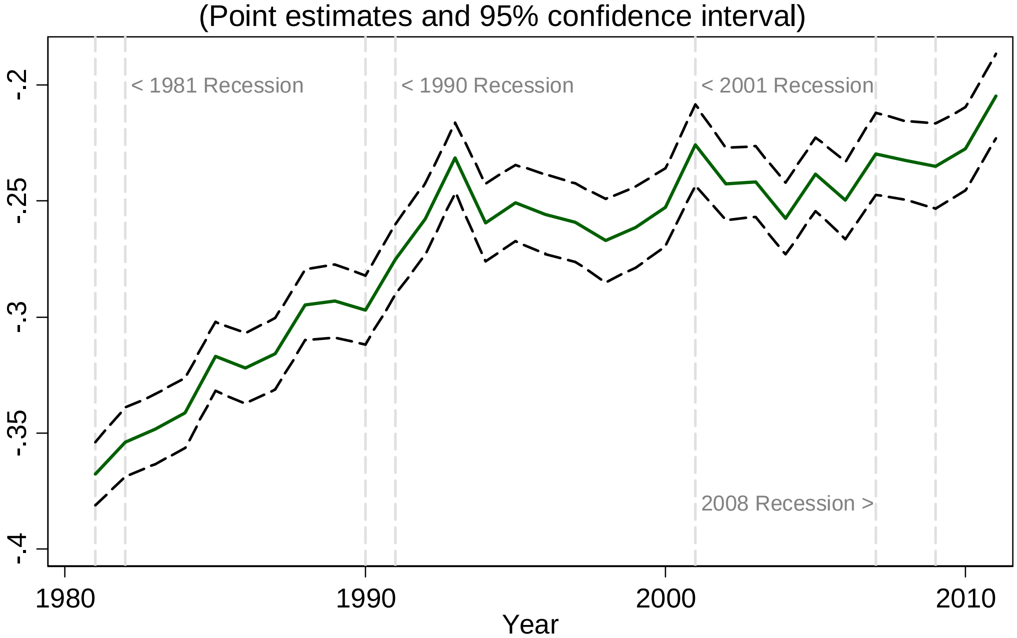
(Point estimates and 95% confidence interval)



Note: Dashed Lines represent 95% confidence interval.

Figure 7b: Gender Earnings Differential Over Time, Conditional Case

(Point estimates and 95% confidence interval)



Note: Dashed Lines represent 95% confidence interval.

