PROMOTION INEQUALITY AND BELIEF FLIPPING: THEORY AND EVIDENCE FROM EGYPT

Lamia E. Kandil*

June 2010

Abstract

Asymmetric allocation of men and women across occupations had been widely considered as a main factor that could explain gender wage differentials, especially at the top of the distribution of wages. Whether this difference in the occupation structure between the two sexes is essentially due to differences in productive characteristics, to self-selection or to employer's discrimination is still an unaccomplished debate. We propose in this paper a dynamic model of statistical discrimination in job assignment and promotion which takes into account both the endogeneity of investment in human capital and fertility decision, and where employer's prior belief are self-fulfilling in equilibrium. Building on Lazear and Rosen's (1990) model we show how, under certain conditions, discrimination/self-selection at the hiring stage may change equilibrium's results by altering employer's believes about expected quit rates and ability of workers. We test the hypotheses of our model using a multivariate simulated maximum likelihood. The inequality in job promotion is analyzed by applying a generalized residuals approach. Our Main results seem to confirm the model's assumption. That is, when adversity against women is significant during the hiring process, the group who overcome this initial discrimination becomes as likely as promoted as their male colleagues.

Key words: Efficient promotion, simulated maximum likelihood, generalized decomposition analysis.
JEL classification: J16, J71.

*Corresponding author. Université Paris I Panthéon-Sorbonne. 106-112, boulevard de l'Hôpital 75647 PARIS Cedex 13.Tel: (+33) 1 44 07 82 51/52. Fax:(+33) 1 44 07 82 47. Mob.: (+33) 6 73 49 49 79.
E-mail: lamia.kandil@univ-paris1.fr

1 Introduction

Numerous Empirical research which analyze the male-female wage differential found that a considerable part of the gender wage gap could be explained by the fact that women are scarcely represented at the highest paying jobs. Notably, it is always argued that women are less likely to be promoted to higher job levels than men. It is not unreasonable to think that this differential in promotion opportunities may be simply due either to differences in abilities between males and females or to individuals who self-select themselves into jobs with comparative advantages. Female comparative advantage in non-market activities (e.g. childbearing) affects their perception about the career path, makes them more likely to quit than men and relatively discourages their human capital investment. However, we do not neglect the existence of barriers to promotion which prevent women from advancement to higher job levels, and which has often been referred to as the "glass ceiling" phenomenon.

Statistical discrimination literature that seek to consider unequal promotions opportunities mostly rely on the differences between male and female attitudes with regard to non-market work[1]. The Lazear and Rosen's model (1990) considers that female higher expected value of home time entails less attachment to the labour market, and proves that the optimal and socially efficient response is to require higher threshold levels of ability for promotion by females. This implies that more able women will be passed over in favour of less able men. Generally, such models on promotion inequality take place in a static environment, where the employer can not evaluate perfectly a worker's ability but is able to observe some information about the worker which can be used to estimate his ability. Employer's decision of promotion is therefore determined at one period of time according to this predicted ability. Thus, it has been ignored within these models that the employer progressively learns more about worker's ability over the career life and may plausibly change his prior beliefs. Specifically, in the model of Lazear and Rosen (1990) the possible discrimination against women at the hiring process is not taking into account. The employer is assumed to be gender blind during the hiring stage and job assignment therefore, is irrelevant. By restricting their model in this manner, they do not address the potential bias due to the selection of workers during the hiring stage and how this could affect later on employer's beliefs about workers who overcome this initial adversity. We query then how equilibrium in these models would change when we consider a more realistic dynamic environment.

For this reason, we propose in this study a theoretical model of statistical discrim-

[1] See Becker (1985), Bulow and Summers (1986), Lazear and Rosen (1990) for further theoretical discussion about the asymmetric allocation of men and women across occupations.

ination in job assignment and promotion which incorporates such a dynamic setting. Moreover, the model we propose here accounts for both the endogeneity of human capital investment and fertility decision, where employer's prior beliefs are self-fulfilling in equilibrium. We show how, under certain conditions, adversity against women at the hiring stage may change equilibrium's results of standard discrimination theories by altering employer's beliefs about expected quit rates and ability of workers. In the empirical part of this study we test the hypotheses of our model in the Egyptian labour market during the year 2006. Precisely, two main questions are raised in this paper. First, is there discrimination against women at the hiring stage, or does it seems to exist an efficient hiring/self-selection process? Second, do employer's beliefs flip and turn into the favour of females during the promotion stage?

In order to carry on our empirical analysis a multivariate Maximum Simulated Likelihood MSL is used. Then, we examine differences in the hiring and promotion outcomes between males and females by applying a generalized residual approach that extend the Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973).

The paper proceeds as follows. The theoretical model is illustrated in section 2. Section 3 presents the data, in line with some elementary support to our theoretical model. The maximum simulated likelihood and the methodology used to analyze differentials in the hiring and promotion outcomes are described in section 4. We present our empirical results in section 5. Section 6 concludes.

2 Theoretical model

In this section, we present the theoretical foundation of our empirical model. We begin by pointing briefly how our model is related to the previous literature on employment discrimination and at what extent we depart from these models. The model in its technical form is presented then in more details.

The model is to some point related to the classical statistical discrimination literature in that it relies on imperfect information about worker's productivity. Like Phelps (1972), we assume that the employer only observe a noisy signal on worker's ability, but noisier measures for the disadvantaged group is not a condition in our model in order to observe unequal treatment for this group. We consider, in line with Arrow (1973), that employer's prior beliefs about each group are sufficient to lead to an equilibrium where groups are not treated equally. However, unlike these two models, prior beliefs are not directly referring to premarket investment in human capital, they are rather and essentially related to employer's expectation about the separation probability which, in turn, would affect worker's investment decision. This is an important feature in our analysis and implies that our model incorporates a dynamic element, as it will be seen later on. Additionally, we provide here a theory of statistical discrimination in job assignment and promotion rather than wages as in classical statistical discrimination literature. We implicitly suppose that wage differential occurs between jobs and that workers are paid equally within the same job.

The model presented here extends the Lazear and Rosen's (1990) model, being close in spirit to Coate and Loury's (1993) and Fryer's (2007) works. Our first contribution and a key difference between the model presented below and the one proposed by Lazear and Rosen (1990) is to account for the hiring stage procedure. Precisely, Lazear and Rosen assume that employers are gender blind at the hiring stage, so that there is no differential treatment between men and women in the assignment procedure when first enter the labour market, even though men receive preferential treatment at promotion. We thought that it is more reasonable to assume that selection occurs during the hiring process and we show how this could alter, under certain conditions, the Lazear and Rosen main equilibrium results.

We depart as well from the Lazear and Rosen's model by explicitly introducing both the endogeneity of investment in human capital and fertility decision. We consider the investment in human capital prior to entry into the labour market and after the hiring process has been occurred, over one's career life. Although, Coate and Loury's (1993) and Fryer's (2007) models consider the endogenous aspect of worker's productivity, the former takes place in a static environment, and both of these two models ignore non-market alternatives and how expectation about labour market separation might affect agents' decision.

Therefore our contribution here is to develop a model where expectations later on the career life affect in a different manner both the hiring and the promotion stages which, in turn, influence each other in a dynamic setting. We demonstrate what happens when we consider that the employer is not facing the same population before and after the hiring process and how this could modify agents' behavior. Equilibrium occurs where the employer's prior beliefs about the probability of quitting and hence worker's ability could be self-fulfilling. we turn now to the formal specification of the model.

Consider an environment with imperfect information about worker's ability. The Employer is unable to observe perfectly prior to the hiring/promotion stages whether a worker is qualified for the job[2]. Nature assigns to each worker an identity; male or

[2] Unlike Lazear and Rosen (1990), we do not assume that ability is perfectly revealed to everyone after the initial period of work during which individuals are reviewed. Since we allow for investment in human capital over the career life, noisy signal about qualification remains when the employer takes the promotion decision.

female and a cost of investment at each stage. The employer observe a noisy signal and each worker's group identity. We assume that the effective ability of the worker η_i^t at each stage $t \in \{h, p\}$ is a function of the emitted signal θ_i^t and a noise ε_i^t : $\eta_i^t = f(\theta_i^t + \varepsilon_i t)$, where i refers to the sex, m for male and f for female. The distribution of the signal θ is assumed to be the same for both sexes, but depends on whether or not the individual has made an ex ante investment[3]. Let $F_q(\theta^t)$ and $F_u(\theta^t)$ be the cumulative distribution functions of θ for the qualified and the unqualified workers respectively, and denote by $f_q(\theta^t)$ and $f_u(\theta^t)$ the corresponding density functions. We could reasonably suppose that $F_q(\theta^t) \leqslant F_u(\theta^t)$, which implies that the likelihood of emitting a high value of θ is more likely when the worker is qualified. Employer's decision to hire/promote a given individual depends on the signal he observes and his prior beliefs about the likelihood that a worker is qualified. These prior beliefs rely on subsequent expected propensity to remain on the job, and thus differ according to the sex of the worker. Since Women are assumed to have superior ability in non-market activities, they are more likely to quit than men, and this higher probability of separation leads to a lower human capital investment for women. Anticipating this, the employer forms different beliefs about the probability of qualification for each sex, so that the assignment process would be biased[4]. Let $\psi_i^t \in [0, 1]$ be the employer's prior beliefs about worker's qualification at stage t. Starting with the employer's behavior at the hiring stage, the employer observes θ_i^h and must take a hiring decision. We know, by assumption, that $\psi_m^h > \psi_f^h$, and conditional on θ_i^h and ψ_i^h, he formulates a posterior probability that the worker is qualified, denoted by $\Psi(\psi_i^h, \theta_i^h)$[5]. The employer's get a payoff of $\zeta_q^h(-\zeta_u^h)$ if he hire a qualified (unqualified) worker, and a payoff of *zero* if he reject the worker regardless of his qualification. Thus, the employer's expected payoff from hiring a worker is: $\Psi(\psi_i^h, \theta_i^h)(\zeta_q^h + V(\psi_i^p)) - (1 - \Psi(\psi_i^h, \theta_i^h))\zeta_u^h$, and his expected payoff if he reject the worker is *zero*. He will decide to hire a given worker only if

$$\Psi(\psi_i^h, \theta_i^h)(\zeta_q^h + V(\psi_i^p)) \geqslant (1 - \Psi(\psi_i^h, \theta_i^h))\zeta_u^h,$$

[3]For simplicity, we assume identical distribution of the ability signal for both males and females, but this is not a restrictive assumption. Imposing alternative distribution's assumptions would lead to similar results.

[4]Notice that employer's beliefs in this model are linked to worker's qualification through perceived separation probabilities. Employers might be acting rationally if quit rates are correctly estimated and corresponds to women preferences. In this case, there beliefs would be consistent with their experiences. However, as we will show later in the model, we do not neglect the effect of employer's beliefs on women's behavior regarding fertility and hence human capital investment.

[5]Using Bayes' rule, $\Psi(\psi_i^t, \theta_i^t) \equiv \frac{\psi_i^t f_q(\theta_i^t)}{\psi_i^t f_q(\theta_i t) + (1-\psi_i^t) f_u(\theta_i^t)}$.

or

$$\frac{\zeta_q^h + V(\psi_i^p)}{\zeta_u^h} \geqslant \frac{1 - \Psi(\psi_i^h, \theta_i^h)}{\Psi(\psi_i^h, \theta_i^h)}, \tag{1}$$

where $V(\psi_i^p)$ is the employer's expected value at the promotion stage if the worker has been hired[6]. Therefore, the employer's policy will be to set, prior to observe a signal, a threshold standard θ_i^{*h}, respecting the previous hiring condition, and to hire the worker if his emitted signal is no less than θ_i^{*h}. So, for a given observed signal θ_i^h, higher prior beliefs will increase posterior probabilities about worker's qualification, thus decreasing the right hand side of condition (1) and resulting in easier threshold standard θ^{*h}. It is relevant to our model to point out that $\theta^{*h}(\psi_i^h, \psi_i^p)$ is a function of both ψ_i^h and ψ_i^p. Obviously, the threshold standard is decreasing in ψ_i^h, while it is rather an increasing function of ψ_i^p[7]. Positive beliefs at the promotion stage raise the threshold standard during the hiring process, this is a characteristic of the dynamic setting of the model where decisions over the two periods interact with each other. We will discuss afterward how this effect could be interpreted within the context of our model. After the hiring process has been occurred, and before taking the promotion decision, the employer discovers the hiring stage investment decision of those workers who have overcome the hiring stage. He know then whether a worker who has been hired was qualified or not to be hired. Workers who do not invest in the hiring stage, are not eligible for a promotion regardless of their promotion stage signal. Similarly, conditional upon hiring a worker, the employer decides to promote a given worker if $\Psi(\psi_i^p, \theta_i^p)\zeta_q^p \geqslant (1 - \Psi(\psi_i^p, \theta_i^p))\zeta_u^p$, since his expected payoff if he decides not to promote him is *zero*.

