

Wage Growth and Job Mobility in the Early Career: Testing a Statistical Discrimination Model of the Gender Wage Gap*

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Abstract

This paper investigates the links between statistical discrimination, mobility, tenure and wage profiles in the early career of workers. The model assumes that female workers' productivity is noisier 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 predictions are tested using data from the 1979 cohort of the National Longitudinal Survey of Youth. As predicted, we find that men and women have the same wage at the start of their career, but that female wages grow at a slower rate thus generating a gender wage gap.

JEL Classification: J16, J71, J41

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1 Introduction

There is considerable interest in understanding why women earn less than men. Blau and Kahn (2007) show that the female-to-male ratio in annual (and weekly) earnings among full-time U.S. workers remained stable at about 60% in the 1960s and 1970s. This ratio then grew steadily in the 1980s and more slowly in the 1990s.¹ Part of this gender wage gap has been shown to be explained by differences in qualifications, namely accumulated work experience and occupation. But part of the gender wage gap remains “unexplained”.

This paper focuses on a sample of men and women workers who have very similar qualifications: all have some college education and all are observed early in their career with little work experience. We pay particular attention to how differences in wage growth may generate the gender wage gap. We empirically observe that the gender wage gap is fairly small at the entry into the labor market, but it grows as women experience weaker wage growth than men [Loprest (1992); Manning and Swaffield (2008); Napari (2009); Del Bono and Vuri (2011)]. Focusing on career starts is particularly interesting since some of the common explanations for the gender wage gap are irrelevant at this stage. For example, male and female workers differ fairly little in terms of career interruptions and so the gender wage gap cannot be convincingly explained by gender differences in promotion opportunities (glass ceilings) given the short durations of jobs and the small experience of young workers. By contrast, models of job mobility, which point to the heterogeneity in the quality of employee-employer matches [Burdett (1978); Jovanovic (1979)] could be relevant. There is evidence that mobility plays a less important role in terms of wage growth for young women: not only are young women less likely to quit a job, but they also seem to receive lower returns to mobility than young men [Simpson (1990); Light and Ureta (1992); Loprest (1992)].

To better understand the weaker wage growth of female workers we use the statistical discrimination model proposed by Oettinger (1996) as a starting point. A worker’s productivity is assumed to depend on the quality of the job match and is imperfectly observed by both employers and workers. It is further assumed that the imperfect signal which reveals productivity is less reliable for women than for men. Finally, the model allows productivity to become less noisy with tenure. As in Altonji and

¹Data from the Current Population Survey published by the U.S. Bureau of Labor Statistics show that the female-to-male ratio of weekly earnings for full-time workers increased in the early 2000s, and has since then stabilized at about 80%.

Pierret (2001) and Altonji (2005), we assume that employers learn about workers' characteristics and productivity over time. 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. To justify this hypothesis of differential signal quality, we argue that differences in educational choices and workplace behavior across genders could lead predominantly male employers to have more difficulty assessing female productivity.

Oettinger (1996) conjectured 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 revelation for women, our model does indeed show 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.²

The model generates a series of predictions that we test against U.S. data from the 1979 cohort of the National Longitudinal Survey of Youth. 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 and Section 5 concludes the paper.

2 The Structure of the Model

Our approach is based on the dynamic statistical discrimination model setup by Oettinger (1996), which incorporates the notion of job-matching. In particular, like Oettinger, we assume that the productivity of any job match is imperfectly observed *ex ante*, that the initial productivity signal is noisier for the “minority” group (*i.e.* women in the present paper) and that additional information about the productivity of the match is revealed with tenure on the job. One of our contribution is to extend Oettinger's framework by allowing for the possibility that match productivity is not revealed *completely* for women as job tenure accumulates and consequently female workers' productivity remains less reliable.

²There is a large literature relating wage rates and early labor market mobility (Neal and Johnson, 1998; Neal, 1999). This literature considers job offers as exogenous and focuses on the workers' behavior. Our model considers the *equilibrium outcomes* as arising from the interaction between employers and workers under uncertainty.

It turns out that this simple generalization substantially expands the set of empirical predictions with respect to male-female differences in starting wages, wage levels for experienced workers and wage growth.

In our model, the agents are competitive firms who negotiate compensation with employees one-on-one and offer each a wage equal to his or her expected productivity, conditional upon all available information, and income-maximizing workers who take mobility decisions based on their expected wage schedules. Before we describe the agent's objective functions and determine the equilibrium, it is essential to specify the informational context in which firms make their wage decisions.

Employees are assumed to work for two periods ($t = 1, 2$) and maximize expected compensation over their working lives.³ 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_{ti} , is a random variable whose distribution is known and identical for men and women: $\mu_{ti} \sim \mathcal{N}(\bar{\mu}, \sigma_\mu^2)$.

Individuals' productivity depends on the quality of their job match. Moreover, for each individual, the true quality of the new job offers received in the two periods, μ_{1i} and μ_{2i} , are independent draws from the underlying match productivity distribution. This latter assumption, standard in Jovanovic (1979) ensures that employees' history is irrelevant to the evaluation of his/her productivity in any newly formed match.

