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Career Starts and the Male-Female Wage Gap

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Abstract: The paper focuses on the early career patterns of young male and female workers. It investigates potential dynamic links between statistical discrimination, mobility, tenure and wage profiles. The model assumes that it is more costly for an employer to assess female workers' productivity and that the noise/signal ratio tapers off more rapidly for male workers. These two assumptions yield numerous theoretical predictions pertaining to gender wage gaps. These are tested using French data. It turns out most predictions are supported by the data.

Keywords: Gender wage gap, job transitions, mover-stayer model

JEL Classification: J16, J71, J41

1 Introduction

Economic analysis has made numerous contributions to our understanding of the causes of occupational segregation and the existence of earnings disparities between men and women on the labor market.[1] In particular, several theories of discrimination have attempted to explain why two groups with identical average productivity are paid different average wages. The literature is divided into two main strands: taste discrimination (Becker (1957)), and statistical discrimination (Phelps (1972)). Models built on taste discrimination are little helpful in understanding gender discrimination as they fail to explain the root of the prejudices. Models of statistical discrimination are more appealing because they suggest gender discrimination may be a rational response by firms to imperfect information on individual productivity. They are based on the notion that employers are unable to precisely know the productivity of each employee insofar as the signals available to them (recruitment tests, diplomas, *etc.*) are less reliable for women than for men.

In their simplest version, models based on statistical discrimination have proved deceptive since they were unable to generate a gender/racial gap in mean wages. Recent work has thus extended Phelps's (1972) seminal contribution by introducing human capital investment decisions (Lundberg and Startz (1983)) or by accounting for job matching (Rothschild and Stiglitz (1982) and Oettinger (1996)). In both cases, it turns out wage gaps arise endogenously.[2]

This paper focuses on the early career patterns of young male and female workers. It seeks to illustrate potential links between statistical discrimination, mobility, tenure and wage profiles. We use the statistical discrimination model proposed by Oettinger (1996) to explain racial wage gaps as our starting point. Thus a worker's productivity is assumed to depend on the quality of the job match. It is further assumed that it is more costly for an employer to assess female workers' productivity. Finally, the model allows productivity to become less noisy with tenure. However, unlike Oettinger (1996), we assume that female workers' productivity remains noisy with tenure, while male workers' noise/signal ratio is assumed to be zero in the second period of their two-period lives.

Oettinger (1996) speculated that even if asymmetries and informational imperfections were only transient, they could nevertheless generate permanent wage differentials between racial groups. By assuming away perfect productivity reve-

[1]For a literature review, see Cain (1986) and, more recently, Altonji and Blank (1999).

[2]For the basics of job matching theory, see Jovanovic (1979a, 1979b), and Johnson (1978).

lation for women, our model shows that gender wage gaps may appear within the first years of the working lives and may be permanent. Furthermore, the model provides a simple framework within which gender differences in terms of tenure, experience and mobility can be better understood.

The model generates a series of predictions that we test against French data. It turns out most theoretical predictions are supported by the data. The paper is organized as follows. Section 2 describes the structure of the model and its basic assumptions. Section 3 presents the wage profiles that characterize the equilibrium and emphasizes theoretical implications with respect to gender differences in mobility. Finally, section 4 presents the empirical results.

2 The Structure of the Model

Our model incorporates both notions of job-matching and statistical discrimination. As in Jovanovic (1979a, 1979b), we assume that individual productivity is linked to the quality of the job match and that it can only be measured through experience. Following Phelps (1972), we also assume that women's productivity indicators are less reliable than those of men. Employers thus negotiate compensation with employees one-on-one and will offer each a wage equal to his or her expected productivity, given the available information.

2.1 The Quality of Job Matching and Imperfect Information

Our model builds on the general framework setup by Oettinger (1996).[3] Employees work for two periods $(t = 1, 2)$ and maximize expected compensation over their entire working lives. At the beginning of each period t, a worker receives exactly one job offer. The true productivity of an employee in the job offered at period t, μ_t, is a random variable whose distribution is known and identical for men and women: $\mu_t \sim \mathcal{N}\left(\bar{\mu}, \sigma_\mu^2\right)$.

Individuals' productivity depends on the quality of their job match. Moreover, the productivity of individual i in the first-period job, μ_{1i}, is assumed independent of μ_{2i}, his/her productivity in the second period. This latter assumption, standard in Jovanovic (1979a, 1979b), ensures that employees' history is irrelevant to the evaluation of his/her productivity in any newly formed match.

The quality of the job matching is vulnerable to informational imperfections on both sides of the market. Productivity is *ex ante* unknown in any potential,

[3]We start from the assumption that wages are equal to expected productivity.

but untested, match. Before the match actually occurs, employers and employees alike do not know precisely what the exact productivity will be. It can only be ascertained by observing employee i in the job offered at t. More precisely, during the first period all workers will be employed in the job they were offered at the beginning of the period. Let the observed productivity of worker i be given by:

$$s_{1i}^{j} = \mu_{1i} + \varepsilon_{1i}^{j}, \quad \text{where } \varepsilon_{1i}^{j} \sim \mathcal{N}\left(0, \sigma_{\varepsilon^j}^2\right), \quad j \in \{f, m\}, \tag{1}$$

and where superscripts *f* and *m* stand for female and male workers, respectively. We assume that μ_{1i} and ε_{1i} are not correlated. At the start of the second period, the worker must decide whether to stay on the job or move to a new job. If the new offer is accepted, both parties will observe the productivity in the new match with error, as in the first job, *i.e.*

$$s_{2i}^{j} = \mu_{2i} + \varepsilon_{2i}^{j}, \quad \text{where } \varepsilon_{2i}^{j} \sim \mathcal{N}\left(0, \sigma_{\varepsilon^j}^2\right), \quad j \in \{f, m\}. \tag{2}$$

If the worker stays in the first-period job, his/her true productivity remains μ_{1i}, since our model assumes away investment in human capital. On the other hand, the two parties will better assess the true productivity, μ_{1i}. Consequently, we may write:

$$s'^{j}_{1i} = \mu_{1i} + v_i^j, \quad \text{where } v_i^j \sim \mathcal{N}\left(0, \sigma_{v^j}^2\right) \text{ and } \sigma_{v^j}^2 < \sigma_{\varepsilon^j}^2, \quad j \in \{f, m\}. \tag{3}$$

As in Phelps (1972), gender differences occur essentially through the quality of the productivity signal, *i.e.* $\sigma_{\varepsilon^f}^2 > \sigma_{\varepsilon^m}^2$. We further assume that the gap remains irrespective of tenure. This assumption departs from Oettinger (1996) who assumed that the noise/signal ratio vanished after the first period. In fact we assume this to be the case for men, but not for women, *i.e.* $0 = \sigma_{v^m}^2 < \sigma_{v^f}^2 < \sigma_{\varepsilon^f}^2$.