Figure 8: Gender Gap in Log Hourly Earnings by Percentile and Year

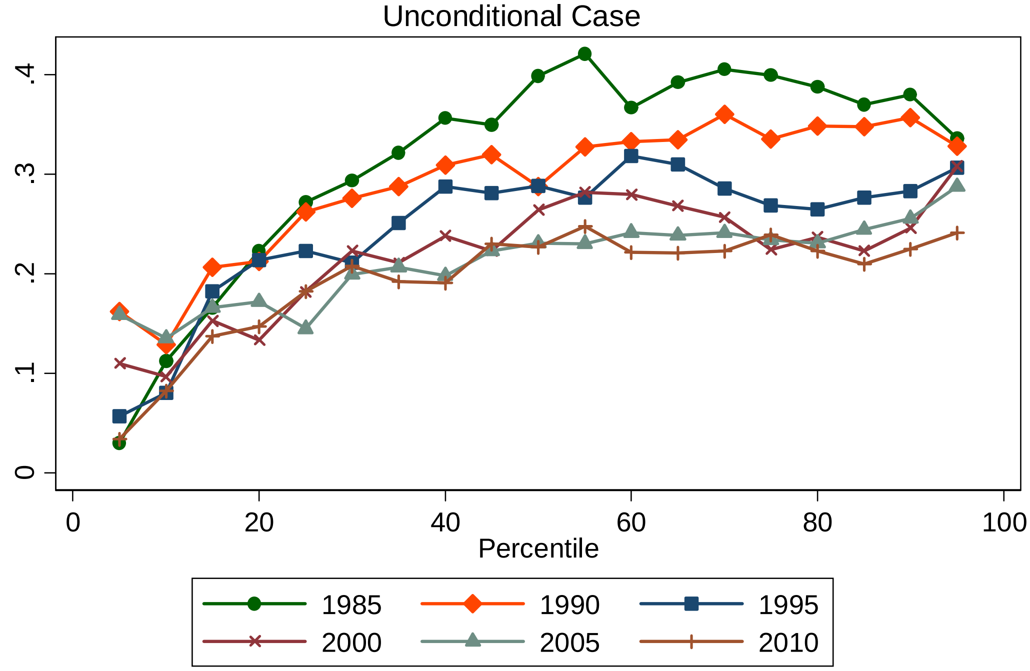


Figure 9: Gender Composition of Managerial Occupations

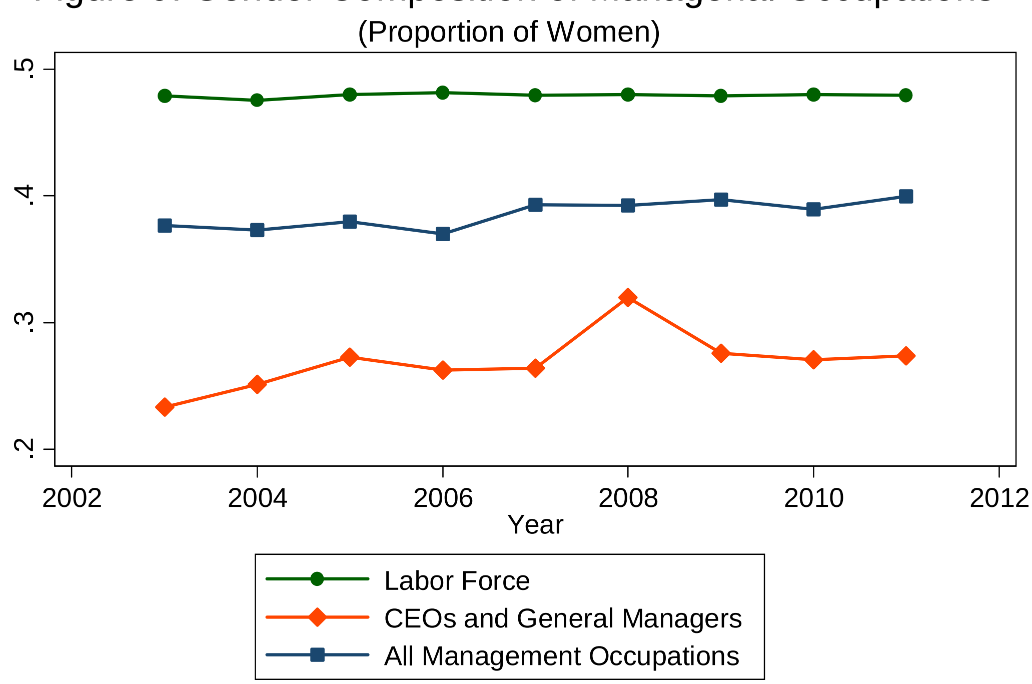
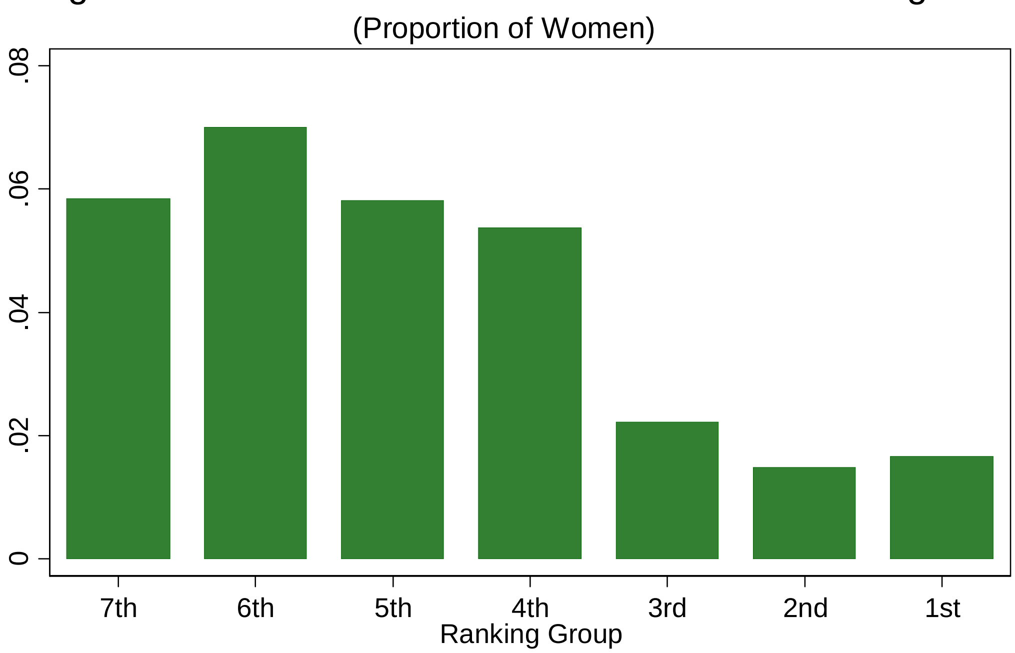