Considering now the worker's behavior at each stage. Denote by η_1 the worker's gross return if he is hired at the first stage and by η_2 his gross return at the second period if he is promoted conditional upon being hired[8]. The worker must take an ex ante investment decision about whether making the costly investment, and then becoming qualified, is worthwhile. He should compare between his expected return if he invest at the hiring stage and his expected return if he does not invest and remain unqualified. Formally, a rational worker would invest at the hiring stage if his cost of investment does not exceed his net expected benefit over his career life.

[6]This expected value is a function of prior beliefs at the promotion stage, since the signal θ^p has not been revealed yet while taking the hiring decision. $V(\psi_i^p) \equiv \psi_i^p \zeta_q^p - (1 - \psi_i^p)\zeta_u^p$, where $\zeta_q^p(\zeta_u^p)$ is the employer's payoff if he decides to promote a qualified (unqualified) worker. If the employer decides not to promote a worker who was qualified in the hiring stage, he gets a payoff of *zero*.

[7]We could easily observe from the hiring condition that higher values of ψ_i^p increases the expected value $V(\psi_i^p)$, thus raising the threshold required for a hiring decision.

[8]We assume for simplicity that the worker's gross return is equal to the average effective ability of all workers at each stage, or equivalently to the average output.

A qualified worker who make the costly investment has an expected return of (omitting the i subscript)

$$\eta_1[1 - F_q^h(\theta^{*h})] + \eta_2[1 - F_q^p(\theta^{*p})] \int_0^{\eta_2} h(\omega)d\omega + [1 - F_q^p(\theta^{*p})] \int_{\eta_2}^{\infty} \omega h(\omega)d\omega + \eta_1 F_q^p(\theta^{*p}) \int_0^{\eta_1} h(\omega)d\omega + F_q^p(\theta^{*p}) \int_{\eta_1}^{\infty} \omega h(\omega)d\omega - c^h \quad (2)$$

and if he does not invest (unqualified) he has an expected return of

$$\eta_1[1 - F_u^h(\theta^{*h})] + \eta_1 \int_0^{\eta_1} h(\omega)d\omega + \int_{\eta_1}^{\infty} \omega h(\omega)d\omega \quad (3)$$

Then, the criterion of investment is[9]

$$\eta_1[F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})] + [1 - F_q^p(\theta^{*p})] \int_{\eta_1}^{\eta_2} H(\omega)d\omega \geqslant c^h \quad (4)$$

The first terms in equations (2) and (3) refer to the expected return from the first period after being hired. This value is the product of the gross return η_1 and the probability of being hired $[1 - F_q^h(\theta^{*h})]$ if the worker is qualified and $[1 - F_u^h(\theta^{*h})]$ if he is unqualified[10]. Note that the worker's evaluation of his chance to be hired is a function of the threshold he is expecting to face θ^{*h}, since this chance is simply equal to the fraction of workers who emit a signal no less than θ^{*h}. For a promoted worker, the promotion stage is identified by the second and the third terms when the worker stays within the firm and when he quits, respectively[11]. The two last values of equation (2) define the expected return at the promotion stage when the qualified worker has not been promoted. ω denotes the non market alternative value of time and $h(\omega)$ its corresponding density function. Following Lazear and Rosen (1990), we assume that ω is a random variable, revealed to the worker and the employer alike only after the promotion stage. Although ω is unknown when both agents make their decisions, the cdf $H(\omega)$ of this variable is known prior to the hiring stage. Recall that our model assumes that women are more likely to quit than men due to their higher ability in non market activities. This implies that the female distribution of reservation wages first-order stochastically dominates that of men, that is $H(\omega_m) > H(\omega_f)$. The cost of being qualified in equation (2) is denoted by c^h, and it is assumed to have the same

[9]Details concerning the derivation of this condition are shown in the Appendix.

[10]We assume that the expected return when the worker is not hired is *zero*.

[11]The qualified worker has a chance to be promoted at the second period and to get η_2, in opposition to the unqualified worker who conserves the same payment as the first period.

distribution function $G^h(c)$ for both males and females at the hiring stage.

We will examine now how each element in equation (4) affect the proportion of individuals who choose to become qualified. Particularly, we show how the threshold standard θ^* which is a function of employer's prior beliefs influence individuals' behavior, resulting in an equilibrium where beliefs about each group are self-confirming. For notation convenience, let b denotes the net expected benefit (the left-hand side of equation (4)). It is straightforward to see then that the fraction that chooses to become qualified is determined by $G^h(b)$, the proportion of individuals who have a cost no more than b. Hence, a high value of b would increase the proportion of workers that becomes qualified. When θ^{*h} rises, this would reduce the increased probability of being hired due to investment, $F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})$, decreasing then the amount of b and the fraction of workers who will invest prior to the hiring stage. The threshold standard of promotion θ^{*p} has also the same effect through the probability of promotion, $1 - F_q^p(\theta^{*p})$. Remember that $H_m(\omega) > H_f(\omega)$, this implies that, every thing being equal, men would have a higher fraction of qualified workers at the hiring stage than do women due to the positive effect of $H(\omega)$ on the net expected benefit. Evidently, a wider wage profile would lead to a higher expectation about the net benefit and would increase the fraction of qualified workers.

Conditional on being hired, the worker must decide whether to be qualified for the promotion stage is sufficiently valuable. Again, he would invest if his cost of investment does not exceed his net expected benefit over the career life.

When the worker invests and becomes qualified for promotion he would have an expected return of

$$\begin{aligned} &\eta_2[1 - F_q^p(\theta^{*p})] \int_0^{\eta_2} h(\omega)d\omega + [1 - F_q^p(\theta^{*p})] \int_{\eta_2}^{\infty} \omega h(\omega)d\omega \\ &+\eta_1 F_q^p(\theta^{*p}) \int_0^{\eta_1} h(\omega)d\omega + F_q^p(\theta^{*p}) \int_{\eta_1}^{\infty} \omega h(\omega)d\omega - c^p \end{aligned} \tag{5}$$

His expected return if he remains unqualified for promotion would be

$$\begin{aligned} &\eta_2[1 - F_u^p(\theta^{*p})] \int_0^{\eta_2} h(\omega)d\omega + [1 - F_u^p(\theta^{*p})] \int_{\eta_2}^{\infty} \omega h(\omega)d\omega \\ &+\eta_1 F_u^p(\theta^{*p}) \int_0^{\eta_1} h(\omega)d\omega + F_u^p(\theta^{*p}) \int_{\eta_1}^{\infty} \omega h(\omega)d\omega \end{aligned} \tag{6}$$

Then, the worker will invest for promotion if the following condition is satisfied[12]

$$(F_u^p(\theta^{*p}) - F_q^p(\theta^{*p})) \int_{\eta_1}^{\eta_2} H(\omega) d\omega \geqslant c^p \tag{7}$$

The condition of investment at the promotion stage is a function of the threshold standard of promotion θ^{*p}, the distribution of the reservation wages and the wage profile. These factors affect in the same manner as in the hiring stage the fraction of workers who decide to make the costly investment for promotion.

Considering now how equilibriums are determined according to the previous analysis. Equilibrium at each stage is defined as a pair of self-fulfilling employer's beliefs about the fraction of workers from each sex who make the requisite investment for stage t.

Different expectations about each sex separation rates form the employer's prior beliefs and these beliefs settle the equilibrium ability cutoffs for individuals of each sex. Workers make their investment decision at each stage by anticipating the employer's behavior as well as their own probability of quitting.

Specifying equilibrium at the hiring stage as:

$$\psi_i^{*h} \equiv G^{*h}(c^h(\theta_i^{*h}(\psi_i^h, \psi_i^p))) \tag{8}$$

$$c_i^{*h}(\theta_i^{*h}, \theta_i^{*p}, H_i(\omega), \eta), \qquad \theta_i^{*h}(\psi_i^h, \psi_i^p) \qquad i = m, f.$$

and equilibrium at the promotion stage as:

$$\psi_i^{*p} \equiv G^{*p}(c^p(\theta_i^{*p}(\psi_i^p))) \tag{9}$$

$$c_i^{*p}(\theta_i^{*p}, H_i(\omega), \eta), \qquad \theta_i^{*p}(\psi_i^p), \qquad \psi_i^p(c_i^{*h}) \qquad i = m, f.$$

These equilibriums have straightforward implications not only on gender differences in terms of hiring and promotion processes, but as well and particularly on the distribution of ability.

Under our previous assumptions, that is $F_m^h(\theta)$ and $F_f^h(\theta)$ are identical at the hiring stage, and similarly for $G_m^h(c)$ and $G_f^h(c)$:

1. Every thing else being equal, women will be less likely to be hired
   $1 - F_f^h(\theta_f^{*h}) < 1 - F_m^h(\theta_m^{*h}) \quad \text{if } \theta_f^{*h} > \theta_m^{*h}$

[12] See the Appendix for details about this result.

2. Consequently, conditional upon being hired women will be on average more productive than their males colleagues. The condition of investment in equation (4) involves $G^h_m(c^{*h}_m) > G^h_f(c^{*h}_f)$, since $c^{*h}_m > c^{*h}_f$

A lower equilibrium cost cutoff for females means that even though the fraction of women who make the costly investment is smaller, these women are on average more qualified than men who decide to make this investment. This is an obvious but a crucial result in our model, because it shows how subsequent stages interact with each other and affect agents' behavior. It allows the modification of the main equilibrium results found in standard promotion models, and so it is central to our contribution here.

This difference in the average productivity between men and women appears in their promotion-stage investment cost distribution functions. Now, The male cost distribution first-order stochastically dominates that of women, $G^p_m(c) < G^p_f(c)$. Therefore, one could plausibly thought that at the promotion stage the employer's prior beliefs ψ^p_i should alter and become relatively more optimistic about female qualifications relative to men. This simple intuition has been addressed by Fryer (2007), referring to it as "belief flipping" Although, there could have been discrimination against women in the hiring process, the successful group who overcome this initial adversity may be subject to favoritism during the promotion decision, since they have previously been held to a more exacting standard. As a result, the female threshold standard of promotion would be no greater than that of men and the fraction of women who invest for promotion would be at least equal to that of men.

However, this equilibrium is not necessarily true. One could reasonably imagine an equilibrium where adversity against women remain during the promotion stage.

It is true that a high hiring stage standard serves as a selection and ensures a more qualified pool of workers, but what would make these highly qualified women to believe that the employer will take this selection in their favor at the promotion stage, inducing them to invest for promotion ? Making use of the investment criterion, one could deduct conditions under which the "belief flipping" equilibrium arises. By setting an extended wage profile, the employer insures that women would have the incentive to invest for promotion, due to the gain which occurs once being promoted. However, a largely extended wage profile increases as well the pool of women who will be hired (irrespective to the initial threshold standard), reducing the selection mechanism, and making the employer more exigent at the promotion stage. Precisely, the hiring cutoff standard might be positively related to the wage profile, and both of them are inversely proportional to the promotion threshold standard. This means that there exists a conforming set of hiring and promotion cutoffs standard, and a wage structure where negative beliefs about women at the initial hiring process turns into their favor during the promotion stage.