The assumption that women's productivity is always imperfectly observed may be justified as follows. Women who pursue their careers without interruption[4] must often strive to reconcile their professional and family lives, as they traditionally assume most household chores.[5] Otherwise identical women may not share the same relationship to domestic production. Consequently, women's sensitivity to some features of their jobs (work shift, working conditions, authorized leave, flexibility or ability to take time off to attend to family matters, *etc.*) will depend on how they manage their activities outside of the labor force. This unobserved heterogeneity is partly responsible for their signal being less precise than that of men.

[4] Issues of attachment to, and withdrawal from, the work force are not modeled here. Thus our reference population does not interrupt its working life even temporarily.

[5] According to Glaude (1999), nearly 80% of basic domestic production (errands, cooking, dishes, laundry, childcare, *etc.*) is assumed by women in France.

2.2 Wage Contracts and Endogenous Mobility

We assume that firms are competitive and risk-neutral, negotiating employee compensation on an individual basis. Employers will offer wages equal to individual expected productivity due to the binding zero expected profits in both periods. In the first period, wage profiles can thus be written as:[6]

$$w_{1i}^{j} = \mathbb{E}\left(\mu_{1i} \left| s_{1i}^{j}\right.\right), \quad j \in \{f, m\}. \tag{4}$$

Likewise, second period wage contracts are determined by individuals' productivity signal, *i.e.* ${s'}_{1i}^{j}$ if individual i remains on the job, and s_{2i}^{j} otherwise. We thus have $w_{2i}^{j} = \mathbb{E}(\mu_{1i}|{s'}_{1i}^{j})$ for "stayers" and $w_{2i}^{j} = \mathbb{E}(\mu_{2i}|s_{2i}^{j})$ for "movers". A worker will choose to change jobs if, and only if, the expected wage in the second-period job offer exceeds the expected wage in the current job, that is if $\hat{\mu}_{2i}^{j} = \mathbb{E}\left(\mu_{2i}\left|s_{2i}^{j}\right.\right) > \tilde{\mu}_{1i}^{j} = \mathbb{E}\left(\mu_{1i}\left|{s'}_{1i}^{j}\right.\right)$. Wages in the second period can thus be written

$$w_{2i}^{j} = \begin{cases} \tilde{\mu}_{1i}^{j}, & \text{if} \quad \tilde{\mu}_{1i}^{j} = \mathbb{E}\left(\mu_{1i}\left|{s'}_{1i}^{j}\right.\right) \geq \hat{\mu}_{2i}^{j} = \mathbb{E}\left(\mu_{2i}\left|s_{2i}^{j}\right.\right) \text{ (stayer)}, \\ \hat{\mu}_{2i}^{j}, & \text{if} \quad \tilde{\mu}_{1i}^{j} < \hat{\mu}_{2i}^{j} \text{ (mover).} \end{cases} \tag{5}$$

Note that the productivity of a male worker who chooses to remain on his initial job will be perfectly observed. His compensation will be $w_{2i}^{m} = \tilde{\mu}_{1i}^{m} = \mu_{1i}$ and the mobility condition is $\hat{\mu}_{2i}^{m} > \mu_{1i}$. These conditions do not apply to female workers. We will now examine the consequences for the equilibrium solution.

3 Equilibrium Wage Profiles

Equilibrium is determined by the optimization behavior of employers and employees. We will characterize wage profiles in the two periods before drawing conclusions about the profitability of mobility, tenure, and experience.

3.1 First-Period Wages

For the first period, our analytical framework is identical to the initial statistical discrimination model developed by Phelps (1972) and Aigner and Cain (1977). We obtain the standard result according to which wage contracts are a weighted average of mean productivity ($\bar{\mu}$) and of the individual signal, s_{1i}^{j}:

$$w_{1i}^{j} = \mathbb{E}(\mu_{1i}|s_{1i}^{j}) = (1-\rho_j^2)\bar{\mu} + \rho_j^2 s_{1i}^{j}, \quad j \in \{f, m\}, \tag{6}$$

[6] Note that the first subindex on wage rates refers to the period.

where $\rho_j^2 = \sigma_\mu^2 / \left(\sigma_\mu^2 + \sigma_{\varepsilon^j}^2\right)$.[7]

The weight ρ_j^2 can be interpreted as a measure of the quality of the signal. Thus the greater the reliability of the signal, the more employers will individualize wage rates. Clearly, given the assumption that women's signals are less reliable,[8] employers will discriminate —rationally— between men and women by offering them different wages. When setting the starting wage of women, they will tend to emphasize the average characteristics of the group over individual performance in order to guard against possible measurement errors. Consequently, men and women with the same productivity signals, s_1, will receive different compensation. Women with a strong initial signal will receive a lower pay than their male counterparts, and conversely for a weak productivity signal. The wage profile offered to women during the first period is thus less steep than that offered to men, and women's compensation is more clustered around mean productivity, $\bar{\mu}$. Men's wages will in fact have a higher variance $\left(\rho_m^2 \sigma_\mu^2\right)$ than women's $\left(\rho_f^2 \sigma_\mu^2\right)$. Yet, men and women will receive the same wage rate upon entry into the labor market. Indeed, expected pay in the first period is invariant with respect to the reliability of the signals

$$\mathbb{E}\left(w_{1i}^j\right) = \bar{\mu}, \quad j \in \{f, m\}, \ \forall \rho_j^2. \tag{7}$$

Thus first period mean wages are equal to mean productivity, which we assume identical across gender.