Figure 10: Positions within CEOs and General Managers



Note: Gayl, Golan and Miller (2009), Table 1.

Table 1. Descriptive Statistics - Estimation Sample

		Master and PhD		College		High School	
		1995	2005	1995	2005	1995	2005
Observations							
N		711	861	2290	2891	3942	4019
N (Wages,Women)		306	437	1071	1420	1856	1850
N (Duration,Women)		5	9	45	54	92	106
N (Wages,Men)		394	403	1141	1362	1867	1933
N (Duration,Men)		6	12	33	55	127	130
Hourly Earnings in Dollars							
Overall							
	Average	27.79	31.26	22.86	24.74	15.60	16.46
	Std. Dev.	12.89	36.74	11.73	15.44	7.35	8.22
Women							
	Average	24.55	26.43	19.79	21.83	12.88	14.20
	Std. Dev.	10.10	12.04	10.19	15.97	5.92	7.11
Men							
	Average	30.30	36.49	25.74	27.78	18.30	18.63
	Std. Dev.	14.20	51.06	12.34	14.24	7.63	8.62
Diff(%)							
	Average	-18.97	-27.56	-23.11	-21.41	-29.64	-23.81
Monthly Unemployment Duration							
Overall							
	Average	6.73	3.87	4.38	5.06	4.12	4.36
	Std. Dev.	7.07	4.19	5.15	5.79	5.12	5.15
Women							
	Average	4.02	4.18	3.82	4.42	3.69	4.20
	Std. Dev.	4.14	4.40	4.39	5.16	3.97	5.37
Men							
	Average	9.00	3.63	5.13	5.69	4.42	4.49
	Std. Dev.	8.52	4.21	6.04	6.33	5.81	4.98
Diff(%)							
	Average	-55.38	14.99	-25.57	-22.26	-16.52	-6.37

Note: Data extracted from the Annual Social and Economic Supplement (March Supplement) of the CPS for the years 1995 and 2005. In each education label the sample includes individuals who are white and 30 to 55 years old.