3 Data and model suitability

3.1 The data

Two sources of data are used in this study. We rely primarily on the Egyptian Labour Market Survey ELMS for 2006[13]. This is a cross-sectional household survey, carried out by the Economic Research Forum ERF in cooperation with CAPMAS[14] and was gratefully made available to us by *The Population Council* and *The Social Research Center of the American University in Cairo.*

The surveys' questionnaire hold three sources of information: the household questionnaire, the individual questionnaire and the household enterprise and income module containing information about all agricultural and non-agricultural enterprises operated by the household as well as migration, remittances, transfers and all non-labour income. Household basic characteristics apply to all current members of the household and are collected from most knowledgeable person. Individual characteristics apply to individuals six years and above. And information from the third questionnaire applies to most knowledgeable person in the household.

To analyze job promotion opportunities, we restrict our samples to regular wage earners who have finished their education and to individuals between 16 and 65 years of age inclusive with valid observations on all the variables used in our model[15]. However, since we account for the hiring/self-selection process into the labour market, we use as well information on a full sample of working and non working individuals between 16 and 65 years of age inclusive[16]. After having cleaned the data, we are left with a sample of 8609 men and 7109 women. We refer to job promotion as promotion opportunity in the primary main job[17]. Each worker was asked how many times he has been promoted since he joined his current employment. Answering once, twice, three or more times were considered as having a positive promotion probability, while responding never been promoted or does not apply mean a non promotion opportunity. Notice two aspects from this specification of promotion outcomes. First, we could not

[13]For a detailed sampling, data description and questionnaire design of the ELMS see Assaad and Barsoum (1999), and Barsoum (2007), Final Report. The Population Council, Cairo, Egypt.

[14]Central Agency for Public Mobilization and Statistics.

[15]A detailed description of the variables used in our estimations is given in Appendix B.

[16]Employers, self-employed and unpaid individuals working for family are excluded from the sample.

[17]The period of reference for a primary main job is the complete three months preceding the survey. Complete three months denotes full three months payments.

distinguish between workers who have never been promoted while being in jobs that offer promotion opportunities and those who are in jobs that do not offer opportunities for promotion. Actually, this may bias our estimation of promotion differential between men and women if women are less likely promoted to higher hierarchical levels, because they are more frequently in "dead-end" jobs with no opportunities for promotion. Second, the promotion variable as we specify here has the advantage to ensure that job changes were in fact changes to a higher hierarchical level. However, the survey's questionnaire does not provide clear information about whether the worker has been with the same employer since his first employment or does mobility has taken place. This would be a problem since women are supposed to be less mobile than men. This means that conditional on employment, the separation probability should be lower for women than for men, and this could underestimate differences in promotion outcomes between both genders. Although, "stayers" and "movers" employees are not easily separable in this context, we attempt a procedure in order to distinguish each group. Thus, workers who report having the same current job's location, economic activity and sector as the first job are defined as "stayers"[18]. When we consider only the group of stayers, 6568 observations for men and 6701 observations for women are now available to be used for our empirical analysis.

In order to account for the impact of employer's perception about different separation rates for both genders, we construct a fertility index as a proxy for higher quit rates for females due to the risk of child bearing. For this purpose, we employ data from the Egypt Demographic and Health Survey EDHS for 2008[19]. Following Winter-Ebmer and Zweimüler (1997), the variable was computed according to women's age and current number of children as follows:

$$F_{jk} = 1 - \prod_{l=1}^{5} [1 - P(\text{birth}|\text{age}\, j + l, \text{n}^\circ \text{ of children } k)], \tag{10}$$

where the fertility index F_{jk} is the probability that a women of age j having k children will bear a further child within the next five years.

[18]The same location denotes the same governorate, city or town and urban/rural areas. Sectors of job are government, public enterprise, private, investment, foreign, non-profitable government organization, and other including co-operatives. Given the possibility of privatization of some enterprises during once career life, individual may have been with the same employer, while the type of the sector could have changed as a result of privatization. So, for those who have been considered as stayers according to the previous definition, we look at such cases where the sector at the first job was a government or public enterprise, then becomes a private sector. There were only 14 observations (10 men and 4 women) in this case.

[19]The 2008 Egypt Demographic and Health Survey (2008 EDHS) was conducted on behalf of the Ministry of Health by El- Zanaty and Associates.

3.2 Suitability of our model's assumptions.

We will present in this part some evidence which provides elementary support to our model. Figure C1 in the Appendix compares the males and females density functions of education[20] (the left-side column) and the corresponding cumulative distribution functions (the right-side column) for three distinct samples[21]. The first row presents the whole sample used in our empirical analysis, including employed and non employed individuals. The second row corresponds to the group of wage workers, and the last row depicts the pool of promoted individuals. As it could be seen, the male distribution function of education first-order stochastically dominates that of women in the first row of the figure[22]. However, upon the hiring process, the pool of working women is now more qualified than that of men. The female distribution function of education in the second and third rows of figure C1 first-order stochastically dominates the male distribution. The following descriptive statistics illustrates the same findings[23]. The average number of years of schooling is higher for men than for women when one considers the whole sample ($12,19\%$ versus $11,63\%$), while women have higher years of schooling among both the working and the promoted groups ($14,85\%$ and $15,59\%$ for females as compared to $12,92\%$ and $14,7363\%$ for males)[24]. In addition, women are less likely to be hired than men ($19,18\%$ versus $54,66\%$). They have as well less chance to be promoted unconditional of being hired, but interestingly they are more frequently promoted than men once being hired ($49,94\%$ versus $34,29\%$)[25]. These findings could not be satisfied unless the hiring threshold standard for women is greater than that of men. When the male ability distribution first-order stochastically dominates that of females, women could still less frequently be hired for some values of males hiring criteria greater than females one. However, in order to be simultaneously less likely to be hired and more qualified upon the hiring process than their males colleagues, they have to face more tougher hiring criteria than men. Evidence provides then preliminary supports to our model. Adversity against women at the hiring stage which leads

[20]Education corresponds to the number of years of schooling.

[21]The estimation procedure was a kernel- density with an Epanechnicov kernel function.

[22]Although, our model assumes for illustration purposes that prior to be hired both genders have identical distribution of the ability signal and of the cost distribution functions, supposing alternative distributions would not change our main hypotheses. That is, in order that women be simultaneously less likely to be hired and more qualified upon the hiring process than their males colleagues, they have to face more tougher hiring criteria than men.

[23]All statistics are weighted by the appropriate survey sampling weights.

[24]The percentage of both working and promoted women who have attained high level of education is distinctly greater than that of their males colleagues, while this percentage is not significantly different between the two genders in the whole sample. We denote by the high level of education general and vocational high schools, post-secondary, university and above university degrees, while the low level corresponds to the illiterate, literate without any diploma, elementary and middle schools degrees.

[25]See table 2 in the Appendix.

the employer to settle higher hiring standard, results in a pool of working women more qualified in average than their male colleagues. This adversity may then turn into their favour during the promotion stage, and women would have at least equal opportunity of promotion as men.

4 Model specification

4.1 Multivariate promotion model by maximum simulated likelihood

As we discussed earlier, on the basis of our theoretical model, the approach adopted in this paper considers that the investment in human capital and fertility are determined jointly and that they are both endogenous to the hiring and promotion processes. Thus, this approach does not affirm neither one way, nor mutual causality between education and fertility. They are simultaneous decisions, not in the timing in which they occur but in the sense that they are the joint solution to a common constrained maximization problem. In addition, the model analyzes job promotion accounting for the selection into the labour market. Therefore, our model contains equations for 4 response variables, of which the probability of promotion p is viewed as the primary variable of interest. The variable s is the selection variable, which could also be defined as the probability to be hired. Fertility f and education e are endogenous regressors in the model of hiring and promotion.

Formally, we adopt a multivariate probit model where, for individual $i = 1, ..., n$ and sex $g = m, f$, the following equations are estimated simultaneously:[26]

$$s^*_{ig} = x_{ig1}\beta_1 + f_{ig}\alpha_1 + e_{ig}\alpha_2 + \varepsilon_{i1} \tag{11}$$

$$f^*_{ig} = x_{ig2}\beta_2 + \varepsilon_{ig2} \tag{12}$$

$$e^*_{ig} = x_{ig3}\beta_3 + \varepsilon_{ig3} \tag{13}$$

$$p^*_{ig} = z_{ig}\gamma + f_{ig}\delta_1 + e_{ig}\delta_2 + \varepsilon_{ig4} \tag{14}$$

[26]The simultaneous estimations allows us to identify the correlation coefficients among the stochastic components of all the dependent variables of our model, and so accounts not only for the endogeneity issue but also for the selection issue.

where x_{1i}, x_{2i}, x_{3i} and z_{ig} are vectors of exogenous covariates for individual i of sex g. The coefficients $\beta_1, \beta_2, \beta_3$ and γ are the corresponding vectors of parameters. $\varepsilon_1, \varepsilon_2, \varepsilon_3$ and ε_4 are error terms distributed as multivariate normal, each with a mean of zero, and variance-covariance matrix Σ. For identification purpose, the variances of the error terms must be set to 1. We do not observe the latent variables, $s^*_{ig}, f^*_{ig}, e^*_{ig}, p^*_{ig}$; instead, we use observable variables, defined as follow: $f_{ig} = 1(f^*_{ig} > 0)$ and $e_{ig} = 1(e^*_{ig} > 0)$, where 1(.) is the usual indicator function. According to our theoretical model, the risk of quitting (the separation probability) is determined by the propensity to fertility f^*_{ig}, which is approximated in our model according to two alternative specifications. The first one is the number of children a women has. Thus, we consider simply that f_{ig} takes one if a women has children and *zero* if she does not have children. The propensity to fertility under this specification is probably endogenous to our model. To account for this endogeneity, we use a second specification which is our computed demographic fertility index as defined in equation (10). In this case, f_{ig} takes one if the probability that a women will bear a further child within the next five years is greater than $0,5$ and *zero* otherwise[27]. Education, is also a binary variable, which takes one for high levels of education and zero for low level[28]. The hiring and promotion probabilities are defined as: $s_{ig} = 1(s^*_{ig} > \theta^{*h}_g)$ and $p_{ig} = 1(p^*_{ig} > \theta^{*p}_g)$. Thus, the individual is hired (promoted) if his propensity to be hired (promoted) is greater than $\theta^{*h}_g(\theta^{*h}_g)$, with θ^{*h}_g and θ^{*p}_g the hiring and promotion threshold standard, respectively[29]. These two last equations provide the threshold conditions for hiring and promotion, implicitly defined by equations (4) and (7).

Methodology of estimation

The structure of the model is similar to that of a seemingly unrelated regression (SUR) model, except that the dependent variables are binary indicators. In the case of multivariate normal distribution functions, computations based on standard linear numerical approximations, such as those based on the Newton-Raphson method, are relatively inefficient and may provide poor approximations (Hajivassiliou and Ruud, 1994). For this reason we use instead a simulation-based method that have much better properties. The method of simulated likelihood is based on the fact that the

[27]Obviously, equation (12) is only estimated for women. Since the propensity to fertility determines the separation probability, we assume implicitly that the risk of quitting for males is *zero*. Thus, our model deals only with quitting for non-market activities, quitting job for other job is not considered.

[28]The low level corresponds to the elementary, middle, general high and vocational high schools degrees, while the high level denotes post-secondary, university and above university degrees. A detailed description of the variables used in our model is given in Appendix B.

[29]Remember that our theoretical model predicts that the female hiring threshold standard should be greater than that of males, while their promotion threshold standard should be equal, if not less, than that of their male colleagues.

integrals of the likelihood function are probabilities of a certain event in a random process. These integrals are then approximated by simulation rather than computing high dimensional integrals in the likelihood function. In particular, Maximum simulated likelihood (MSL) consists in simulating a likelihood and then averaging over these simulated likelihoods. In this paper, we use the Geweke-Hajivassiliou-Keane (GHK) "Smooth Recursive Conditioning" (SRC) simulator, proposed by Geweke (1989) and Borsh-Saupan and Hajivassiliou (1993), in order to approximate the integrals of interests[30].