3.2 Second-Period Wages

Second period wage profiles depend on mobility behavior. As shown previously, stayers' wage rates are characterized by $w_{2i}^j = \mathbb{E}\left(\mu_{1i} \left| s_{1i}^{\prime j}\right.\right)$ and those of the movers by $w_{2i}^j = \mathbb{E}\left(\mu_{2i} \left| s_{2i}^j\right.\right)$. More precisely, we can show[9] that:

- stayer i, of gender j, will be paid

$$\begin{aligned} w_{2i}^j &= \mathbb{E}\left(\mu_{1i} \left| s_{1i}^{\prime j}\right.\right) \qquad (8) \\ &= \left(1 - \delta_j^2\right) \bar{\mu} + \delta_j^2 \ s_{1i}^{\prime j} \text{ with } \delta_j^2 = \sigma_\mu^2 / \left(\sigma_\mu^2 + \sigma_{v^j}^2\right), \quad j \in \{f, m\}, \end{aligned}$$

[7] To show this, observe that μ_{1i} and s_{1i}^j are normal bivariates with correlation coefficient $\rho_j^2 = \sigma_\mu^2 / \left(\sigma_\mu^2 + \sigma_{\varepsilon^j}^2\right)$. The result follows from computing the conditional expectation.

[8] The assumption $\sigma_{\varepsilon^m}^2 < \sigma_{\varepsilon^f}^2$ implies $\rho_f^2 < \rho_m^2$.

[9] Again, it suffices to use the fact that $\left(\mu_{1i}, s_{1i}^{\prime j}\right)$ and $\left(\mu_{2i}, s_{2i}^j\right)$ are normal bivariates and to compute conditional expectations.

- and mover i, of gender j, will be paid

$$w_{2i}^{j} = \mathbb{E}\left(\mu_{2i}\left|s_{2i}^{j}\right.\right) = \left(1-\rho_{j}^{2}\right)\bar{\mu} + \rho_{j}^{2}\ s_{2i}^{j},\ j \in \{f,m\}\,. \tag{9}$$

As in the first period, the wages received in the second period are a weighted mean of the group average and a measure of individual productivity. In this case, however, the weight associated with the latter is more reliable.[10] We find that male workers' compensation relies more heavily on individual signals, and that their wage profiles are steeper than those of female workers.

It is worth noting that for workers who change jobs the wage structure in both periods is based on the same weight, ρ_j^2. This result derives directly from the assumption that employment history plays no role in the newly formed match. However, for those who remain on the same job, employers weight more heavily individual productivity signals when setting wages. Indeed, $\sigma_v^2 < \sigma_\varepsilon^2$ and therefore $\rho_j^2 < \delta_j^2$.

Workers will remain with the same employer if $\tilde{\mu}_{1i}^{j} \geq \hat{\mu}_{2i}^{j}$ and will move if $\tilde{\mu}_{1i}^{j} < \hat{\mu}_{2i}^{j}$. Because mobility is endogenous, non-random selection between movers and stayers must be accounted for when characterizing mean compensation. Thus,

- the mean wage during the second period is given by:

$$\mathbb{E}\left[\left.\tilde{\mu}_{1i}^{j}\right|\tilde{\mu}_{1i}^{j} - \hat{\mu}_{2i}^{j} \geq 0\right] = \bar{\mu} + \frac{\delta_j^2}{\sqrt{\delta_j^2 + \rho_j^2}}\left(\frac{2\sigma_\mu^2}{\pi}\right)^{1/2}, \quad j \in \{f,m\} \tag{10}$$

  for stayers.

- and

$$\mathbb{E}\left[\left.\hat{\mu}_{2i}^{j}\right|\hat{\mu}_{2i}^{j} - \tilde{\mu}_{1i}^{j} > 0\right] = \bar{\mu} + \frac{\rho_j^2}{\sqrt{\delta_j^2 + \rho_j^2}}\left(\frac{2\sigma_\mu^2}{\pi}\right)^{1/2}, \quad j \in \{f,m\} \tag{11}$$

  for movers.

[10] For the stayers, δ_j^2 is an indicator of the quality of the productivity signal similar to ρ_j^2 in the first period. Moreover, since the productivity revelation mechanism is perfect for men $\left(\sigma_{vm}^2 = 0\right)$, but imperfect for women $\left(\sigma_{vf}^2 > 0\right)$, we have $1 = \delta_m^2 > \delta_f^2$.

Note that the mean conditional wage rate in the second period is equal to the worker's mean productivity $(\bar{\mu})$, adjusted for the quality of the signal. Moreover, the expected wage of a mover is lower than that of a stayer $\left(\rho_j^2 < \delta_j^2\right)$.

Our model generates positive returns to work experience and tenure. At the beginning of the second period, a mover has one period of experience as an asset, but no tenure, whereas a stayer has both one period of experience and one period of tenure. Thus movers' mean wage differential between the first and the second period characterizes the average return to experience, while the average return to tenure is given by the second-period mean wage differential between stayers and movers. Average returns to experience and tenure are thus given respectively by:

$$\frac{\rho_j^2}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi}\right)^{1/2} \quad \text{and} \quad \frac{\delta_j^2 - \rho_j^2}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi}\right)^{1/2} .$$

The positive return to tenure captures the fact that stayers had a better initial match. The unconditional second-period mean wage of group j can be derived from equations (10) and (11):

$$\begin{aligned} \mathbb{E}(w_{2i}^j) &= \Pr\left(\tilde{\mu}_{1i}^j \geq \hat{\mu}_{2i}^j\right) \mathbb{E}\left[\,\tilde{\mu}_{1i}^j \middle|\, \tilde{\mu}_{1i}^j - \hat{\mu}_{2i}^j \geq 0\right] \\ &\quad + \Pr\left(\hat{\mu}_{2i}^j > \tilde{\mu}_{1i}^j\right) \mathbb{E}\left[\,\hat{\mu}_{2i}^j \middle|\, \hat{\mu}_{2i}^j - \tilde{\mu}_{1i}^j < 0\right] \\ &= \bar{\mu} + \left[\frac{(\delta_j^2 + \rho_j^2)\sigma_\mu^2}{2\pi}\right]^{1/2}, \quad j \in \{f, m\} . \end{aligned} \tag{12}$$

Thus on average workers earn more in the second period because they self-select into the best possible match. Unlike first-period wage rate, second-period wages increase with the reliability of the signals, δ_j^2 and ρ_j^2. The better they are, the more profitable the selection process is likely to be on average. Indeed, mistakes such as changing jobs that prove to be a worse match, or foregoing a job change that would have been profitable can be better avoided when productivity signals are more precise.