Table 2. Maximum Likelihood Estimation Results (Entire Sample) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
λ_M	0.1119	0.2781	0.1965	0.1798	0.2298	0.2299
	(0.0457)	(0.0803)	(0.0342)	(0.0243)	(0.0204)	(0.0202)
λ_W	0.2906	0.3003	0.2731	0.2345	0.2869	0.2493
	(0.1355)	(0.1249)	(0.0410)	(0.0324)	(0.0304)	(0.0246)
η_M	0.0017	0.0082	0.0056	0.0071	0.0154	0.0150
	(0.0010)	(0.0034)	(0.0014)	(0.0014)	(0.0020)	(0.0019)
η_W	0.0041	0.0049	0.0110	0.0086	0.0134	0.0136
	(0.0026)	(0.0023)	(0.0023)	(0.0017)	(0.0020)	(0.0019)
μ_M	3.7536	3.8622	3.5851	3.6000	3.2107	3.1833
	(0.0290)	(0.0335)	(0.0184)	(0.0193)	(0.0135)	(0.0152)
σ_M	0.5587	0.6426	0.5983	0.6499	0.5477	0.5910
	(0.0220)	(0.0258)	(0.0140)	(0.0152)	(0.0105)	(0.0120)
μ_W	3.6618	3.6937	3.5879	3.4058	3.0319	2.9675
	(0.0374)	(0.0518)	(0.1058)	(0.0411)	(0.1003)	(0.0459)
σ_W	0.4289	0.4931	0.4607	0.6153	0.4876	0.5563
	(0.0246)	(0.0378)	(0.0398)	(0.0253)	(0.0390)	(0.0236)
p	0.1506	0.2117	0.7584	0.1231	0.9999	0.2811
	(0.0469)	(0.1079)	(0.2790)	(0.1391)	(0.0039)	(0.2609)
k	1.3796	1.3796	0.2513	0.2513	0.1399	0.1399
	(3.8471)	(3.8471)	(0.0679)	(0.0679)	(0.0763)	(0.0763)
w^*_M	10.8382	10.8800	8.5801	10.0000	7.6605	8.0000
w^*_W	8.9373	10.0713	6.4249	7.2500	5.5156	6.0000
$\ln L$	-6142		-19721		-26548	
N	1572		5181		7961	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 3. Maximum Likelihood Estimation Results (Married) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
λ_M	0.0534	0.2798	0.2062	0.1975	0.2539	0.2649
	(0.0378)	(0.0885)	(0.0404)	(0.0305)	(0.0251)	(0.0269)
λ_W	0.2312	0.2082	0.3018	0.2256	0.2873	0.2503
	(0.1220)	(0.1275)	(0.0477)	(0.0347)	(0.0316)	(0.0256)
η_M	0.0003	0.0077	0.0054	0.0068	0.0155	0.0150
	(0.0003)	(0.0034)	(0.0015)	(0.0015)	(0.0022)	(0.0022)
η_W	0.0031	0.0021	0.0126	0.0076	0.0135	0.0141
	(0.0022)	(0.0013)	(0.0028)	(0.0016)	(0.0021)	(0.0021)
μ_M	3.7581	3.8349	3.6079	3.6389	3.2447	3.2280
	(0.0314)	(0.0396)	(0.0196)	(0.0197)	(0.0136)	(0.0153)
σ_M	0.5557	0.6734	0.5932	0.6303	0.5251	0.5719
	(0.0241)	(0.0312)	(0.0149)	(0.0154)	(0.0106)	(0.0120)
μ_W	3.6321	3.6891	3.5690	3.3913	2.9446	2.9363
	(0.0423)	(0.0598)	(0.1208)	(0.0450)	(0.0950)	(0.0154)
σ_W	0.4497	0.4867	0.4702	0.6191	0.5168	0.5696
	(0.0312)	(0.0604)	(0.0443)	(0.0278)	(0.0402)	(0.0121)
p	0.1208	0.2398	0.7242	0.1074	0.9998	0.0003
	(0.0875)	(0.2045)	(0.3361)	(0.1480)	(0.0189)	(0.0121)
k	1.5765	1.5765	0.2731	0.2731	0.0718	0.0718
	(6.9760)	(6.9760)	(0.0803)	(0.0803)	(0.0626)	(0.0626)
w_M^*	11.8227	12.5000	8.9373	10.2427	10.8382	10.8800
w_W^*	9.2520	10.0750	6.6678	7.4010	8.9373	10.0713
$\ln L$	-5309		-17222		-23545	
N	1365		4532		7086	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 4. Maximum Likelihood Estimation Results (Married with Children) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
λ_M	0.0534	0.2798	0.2062	0.1975	0.2539	0.2649
	(0.0378)	(0.0885)	(0.0404)	(0.0305)	(0.0251)	(0.0269)
λ_W	0.2312	0.2082	0.3018	0.2256	0.2873	0.2503
	(0.1220)	(0.1275)	(0.0477)	(0.0347)	(0.0316)	(0.0256)
η_M	0.0003	0.0077	0.0054	0.0068	0.0155	0.0150
	(0.0003)	(0.0034)	(0.0015)	(0.0015)	(0.0022)	(0.0022)
η_W	0.0031	0.0021	0.0126	0.0076	0.0135	0.0141
	(0.0022)	(0.0013)	(0.0028)	(0.0016)	(0.0021)	(0.0021)
μ_M	3.7581	3.8349	3.6079	3.6389	3.2447	3.2280
	(0.0314)	(0.0396)	(0.0196)	(0.0197)	(0.0136)	(0.0153)
σ_M	0.5557	0.6734	0.5932	0.6303	0.5251	0.5719
	(0.0241)	(0.0312)	(0.0149)	(0.0154)	(0.0106)	(0.0120)
μ_W	3.6321	3.6891	3.5690	3.3913	2.9446	2.9363
	(0.0423)	(0.0598)	(0.1208)	(0.0450)	(0.0950)	(0.0154)
σ_W	0.4497	0.4867	0.4702	0.6191	0.5168	0.5696
	(0.0312)	(0.0604)	(0.0443)	(0.0278)	(0.0402)	(0.0121)
p	0.1208	0.2398	0.7242	0.1074	0.9998	0.0003
	(0.0875)	(0.2045)	(0.3361)	(0.1480)	(0.0189)	(0.0121)
k	1.5765	1.5765	0.2731	0.2731	0.0718	0.0718
	(6.9760)	(6.9760)	(0.0803)	(0.0803)	(0.0626)	(0.0626)
w_M^*	11.8227	12.5000	8.9373	10.2427	10.8382	10.8800
w_W^*	9.2520	10.0750	6.6678	7.4010	8.9373	10.0713
$\ln L$	-5309		-17222		-23545	
N	1365		4532		7086	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 5. Estimation Results - Predicted Productivity and Wages