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

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

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

³As in Oettinger (1996) we ignore the issue of labor supply. As a result the empirical test of the model is implemented on a sample of men and women who are known to be strongly attached to the labor market.

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.*

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

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} . For stayers we may write observed second-period productivity as:

$$s_{1i}^j = \mu_{1i} + v_i^j, \quad \text{where } v_i^j \sim \mathcal{N}(0, \sigma_{v_j}^2) \text{ and } \sigma_{v_j}^2 < \sigma_{\varepsilon_j}^2, \quad j \in \{f, m\}. \quad (3)$$

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 a 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.* $0 = \sigma_{v_m}^2 < \sigma_{v_f}^2$.

Differences in productivity uncertainty have often been justified on cultural grounds [Cornell and Welch (1996)]. But this argument may be tenuous when considering gender rather than race. On the other hand, some have suggested that a number of gender differences may make it harder for employers to adequately ascertain women's productivity. For example, it is an empirical fact that a large majority of students majoring in engineering, sciences, and business are men, and that women represent more than half of those majoring in education, health sciences, and humanities [Turner and Bowen (1999), Dey and Hill (2007)]. Although completing a college degree in these "softer" fields might be sufficient for entry-level positions, it may make it harder for managers to evaluate productivity in higher level positions. Recently, Goldin (2014) has argued that firms in some sectors tend to disproportionately reward individuals who labor long hours and work particular hours. Because fewer women may be attracted to such jobs, employers may find it hard to tell *a priori* whether a female candidate will *ex post* perform as well as male candidates.

Other intrinsic differences in behavior across gender may lead to noisier productivity for women. Bertrand (2010) reviews a number of articles showing through laboratory experiments that, relative to men, women are more averse to risk, are more likely to avoid competing in "winner-takes-all"

tournaments, that they are more likely to display altruistic behavior, and that they are less inclined to negotiate. Henley (1977) and Lang (1986) stress that men and women differ in their communication style. Gneezy et al. (2003) provide evidence that women tend to perform worse than men in competitive environments even if they are able to perform similarly in a non-competitive setting. Beugnot et al. (2013) get a similar result and find in addition that women tend to perform less when competing against men. Babin and Boles (1998) find that job related stress affects more negatively the performance of women relative to men. In the same vein, Beyer and Bowden (1997) find that women's self-evaluation of performance in "masculine tasks" were inaccurately low. Byrnes et al. (1999) and Eagly (1995) review empirical evidence showing gender disparities in risk taking and social behavior.⁴ To the extent that employers are unaware of these disparities in behavior across genders, and that most employers are disproportionately men, these differences may make it harder for them to accurately assess the productivity of female workers. Indeed Flabbi et al. (2014) find empirical evidence consistent with women executives being better at interpreting female productivity signals.

Formally 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 zero expected profits in both periods. In the first period, wage profiles can thus be written as:

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

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 $\hat{\mu}_{2i}^j \equiv \mathbb{E}(\mu_{2i} | s_{2i}^j) > \tilde{\mu}_{1i}^j \equiv \mathbb{E}(\mu_{1i} | s_{1i}^j)$. Wages in the second period can thus be written

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

Note that the productivity of a male stayer will be perfectly observed. His compensation will be

⁴Different explanations for these differences in behavior and personality traits are reviewed in Section 2.7 of Bertrand (2010).

$w_{2i}^m = \tilde{\mu}_{1i}^m = \mu_{1i}$ and the condition to remain on his original job is $\hat{\mu}_{2i}^m \leq \tilde{\mu}_{1i}$. Naturally these conditions do not apply to female workers. We will now examine the equilibrium solution and analyze how gender wage gaps may arise.

3 Equilibrium Wage Profiles

Equilibrium is determined by the optimization behavior of employers and employees. Firms, which are in a competitive environment, maximize profits by proposing wages, which reflect expected productivity conditional on the individual signal and the group membership. Workers take mobility decisions that maximize their expected lifetime earnings. We will characterize wage profiles in the two periods before drawing conclusions about the returns 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 :

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

where $\rho_j^2 = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_{\epsilon^j}^2)$.⁵

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,⁶ 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 compensations. 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

⁵To show this, observe that μ_{1i} and s_{1i}^j are normal bivariate with correlation coefficient $\rho_j^2 = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_{\epsilon^j}^2)$. The result follows from computing the conditional expectation.

⁶The assumption $\sigma_{\epsilon^f}^2 > \sigma_{\epsilon^m}^2$ implies $\rho_f^2 < \rho_m^2$.