In this context, male workers should benefit more from mobility. In the second period they should on average receive higher wages than their female co-workers. Our model thus predicts that even if there is no gender wage gap at entry into the labor market, it will appear as careers unfold.

3.3 Wages and Mobility

The expected wage change for stayers is given by $\mathbb{E}\left[\tilde{\mu}^j_{1i} - \hat{\mu}^j_{1i} \middle| \tilde{\mu}^j_{1i} - \hat{\mu}^j_{2i} \geq 0\right]$ while that of movers is given by $\mathbb{E}\left[\hat{\mu}^j_{2i} - \hat{\mu}^j_{1i} \middle| \hat{\mu}^j_{2i} - \tilde{\mu}^j_{1i} > 0\right]$. It can easily be shown that

$$\mathbb{E}\left[\tilde{\mu}^j_{1i} - \hat{\mu}^j_{1i} \middle| \tilde{\mu}^j_{1i} - \hat{\mu}^j_{2i} \geq 0\right] = \frac{\delta^2_j\left(1-\rho^2_j\right)}{\sqrt{\delta^2_j+\rho^2_j}}\left(\frac{2\sigma^2_\mu}{\pi}\right)^{1/2}, \tag{13}$$

$$\mathbb{E}\left[\hat{\mu}^j_{2i} - \hat{\mu}^j_{1i} \middle| \hat{\mu}^j_{2i} - \tilde{\mu}^j_{1i} > 0\right] = \frac{\rho^2_j\left(1+\delta^2_j\right)}{\sqrt{\delta^2_j+\rho^2_j}}\left(\frac{2\sigma^2_\mu}{\pi}\right)^{1/2}. \tag{14}$$

From equations (13) and (14) it is clear that the expected wage change is positive for both stayers and movers. This result is not surprising since mobility is endogenous. If $\sigma^2_\varepsilon < \sigma^2_\mu$ —a reasonable assumption— movers will clearly experience greater wage increases than stayers on average. Indeed wage changes for stayers solely reflect corrections to productivity measurement errors. Conversely, wage changes are essentially attributable to productivity changes in the case of movers.

In summary, our model yields many unambiguous theoretical predictions that can be empirically tested. For both sexes we find that:

1. wage profiles are increasing, on average;
2. experience and tenure show positive returns;
3. movers' mean wage is lower than that of stayers. But
4. their wage growth is greater (assuming that $\sigma^2_\varepsilon < \sigma^2_\mu$).

As for the male-female wage gap, several results emerge:

1. for identical productivity signals, employers offer compensations that differ across gender;
2. upon entry into the labor market, men and women earn the same wage on average;
3. however, a gender wage gap emerges in the initial years of their working lives.

Some of these predictions are similar to those derived by Oettinger (1996). In fact, the equilibrium described by Oettinger (1996) is a special case of our model in which $\delta^2_j = 1,\ \forall j$. However, this assumption is not innocuous since the productivity revelation mechanism plays an important role in the determination of the

the second period wage rate. Moreover, our generalization complicates the analysis with respect to differences in the yield to mobility and tenure, and changes a number of conclusions. For instance, unlike Oettinger (1996), we cannot assert that women should always have higher returns to tenure than men, because the reliability of the initial signals $\left(\rho_j^2\right)$ and the precision of the revelation mechanism $\left(\delta_j^2\right)$ act in opposite directions. Likewise, the impact of δ_j^2 on movers' mean wage increase is ambiguous.

3.4 Male-Female Gap in the Return to Mobility

Gender differences in terms of returns to job mobility and tenure is more complex. However, we will show that the sign of these differences not only depends on the male-female gap in the reliability of the initial signals, but also on the magnitude of the variances of the shocks $\left(\sigma_{\varepsilon f}^2, \sigma_{vf}^2\right)$ relative to the variance of the productivity $\left(\sigma_\mu^2\right)$.

Let $k \in \left]0,1\right]$ be such that $\sigma_{\varepsilon m}^2 = k\sigma_{\varepsilon f}^2$, $\alpha = \frac{\sigma_{\varepsilon f}^2}{\sigma_\mu^2}$, and $\beta = \frac{\sigma_{vf}^2}{\sigma_\mu^2}$. We can rewrite the conditions pertaining to the gender differences in job mobility and tenure in terms of k, α and β. For example, for the average wage of male movers to be higher to that of female movers, it is necessary and sufficient according to equation (10) that:

$$\frac{1}{\sqrt{1+\rho_m^2}} \geq \frac{\delta_f^2}{\sqrt{\delta_f^2+\rho_f^2}}, \quad \text{or} \quad k \geq k_A = \frac{\alpha - \beta\left(3+\alpha+\beta\right)}{\alpha[1+\beta\left(3+\alpha+\beta\right)]}. \tag{15}$$

By the same reasoning, we can derive the following predictions:[11]

1. Among the stayers, men's average wage will be higher than women's if $k_A \leq k \leq 1$;

[11] The expressions for k_B, k_C, and k_E are respectively:

$$\begin{aligned} k_B &= \frac{-3(1+\beta)+\sqrt{9(1+\beta)^2+4(1+\alpha)(1+\beta)(2+\alpha+\beta)-8(1+\beta)^2}}{2\alpha(1+\beta)}, \\ k_C &= \frac{3\alpha+\sqrt{9\alpha^2+8[(1+\alpha)(1+\beta)(2+\alpha+\beta)-\alpha^2]}}{2[(1+\alpha)(1+\beta)(2+\alpha+\beta)-\alpha^2]}, \\ k_E &= \frac{(\alpha-\beta)[3\alpha-3\beta+\sqrt{9(\alpha-\beta)^2+8[(1+\alpha)(1+\beta)(2+\alpha+\beta)-(\alpha-\beta)^2]}}{2\alpha[(1+\alpha)(1+\beta)(2+\alpha+\beta)-(\alpha-\beta)^2]}. \end{aligned}$$

The derivation of k_B, k_C and k_E is available from the authors.