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
			Men			
Productivity						
Average	49.88	58.48	43.12	45.20	28.81	28.73
	(1.509)	(2.052)	(0.828)	(0.876)	(0.393)	(0.422)
Variance	911.33	1748.68	800.26	1074.05	290.35	345.02
	(113.068)	(241.048)	(61.566)	(82.764)	(16.632)	(20.879)
Offered Earnings						
Average	30.36	34.68	25.85	27.60	18.24	18.36
	(0.754)	(1.026)	(0.414)	(0.438)	(0.196)	(0.211)
Accepted Earnings						
Average	30.50	34.95	26.00	28.04	18.42	18.72
	(0.753)	(1.028)	(0.414)	(0.437)	(0.194)	(0.207)
			Woman			
Productivity						
Average	42.68	45.39	40.21	36.42	23.35	22.70
	(1.485)	(2.210)	(3.587)	(1.091)	(1.916)	(0.796)
Variance	367.94	567.13	382.25	610.60	146.42	186.91
	(50.505)	(113.378)	(33.931)	(49.093)	(8.280)	(11.983)
Offered Earnings						
Average	25.03	25.92	20.20	21.75	12.42	14.19
	(2.600)	(5.538)	(0.777)	(1.202)	(0.213)	(0.817)
Average at Prejudiced	20.63	19.19	19.21	21.14	12.42	13.78
	(15.127)	(24.569)	(0.378)	(0.702)	(0.213)	(0.600)
Average at Unprejudiced	25.81	27.73	23.31	21.84	14.44	14.35
	(0.742)	(1.105)	(1.794)	(0.546)	(0.958)	(0.398)
Accepted Earnings						
Average	24.53	26.44	19.77	21.66	12.88	14.17
	(1.711)	(3.453)	(0.369)	(0.325)	(0.204)	(0.162)
Average at Prejudiced	17.32	21.46	18.64	19.31	12.88	13.32
	(9.401)	(16.124)	(1.169)	(0.503)	(0.204)	(0.503)
Average at Unprejudiced	25.81	27.78	23.32	21.99	14.47	14.51
	(0.740)	(1.092)	(1.790)	(0.493)	(0.913)	(0.332)