Consider the log-likelihood function of our model:

$$L = \sum_{i=1}^{n} log\Phi_4(\mu_i; \Omega),$$

where $\Phi_4(.)$ is the multivariate standard normal distribution[31].
The argument $\mu_i = (K_{i1}(x_{i1}\beta_1 + f_i\alpha_1 + e_i\alpha_2), K_{i2}x_{i2}\beta_2, K_{i3}x_{i3}\beta_3, K_{i4}(z_i\gamma + f_i\delta_1 + e_i\delta_2))$, with $K_{ik} = 2s_i - 1, 2f_i - 1, 2e_i - 1$ and $2p_i - 1$ respectively, for each $k = 1, ..., 4$. Ω refers to the matrix of the correlation coefficients between the stochastic components of the multivariate distribution function[32].

To evaluate the likelihood function, one needs to compute multivariate normal integrals corresponding to different possible combination of successes and failures of the outcome variables. Consider the probability of observing that every outcome is a success. The joint probability is given by:

$$\begin{aligned} Pr(s = 1, f = 1, e = 1, p = 1) &= \int_{-\infty}^{\mu_1}\int_{-\infty}^{\mu_2}\int_{-\infty}^{\mu_3}\int_{-\infty}^{\mu_4} \phi_4(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4; \Omega_{kj}) d\varepsilon_1 d\varepsilon_2 d\varepsilon_3 d\varepsilon_4 \\ &= Pr(\varepsilon_1 \leqslant \mu_1, \varepsilon_2 \leqslant \mu_2, \varepsilon_3 \leqslant \mu_3, \varepsilon_4 \leqslant \mu_4) \end{aligned} \quad (15)$$

The GHK simulator exploits the fact that this multivariate normal distribution func-

[30]The GHK simulator is convenient for use in empirical applications; it outperforms all other probability simulators by keeping a good balance between accuracy and computational costs, it is relatively simple to program and it can be generalized to any distributional assumption. For more details about the GHK simulator, its properties and the properties of other available probability simulators, see Hajivassiliou *et al.*, 1996; Hajivassiliou, 1993; Feenberg and Skinner, 1994; Chen and Cosslett, 1998.

[31]Note that for males, we are in the case of a trivariate probit model since the equation of fertility is omitted from the model.

[32]The correlation coefficients matrix would then be:

$$\begin{pmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \Omega_{34} \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} \end{pmatrix}$$

where $\Omega_{kk} = 1$ and $\Omega_{jk} = \Omega_{kj} = K_{ik}K_{ij}\rho_{kj}$ with $j \neq k$, for each $j, k = 1, ..., 4$.

tion can be expressed as the product of a sequentially conditioned univariate normal distribution functions, such that equation (15) could be written as

$$Pr(\varepsilon_1 \leqslant \mu_1) \times Pr(\varepsilon_2 \leqslant \mu_2 | \varepsilon_1 \leqslant \mu_1) \times Pr(\varepsilon_3 \leqslant \mu_3 | \varepsilon_1 \leqslant \mu_1, \varepsilon_2 \leqslant \mu_2) \times Pr(\varepsilon_4 \leqslant \mu_4 | \varepsilon_1 \leqslant \mu_1, \varepsilon_2 \leqslant \mu_2, \varepsilon_3 \leqslant \mu_3) \quad (16)$$

Then approximations of these conditional distributions is derived due to the structure of the lower triangular Cholesky matrix of Σ, which could be therefore expressed as unconditional probabilities, easily simulated in order to evaluate the likelihood function.

Let C be the lower triangular Cholesky decomposition corresponding to the covariance matrix of the errors, such that: $E(\varepsilon\varepsilon^{'}) \equiv \Sigma = C\nu\nu^{'}C$,
where ν is a vector of four uncorrelated standard normal random variables and c_{kj} is the *jkth* element of the matrix C.
It follows that,
$\varepsilon_1 = c_{11}\nu_1$
$\varepsilon_2 = c_{21}\nu_1 + c_{22}\nu_2$
$\varepsilon_3 = c_{31}\nu_1 + c_{32}\nu_2 + c_{33}\nu_3$
$\varepsilon_4 = c_{41}\nu_1 + c_{42}\nu_2 + c_{43}\nu_3 + c_{44}\nu_4$

Equation (16) could now be expressed as the product of univariate conditional probabilities, but conditional on independent standard normal variables:

$$Pr(\nu_1 \leqslant \mu_1/c_{11}) \times Pr(\nu_2 \leqslant (\mu_2 - c_{21}\nu_1)/c_{22} | \nu_1 \leqslant \mu_1/c_{11}) \times Pr(\nu_3 \leqslant (\mu_3 - c_{31}\nu_1 - c_{32}\nu_2)/c_{33} | \nu_1 \leqslant \mu_1/c_{11}, \nu_2 \leqslant (\mu_2 - c_{21}\nu_1)/c_{22}) \times Pr(\nu_4 \leqslant (\mu_4 - c_{41}\nu_1 - c_{42}\nu_2 - c_{43}\nu_3)/c_{44} | \nu_1, \nu_2, \nu_3 \leqslant (\mu_3 - c_{31}\nu_1 - c_{32}\nu_2)/c_{33}) \quad (17)$$

Since the standard normal variables ν are uncorrelated with each other, the last three conditional probabilities could be further rewritten as unconditional ones:

$$Pr(\nu_1 \leqslant \mu_1/c_{11}) \times Pr(\nu_2 \leqslant (\mu_2 - c_{21}\nu_1^*)/c_{22}) \times Pr(\nu_3 \leqslant (\mu_3 - c_{31}\nu_1^* - c_{32}\nu_2^*)/c_{33}) \times Pr(\nu_4 \leqslant (\mu_4 - c_{41}\nu_1^* - c_{42}\nu_2^* - c_{43}\nu_3^*)/c_{44}) \quad (18)$$

where v_1^*, v_2^* and v_3^* are drawn sequentially from a truncated standard normal distribution with upper-truncated points at $\mu_1/c_{11}, (\mu_2-c_{21}v_1^*)/c_{22}$ and $(\mu_3-c_{31}v_1^*-c_{32}v_2^*)/c_{33}$, respectively. So, the GHK simulator draws random values for v^*, and then recursively computes a multivariate probability value; the product of the unconditional probabilities in equation (18). This process is replicated R times, and the GHK simulator is the arithmetic mean of the simulated probabilities from each replication. That is,

$$\widetilde{Pr}_{GHK} = \frac{1}{R}\sum_{r=1}^{R}\{\Phi(\mu_1/c_{11})\Phi(\mu_2 - c_{21}v_1^{*r})/c_{22})\Phi(\mu_3 - c_{31}v_1^{*r} - c_{32}v_2^{*r})/c_{33}) \\ \Phi(\mu_4 - c_{41}v_1^{*r} - c_{42}v_2^{*r} - c_{43}v_3^{*r})/c_{44})\} \quad (19)$$

This simulated probability given by equation (19) is the value that is included into the log-likelihood function at each iteration.

4.2 Decomposition of promotion inequality using a generalized residuals approach

We turn now to the analysis of the differences in the gender promotion probabilities. Our main purpose is to know whether there exists a gender gap in promotion, once we take into account the hiring process, and once we control for differences in endowments and separation probabilities between sexes. We refer to this remaining gap as an unequal promotion opportunities. This unequal promotion is due to different evaluation of endowments or to unjustifiable promotion threshold differences between males and females. It is worth noting, and a crucial issue in our discussion, that the risk of quitting (separation probabilities) as it is perceived by the employer could be seen as well as a form of statistical discrimination (Phelps, 1972) if there exists a misperception about female separation rates by the firm, mainly as a result of a "stereotyping", or if these prior beliefs have feedback effects, altering therefore individual quit behavior. This issue is treated in our theoretical and econometric model by the endogenization of the fertility decision. Hence, if separation probabilities are correctly perceived, differences in promotion opportunities due to a gender gap in separation probabilities could then be seen as an efficient promotion and no gender discrimination is justified in this case.

The method we adopt here for the decomposition analysis is similar to that introduced by Yun (1999) to perform the decomposition of wage differentials when selection effects are present. This approach is called the Generalized Selection Bias (GSB)[33]. It

[33]They called it this way because the decomposition analysis uses the joint estimation of the structural and selection equations to evaluate the selection bias, as opposed to the "selection bias correction approach" (SBC) which relies rather on Heckman's two-step method.

is based as well - with some modification - on the methodology of decomposition for a probit model in the presence of a selection bias developed by Yun (2000).

The principal idea behind the GSB approach is that the decomposition of wage differentials is based on the joint estimation of log-wages and selection equations using Maximum likelihood estimation method (MLH). This is a primary reason why we choose to implement a methodology based on the GSB approach. In particular, the approach provides a general framework for decomposition analysis which could be extended to our case of a multivariate model. Almost all studies which attempt to analyze gender wage inequality have been restricted to models with single selection (e.i. two equation model), using Heckman's two-step method or Maximum likelihood, because no method was available in order to execute the decomposition when more than two equations are estimated simultaneously. Actually, according to this approach the computation of the selection bias relies only upon the expectations of the residuals computed using the consistent estimates from the joint estimation, and hence -as we will see later on- does not require the computation of the analytical formula of the selection bias. This makes the decomposition analysis much more easier and feasible, especially when we are in order to evaluate a multivariate normal distribution, somewhat more complicated than the standard two equations model.

Furthermore, the approach adopted here would provide us with a suitable decomposition analysis. First, it is based on the full information MSL estimation which makes it an efficient methodology. And second, it uses joint simulated estimation MLH method, which allows therefore to obtain consistent estimates of parameters by accounting for the correlation among the stochastic components of our model.

Let us consider formally how we apply the GSB approach to our multivariate probit model. Remember that we seek to study the gender gap in the observed promotion probabilities, that is the average expectation of p_{ig} conditional on being hired and considering the endogeneity issue. So, we can define the conditional expectation of the stochastic element ε_{ig4} given the values of the other equations by $E(\varepsilon_{ig4}|s_{ig}, z_{ig}, f_{ig}, e_{ig}) = \Lambda_{ig}$[34], and its conditional variance by $V(\varepsilon_{ig4}|.) = \sigma^2$.

Assume that we get consistent estimates of our model using maximum simulated likelihood. Then, the promotion equation (14) given the values of other equations and using our consistent estimators is:

$$p^*_{ig} = z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2 + \hat{\Lambda}_{ig} + \hat{\epsilon}_{ig}, \tag{20}$$

where $\hat{\gamma}, \hat{\delta}_1, \hat{\delta}_2$ is the vector of consistent estimators, $\hat{\varepsilon_{g4}} = \hat{\Lambda}_{ig} + \hat{\epsilon}_{ig}, \hat{\Lambda}_{ig} = E(\hat{\varepsilon_{g4}}|.)$,

[34] Λ_{ig} is the so called "generalized residuals". See Gourieroux, Monfort, Renault, and Trognon (1987).

$\hat{\epsilon}_{ig} = \hat{\varepsilon_{g4}} - \hat{\Lambda}_{ig}, E(\hat{\epsilon}_{ig}|.) = 0$, and $V(\hat{\epsilon}_{ig}) = \hat{\sigma^2}$.