2. Among the movers, men's average wage will be higher than women's if $0 \leq k \leq k_B$;
3. For male stayers to experience greater wage growth, it must be the case that $k_C \leq k \leq 1$;
4. The condition for the male movers' wage growth to exceed that of female movers always obtains;
5. Men's return to tenure will be higher than women's if $k_E \leq k \leq 1$.

Ranking these various threshold values of k would allow us to characterize a limited number of baseline cases. The complexity of k_A, k_B, k_C, and k_E is such that we must turn to numerical simulation. However, if we make the reasonable assumption that the residual variances ($\sigma^2_{\varepsilon^f}$, $\sigma^2_{v^f}$) are much smaller than the variance of productivity (σ^2_μ), then α will be comprised in the interval $[0, 1]$, and β in $[0, \alpha]$ due to the manner in which productivity gets less noisy with job tenure[12]. It can be shown that $(k_A - k_E)$, $(k_E - k_C)$, $(k_E - k_B)$ are always negative irrespective of α and β, while $(k_B - k_C)$ can be both positive or negative. Consequently only six baseline cases need be examined. Our model's predictions are summarized in Table 1.

TABLE 1: MALE-FEMALE DIFFERENCES IN THE RETURN TO JOB MOBILITY AND TENURE

	Case 1 $0 \leq k \leq k_A$	Case 2 $k_A \leq k \leq k_E$	Case 3 $k_E \leq k \leq k_B$	Case 4 $k_B \leq k \leq k_C$	Case 5 $k_C \leq k \leq k_B$	Case 6 $k_C \leq k \leq 1$
Mean Wages of stayers	in favor of women	in favor of men	in favor of men	in favor of men	in favor of men	in favor of men
Mean Wages of movers	in favor of men	in favor of men	in favor of men	in favor of women	in favor of men	in favor of women
Return to Tenure	in favor of women	in favor of women	in favor of men	in favor of men	in favor of men	in favor of men
Mean-Wage Gain, stayers	in favor of women	in favor of women	in favor of women	in favor of women	in favor of men	in favor of men
Mean-Wage Gain, movers	in favor of men	in favor of men	in favor of men	in favor of men	in favor of men	in favor of men

Contrary to Oettinger (1996), our results depend on the discrepancy in the reliability of men's and women's signals. In Oettinger (1996), productivity revelation is perfect, *i.e.* $\sigma^2_{v^f} = 0$, implying $\beta = 0$. This assumption has important repercussions for the threshold values. In fact, for $\beta = 0$ we find that $k_A = k_B = k_C = k_E = 1$. Consequently, whatever the value of $k \in]0, 1]$, we find that $k \leq k_A$. Furthermore, we can show that the predictions in Oettinger (1996)

[12] $\sigma^2_{\varepsilon^f} \geq \sigma^2_v$ implies that $\beta \leq \alpha$.

correspond to the first column of Table 1. Recall that his model yielded a positive gap in men's returns to mobility, and that tenure was more highly valued by women.

An empirical study based on wage equations will allow us to distinguish between the differences in the returns of job mobility and tenure for men and women. We can then establish whether the data are consistent with any of our theoretical predictions.

4 Data and Empirical Analysis

4.1 The Sample

In this section, we test the unambiguous predictions of our statistical discrimination model and focus on the theoretical ambiguities surrounding differences in the returns to job mobility and tenure. In particular, the analysis will attempt to shed some light on how the wage gap evolves in the earliest stages of work and on the importance of job mobility in the process.

To test the theory, we use data drawn from the French labor market survey "Jeunes et Carrières 1997". This survey contains relatively detailed information on the first job held for more than six months by youths upon leaving school and on their professional status in 1997. For instance, we do know whether a worker is still with his original employer. Unfortunately, little information is available between the first job and 1997. For those who are not with their initial employer, it is not possible to determine how many transitions have occurred since leaving school and 1997. In order to limit the number of job transitions, we restrict the sample to individuals under the age of 30 who had their first "permanent" job between 1992 and 1996. This selection rule allows us to focus on the early career paths as required by our model.

Individuals who had discontinuous labor force participation are dropped from the sample because our model is not setup to address this issue. It should be noted that (temporary) withdrawal from the work force is strongly correlated to the presence of preschoolers. Because of our selection rule, as many as 92% of our sample had no children at the time of their first job, and 80% were still childless by 1997. Consequently, it is probably fair to assume that most of the observed job changes occurred for reasons related to matching, although we can not entirely rule out the possibility that some did occur for other reasons (authorized leave, flexibility or ability to take time off to attend to family matters, *etc.*).

Our sample consists of 483 women and 521 men. Table 2 provides summary statistics on some of the variables used in the empirical analysis. Several features of the data are worth highlighting. First, in France, as in many countries, women are better educated than men. For instance, the proportion of workers with post-secondary schooling is 7 percentage points higher among women. Women are also somewhat more likely to hold "white-collar" jobs both upon entry into the labor market as well as several years hence. On the other hand, the proportion of part-time workers is much higher among women. Interestingly, the hourly wage rates on the first job are nearly identical across gender. In 1997, though, men's wage rate was 7.3% higher. Finally, job turnover is nearly identical.

4.2 Estimation Results

We test our theoretical predictions using reduced-form wage regressions. In line with the previous section, we initially focus on first and second period wage gaps. We next investigate the relationship between mobility and wages. Finally, we look at potential gender gaps in wage growth.

4.2.1 Evolution of the Male-Female Wage Gap

Table 3 presents evidence on the size of the gender wage gap at labor force entry and several years later in 1997. The specifications in the table are standard human capital wage regressions. Recall that our model predicts women should have a flatter wage profile for a given signal. In the empirical analysis, we consider educational achievement as the only signal available to the employers.