Notes: The table reported predicted values based on the Maximum Likelihood estimated structural parameters. Estimated parameters are reported in Table 2. Asymptotic standard errors by Delta method in parentheses.

Table 6. Estimation Results - Predicted Labor Market Dynamics

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
			Men			
Hazard Rate out of Unemployment						
Overall	0.1111	0.2751	0.1948	0.1757	0.2261	0.2228
	(0.0454)	(0.0794)	(0.0339)	(0.0237)	(0.0201)	(0.0195)
To a Prejudiced	0.0167	0.0582	0.1478	0.0216	0.2261	0.0626
	(0.0086)	(0.0341)	(0.0601)	(0.0246)	(0.0201)	(0.0584)
To an Unprejudiced	0.0943	0.2169	0.0471	0.1541	0.00001	0.1602
	(0.0389)	(0.0693)	(0.0550)	(0.0321)	(0.0009)	(0.0598)
Hazard Rate out of Employment						
Overall	0.0017	0.0082	0.0056	0.0071	0.0154	0.0150
	(0.0010)	(0.0034)	(0.0014)	(0.0014)	(0.0020)	(0.0019)
Labor Market Status						
Emp. Rate at Prejudiced	0.1483	0.2056	0.7371	0.1183	0.9362	0.2634
	(0.0462)	(0.1048)	(0.2712)	(0.1337)	(0.0066)	(0.2445)
Emp. Rate at Unprejudiced	0.8367	0.7655	0.2348	0.8429	0.0001	0.6736
	(0.0465)	(0.1050)	(0.2712)	(0.1338)	(0.0036)	(0.2445)
Unemployment Rate	0.0150	0.0289	0.0281	0.0388	0.0637	0.0630
	(0.0061)	(0.0082)	(0.0048)	(0.0051)	(0.0055)	(0.0053)
			Woman			
Hazard Rate out of Unemployment						
Overall	0.2491	0.2393	0.2619	0.2261	0.2709	0.2380
	(0.1114)	(0.0798)	(0.0390)	(0.0308)	(0.0282)	(0.0231)
To a Prejudiced	0.0023	0.0031	0.1959	0.0226	0.2709	0.0619
	(0.0271)	(0.0315)	(0.0823)	(0.0273)	(0.0283)	(0.0620)
To an Unprejudiced	0.2468	0.2361	0.0660	0.2035	0.00002	0.1761
	(0.1136)	(0.0848)	(0.0776)	(0.0388)	(0.0011)	(0.0640)
Hazard Rate out of Employment						
Overall	0.0041	0.0049	0.0110	0.0086	0.0134	0.0136
	(0.0026)	(0.0023)	(0.0023)	(0.0017)	(0.0020)	(0.0019)
Labor Market Status						
Emp. Rate at Prejudiced	0.0092	0.0128	0.7179	0.0963	0.9527	0.2459
	(0.1070)	(0.1287)	(0.2821)	(0.1157)	(0.0062)	(0.2451)
Emp. Rate at Unprejudiced	0.9747	0.9670	0.2418	0.8671	0.0001	0.6999
	(0.1072)	(0.1294)	(0.2821)	(0.1161)	(0.0039)	(0.2452)
Unemployment Rate	0.0161	0.0202	0.0403	0.0366	0.0472	0.0542
	(0.0071)	(0.0123)	(0.0059)	(0.0108)	(0.0048)	(0.0090)