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 ($\rho_m^2 \sigma_\mu^2$) than women's ($\rho_f^2 \sigma_\mu^2$). Yet, men and women will receive on average 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

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

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 $w_{2i}^j = \tilde{\mu}_{1i}^j \equiv \mathbb{E}(\mu_{1i}^j | s_{1i}^j)$ and those of the movers by $w_{2i}^j = \hat{\mu}_{2i}^j \equiv \mathbb{E}(\mu_{2i}^j | s_{2i}^j)$. A worker continues with the same job only if $\tilde{\mu}_{1i}^j \geq \hat{\mu}_{2i}^j$ and conversely changes jobs if $\tilde{\mu}_{1i}^j < \hat{\mu}_{2i}^j$. Thus,

- the average second-period wage for stayers is given by:

$$\mathbb{E}[\tilde{\mu}_{1i}^j | \tilde{\mu}_{1i}^j - \hat{\mu}_{2i}^j \geq 0] = \bar{\mu} + \frac{\delta_j^2}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi} \right)^{1/2}, \quad j \in \{f, m\} \quad (8)$$

and

- the average second-period wage for movers is given by

$$\mathbb{E}[\hat{\mu}_{2i}^j | \hat{\mu}_{2i}^j - \tilde{\mu}_{1i}^j > 0] = \bar{\mu} + \frac{\rho_j^2}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi} \right)^{1/2}, \quad j \in \{f, m\}, \quad (9)$$

where $\delta_j^2 = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_{v_j}^2)$. For stayers, δ_j^2 is a measure of the quality of the signal similar to ρ_j^2 in the first period.⁷ Moreover, since the productivity revelation mechanism is perfect for men ($\sigma_{v_m}^2 = 0$) but imperfect for women ($\sigma_{v_f}^2 > 0$), 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. The expected wage of a mover is lower than that of a stayer ($\rho_j^2 < \delta_j^2$ because $\sigma_v^2 < \sigma_\varepsilon^2$).

⁷Their wage profile is $w_{2i}^j = (1 - \delta_j^2)\bar{\mu} + \delta_j^2 s_{1i}^j$

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 the signal is less noisy in the second period. The unconditional second-period mean wage of group j can be derived from equations (8) and (9):

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

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 by reducing the likelihood of changing to jobs that are worse match, or of foregoing profitable job changes. Given our assumption of better signal quality for men, they should benefit more from mobility. In the second period they should on average receive higher wages than their female co-workers, as made clear in equation (10). 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

We now consider between-period wage changes. The expected wage change for stayers is given by $\mathbb{E}[\tilde{\mu}_{1i}^j - \hat{\mu}_{1i}^j | \tilde{\mu}_{1i}^j - \hat{\mu}_{1i}^j \geq 0]$ while that of movers is given by $\mathbb{E}[\hat{\mu}_{2i}^j - \tilde{\mu}_{1i}^j | \hat{\mu}_{2i}^j - \tilde{\mu}_{1i}^j > 0]$. It can easily

be shown that

$$\mathbb{E} \left[\tilde{\mu}_{1i}^j - \hat{\mu}_{1i}^j \mid \tilde{\mu}_{1i}^j - \hat{\mu}_{2i}^j \geq 0 \right] = \frac{\delta_j^2 (1 - \rho_j^2)}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi} \right)^{1/2}, \quad (11)$$

$$\mathbb{E} \left[\hat{\mu}_{2i}^j - \hat{\mu}_{1i}^j \mid \hat{\mu}_{2i}^j - \tilde{\mu}_{1i}^j > 0 \right] = \frac{\rho_j^2 (1 + \delta_j^2)}{\sqrt{\delta_j^2 + \rho_j^2}} \left(\frac{2\sigma_\mu^2}{\pi} \right)^{1/2}. \quad (12)$$

From equations (11) and (12) it is clear that the expected wage change is positive for both stayers and movers. This result is not surprising since mobility is generated by the earnings maximization of workers. If $\sigma_\varepsilon^2 < \sigma_\mu^2$ —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 $\sigma_\varepsilon^2 < \sigma_\mu^2$).

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 $\delta_j^2 = 1, \forall j$. However, this assumption is not innocuous since the productivity revelation mechanism plays an important role in the determination of the second period wage rate. Moreover, our generalization complicates the analysis with respect to differences in the return 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 (ρ_f^2) and the precision of the revelation mechanism (δ_f^2) act in opposite directions. Likewise, the impact of δ_f^2 on movers' mean wage increase is ambiguous.

3.4 Male-Female Gap in the Return to Mobility

The analysis of gender differences in terms of return to job mobility and tenure is slightly 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 $(\sigma_{\epsilon_f}^2, \sigma_{v_f}^2)$ relative to the variance of the productivity (σ_μ^2) .

To ease the derivation of the results let $k \in]0, 1]$ be such that $\sigma_{\epsilon_m}^2 = k\sigma_{\epsilon_f}^2$, $\alpha = \frac{\sigma_{\epsilon_f}^2}{\sigma_\mu^2}$, and $\beta = \frac{\sigma_{v_f}^2}{\sigma_\mu^2}$. We can rewrite the conditions pertaining to the gender differences in job mobility and tenure in terms of k , α and β . Thus for the average wage of male stayers to be higher to that of female stayers, it is necessary and sufficient according to equation (8) that:⁸

$$\frac{1}{\sqrt{1+\rho_m^2}} \geq \frac{\delta_f^2}{\sqrt{\delta_f^2 + \rho_f^2}}, \text{ or equivalently that } k \geq k_A = \frac{\alpha - \beta(3 + \alpha + \beta)}{\alpha[1 + \beta(3 + \alpha + \beta)]}. \quad (13)$$

By the same reasoning, we can derive the following predictions based on equations (8),(9),(11) and (12):⁹

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

⁸Recall that Oettinger (1996)'s model implicitly assumes that: $\sigma_{v_f}^2 = 0$ and thus that $\beta = 0$ in our framework. His model thus boils down to assuming that $k = 1$, i.e. that women's productivity signal is no more noisy than men's signal. Consequently his model precludes male stayers to have a higher mean average wage.