The conditional expectation of $p_{ig}, E(p_{ig}|.)$, that is the conditional probability of promotion ($Pr(p_{ig} = 1|.)$) is given by $\hat{P}_{ig|.} = \Phi((z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2 + \hat{\Lambda}_{ig})/\hat{\sigma})$. Similarly, we denote the unconditional probability of promotion by $\hat{P}_{ig} = \Phi(z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2)$. Therefore, asymptotically the average conditional expectation of p_{ig} could be written as,

$$\bar{p_g} = \overline{\hat{P}}_{g|.} = \overline{\Phi\left(\frac{z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2 + \hat{\Lambda}_{ig}}{\hat{\sigma}}\right)}$$

This average conditional probability (The observed probability of promotion) is the outcome of two effects: the average unconditional expectation of p_{ig} ($\overline{\hat{P}}_g$), and the average effects of the other equations on the probability of promotion, that we denote by $\overline{\hat{P}}_{g\hat{\Lambda}_g}$. Thus, we have:

$$\bar{p_g} = \overline{\hat{P}}_{g|.} = \overline{\hat{P}}_g + \overline{\hat{P}}_{g\hat{\Lambda}_g} \tag{21}$$

$$= \overline{\Phi(z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2)} + [\bar{p}_g - \overline{\Phi(z_{ig}\hat{\gamma} + f_{ig}\hat{\delta}_1 + e_{ig}\hat{\delta}_2)}] \tag{22}$$

The first term at the right hand side of equation (22) is the univariate standard normal distribution function, and the second term; the effects of the other equations, is simply the difference between the observed probability of promotion and the average unconditional expectation of p_{ig}.

The difference in the observed promotion probability between males and females could then be decomposed as follows:

$$\begin{aligned}\bar{p_m} - \bar{p_f} = & [\overline{\Phi(z_{im}\hat{\gamma}_m + e_{im}\hat{\delta}_{2m})} - \overline{\Phi(z_{if}\hat{\gamma}_m + e_{if}\hat{\delta}_{2m})}] \\ & + [\overline{\Phi(z_{if}\hat{\gamma}_m + e_{if}\hat{\delta}_{2m})} - \overline{\Phi(z_{if}\hat{\gamma}_f + e_{if}\hat{\delta}_{2f})}] \\ & + [\overline{\Phi(z_{if}\hat{\gamma}_f + e_{if}\hat{\delta}_{2f})} - \overline{\Phi(z_{if}\hat{\gamma}_f + e_{if}\hat{\delta}_{2f} + f_{if}\hat{\delta}_1)}] \\ & + \overline{\hat{P}}_{m\hat{\Lambda}_m} - \overline{\hat{P}}_{f\hat{\Lambda}_f}\end{aligned} \tag{23}$$

The first part of the equation represents the difference in the promotion opportunities due to differences in the observed characteristics between males and females and the second part is the effect of differences in the corresponding coefficients. The effect of efficiency in promotion which accounts for differences in separation probabilities corresponds to the third term, and the last term stands for differences in the effects of the other equation on the probabilities of promotion between the two gender[35].

5 Results

Before examining in detail gender inequality in the hiring and promotion outcomes, we will have a glance at our results of the maximum simulated likelihood MSL model. Estimations are presented in table 6 to 9 of the Appendix for each sex separately[36].

The model was run for the whole sample (mover and stayer), and for the only group of stayers as it has been defined previously. In table 6 and 8 we compare results of men and women without considering the effect of the employer's beliefs about the risk of quitting on the hiring and the promotion processes. Thus, we neglect at this stage the propensity to fertility for women. We refer to this model by model 1[37]. As it could be seen, the correlation coefficients among the stochastic components of the selection and promotion equations are positive and statistically significant in each model and for both genders[38]. This means that the hiring stage has a non negligible effect on the promotion probabilities, and thus taking it into account is relevant in the analysis of unequal promotion opportunities between males and females. Investment in human capital is endogenous to both the hiring and the promotion processes, except in the all sample of men. The correlation between the stochastic component of the education and the hiring equations is not statistically significant[39]. Considering estimates of the threshold standards, they are all positive and statistically significant. Obviously, we notice that for both genders the threshold standards of the promotion stage are remarkably higher than those of the hiring stage. That is, a relatively more exigent criteria is required in order to be promoted in comparison to the hiring procedure. We find in line with our theoretical model that the hiring criteria for women is greater than that of their male colleagues. The female promotion standard is as well somehow greater than that of males according to this model (model 1) where we are not yet accounting for the effect

[35] We emphasize that the first three parts of the decomposition are differences in the observed promotion probabilities assuming that the the stochastic component (unobserved individual characteristics) of the unconditional promotion equations for both gender has the same shape (i.e., same normal distribution with mean zero and variance one). The last part refers to differences in the probabilities caused by the differences in the distribution of the unobserved individual characteristics.

[36] A likelihood-ratio test rejects simultaneously the hypotheses of equal parameters between men and women for all the respondents variables in our model with a p-value of *zero*. The hypotheses of equal parameters is also rejected for each equation separately (a p-value equal to *zero* for the selection and the promotion equation, and a p-value of $0,0014$ for the education equation.

[37] Remember that we assume a risk of quitting equal to *zero* for males.

[38] Those who have been hired are more likely to be promoted.

[39] A likelihood ratio test of the absence of correlation among the stochastic components in all our models is rejected with a p-value equal to zero for both genders.

of the risk of quitting.

We chow in table 7 and 9 our estimates of the full model which considers the propensity to fertility for females. In a first estimation, we approximate the separation probability by the number of children a women has, and we refer to this model as model 2[40]. In the third model (model 3) we employ the fertility index as computed from equation 10. Actually, we suppose that the separation probability as approximated in model 2 is possibly endogenous to our model. Employer's beliefs have feedback effects on women's behavior. Expected hiring and promotion discrimination could discourage women from investment in human capital, facilitate fertility decisions, weaken their attachment to the labour force, and thus increase their quit rates. For this reason we use the demographic fertility index in model 3 which is considered to be an exogenous variable to our model, and hence is supposed to better inform about employer's expectation about separation probabilities. These two models provide almost similar results. Nevertheless, it is worth noting some important issues, particularly in comparison to model 1. First, once we consider the effect of employer's expectation about the risk of quitting (the propensity to fertility) in the hiring and promotion equations, the threshold standards decrease considerably, and they are insignificant in the hiring equation. Our variable of interest, the propensity to fertility, has always the expected negative and significant effect on the hiring and the promotion outcomes. Thus, it seems that employer's beliefs about the risk of quitting does have a non negligible effect in determining the hiring and promotion criteria for women. This appears to confirm in some manner the hypotheses of our theoretical model.

Decomposition analysis

We present in tables 2 to 5 of the Appendix the average predictions of the marginal distribution functions for the hiring and the promotion equations, the conditional distribution functions of promotion, as well as the counterfactual distributions for females[41]. For a seek of comparison predicted probabilities from the three model for females as well as the observed probabilities are also reported[42].

Results of the decomposition analysis are summarized in table 1. The first two panels provide a comparison between the full sample and the group of stayers.

When looking to differentials in the hiring distribution functions (the left-hand side of table 1), we observe that women are on average less likely to be hired than men.

[40]Estimations of this model is not presented here in order to save place.

[41]The counterfactual distribution is defined as the hiring (promotion) distribution function of males that would prevail if all covariates were distributed as for females.

[42]Notice that we compute average predicted probabilities and not probabilities for a representative individual with average endowments.

This inequality in the hiring probabilities is smaller in the case of stayers. The raw differential in model 1 is about 35 percentage points in favor of males for the whole sample and $25,5$ percentage points for stayers. The main part of this differential is due either to differences in coefficients or to unjustifiable differential in the hiring threshold standards[43]. The effect of differences in characteristics are rather in favor of females.

From model 2 and 3, we notice that an efficient hiring process which accounts for expectations about separation rates has a negative effect on female hiring opportunities. That is, if women had identical risk of quitting as men, properly if the employer affirms same beliefs about female risk of quitting as men, the chance to get hired for women would have increased by nearly 13 percentage points if we consider the whole sample and 11 percentage points for stayers. Thus, around 35% ($38,5\%$) of the hiring differential for the whole sample (stayers) is due to an efficient hiring process which takes into account different expectations about separation rates. Evidently, we realize a reduction in the unexpained component once we take into account this effeciency in the hiring outcomes. Note that in model 3 we obtain always a slitely smaller effect of efficiency than in model 2. This indicates that our computed demographic fertility index provides a better control for the endogeneity of the risk of quitting.

Our model suggest that conditional on being hired, women would have on average the same opportunities to promotion as their male colleagues. According to our results, women have an advantage in term of promotion opportunities of about 10 percentage points greater than men for the whole sample. Not surprisingly, the privilege is higher for stayers women. However, this advantage is mainly due to differences in the effect of other equations on the promotion probabilities $\Delta(\overline{\hat{P}}_{g\hat{\Lambda}_g})$ and to differences in endowments. These findings are in line with our model, since it asserts that conditional on being hired women would be on average more qualified than their male colleagues. 8 percentage points (all the sample) and 4 percentage points (stayers) remain unexplained in the first model. Nevertheless, when we account for differences in promotion opportunities due to an efficient promotion process (model 2 and 3), the effect of differences in the coefficients and the threshold standard vanishes, and even turns into the favor of stayers women. As we said previously, once separations rates are correctly predicted by the employer and are exogenous to our model, differential due to an efficient promotion could be seen as a pure efficient promotion effect, it is not perceived as an adversity against women. Hence, the unexplained part is the only part which may be considered

[43] It is worth noting that differences in coefficients could be interpreted either as discrimination, if we consider that the hiring process is the entire result of the employer's decision, or as differences in behavioral response to individual characteristics when we are talking about self selection into employment. Unfortunately, we could not ensure that this unexplained part is entirely due to employer's discrimination.

as discrimination in promotion opportunities between males and females.

We do not ignore however that the hiring and promotion processes are certainly different between the public and the private sectors. This may affect substantially male and female differential in term of the hiring and promotion outcomes, especially when women are more likely to be in the public sector than do men, while they are denied from entry into the private sector. For this reason, we refine our analysis by splitting our sample of stayers into public and private sectors, and we run our MSL model for each sex and sector separately[44]. The third and fourth panel in table 1 shows the decomposition analysis for the public and the private sectors, respectively[45]. As expected, gender inequality in the hiring outcome is distinctly greater in the private sector than it is in the public sector. The advantage that women have in term of endowments is only observed in the private sector. This suggest that women have to fulfill higher ability standard than men in order to be hired, and thus support the fact that low educated women face barriers to entry into the private sector. Conditional on being hired, there still be an unexplained differential in promotion opportunities between men and women in the public sector, even when efficiency in promotion is considered. However, it seems that in the private sector unequal treatment in promotion opportunities disappears[46]. Since women have been held to a relatively more exigent hiring criteria than men, the successful group who overcome this adversity is more qualified than their male colleagues. Employer's beliefs become then more optimistic about female separation rates and women would at least be treated equally alike men during the promotion stage.

[44]Estimates of these models are not presented here, they are available from the author upon request.

[45]Unfortunately, we were not able to estimate model 2 and 3 in the private sector due to a large amount of missing observations on the fertility index.

[46]Although, results which accounts for the efficiency in promotion are not available for the private sector, we would expect at least a non significant effect of the unexplained component, and plausibly a positive discrimination in favour of female.