Notes: The table reported predicted values based on the Maximum Likelihood estimated structural parameters. Estimated parameters are reported in Table 2. Asymptotic standard errors by Delta method in parentheses.

Table 7. Wage Gap Decomposition - Woman/men ratio on average accepted wage

Gap Generated by:	1995 Overall	1995 Top 50%	1995 Top 25%	1995 Top 10%	2005 Overall	2005 Top 50%	2005 Top 25%	2005 Top 10%
Master and PhD								
Productivity	0.835	0.883	0.865	0.857	0.699	1.628	1.344	1.130
Prejudiced	0.935	0.958	0.971	0.982	0.881	0.923	0.950	0.974
Search Frictions	1.337	1.195	1.139	1.088	1.052	1.031	1.021	1.013
All Parameters	0.804	0.867	0.853	0.849	0.756	0.857	0.841	0.834
Sample	0.823	0.791	0.793	0.812	0.728	0.682	0.638	0.568
College								
Productivity	0.911	0.937	0.911	0.892	0.758	0.827	0.838	0.857
Prejudiced	0.801	0.862	0.898	0.931	0.976	0.984	0.988	0.993
Search Frictions	1.116	1.073	1.054	1.036	1.106	1.066	1.047	1.030
All Parameters	0.760	0.824	0.824	0.828	0.773	0.837	0.846	0.862
Sample	0.779	0.779	0.775	0.797	0.794	0.793	0.806	0.869
High School								
Productivity	0.769	0.777	0.772	0.770	0.742	0.766	0.771	0.780
Prejudiced	0.853	0.888	0.910	0.932	0.964	0.974	0.980	0.985
Search Frictions	1.091	1.063	1.050	1.038	1.036	1.025	1.019	1.014
All Parameters	0.699	0.718	0.723	0.731	0.757	0.776	0.779	0.787
Sample	0.701	0.711	0.724	0.745	0.763	0.763	0.778	0.793

Notes: Women/men ratio on average accepted earnings computed over the entire distribution and over the top 50%, the top 75% and the top 10%. All counterfactual s are generated taking into account equilibrium effects.

Table 8. Wage Gap Decomposition Conditioning on Marital Status and Children - Woman/men ratio on average accepted wage

Gap Generated by:	1995 Entire Sample	1995 Married	1995 Married with Kids	2005 Entire Sample	2005 Married	2005 Married with Kids
			Master and PhD			
Productivity	0.835	0.835	0.884	0.699	0.698	0.874
Prejudiced	0.935	0.964	0.960	0.881	0.878	0.812
Search Frictions	1.337	1.387	1.373	1.052	0.895	1.064
All Parameters	0.804	0.793	0.778	0.756	0.727	0.729
Sample	0.823	0.820	0.809	0.728	0.700	0.752
			College			
Productivity	0.911	0.872	0.754	0.758	0.719	0.735
Prejudiced	0.801	0.795	0.877	0.976	0.976	0.984
Search Frictions	1.116	1.135	1.072	1.106	1.051	1.070
All Parameters	0.760	0.737	0.736	0.773	0.753	0.751
Sample	0.779	0.758	0.753	0.794	0.774	0.775
			High School			
Productivity	0.769	0.697	0.628	0.742	0.701	0.666
Prejudiced	0.853	0.933	0.794	0.964	1.000	0.937
Search Frictions	1.091	1.049	1.126	1.036	0.982	0.941
All Parameters	0.699	0.744	0.646	0.757	0.818	0.721
Sample	0.701	0.683	0.652	0.763	0.748	0.727

Note: Women/men ratio on average accepted earnings computed over the entire distribution. All counterfactual s are generated taking into account equilibrium effects.