⁹The 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.

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 ($\sigma_{\epsilon_f}^2$, $\sigma_{v_f}^2$) are much smaller than the variance of productivity (σ_μ^2), 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 tenure¹⁰. 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.* $\sigma_{v_f}^2 = 0$, 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) 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.

¹⁰ $\sigma_{\epsilon_f}^2 \geq \sigma_{v_f}^2$ implies that $\beta \leq \alpha$.

4 Data and Empirical Analysis

4.1 The Sample

Our model makes a number of predictions regarding the relationship of average wages and wage growth with gender, job mobility, and labor market experience. The main wage determinant in our theoretical model is the productivity signal generated by an employee-employer match. The productivity signal is however unobserved in the data. So our identification relies on having variables that correlate with this unobserved productivity signal. Our model suggests that gender, work experience, tenure, and job changes should correlate in predictable directions with this unobserved productivity signal. To test these predictions we therefore estimate wage equations that include job tenure, years of labor market activity, and indicator variables for gender and job changes. These in essence serve as proxies for the evolution of the unobserved productivity signal.

We use data drawn from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY). This survey follows a cohort representative of young Americans aged 14 to 21 in 1979. It provides extensive longitudinal data for 12,686 respondents on educational achievements, wages, and work experience yearly from 1979 to 1993 and every two years from 1994 to 2012. In this study we focus on white individuals from the cross-sectional sample of the NLSY and exclude the supplemental sample of economically disadvantaged whites.

Our aim is to follow the evolution of wages at the beginning of young adults' careers. Since our model does not include labor supply, we follow Oettinger (1996) by focusing on an individual's first observable transition from weak to strong labor force attachment. Respondents are considered to be strongly attached to the labor force during a specific survey year if they worked at least half of all weeks since the last survey,¹¹ and if they worked at least an average of 30 hours during each of those weeks. The onset of a respondent's career is the first of three consecutive survey years of strong labor force attachment that follow one year of weak labor force attachment.¹² We then follow each respondent's wage evolution for up to ten years following that first transition into strong labor force attachment, keeping in our sample only wage observations preceded by a year of strong labor force

¹¹The number of weeks between the interviews of two consecutive survey years is not necessarily 52 weeks, so we restrict our sample to survey years with an interview that took place 45 to 59 weeks after the preceding interview.

¹²Respondents who are observed to have strong labor force attachment in survey year 1979 are excluded from the sample.

attachment.¹³ Consistent with our requirement of measuring wages every year, we do not consider NLSY data collected after 1994 since surveys were then conducted every two years.

The wage is measured at the end of each year of strong labor force attachment.¹⁴ At every survey interview the respondent is asked to describe each job held at the time of the last interview and each job held since that last interview. We use hourly wage for a job held at the time of the survey. If a respondent holds more than one job at the time of the survey, we use the hourly wage for the job at which the respondent worked most hours. Wages are measured in 2004 dollars and included in the sample if they are greater than \$1 and less than \$60.

Every survey interview respondents are asked if they are currently enrolled in school and what is their highest educational achievements as measured by years of completed schooling. We focus on individuals who have completed at least 13 years of education at the end of their career's first year. The rationale is that our model assumes male and female workers to have the same level of commitment to the labor market. This assumption is more likely to hold in a sample of individuals who have invested in post-secondary education. The sample of individuals with no post-secondary education may display greater variation in their attachment to the labor force, and the mechanisms behind this variation likely differ between men and women given that women's educational and labor supply choices are affected by their fertility decisions. Although fertility decisions also affect female workers with post-secondary decisions, it can be argued that higher household earnings and stronger investments in human capital of more educated couples reduce the scope for fertility decisions affecting female labor supply.

The model has strong predictions about the impact of work experience, job tenure, and job changes on wages. Work experience is a variable that counts the number of years of strong labor force attachment since the first transition into strong attachment. Job tenure measures the number of consecutive weeks at a given job, which we then divide by 12 to ease the interpretation of its coefficient. To identify a job change, we gather information on all jobs that ended for a worker since the date of

¹³We also experimented with a sample that excluded any wage observation that follows a year of weak LFA. This results in a much smaller sample, larger standard errors, but qualitatively similar results.

¹⁴Ideally we would have identified the respondent's "first job" and the wage associated with that job. However, the NLSY provides no question or variable referring to an individual's first job. Many respondents hold jobs while enrolled in school, but these may not be jobs associated with their eventual careers. Other respondents may be out of school and hold jobs, but are not strongly attached to the labor market. This makes it hard to identify the first job associated with their eventual career and we opted instead to look at hourly wage for jobs held at the end of each year of strong labor force attachment.

the last survey interview. If we find that no job ended since the last interview the worker is considered to not have changed job. Otherwise we code the worker as having changed job, and record whether the most recent job ended for a voluntary or involuntary reason.