Table 1: Decomposition for the differences in the hiring and promotion cumulative distribution functions (Standard errors in parenthesis[†])

	Hiring			*Promotion*		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
A*ll*						
Raw	35,12*** (0,0027)	37,92*** (0,0035)	35,97*** (0,0035)	-9,52*** (0,0078)	-9,89*** (0,0088)	-10,27*** (0,0088)
Covariances	0,63* (0,0026)	-4,28*** (0,0029)	-4,28*** (0,0029)	-4,85*** (0,0058)	-5,74*** (0,0065)	-5,74*** (0,0065)
Unexplained (coeffs+threshold θ^*)	34,48*** (0,0017)	28,67*** (0,0025)	28,93*** (0,0025)	8*** (0,0020)	0,55*** (0,0032)	1,12*** (0,0031)
Efficiency	-	13,52*** (0,0016)	13,31*** (0,0016)	-	6,61*** (0,0022)	6,03*** (0,0020)
Effects of other equations $\Delta(\bar{\hat{P}}_{g\hat{\Lambda}_g})$	-	-	-	-12,57*** (0,0040)	-11,31*** (0,0038)	-11,69*** (0,0039)
S*tayers*						
Raw	25,49*** (0,0024)	27,92*** (0,0029)	27,92*** (0,0029)	-11,51*** (0,0095)	-13,30*** (0,0107)	-13,34*** (0,0108)
Covariates	-0,98*** (0,0024)	-5,72*** (0,0026)	-5,72*** (0,0026)	-4,28*** (0,0057)	-5,76*** (0,0067)	-5,76*** (0,0067)
Unexplained (coeffs+threshold θ^*)	26,47*** (0,0017)	20,97*** (0,0024)	22,91*** (0,0023)	4,16*** (0,0020)	-1,97*** (0,0035)	-0,66* (0,0034)
Efficiency	-	12,67*** (0,0016)	10,77*** (0,0014)	-	6*** (0,0022)	4,81*** (0,0018)
Effects of other equations $\Delta(\bar{\hat{P}}_{g\hat{\Lambda}_g})$	-	-	-	-11,40*** (0,0053)	-11,58*** (0,0055)	-11,73*** (0,0056)
S*tayers*(*public*)						
Raw	9,44*** (0,0032)	9,69*** (0,0035)	9,84*** (0,0035)	7,49*** (0,0107)	11,87*** (0,0124)	11,16*** (0,0125)
Covariates	2,42*** (0,0034)	1,15*** (0,0037)	1,15*** (0,0037)	1,68*** (0,0075)	3,64*** (0,0084)	3,64*** (0,0084)
Unexplained (coeffs+threshold θ^*)	7,02*** (0,0009)	0,48** (0,0018)	2,10*** (0,0017)	4,90*** (0,0020)	1,43*** (0,0032)	2*** (0,0032)
Efficiency	-	8,05*** (0,0012)	6,58*** (0,0009)	-	2,73*** (0,0011)	2,21*** (0,0009)
Effects of other equations $\Delta(\bar{\hat{P}}_{g\hat{\Lambda}_g})$	-	-	-	0,91 (0,0032)	4,07*** (0,0072)	3,31*** (0,0073)
S*tayers*(*private*)						
Raw	24,21*** (0,0020)			-0,35 (0,0053)		
Covariates	-1,69*** (0,0024)			-0,71*** (0,0030)		
Unexplained (coeffs+threshold θ^*)	25,99*** (0,0018)			2,46*** (0,0024)		
Efficiency	-			-		
Effects of other equations $\Delta(\bar{\hat{P}}_{g\hat{\Lambda}_g})$	-	-	-	-2,11*** (0,0046)		

Note: Values are reported in percentages.
* p<0.05); ** p<0.01; *** p<0.001
[†] Standard errors are obtained through 1000 bootstrapping replications.

6 Conclusion

This paper aims to study differences in the promotion opportunities between males and females in the Egyptian labour market. A fact, which we suppose to provide a credible explanation for the glass ceiling phenomenon. For this purpose, we suggest a dynamic statistical discrimination model in job promotion which accounts for the hiring stage procedure, as well as for the endogeneity of investment in human capital and fertility decision. We show how standard equilibrium results in one-stage statistical discrimination models could be misleading when we consider a more realistic dynamic environment. Precisely, we argue that in a dynamic model a significant adversity against women at the hiring stage could affect employer's beliefs which flip into the favor of females in later stages. In some words, it may be tough for women to get hired, but once being hired, it is easy to get promoted. We test this assumption by running a multivariate Simulated Maximum Likelihood SML which allows us to undertake the selection and endogeneity issues in our model. As women are supposed to hold fewer jobs in the labour force than do men, we attempt to refine our empirical analysis by considering only those workers who still with the same employer since their first entry into the labour market. Then the sources of inequality in the hiring and promotion outcomes were examined using a generalized residual decomposition approach. Our main results support the model's assumption. There exists a significant discrimination against women at the hiring stage which could not be attributed neither to differences in endowments nor to the worker attachment to the labour force. However, women who surpass this initial adversity are at least, everything else being equal, as likely as promoted as men. These findings holds essentially for the private sector, but things are somehow different in the public sector. Adversity against women during the hiring process is substantially lower in the public sector than it is in the private sector. Nevertheless, once getting hired, "unequal" promotion opportunities remains in the public sector. This seems to be a surprising result since we would rather expect a more equal promotion treatment in the public sector as opposed to the private sector. These findings are justified in light of our theoretical model by answering to the following question: why does "belief flipping" arises in the private sector, while employer in the public sector still hold negative beliefs about women during the promotion decision? The answer is simply due to the fact that the private sector satisfies the required conditions under which belief flipping could arise in the workplace. Properly, the private sector is characterized by a relatively higher risk of quitting, likely as a result of a specific on the job training. In order to insure that women will have the incentive to invest for promotion and would remain within the job once getting promoted, the employer have to set an extended wage profile. Such a wage profile, according to our model, weaken the selection mechanism at the hiring stage, and hence requires a more tougher hiring cutoff standard. Under these conditions, employer's belief flip and women are held to a much easier promotion criteria. In contrast, the public sector has a narrower wage structure, less barriers to entry and thus employers are uncertain about women eligibility for promotion.

We are aware that these results are subject to some limitations. Actually, in order to test job promotion in such a dynamic environment, one would obviously need to employ panel data which allows one to follow the individuals over time. Using cross-sectional data in our analysis prevents us from estimating a more advanced dynamic model. The currently 2-years panel data available in Egypt is still limited, with a lot missing values for essential variables. It will be possible to estimate a more developed model strategies when more panel surveys become available.

Finally, we would like to emphasize that an important characteristic of the econometric specification we adopt here, and which constitutes its particularity, is the inclusion of a measure of worker attachment to the labour force, which has been approximated by our demographic fertility index. This allow us to distinguish between differences in the hiring and the promotion opportunities attributed to informal and institutional factors such as discrimination which may not be efficient, and differences which accounts for workers attachment to the labour force and hence could be considered as efficient.

Appendix A

Condition of investment at the hiring stage:

$$\eta_1[F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})] + \eta_2[1 - F_q^p(\theta^{*p})]\int_0^{\eta_2} h(\omega)d\omega + [1 - F_q^p(\theta^{*p})]\int_{\eta_2}^{\infty} \omega h(\omega)d\omega$$
$$+\eta_1 F_q^p(\theta^{*p})\int_0^{\eta_1} h(\omega)d\omega + F_q^p(\theta^{*p})\int_{\eta_1}^{\infty} \omega h(\omega)d\omega - \eta_1\int_0^{\eta_1} h(\omega)d\omega - \int_{\eta_1}^{\infty} \omega h(\omega)d\omega \geqslant c^h \tag{24}$$

$$\eta_1[F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})] + \eta_2[1 - F_q^p(\theta^{*p})]H(\eta_2) + [1 - F_q^p(\theta^{*p})]\int_{\eta_2}^{\infty} \omega h(\omega)d\omega$$
$$-\eta_1[1 - F_q^p(\theta^{*p})]H(\eta_1) - [1 - F_q^p(\theta^{*p})]\int_{\eta_1}^{\infty} \omega h(\omega)d\omega \geqslant c^h \tag{25}$$

$$\eta_1[F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})] + [1 - F_q^p(\theta^{*p})]\int_{\eta_1}^{\infty} H(\omega)d\omega - [1 - F_q^p(\theta^{*p})]\int_{\eta_2}^{\infty} H(\omega)d\omega \geqslant c^h \tag{26}$$

$$\eta_1[F_u^h(\theta^{*h}) - F_q^h(\theta^{*h})] + [1 - F_q^p(\theta^{*p})]\int_{\eta_1}^{\eta_2} H(\omega)d\omega \geqslant c^h \tag{27}$$

Condition of investment at the promotion stage:

$$\eta_2(F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_0^{\eta_2} h(\omega)d\omega + (F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_{\eta_2}^{\infty} \omega h(\omega)d\omega$$
$$-\eta_1(F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_0^{\eta_1} h(\omega)d\omega - (F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_{\eta_1}^{\infty} \omega h(\omega)d\omega \geqslant c^p \tag{28}$$

$$(F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_{\eta_1}^{\infty} H(\omega)d\omega - (F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_{\eta_2}^{\infty} H(\omega)d\omega \geqslant c^p \tag{29}$$

$$(F_u^p(\theta^{*p}) - F_q^p(\theta^{*p}))\int_{\eta_1}^{\eta_2} H(\omega)d\omega \geqslant c^p \tag{30}$$

Appendix B

Definitions of variables used in our estimations.

Response variables:

- Hiring probability: a binary variable that takes one if the individual is currently employed and zero otherwise, excluding employers, self-employed and unpaid individuals working for family.
- Promotion probability: a binary variable that takes one if the worker has been promoted once, twice, three or more times and zero if he has never been promoted. Have never been promoted includes those workers who did have the opportunity to be promoted but were not eligible for promotion, and those who were in jobs that do not offer promotion opportunities.
- Education: a binary variable that takes one if the individual have attained a high level of education and zero if he hold a low level of education. High level of education corresponds to general and vocational high-schools, post-secondary, university and above university degrees, while the low levels stays for illiterate, literate without any diploma, elementary and middle schools degrees.
- Propensity to fertility: in model 2, it is a binary variable that takes one if the women has at least one child and zero if she does not have a child. In model 3, it is a binary variable that takes one if the probability that a women will bear a further child within the next five years is greater than $0,5$ and zero otherwise. This probability is computed conditional on the age of each women and her current number of children.

Explanatory variables for the hiring equation:

- Age.
- The square of age.
- Marital status: single, married, divorced, widowed. The omitted category is being single.
- The highest education degree attained: we use nine levels of education as dummy variables: nothing (Education1), primary (Education2), preparatory (Education3), general secondary (Education4), technical secondary 3-years (Education5), technical secondary 5-years (Education6), above intermediate (Education7), university (Education8), post graduate (Education9).
- Non labour income.
- Region: dummy variables for the region of residence. Six regions are defined: the Great Cairo (Region1), Alexandria and Suez Canal (Region2), Urban Lower (Region3), Urban Upper (Region4), Rural Lower (Region5), Rural Upper (Region6). The Great Cairo is the base category.

- The propensity to fertility for females as defined previously.

Explanatory variables for the promotion equation:

- Age, the square of age, marital status, the region of residence, the propensity to fertility for females. (These variables are as defined previously)
- The number of years of schooling.