Table 9. Welfare Returns to Schooling - Ratio of Average Welfare Measures

	1995			2005		
	MA and PhD / College	MA and PhD / High School	College / High School	MA and PhD / College	MA and PhD / High School	College / High School
Entire Sample						
Overall						
All Parameters	1.268	1.925	1.518	1.238	1.926	1.555
Without Prejudiced	1.177	1.840	1.564	1.314	2.032	1.547
Men						
All Parameters	1.215	1.824	1.501	1.240	1.941	1.565
Without Prejudiced	..	..	..	..	..	..
Women						
All Parameters	1.307	2.007	1.535	1.242	1.944	1.565
Without Prejudiced	1.120	1.832	1.635	1.406	2.167	1.541
Married with Children:						
Overall						
All Parameters	1.311	2.026	1.545	1.242	1.999	1.609
Without Prejudiced	1.259	1.863	1.480	1.379	2.168	1.572
Men						
All Parameters	1.224	1.812	1.481	1.201	1.930	1.606
Without Prejudiced	..	..	..	..	..	..
Women						
All Parameters	1.372	2.219	1.617	1.274	2.079	1.632
Without Prejudiced	1.261	1.849	1.466	1.608	2.481	1.543

Notes: The table presents ratio of the average welfare measures of the corresponding education levels. Welfare measures are computed using the estimated structural parameters. See main text for the complete definition. Married with Children means married and with children younger than 18 years old.

Table 10. Policy Experiments - Relative Average Welfare Measures

	1995			2005		
	All Parameters	Equal Pay	Affirmative Action	All Parameters	Equal Pay	Affirmative Action
Entire Sample						
Master and PhD						
Men	1.0000	0.9459	0.9861	1.0000	0.9149	0.9799
Women	0.7857	0.8088	0.8067	0.7659	0.7656	0.7841
Overall	0.9063	0.8860	0.9076	0.8787	0.8376	0.8785
College						
Men	1.0000	0.9111	0.9826	1.0000	0.9678	0.9830
Women	0.7299	0.8250	0.7487	0.7650	0.7950	0.7827
Overall	0.8684	0.8691	0.8686	0.8802	0.8797	0.8809
High School						
Men	1.0000	0.9202	0.9816	1.0000	0.9624	0.9827
Women	0.7138	0.7985	0.7327	0.7650	0.8040	0.7837
Overall	0.8586	0.8601	0.8586	0.8856	0.8853	0.8858
Married with Children						
Master and PhD						
Men	1.0000	0.9653	0.9900	1.0000	0.9108	0.9825
Women	0.7618	0.8401	0.7836	0.7703	0.8737	0.7896
Overall	0.9035	0.9146	0.9064	0.8895	0.8929	0.8897
College						
Men	1.0000	0.9360	0.9816	1.0000	0.9669	0.9834
Women	0.6794	0.7337	0.6984	0.7265	0.7570	0.7435
Overall	0.8432	0.8371	0.8431	0.8604	0.8598	0.8610
High School						
Men	1.0000	0.8605	0.9797	1.0000	0.9323	0.9806
Women	0.6222	0.6696	0.6409	0.7151	0.7495	0.7332
Overall	0.8084	0.7637	0.8079	0.8588	0.8417	0.8580

Notes: The table reports average welfare normalized with respect to men in the Benchmark Model. Benchmark Model is the model at the estimated parameters. Equal Pay means each employer must pay one wage at same productivity. Affirmative Action means employers receive a flow subsidy equal to 5% of the men average accepted wage when hiring a woman and the subsidy is financed by a lump-sum tax on all workers. . Married with Children means married and with children younger than 18 years old.