In the two wage equations, many variables are statistically significant and have the expected *a priori* sign. For instance, wages are increasing both with education and experience, and white-collar jobs pay better wages than blue-collar or manual jobs. We also find a well established hierarchy between employment contracts in France: trainees earn less than workers with fixed-term contracts, who in turn earn less than those with open-ended contracts. Interestingly, nearly all the schooling variables that are interacted with gender are not statistically significant. This suggests that the male and female education-wages profiles have the same slope. This result is inconsistent with our expectations. It can perhaps be explained by the fact that the schooling categories used in our regressions are too broad. Unfortunately, the information at our disposal did not allow to refine them in greater details.

The most interesting result is that, although the estimated gender wage gap is small and statistically insignificant at labor force entry, it becomes larger and highly significant in 1997 as labor force experience accumulates. These results are consistent with the predictions of the model. However, Oettinger (1996) justly emphasized that they are also consistent with a model of taste discrimination if prejudices against women increase with experience or as they occupy higher positions. The remaining predictions of our model are more original. We shall illustrate them by examining the importance of mobility on wages.

4.2.2 Impact of Job Mobility on Wages

Our model generates unambiguous predictions about relative gains from moving or remaining on the current job. Thus movers should have smaller average wage rates than stayers because of their lower tenure, but greater average growth. Since optimal mobility behavior is determined by individuals' income maximization program, we must take into account the endogeneity of job mobility in the wage regressions. Therefore, we instrument the mobility variable using a dichotomous probit regression.

Table 4 summarizes the probit regression. According to our model, an individual chooses to change jobs if and only if the expected wage of the second-period job offer exceeds the wage in the first job. The reduced-form probit regression thus includes all the explanatory variables included in Table 3. Consequently, the parameter estimates must be interpreted as indirect effect on wages. Variables that have a positive impact on the wage rate in the first-period job should reduce the probability of moving. The results presented in Table 4 are consistent with the model. For instance, youths hired directly into white-collar jobs are much less likely to move. Likewise, schooling variables have no impact on mobility since they increase the expected wages both at entry and in 1997.

The regression of Table 4 is used to compute the predicted probability of moving between entry into the labor market and 1997. This probability is then used as a regressor in the 1997 wage regression of Table 5 and in the wage growth equation in Table 6.[13] The identifying restrictions include all the variables that pertain to the first-period job.

When we include the probability of moving we find it has a negative impact on wage levels (Table 5) and a positive impact on wage growth (Table 6), respectively, as our model predicts. The average wage growth of movers is greater by as much as 17% to that of stayers. However, the mover-stayer wage gap in 1997 is not statistically significant.

[13] The standard errors are corrected to account for the inclusion of a generated regressor.

4.2.3 Gender Wage Gap Among Movers and Stayers

The model generates ambiguous predictions about the sign of the gender wage gap among movers and stayers. Table 1 showed that they depend on the reliability of the signals. The most direct test of the six baseline cases is to estimate the econometric mover/stayer model. Its structural equations are:

$$w_i \quad = \begin{cases} w^*_{mv,i} = X_{mv,i}\beta_1 + \varepsilon_{mv,i} & \text{if} \quad y_i = 1 \text{ (movers)} \\ w^*_{st,i} \;= X_{st,i}\beta_2 \;+ \varepsilon_{st,i} & \text{if} \quad y_i = 0 \text{ (stayers)}, \end{cases} \tag{16}$$

$$\text{with} \quad y_i \quad = \begin{cases} 1 & \text{if} \quad y^*_i = Z_i\gamma + u_i > 0 \\ 0 & \text{if} \quad y^*_i = Z_i\gamma + u_i \leqslant 0, \end{cases} \tag{17}$$

$$\text{and} \qquad \begin{pmatrix} u_i \\ \varepsilon_{li} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \sigma_{lu} \\ \sigma_{lu} & \sigma^2_l \end{pmatrix}\right], l = mv, st. \tag{18}$$

Observed data consist of y_i, a dichotomous variable equal to 1 for movers and to 0 for stayers, w_i, X_{il} and Z_i. We estimate this model by full-information maximum likelihood (FIML).[14] Columns 2 and 3 of Tables 5 and 6 present the FIML parameter estimates of the 1997 wage regression and the wage growth equation, respectively.[15]

Among job movers, the wage level is approximately 9% lower for women, but the difference is not statistically significant. Among job stayers, however, wage level is about 11.5% smaller for women, and this difference is significant at conventional levels. We thus find that the return from remaining with the same employer is larger for men, which contradicts one of the conclusions of the original Oettinger (1996) model, but is consistent with our own. Our results also show that tenure yields a positive return to stayers' wage rate but has no impact on movers. Recall that our model predicts that stayers' wages will increase with tenure because good matches have no incentive to move.[16] However, there are alternative theories that also predict wage gains with tenure. For example, theories of firm-specific human capital and efficiency wages [Lazear (1981)] assume the existence of implicit contracts according to which wages increase with the time spent in a job so as to provide appropriate incentives vis-à-vis job mobility and/or

[14] Since only one wage is observed for a given individual, the correlation ρ_{12} between the two wage equations can not be estimated. On the other hand, the correlation coeffi cients between the wage rates and the decision to change job (ρ_{10} and ρ_{20}) can be estimated.

[15] Parameter estimates of $\hat{\gamma}$ are omitted for the sake of brevity.

[16] The relation between tenure and quality of job matching is examined in details by Burdett (1978), Mortensen (1978) and Topel (1986).

effort. However, Abraham and Farber (1987) showed that a significant share of the estimated return to tenure is generally related to the quality of the matching, and can thus be interpreted in line with our model.

When interacted with gender, tenure yields greater return to male movers. Only two of the baseline cases (cases 3 and 5) in Table 1 are consistent with this result. We shall attempt to discriminate between the two by examining the results pertaining to wage growth.