Instruments used in order to account for the endogeneity of education

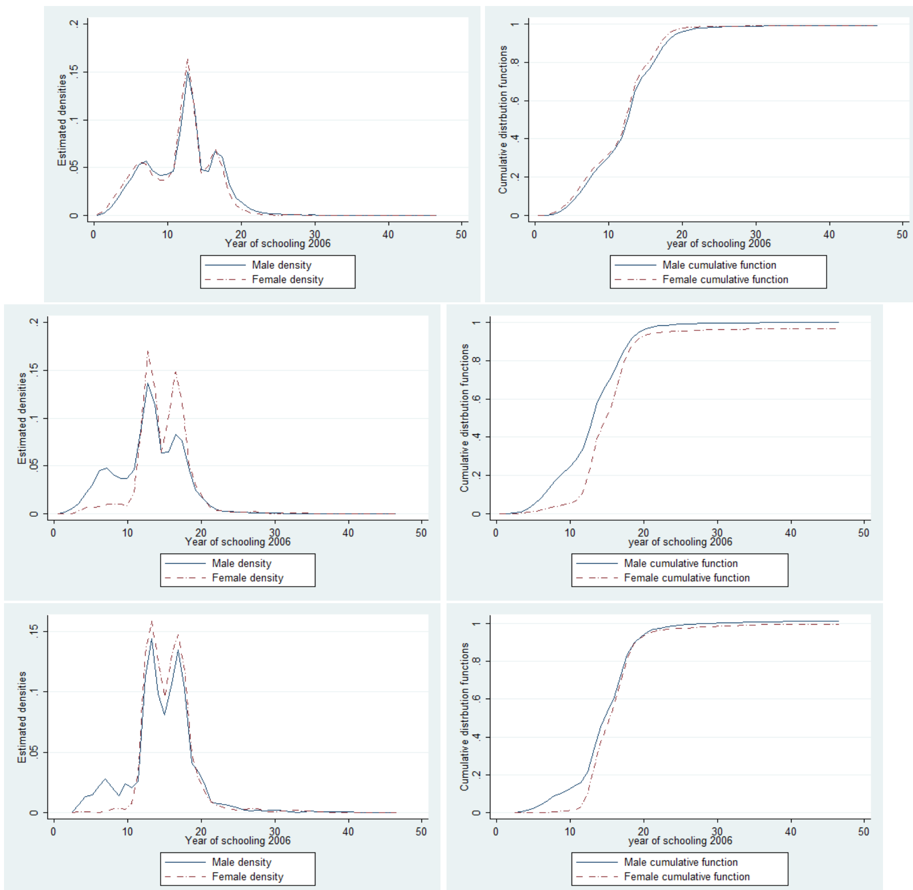
- Father's highest educational certificate: nine levels of educational certificate are defined and used as dummy variables: illiterate, read and write, primary, preparatory, general/technical secondary, above intermediate, higher institute, university, post graduate.
- Mother's highest educational certificate (similarly defined).
- Father's waged status: six status are used as dummy variables: waged in regular job, waged in irregular job, employer, self employed, work for family (non-waged), no job. For individuals whose father was absent from the household, we can identify father's waged status when the individual was 15 years old. If the individual is less than 15 years old, father's current waged status is used, and when the father is died before the individual reached 15, father's last work is then reported. Unfortunately, for individuals whose father was currently present in the household, we only could have information on father's current wage status.
- Sector of father's job: seven sectors are defined: government, public enterprise, private, investment, foreign, non-profitable, non-governmental organization, other including cooperatives.
- The number of siblings.
- The number of children for females
- Marital status and the region of residence as defined previously.

Explanatory variables for the fertility equation:

- Age, the square of age, the number of years of schooling, non labour income and the region of residence.

Appendix C

Figure C1: Kernel density estimates and empirical cumulative distribution functions of the number of years of schooling



Note: Each frame in the left-side column of the figure compares the male and female estimated density functions for the whole sample, for wage workers and for promoted individuals, respectively. The right-side column plots, for each group, the corresponding cumulative distribution functions.

Table 2: Prediction of the hiring and promotion probabilities (Standard deviations in parenthesis)

All				
	Male	*Female*		
		model 1†	*model 2*‡	*model 3*‡
Hiring probabilities				
Marginal (observed)	54.66	19.18	15.70	15.70
Marginal (predicted)	54.47 (0.165)	19.36 (0.178)	16.56 (0.191)	16.50 (0.190)
Counterfactual	-	53.84 (0.162)	58.75 (0.140)	58.75 (0.140)
Promotion probabilities				
Marginal (observed)	18.74	9.58	8.20	8.20
Marginal (predicted) $\overline{\hat{P}}_g$	18.70 (0.179)	9.25 (0.121)	7.91 (0.127)	7.94 (0.127)
Counterfactual	-	15.71 (0.160)	14.93 (0.141)	14.93 (0.141)
Conditional (observed)	34.29	49.94	52.26	52.26
Conditional (predicted)$\overline{\hat{P}}_{g\|.}$	32.91 (0.240)	42.43 (0.263)	42.79 (0.218)	43.18 (0.220)
Effects of other equations $\overline{\hat{P}}_{g\hat{\Lambda}_g}$	9.49 (0.080)	25.19 (0.197)	24.74 (0.141)	25.08 (0.143)
N° Obs.	8609	7109	4246	4246

Note: Values are reported in percentages.
Reported values are weighted by the appropriate survey sampling weights.
† The sample in model 1 includes all women (married and non-married) between 16 and 65 years of age inclusive.
‡ The sample in these two models includes only ever-married women between 16 and 65 years of age inclusive.

Table 3: Prediction of the hiring and promotion probabilities (Standard deviations in parenthesis)

Stayers

	Male	*Female*		
		model 1†	*model 2*‡	*model 3*‡
Hiring probabilities				
Marginal (observed)	40.20	14.72	12.12	12.12
Marginal (predicted)	40.08 (0.143)	14.59 (0.145)	12.16 (0.149)	12.12 (0.148)
Counterfactual	-	41.05 (0.140)	45.80 (0.122)	45.80 (0.122)
Promotion probabilities				
Marginal (observed)	12.51	7.13	6.39	6.39
Marginal (predicted) $\overline{\hat{P}}_g$	11.85 (0.136)	6.68 (0.097)	5.89 (0.099)	5.88 (0.099)
Counterfactual	-	10.54 (0.119)	10.62 (0.109)	10.62 (0.109)
Conditional (observed)	31.11	48.45	52.72	52.72
Conditional (predicted)$\overline{\hat{P}}_{g\|.}$	29.18 (0.252)	40.70 (0.263)	42.48 (0.220)	42.52 (0.222)
Effects of other equations $\overline{\hat{P}}_{g\hat{\Lambda}_g}$	12.52 (0.122)	26.79 (0.210)	27.38 (0.163)	27.72 (0.167)
N° Obs.	6568	6701	4045	4045

Note: Values are reported in percentages.
Reported values are weighted by the appropriate survey sampling weights.
† The sample in model 1 includes all women (married and non-married) between 16 and 65 years of age inclusive.
‡ The sample in these two models includes only ever-married women between 16 and 65 years of age inclusive.

Table 4: Prediction of the hiring and promotion probabilities (Standard deviations in parenthesis)

Stayers (public sector)

	Male	*Female*		
		model 1†	*model 2*‡	*model 3*‡
Hiring probabilities				
Marginal (observed)	20.98	11.36	10.80	10.80
Marginal (predicted)	20.47 (0.191)	11.03 (0.142)	10.78 (0.151)	10.63 (0.147)
Counterfactual	-	18.05 (0.166)	19.32 (0.164)	19.32 (0.164)
Promotion probabilities				
Marginal (observed)	14.12	7.08	6.25	6.25
Marginal (predicted) $\overline{\hat{P}}_g$	13.26 (0.147)	6.63 (0.103)	5.72 (0.100)	5.73 (0.100)
Counterfactual	-	10.98 (0.124)	10.47 (0.114)	10.47 (0.114)
Conditional (observed)	67.29	62.30	57.93	57.93
Conditional (predicted) $\overline{\hat{P}}_{g\|.}$	57.01 (0.215)	49.52 (0.238)	45.14 (0.221)	45.85 (0.224)
Effects of other equations $\overline{\hat{P}}_{g\hat{\Lambda}_g}$	31.64 (0.197)	35.57 (0.257)	36.35 (0.242)	36.41 (0.239)
N° Obs.	4990	6437	3982	3982

Note: Values are reported in percentages.
Reported values are weighted by the appropriate survey sampling weights.
† The sample in model 1 includes all women (married and non-married) between 16 and 65 years of age inclusive.
‡ The sample in these two models includes only ever-married women between 16 and 65 years of age inclusive.

Table 5: Prediction of the hiring and promotion probabilities (Standard deviations in parenthesis)

Stayers (private sector)		
	Male	*Female model 1*[†]
Hiring probabilities		
Marginal (observed)	28.92	4.26
Marginal (predicted)	28.66 (0.128)	4.46 (0.074)
Counterfactual	-	30.35 (0.135)
Promotion probabilities		
Marginal (observed)	2.17	0.36
Marginal (predicted) $\overline{\hat{P}}_g$	2.25 (0.036)	0.37 (0.007)
Counterfactual	-	2.53 (0.038)
Conditional (observed)	7.50	8.53
Conditional (predicted) $\overline{\hat{P}}_{g\vert .}$	7.03 (0.082)	7.38 (0.076)
Effects of other equations $\overline{\hat{P}}_{g\hat{\Lambda}_g}$	4.36 (0.059)	12.70 (0.147)
N° Obs.	5499	5925

Note: Values are reported in percentages.
Reported values are weighted by the appropriate survey sampling weights.
[†] The sample in model 1 includes all women (married and non-married) between 16 and 65 years of age inclusive.

Table 6: Multivariate probit estimates using maximum simulated likelihood model (All)

	Male			*Female* *Model*1		
Variable	**Hiring**	**Education**	**Promotion**	**Hiring**	**Education**	**Promotion**
Age	0.145*** (0.009)		0.251*** (0.013)	0.225*** (0.013)		0.288*** (0.017)
Age2	-0.002*** (0.0001)		-0.003*** (0.0002)	-0.002*** (0.0002)		-0.003*** (0.0002)
Married	0.196*** (0.043)	-0.211*** (0.035)	0.249*** (0.057)	-0.932*** (0.056)	-0.330*** (0.048)	-0.325*** (0.076)
Divorced	-0.004 (0.204)	-0.403 (0.224)	-.125 (0.229)	-0.507*** (0.148)	-0.502*** (0.133)	-0.526** (0.168)
Widowed	-0.064 (0.251)	-0.283 (0.240)	-0.043 (0.274)	-0.772*** (0.113)	-1.294*** (0.087)	0.399*** (0.124)
Nlincome	-0.003e-02*** (4.92e-06)			-0.001e-02** (4.57e-06)		
Education2	0.200*** (0.049)			0.302** (0.096)		
Education3	0.165** (0.061)			0.476*** (0.108)		
Education4	0.145 (0.117)			0.753*** (0.147)		
Education5	0.342*** (0.067)			1.027*** (0.093)		
Education6	0.625*** (0.137)			1.535*** (0.148)		
Education7	0.516*** (0.085)			1.253*** (0.107)		
Education8	0.579*** (0.068)			1.578*** (0.099)		
Education9	0.721*** (0.190)			1.835*** (0.228)		
Yrschool			0.069*** (0.005)			0.088*** (0.007)
Region2	-0.099 (0.056)	-0.101 (0.061)	-0.366*** (0.062)	0.062 (0.068)	-0.246*** (0.063)	-0.257*** (0.077)
Region3	-0.309*** (0.054)	0.051 (0.058)	-0.247*** (0.060)	0.020 (0.066)	0.103 (0.061)	0.028 (0.073)
Region4	-0.295*** (0.050)	0.255*** (0.056)	-0.182*** (0.055)	0.107 (0.062)	0.082 (0.060)	0.052 (0.069)
Region5	-0.205*** (0.048)	0.046 (0.052)	-0.239*** (0.053)	0.047 (0.065)	0.049 (0.056)	-0.057 (0.074)
Region6	-0.505*** (0.052)	0.018 (0.055)	-0.500*** (0.062)	-0.302*** (0.085)	-0.316*** (0.062)	-0.455*** (0.109)
CertF		yes			yes	
EmpstF		yes			yes	
SectF		yes			yes	
CertM		yes			yes	
Nbsiblings		-0.021*** (0.006)			-0.052*** (0.007)	
Constant		0.376*** (0.068)			0.706*** (0.078)	
ρ_{21}	-0.011 (0.036)			0.207*** (0.037)		
ρ_{31}	0.786*** (0.014)			0.902*** (0.011)		
ρ_{32}	0.117*** (0.030)			0.381*** (0.035)		
θ^{*h}	2.639*** (0.170)			5.661*** (0.245)		
θ^{*p}			7.212*** (0.266)			8.338*** (0.347)
N° Obs.	8609			7109		
Loglikelihood	-12652.125			-7321.6021		

Note: * p<0.05; ** p<0.01; *** p<0.001
Estimates are obtained through 100 pseudo-random draws.
Standard errors in parenthesis.