To proxy ability, our regressions include the score percentile of the Armed Force Qualification Test (AFQT).¹⁵ This variable is meant to capture the fact that employers may partly observe the worker's ability and adjust compensation accordingly. We also include a dummy variable that controls for whether the job is covered by a collective bargaining agreement, acknowledging the fact that other external mechanisms may determine wages. In the same vein we include dummy variables for occupation and industry to reflect how work in these different professions and firms are rewarded in the product market.¹⁶

Table 2 here.

Our sample consists of 505 women, and 474 men with at least some college whom we observe a year following their first transition into strong labor force attachment. Table 2 provides summary statistics on some of the variables used in the empirical analysis. It shows the distribution of the years during which workers made their transition into strong labor force attachment. For 90% of the sample, this first transition took place in years 1980 to 1988. On average these workers made their first transition into the labor force at the age of 23, which is consistent with the fact that they completed on average 15 years of education. Almost 57% of the sample had completed 4 years or more of college by the time of their first transition.

At the end of the first year of strong labor force attachment, women and men earn an average hourly wage rate of \$12 and \$13, respectively. Two years later, their respective average hourly wage rate has increased to \$14 and \$16. As many as 62% of men and 56% for women change job at the end of their first year of employment. But mobility decreases as their careers unfold, down to about

¹⁵The AFQT score aggregates results for tests on word knowledge, paragraph comprehension, mathematics knowledge, and arithmetic reasoning. The AFQT is a subset of the Armed Services Vocational Aptitude Battery administered to NLSY respondents in 1980. At that time, age varied from 15 to 22 among respondents. It is known that performance on the AFQT test is positively correlated with age at time of the test. We therefore use AFQT test scores adjusted for age at the time of the test.

¹⁶Previous research has shown that occupations and industries are coded with error in the NLSY. We ignore any industry change that is not associated with a job change. Occupation is allowed to change without any job change. However, we ignore any occupation "cycling" within the same job: if an occupation change is observed within the same job, it is ignored if the occupation at this same job is observed to have changed again at the next survey interview.

35% for men and women by the end of the third year. By that time, 14% of male and female workers are covered by a collective agreement.

Labor supply during that first year of strong labor force attachment is quite similar for men and women. Indeed, men worked on average 1,950 hours over 46 weeks, while women worked 1,800 hours over 45 weeks. Two years on, labor supply is slightly higher for workers of both genders.

After their first year of strong attachment, the majority of women are either professionals (36%) or clerical workers (30%). Two years on, both occupations are still the most prevalent at 43% and 26%, respectively. Early on, men are more likely to work as professionals (37%) or service workers (11%) and managers (11%). Two years on, they are mostly professionals (38%), managers (13%), and sales workers (11%).

The two most prevalent industries for women are professional and related services (39%) and in wholesale or retail trade (21%). Two years on, these two industries represent respectively 38% and 19% of all jobs. Male workers work mostly in wholesale and retail trade, manufacturing and professional services industry (20% each). Two years on, the professional service industry represents 19% while manufacturing's share is higher (24%).

4.2 Estimation Results

We test our model's predictions using reduced-form log-wage regressions. Our sample includes all individuals that have completed at least three years of strong labor force attachment following one year of weak labor attachment. We follow their hourly wage over those first three years of strong labor force attachment and for any subsequent year of strong labor force attachment, up to 10 years following transition. Our sample of individual-wage observations contains real wages (in 2004 dollars) from 1980 to 1994. The main wage determinant in our theoretical model is the noisy productivity signal arising from an employee-employer match. So our identification relies on our work experience, tenure, and job change variables being correlated with these unobserved productivity signals.

4.2.1 The Gender Wage Gap

The main results concerning the gender wage gap are presented in Table 3. All results presented in Table 3 are OLS estimates.¹⁷ The first column contains results for a model where we only control for gender, age, years of education, AFQT, and a dummy variable for collective bargaining. This column shows that female wages are about 9.1% lower than that of men, and that this gender wage gap is statistically significant. Since there is no control for work experience, age is associated with strong wage growth. As expected, years of education, AFQT and collective bargaining are associated with higher wages.

Table 3 here.

Models 2 to 4 gradually add more variables to the model and allows us to study how that affects the gender wage gap. In Model 2 we add a variable for work experience, which is measured by years of strong labor force attachment. As expected years of experience are associated with strong wage growth: 11.8% for each year of strong labor force attachment. Even after adding years of experience, we still find that women earn on average 7.8% less per hour of work.

In Model 3 we add an interaction term between work experience and the gender dummy variable. Remember that the model predicts that male and female workers have the same starting wage, and that the lower quality of productivity signaling for women implies that female wages should grow at a slower rate. Consistent with this, we find that the gender wage gap is reduced to less than 1.1% and is not statistically significant. Moreover, the parameter on the interaction between gender and work experience reveals that wage growth is weaker for women: one year of strong labor force attachment leads to a 10.9% wage growth, compared to 12.4% for men, and this difference is statistically significant.¹⁸

Other mechanisms could generate weaker wage growth for women. If most women in our sample expect to have children and therefore make fewer on-the-job human capital investments, we should

¹⁷Although we do not present the results here, we also include in all models a set of dummy variables to account, year, year of entry in the labor market, occupation, and industry.