The specification of the wage growth equation only includes the following variables: gender, tenure, experience, the number of children born between the first job and 1997, and changes to both marital and full-time/part-time status. We have excluded changes to contracts, profession and firm size from the explanatory variables because these variables may be deemed endogenous. Indeed, many youths may choose to leave their first job for reasons not necessarily related to the wage rate (level of responsibility, *etc.*).

We find that among the two groups, movers and stayers, men experienced greater wage growth than women. This result is consistent only with baseline case 5 ($k_c \leqslant k \leqslant k_b$). However, the gender difference is not statistically significant. Since optimal mobility behavior is the source of all wage growth in the theoretical model, it is not surprising that the correlations ρ_{10} and ρ_{20} are highly statistically significant and that only experience among all explanatory variables is statistically significant in the wage growth regression for movers. On the other hand, in our model differences in the reliability of productivity signals underline the gender gap in the wage growth. If these signals are weak or fuzzy, it may be that men's and women's wage profiles are in fact very close. Lack of statistical significance means our results only provides weak empirical support for baseline case 5.

Overall our results are consistent with our model. Its unambiguous predictions, such as the emergence of a gender wage gap, and the fact that mobility should have negative impact the wage rate, but a positive one on the growth rate, are confirmed by our data. Moreover, one of the baseline cases in Table 1 is compatible with all our parameter estimates.

5 Conclusion

In this paper we investigate the issue of gender wage gaps using a two-period model based on the theories of matching and statistical discrimination. Simply by assuming that women's true productivity is more costly to measure, and that the noisiness of women's signal tapers off less rapidly than men's, it is possible to generate a series of theoretical predictions about wage gaps. These pertain to the relation between wage gaps and mobility, tenure and experience. To our knowledge, only three other papers [Oettinger (1996), Altonji and Pierret (1997) and Neumark (1999)] have empirically tested the validity of the theory of statistical discrimination within a similar framework.

The theoretical predictions are tested using data from the French survey ”Jeunes-Carrières 1997”. Most appear to be consistent with the data. In particular, we find that, though men and women earn identical wages upon entry into the labor market, a substantial gap emerges in men's favor in the next few years. Moreover, the returns to job mobility and job tenure are also found to be lower for women than for men.

The theoretical model and the empirical analysis focus on the very first few years upon entry onto the labor market. Issues such as labor market attachment and fertility are voluntarily omitted from the analysis. Empirically, this has translated into focusing exclusively on young school leavers' first “permanent” job. Human capital investment and labor market participation should clearly be incorporated into the analysis to better assess the dynamics of the gender wage gaps. These, and other issues, will be taken up in future research.

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TABLE 2: DESCRIPTIVE STATISTICS

	MEN	WOMEN
Entry Year		
1992	14.2%	18.2%
1993	16.1%	19.5%
1994	22.8%	19.4%
1995	24.0%	19.7%
1996	22.8%	23.6%
Diplomas		
No Diploma (< 9 years of schooling)	18.0%	10.6%
Technical School Certificate (CAP-BEP)	40.0%	31.3%
High-School (BA)	15.6%	25.5%
High-School + 2 years (BA+2)	15.7%	18.8%
University degree	10.0%	13.9%
White-collar		
In first job	4.8%	6.4%
In 1997	7.5%	8.7%
Open-ended contract		
In first job	32.6%	34.2%
In 1997	78.3%	77.6%
Part-time work		
In first job	10.1%	27.1%
In 1997	8.1%	20.7%
Average wage (Francs/hour)		
In first job	36.7	36.5
In 1997	46.2	42.8
Mobility	27.1%	25.5%

TABLE 3: WAGE EQUATIONS, FIRST JOB AND JOB IN 1997

	First Job		Job in 1997	
Variables	Parameter	T-Stat	Parameter	T-Stat
Intercept	3.023	(18.50)	3.252	(30.66)
Gender (male=1)	0.058	(1.21)	0.084	(2.46)
Age	0.021	(2.93)	0.012	(2.96)
Married	0.140	(0.61)	0.058	(3.48)
No. of siblings	0.005	(0.82)	-0.007	(-1.59)
No. of children	-0.019	(-0.62)	-0.045	(-2.83)
Schooling				
No diploma	-0.135	(-2.30)	-0.175	(-4.33)
No diploma$\times$Gender	0.080	(1.08)	0.044	(0.84)
CAP-BEP	-0.037	(-0.87)	-0.104	(-3.56)
BAP-BEP$\times$Gender	-0.036	(-0.62)	0.015	(0.35)
BA		Reference		
BA + 2	0.109	(2.38)	0.021	(0.64)
BA + 2 $\times$ Gender	-0.073	(-1.06)	0.097	(1.97)
Graduate degree	0.209	(3.66)	0.189	(4.54)
Graduate degree $\times$ Gender	-0.066	(-0.85)	0.009	(0.17)
Type of contract				
Temporary	0.165	(3.52)	0.077	(1.86)
Trainee	-0.262	(-5.98)	-0.149	(-3.81)
Fixed-term		Reference		
Open-ended	0.064	(1.94)	0.095	(3.89)
Other	0.082	(2.27)		
Profession				
Manual	-0.048	(-0.17)	-0.024	(-1.16)
Blue-Collar		Reference		
White-Collar	0.264	(4.69)	0.267	(7.10)
Other	0.014	(2.35)	0.036	(0.60)
Number of employees				
Less than 10	0.022	(0.58)	-0.087	(-4.16)
10–49	0.004	(0.09)	-0.056	(-2.80)
50–199	0.087	(1.59)	-0.038	(-1.22)
200+		Reference		
Year of entry				
1992	Reference			
1993	-0.052	(-1.43)		
1994	-0.088	(-2.52)		
1995	-0.025	(-0.69)		
1996	-0.073	(-2.05)		
Experience	-0.006	(-0.90)	0.038	(6.09)
R^2	0.274	0.480		
N	1 004	1 004		