Table 7: Multivariate probit estimates using maximum simulated likelihood model (All female)

*Model*3

Variable	Hiring	Education	Promotion	Fertility
Age	-0.042		-0.066	0.646
	(0.045)		(0.059)	(0.361)
Age2	0.001		0.002*	-0.025***
	(0.0006)		(0.0008)	(0.006)
Married	-0.400*	0.574***	0.254	
	(0.184)	(0.163)	(0.197)	
Divorced	0.035	0.087		
	(0.249)	(0.225)		
Widowed			0.329	
			(0.261)	
Nlincome	-0.002e-02*			0.003e-02
	(7.99e-06)			(0.002e-02)
Education2	0.357*			
	(0.157)			
Education3	0.574**			
	(0.168)			
Education4	0.830***			
	(0.235)			
Education5	1.291***			
	(0.137)			
Education6	2.047***			
	(0.229)			
Education7	1.682***			
	(0.155)			
Education8	2.157***			
	(0.149)			
Education9	2.340***			
	(0.414)			
Yrschool			0.129***	-0.034*
			(0.010)	(0.017)
Region	yes	yes	yes	yes
Findex	-1.257***		-1.123**	
	(0.343)		(0.390)	
CertF	-0.105	-0.379*		
	(0.070)	(0.153)		
EmpstF	-0.163*	-0.419*		
	(0.075)	(0.162)		
SectF	-0.167*	-0.331*		
	(0.070)	(0.163)		
CertM	-0.210*	-0.361		
	(0.099)	(0.200)		
Nbsiblings		-0.040***		
		(0.010)		
Nchild		-0.200***		0.175***
		(0.015)		(0.067)
Constant		0.373*		-0.008
		(0.190)		(5.396)
ρ_{21}	0.088	(0.046)		
ρ_{31}	0.902***	(0.016)		
ρ_{41}	0.004	(0.068)		
ρ_{32}	0.274***	(0.052)		
ρ_{42}	-0.108	(0.085)		
ρ_{43}	-0.046	(0.071)		
θ^{*h}	1.434			
	(0.953)			
θ^{*p}			2.973*	
			(1.228)	
N° Obs.	4246			
Loglikelihood	-4429.1495			

Note: * p<0.05; ** p<0.01; *** p<0.001
Estimates are obtained through 100 pseudo-random draws.
Table entries refers to estimated coefficients (marginal effects are available from the author upon request).
Standard errors in parenthesis.

Table 8: Multivariate probit estimates using maximum simulated likelihood model (Stayers)

	Male			*Female* *Model1*		
Variable	**Hiring**	**Education**	**Promotion**	**Hiring**	**Education**	**Promotion**
Age	0.104*** (0.011)		0.235*** (0.016)	0.204*** (0.014)		0.273*** (0.018)
Age2	-0.001*** (0.0001)		-0.003*** (0.0002)	-0.002*** (0.0002)		-0.003*** (0.0002)
Married	0.180*** (0.049)	-0.227*** (0.039)	0.256*** (0.069)	-0.903*** (0.060)	-0.364*** (0.049)	-0.382*** (0.079)
Divorced	-0.058 (0.252)	-0.436 (0.266)	-0.069 (0.277)	-0.433** (0.164)	-0.623*** (0.140)	-0.317 (0.198)
Widowed	-0.033 (0.307)	-0.412 (0.267)	-0.070 (0.328)	-0.709*** (0.126)	-1.438*** (0.093)	-0.457*** (0.136)
Nlincome	-0.002e-02** (6.32e-06)			-0.001e-02* (5.84e-06)		
Education2	0.216*** (0.058)			0.317** (0.108)		
Education3	0.172* (0.072)			0.552*** (0.118)		
Education4	0.064 (0.128)			0.832*** (0.162)		
Education5	0.137 (0.076)			1.087*** (0.100)		
Education6	0.583*** (0.151)			1.527*** (0.155)		
Education7	0.382*** (0.094)			1.315*** (0.116)		
Education8	0.449*** (0.078)			1.587*** (0.106)		
Education9	0.669** (0.213)			1.940*** (0.281)		
Yrschool			0.070*** (0.006)			0.095*** (0.008)
Region2	-0.258*** (0.065)	-0.165* (0.072)	-0.532*** (0.079)	-0.034 (0.076)	-0.272*** (0.065)	-0.378*** (0.091)
Region3	-0.255*** (0.059)	0.022 (0.065)	-0.318*** (0.071)	0.062 (0.071)	-0.117 (0.063)	0.066 (0.079)
Region4	-0.390*** (0.057)	0.282*** (0.065)	-0.322*** (0.067)	0.082 (0.068)	0.081 (0.062)	0.044 (0.076)
Region5	-0.282*** (0.055)	0.059 (0.060)	-0.383*** (0.065)	0.059 (0.069)	0.075 (0.058)	0.011 (0.080)
Region6	-0.729*** (0.061)	-0.024 (0.064)	-0.781*** (0.082)	-0.356*** (0.095)	-0.289*** (0.063)	-0.456*** (0.123)
CertF		yes			yes	
EmpstF		yes			yes	
SectF		yes			yes	
CertM		yes			yes	
Nbsiblings		-0.025*** (0.007)			-0.055*** (0.007)	
Constant		0.464*** (0.079)			-0.711*** (0.081)	
ρ_{21}	0.118** (0.040)			0.160*** (0.037)		
ρ_{31}	0.866*** (0.013)			0.914*** (0.012)		
ρ_{32}	0.198*** (0.036)			0.357*** (0.039)		
θ^{*h}	1.884*** (0.195)			5.444*** (0.263)		
θ^{*p}			6.869*** (0.316)			8.179*** (0.371)
N° Obs.	6568			6701		
Loglikelihood	-8987.7954			-6484.0911		

Note: * p<0.05; ** p<0.01; *** p<0.001
Estimates are obtained through 100 pseudo-random draws.
Standard errors in parenthesis.

Table 9: Multivariate probit estimates using maximum simulated likelihood model (Stayers female)

		*Model*3		
Variable	**Hiring**	**Education**	**Promotion**	**Fertility**
Age	-0.061 (0.048)		-0.038 (0.066)	0.741 (0.380)
Age2	0.001* (0.0007)		0.001 (0.0009)	-0.028*** (0.006)
Married	-0.441* (0.197)	0.577*** (0.169)	-0.063 (0.200)	
Divorced	0.017 (0.266)	0.025 (0.235)	-0.347 (0.438)	
Nlincome	-0.004e-02** (0.001e-02)			0.002e-02 (0.002e-02)
Education2	0.372* (0.178)			
Education3	0.655*** (0.182)			
Education4	0.868*** (0.256)			
Education5	1.217*** (0.150)			
Education6	1.955*** (0.237)			
Education7	1.586*** (0.171)			
Education8	2.006*** (0.164)			
Education9	2.271*** (0.420)			
Yrschool			0.113*** (0.012)	-0.056** (0.018)
Region	yes	yes	yes	yes
Findex	-1.148** (0.372)		-1.028* (0.429)	
CertF		yes		
EmpstF		yes		
SectF		yes		
CertM		yes		
Nbsiblings		-0.040*** (0.010)		
Nchild		-0.204*** (0.015)		1.265*** (0.076)
Constant		0.365 (0.196)		1.437 (5.680)
ρ_{21}	0.138**	(0.046)		
ρ_{31}	0.918***	(0.016)		
ρ_{41}	-0.103	(0.080)		
ρ_{32}	0.327***	(0.054)		
ρ_{42}	-0.011	(0.088)		
ρ_{43}	-0.115	(0.080)		
θ^{*h}	1.222 (1.024)			
θ^{*p}			3.099* (1.363)	
N° Obs.	4045			
Loglikelihood	-3954.3534			

Note: * p<0.05; ** p<0.01; *** p<0.001
Estimates are obtained through 100 pseudo-random draws.
Table entries refers to estimated coefficients (marginal effects are available from the author upon request).
Standard errors in parenthesis.

References

Arias C, Cox T.L. 1999. Maximum Simulated Likelihood: A Brief Introduction for Practitioners. University of Wisconsin-Madison. Staff Paper series No. 421.

Arrow K. 1973. The Theory of Discrimination. In: Ashenfelter, Orley, Rees, Albert(Eds.), Discrimination in Labor Markets. Princeton University Press, 3-33.

Assaad R, Barsoum G. 1999. Egypt Labour Market Survey. Final report, Cairo: Economic Research Forum.

Barsoum G. 2007. Egypt Labour Market Panel Survey 2006: Report on methodology and data collection. Economic Research Forum. Working Paper. No.0704.

Becker G.S. 1985. Human Capital, Effort, and the Sexual Division of Labor. *Journal of Labor Economics* **3**:33-58.

Bjerk D. 2008. Glass Ceiling or Sticky Floors? Statistical Discrimination in a Dynamic Model of Hiring and Promotion. *The Economic Journal* **118**:961-982.

Blinder A. 1973. Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources* **8(4)**:436-455.

Börsh-Saupan A, Hajivassiliou V. 1993. Smoothed Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models.. *Journal of Econometrics* **58**:347-68.

Bulow J, Summers L.H. 1986. A Theory of Dual Labor Markets with Application to Industrial Policy, Discrimination, and Keynesian Unemployment. *Journal of Labor Economics* **4**:376-414.

Cappellari L, Jenkins S.P. 2006. Calculation of Multivariate Normal Probabilities by Simulation, with Applications to Maximum Simulated Likelihood Estimation. IZA Discussion Paper No. 2112.

Chen H.Z, Cosslett R.C. 1998. Environmental Quality Preference and Benefit Estimation in Multinomial Probit Models: A Simulation Approach. *American Journal of Agricultural Economics* **80**:512-520.

Coate S, Loury G. 1993. Will Affirmative-Action Polices Eliminate Negative Stereotypes?. *The American Economic Review***83**:1220-1240.

Feenberg D, Skinner J. 1994. The Risk and Duration of Catastrophic Health Care Expenditures. *The Review of Economics and Statistics* **4**:633-647.

Fryer Jr. 2007. Belief Flipping in a dynamic Model of Statistical Discrimination. *Journal of Public Economics* **91**:1151-1166.

Geweke J. 1989. Efficient Simulation from the Multivariate and Normal Distribution Subject to Linear Inequality Constraints and the Evaluation of Constraint Probabilities. Duke University, Durham, N.C: Mimeo.

Gourieroux C, Monfort A, Renault E, Trognan A. 1987. Generalized Residuals. *Journal of Econometrics* **34**:5-32.

Groot H.M, Van Den Brink. 1996. Glass Ceiling or Dead-ends: Job Promotion of Men and Women Compared. *Economics Letters* **53**:221-226.

Hajivassiliou V, McFadden D, Ruud P. 1996. Simulation of Multivariate Normal Rectangle Probabilities and their Derivatives: Theoretical and Computational Results. *Journal of Econometrics* **72**:85-134.

HAJIVASSILIOU V, RUUD P. 1994. Classical Estimation Method for LDV Models using Simulation. In Handbook of Econometrics, R. Engle and D. McFadden (Eds.),**4**:2383-2441, Amsterdam: North-Holland.

HAJIVASSILIOU W.A. 1993. A Simulation Estimation Analysis of the External Debt Crises of Developing Countries. Cowles Foundation for Research in Economics, Working Paper.

LAZEAR E.P, ROSEN S. 1990. Male-Female Wage Differentials in Job Ladders. *Journal of Labour Economics* **8**:S106-S123.

OAXACA R. 1973. Male-Female Wage Differentials in Urban Labour Markets. *International Economic Review* **14**:693-709.

PEKKARINEN T, VARTIAINEN J. 2004 Gender Differences in Job Assignment and Promotion on a Complexity Ladder of Jobs. IZA Discussion Paper No. 1184.

PHELPS E.S. 1972. The Statistical Theory of Racism and Sexism. *American Economic Review*:659-661.

STERN S. 1997. Simulation-Based Estimation. *Journal of Economic Literature* **35**:2006-2039.

WINTER-EBMER R, ZWEIMULLER J. 1997. Unequal Assignment and Unequal Promotion in Job Ladders. *Journal of Labor Economics* **15**:43-71.

YUN M-S. 1999. Generalized Selection Bias and the Decomposition of Wage Differentials. IZA Discussion Paper No. 69.

YUN M-S. 2000. Decomposition Analysis for a Binary Choice Model. IZA Discussion Paper No. 145.