¹⁸These results are consistent with Loprest (1992) who uses the NLSY79 to find that women have weaker wage growth than men. Although she also considers a sample of workers with consecutive years of strong labor force attachment, her sample contains workers who did not go to college. If we consider workers of all educational levels we still find that returns to experience are lower for women, however this difference is not statistically different once marital and parental status are accounted for. This suggests that part of the lower wage growth among less educated women can be explained by marital and fertility choices.

observe weaker wage growth for women. In Model 4, we include variables that control for marital status and the presence of children at home. The dummy variable for being married and its interaction with gender indicate that being married is associated with higher wages, but much less so for women. The parameter on a dummy variable for the presence of at least one child in the household indicates that having children is associated with lower wages.¹⁹ Including these household related variables shows that the gap in wage growth from strong labor force attachment decreases to 0.98%, but remains statistically significant at 1%, compared to 1.5% in Model 3. It suggests that part of the weaker female wage growth may be explained by different on-the-job human capital investments.

4.2.2 Job Changes and Job Tenure

Our model also has predictions regarding the comparative wages of workers who keep the same job (stayers) and those who change job (movers). It is worth noting that while our theoretical model includes only voluntary job, our sample includes individuals whose jobs end involuntarily. In our estimations we therefore separately control for voluntary and involuntary job changes.²⁰ Our theoretical model can inform the interpretation of the impact of voluntary job changes on wages but has nothing to say about the impact of involuntary job changes on wages. Our analysis focuses on voluntary job changes but we discuss the involuntary type at the end of this subsection.

Table 4 here.

Model 5 of Table 4 adds a dummy variables indicating whether the individual experienced a voluntary job change or an involuntary job change since the last survey interview. We also include an interaction between gender and the job change variables. Our results show that voluntary movers have on average lower wages, as predicted by our model (see Section 3.3). The coefficients on gender and gender interacted with voluntary job change are not statistically significant, so there is little evidence that mean wages for stayers or movers differ with gender. This prevents us from using the first and second rows of Table 1 to identify how noisy female productivity signals are relative to male signals.

¹⁹We also tried adding an interaction term between gender and the child dummy variable to Model 4. We found both the child dummy variable and its interaction with gender to be negative, but not statistically significant.

²⁰Among all job changes observed in our sample, roughly 75% of these are voluntary. Among the involuntary job changes, 37.3% resulted from the worker being laid off or displaced due to plant closure. It is well-known that displacement usually entails sizeable earnings losses. See *e.g.* Song (2009).

Model 6 includes a linear term in years of job tenure, as well as interaction between this term and gender. Tenure coefficients indicate that wages grow with tenure, as predicted by our model. Moreover, this growth is significantly stronger for women: one year with the same employer lead to 1.5% wage growth for men, compared to 2.5% for women. This stronger wage growth from tenure is consistent with cases 1 and 2 from Table 1.

In Model 7 we study the joint impact of job changes and tenure. We still find that workers who change jobs have lower average wage. Tenure is still associated with statistically significant wage growth, and this wage growth is stronger for women.²¹

Involuntary job changes are associated with even larger wage penalties, and these gaps are statistically significant for both men and women. Our theoretical model has no prediction about the impact of involuntary job changes but we hypothesize that if random job separations were added to the model it would lead involuntary movers to have lower wages relative to both stayers and voluntary movers, consistent with our empirical estimates here. Indeed involuntary movers would see their job market status reset to what it was in the first period when they suffer an involuntary job separation. That implies their average wage is given by equation (7) in Section 3.1 which is lower than the average wages of stayers (equation (8)) and voluntary movers (equation (9)). A similar pattern would arise if firms had an incentive to terminate jobs with low productivity signal. But the wage gap between stayers and both types of movers would increase as all low productivity matches are purged from stayer population.

4.2.3 Wage Growth and Job Changes

A clear prediction of the model from Section 3.3 is that although movers' mean wage is lower than that of stayers, their wage growth is stronger. To test this prediction, as well as predictions about the mean wage gain across genders of stayers and movers (last two rows of Table 1), we study wage growth in Table 5. The dependent variable is the difference between the current log hourly wage and the log wage recorded at the previous survey. All regressions presented in Table 5 control for collective bargaining coverage, industry, and occupation.²² All regressions also control for age, years

²¹When we add interaction of gender with both types of job change we find them to be statistically insignificant while also making voluntary job change dummy and the interaction of gender with tenure statistically insignificant.

²²We include dummy variables for all possible state transitions. For example, collective bargaining includes a dummy variable for individuals who stayed covered by a collective agreement, a dummy variable for individuals who lost their

of schooling, ability as measured by the AFQT score percentile, as well as a dummy variable for gender, first year of transition into the labor market, and year. Model A shows that, consistent with our previous findings in Table 3, women have weaker wage growth, although the coefficient is not precisely estimated.

Table 5 here.