TABLE 4: PROBIT ESTIMATES OF JOB MOBILITY

Variables				
	Para.	T-stat.		
Intercept	0.011	(0.01)		
Gender (male=1)	0.271	(2.11)		
No. of siblings	0.019	(0.64)		
Schooling				
No diploma	0.038	(0.18)		
BAP-BEP	0.004	(0.03)		
BA	Reference			
BA + 2	0.263	(1.48)		
Graduate Degree	-0.109	(0.38)		
	At first job		**Job In 1997**	
	Para.	T-stat.	Para.	T-stat.
Age	-0.069	(-0.22)		
Married	-0.159	(-1.08)	0.080	(0.58)
No. of children	-0.0745	(-0.33)	0.025	(0.16)
Full-Time	-0.249	(-1.57)	-0.113	(-0.65)
Experience			0.328	(6.78)
Type of Contract				
Temporary	-1.012	(-4.88)	0.100	(0.36)
Trainee	-1.098	(-5.77)	-0.197	(-0.77)
Fixed-term	Reference			
Open-ended	-1.042	(-7.62)	-0.575	(-3.53)
Profession				
Manual	0.217	(1.06)	-0.368	(-1.79)
Blue-Collar	Reference			
White-Collar	-1.312	(-3.39)	1.173	(3.38)
Other	0.156	(0.38)	0.445	(0.82)
Number of employees				
Less than 10			0.523	(3.54)
10–49			0.281	(1.97)
50–99			-0.019	(-0.08)
100+			Reference	
log-likelihood	-363.78			
N	1 004			

TABLE 5: 1997 WAGES AS A FUNCTION OF MOBILITY

	All		Stayers		Movers	
Variables	Para.	T-stat	Para.	T-stat	Para.	T-stat
Intercept	3.513	(78.92)	3.534	(62.30)	3.441	(30.77)
Gender (male=1)	0.093	(3.25)	0.116	(1.98)	0.095	(0.62)
Married	0.060	(3.80)	0.061	(2.61)	0.055	(1.42)
No. of children	-0.039	(-1.98)	-0.039	(-2.19)	-0.056	(-1.96)
No. of siblings	-0.005	(-1.32)	-0.004	(-0.60)	-0.006	(-0.78)
Schooling						
No Diploma	-0.183	(-4.04)	-0.183	(-3.76)	-0.191	(-1.80)
No Diploma× Gender	0.041	(0.72)	0.067	(1.06)	0.065	(0.42)
CAP-BEP	-0.111	(-4.04)	-0.090	(-2.20)	-0.168	(-2.29)
CAP-BEP× Gender	0.007	(0.19)	-0.040	(-0.69)	0.167	(1.28)
BA			Reference			
BA + 2	0.031	(1.05)	0.056	(1.26)	-0.026	(-0.33)
BA + 2 × Gender	0.102	(2.13)	0.071	(1.11)	0.193	(1.41)
Graduate degree	0.210	(5.53)	0.120	(3.99)	0.258	(2.29)
Graduate degree × Gender	0.013	(0.23)	0.040	(0.59)	-0.0953	(-0.63)
Type of Contract						
Temporary	0.074	(2.19)	0.063	(0.78)	0.080	(0.88)
Trainee	-0.149	(-3.19)	-0.091	(-1.61)	-0.251	(-3.31)
Fixed-Term			Reference			
Open-ended	0.084	(2.91)	0.090	(2.53)	0.054	(1.02)
Profession						
Manual	-0.029	(-1.47)	-0.039	(-1.39)	-0.000	(0.01)
Blue-collar			Reference			
White-collar	0.274	(6.45)	0.250	(6.37)	0.367	(4.11)
Other	0.050	(0.70)	0.053	(0.88)	0.100	(0.55)
Number of employees						
Less than10	-0.082	(-4.27)	-0.110	(-3.28)	-0.007	(-0.15)
10–49	-0.059	(-3.35)	-0.081	(-2.75)	0.004	(0.07)
50–99	-0.042	(-1.45)	-0.048	(-1.19)	-0.008	(-0.08)
100+			Reference			
Experience	0.049	(6.81)			6.301	(2.45)
Experience × Gender					-4.980	(-1.45)
Tenure			5.518	(4.60)	-0.174	(-0.07)
Tenure× Gender			-0.138	(-0.09)	5.514	(1.94)
Probability of being moving	-0.043	(-1.30)				
Residual Variance			0.234	(79.96)	0.214	(28.50)
Correlation			0.139	(0.84)	-0.205	(-0.81)
$R^2/log-likelihood$	0.4764		-300.63			
N	1 004		740		264	

TABLE 6: REGRESSIONS OF WAGE GROWTH AS A FUNCTION MOBILITY

	All		**Stayers**		**Movers**	
Variables	Para.	T-stat	Para.	T-stat	Para.	T-stat
Intercept	0.158	(2.40)	-0.033	(-0.81)	-0.520	(-3.70)
Gender (male=1)	0.057	(2.69)	0.039	(1.39)	0.098	(1.38)
No. Births	-0.031	(-1.08)	-0.018	(-0.44)	-0.030	(-0.29)
Marital status						
Single→ Single			Reference			
Single→ Married	0.005	(0.16)	0.013	(0.33)	-0.001	(-0.01)
Married→ Married	0.046	(1.28)	0.083	(2.38)	-0.031	(-0.37)
Married→ Divorced	-0.020	(-0.21)	-0.215	(-2.86)	0.024	(0.10)
Full-time/Part-time						
Full-time→ Full-time			Reference			
Full-time→ Part-time	-0.233	(-2.06)	-0.238	(-3.60)	-0.140	(-0.77)
Part-time→ Part-time	0.001	(0.05)	-0.033	(-0.52)	0.047	(0.37)
Part-time→ Full-time	0.331	(2.67)	0.294	(5.84)	0.092	(0.48)
Hours Variation	-0.023	(-3.13)	-0.023	(-9.04)	-0.012	(-1.14)
Experience	-0.007	(-0.50)			8.069	(2.15)
Tenure	0.069	(4.95)	4.143	(3.61)	4.383	(1.37)
Probability of changing job	0.172	(2.71)				
Residual Variance			0.349	(60.45)	0.467	(36.48)
Correlation			0.876	(8.33)	-0.834	(-10.01)
R^2/log-likelihood	0.108		-662.98			
N	1 004		740		264	