Another prediction of the model in Section 3.3 is that movers should experience stronger wage growth. Model B tests this prediction by adding a dummy variables for voluntary and involuntary job changes. The coefficient on voluntary job change is positive and statistically significant, which is consistent with the prediction of our model that movers should have stronger wage growth relative to stayers. Model C includes an interaction between job change and gender to test among movers and stayers which gender has stronger mean wage gains. The negative and significant coefficient on the interaction of job change and gender implies that female movers have weaker wage growth relative to males. Looking at the last row of Table 1, this stronger wage growth for male movers is consistent with the model's predictions.

Involuntary job changes are associated with weaker wage growth in Model B. We would expect this result in our theoretical model if it included involuntary job separation since involuntary movers do not benefit from voluntarily moving to a better productivity match and they do not benefit from the reward associated with their employer learning about their unobserved productivity.

4.2.4 Implications for Signal Quality and Productivity Revelation Across Genders

Lets consider which cases of Table 1 are consistent with the coefficients presented in Tables 3 to 5. An important empirical result is that returns to tenure are stronger for women, as seen in Models 6 and 7 of Table 4. This is consistent with cases 1 and 2 of Table 1. We then have in Model C of Table 5 that wage growth is stronger for male voluntary movers relative to female voluntary movers. This is also consistent with cases 1 and 2 according to Table 1. It is worth noting that cases 1 and 2 are identical with the exception of which gender is predicted to have the largest wage among stayers. However, the coefficient on the gender in Models 5 and 7 is not statistically significant and prevents

coverage, and a dummy variable for individuals who gained collective bargaining agreement, leaving those who remained uncovered as the base case.

us from distinguishing between either cases. We therefore follow with a discussion of the implications of cases 1 and 2 for the comparison across genders of signal quality in a new job, and the productivity revelation for workers who do not change job. It allows us to make some inferences about the model's mechanisms for wage growth and job mobility.

Cases 1 and 2 entail that signal quality in a new job is good for men. For women signal quality is bad but productivity revelation is good, hence their larger returns to tenure. In case 1, only women with very low productivity or bad post-hiring noise do not keep their current job. This tends to remove the extreme left part of the signal distribution among female stayers, increasing their observed average wage. The average wage of male stayers also increases but to a smaller extent because employers do not revise their expectations about their productivity so much as they do for women. Hence the average wage of stayers is larger for women in case 1. In case 2, the male (female) signal in a new job is noisier (clearer). So there is more scope for employers revising their expectations for males, leading to male stayers having a stronger average wage.

Contrary to women, the majority of male movers are not solely drawn from the extreme left tail of the signal distribution because of the perfect revelation of their productivity if they stay. It follows that male workers move only if they get a much better draw (productivity and noise wise) at a new job, implying that among movers, men have the largest average wage and the largest average wage growth. Estimates from Models 5 and 10 lend support to these conjectures: on average male movers earn more and experience stronger wage growth than female movers (the interaction between gender and job change dummy variables is negative in both models, statistically significant for Model C, and marginally significant in Model 5).

5 Conclusion

In this paper we investigate the gender wage gap 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 the relation between wages, wage growth, mobility, tenure and experience across genders. To our knowledge, only three other papers [Oettinger (1996); Neumark (1999); Altonji and Pierret (2001)] have empirically tested the validity of the theory

of statistical discrimination within a similar framework.

The theoretical predictions are tested using U.S. data from the 1979 cohort of the National Longitudinal Survey of Youth. The data supports most of these predictions. We find that men and women with post-secondary education earn identical wages upon entry into the labor market, but a substantial gap emerges in men's favor in the next few years. Other clear predictions of the model are supported: work experience and tenure are associated with higher wages. Average wages are higher among workers who do not change job (stayers), while job changers (movers) experience stronger wage growth.

The theoretical model has ambiguous predictions about gender-related mean wage among stayers, mean wage among movers, returns to tenure, mean wage gains among stayers, and mean wage gains of movers. However, the model provides enough structure to limit its predictions to six possible cases, which we present in Table 1. Our empirical results support cases 1 and 2 whereby women have stronger returns to tenure, while men movers enjoy stronger wage growth relative to female movers. Both cases implies that employers are better at inferring the productivity of new male employees, while finding it much more difficult to do so with female employees. Both cases also imply that employers eventually get a precise estimate of female workers' productivity with tenure. However, as their career progress, women on average have lower wages because they are much more likely to forego moving to a more productive match that has been hidden by a more noisy signal.

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Table 2: Descriptive statistics

	Men	Women
Entry Year and Age		
Before 1983	23.0%	26.7%
1983	12.2%	14.7%
1984	14.8%	16.4%
1985	14.6%	15.3%
1986	13.5%	10.3%
After 1986	21.9%	16.6%
Age	23.2	22.8
Entry Education		
Years of Education	15.4	15.2
At Least 16 Years of Education	56.3%	57.2%
Wage, Job Change, Job Tenure, Collective Bargaining		
After First Year		
Hourly Wage (2004 \$)	12.96	11.67
Changed Job	61.5%	55.9%
Job Tenure (Years)	1.00	1.03
Collective Bargaining	10.7%	11.7%
After Third Year		
Hourly Wage (2004 \$)	16.32	13.81
Changed Job	34.9%	35.8%
Job Tenure (Years)	2.10	2.05
Collective Bargaining	13.6%	14.1%
Labor Supply		
After First Year		
Weeks Worked	45.6	45.3
Hours Worked	1,956	1,803
After Third Year		
Weeks Worked	50.7	50.3
Hours Worked	2,305	2,131

Sample includes white men and women who are observed transitioning from one year of weak labor force attachment (LFA) to three consecutive years of strong LFA, and who had completed at least one year of college by the end of their first year of strong LFA. The definition of strong LFA is provided in section 4.1. The entry year is the survey year during which the individual is observed having completed their first year of strong LFA.

Table 3: The Gender Wage Gap and Work Experience

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	1.5321 (0.0931)	1.3298 (0.0943)	1.2971 (0.0945)	1.3103 (0.0944)
Female	-0.0910 (0.0112)	-0.0777 (0.0112)	-0.0102 (0.0205)	0.0044 (0.0208)
Experience		0.1180 (0.0123)	0.1240 (0.0124)	0.1154 (0.0124)
Experience × Female			-0.0154 (0.0039)	-0.0098 (0.0041)
Age	0.0174 (0.0035)	0.0178 (0.0035)	0.0176 (0.0035)	0.0179 (0.0035)
Years of Education	0.0291 (0.0041)	0.0338 (0.0041)	0.0336 (0.0041)	0.0318 (0.0042)
AFQT Percentile	0.0025 (0.0003)	0.0025 (0.0003)	0.0025 (0.0003)	0.0025 (0.0003)
Collective Bargaining	0.0767 (0.0158)	0.0760 (0.0159)	0.0739 (0.0159)	0.0742 (0.0159)
Married				0.1003 (0.0167)
Married × Female				-0.0926 (0.0217)
Children (= 1 for 1+ child)				-0.0394 (0.0153)
Sample Size	5,885	5,743	5,743	5,743

Standard errors in parentheses. Dependent variable is log hourly wage. Sample includes white men and women who are observed transitioning from one year of weak labor force attachment (LFA) to three consecutive years of strong LFA, and who had completed at least one year of college by the end of their first year of strong LFA. The definition of strong LFA is provided in section 4.1. Sample includes wages for the first three years following transition, and for any subsequent year of strong LFA, up to 10 years following transition. Experience is accumulated years of strong LFA. AFQT is a score received on a math and reading test administered to all NLSY respondents in 1980. All models include dummy variables for occupation, industry, year, and first year of strong LFA.

Table 4: The Gender Wage Gap, Job Changes and Job Tenure

Variables	Model 5	Model 6	Model 7
Intercept	1.3440 (0.0954)	1.3294 (0.0943)	1.3641 (0.0947)
Female	0.0106 (0.0236)	-0.0194 (0.0206)	-0.0222 (0.0206)
Experience	0.1188 (0.0125)	0.1056 (0.0126)	0.1055 (0.0127)
Experience × Female	-0.0172 (0.0040)	-0.0200 (0.0046)	-0.0197 (0.0046)
Voluntary Job Change	-0.0406 (0.0178)		-0.0294 (0.0135)
Voluntary Job Change × Female	-0.0377 (0.0246)		
Involuntary Job Change	-0.1190 (0.0278)		-0.1386 (0.0205)
Involuntary Job Change × Female	-0.0794 (0.0404)		
Job Tenure		0.0147 (0.0034)	0.0107 (0.0035)
Job Tenure × Female		0.0103 (0.0049)	0.0102 (0.0049)
Age	0.0170 (0.0035)	0.0151 (0.0035)	0.0154 (0.0035)
Years of Education	0.0347 (0.0041)	0.0362 (0.0041)	0.0365 (0.0041)
AFQT Percentile	0.0024 (0.0003)	0.0024 (0.0003)	0.0023 (0.0003)
Collective Bargaining	0.0729 (0.0159)	0.0641 (0.0159)	0.0661 (0.0159)
Sample Size	5,719	5,715	5,692

Standard errors in parentheses. Dependent variable is log hourly wage. Sample includes white men and women who are observed transitioning from one year of weak labor force attachment (LFA) to three consecutive years of strong LFA, and who had completed at least one year of college by the end of their first year of strong LFA. The definition of strong LFA is provided in section 4.1. Sample includes wages for the first three years following transition, and for any subsequent year of strong LFA, up to 10 years following transition. Experience is accumulated years of strong LFA. AFQT is a score received on a math and reading test administered to all NLSY respondents in 1980. Voluntary and involuntary job change refers to whether the last job that a worker ended did so for a voluntary or involuntary reason. Job tenure is accumulated years of work at current employer. All models include dummy variables for occupation, industry, year, and first year of strong LFA.

Table 5: Wage Growth and Job Changes

Variables	Model A	Model B	Model C
Intercept	0.0081 (0.0694)	-0.0041 (0.0696)	-0.0118 (0.0698)
Female	-0.0059 (0.0063)	-0.0067 (0.0063)	0.0010 (0.0071)
Voluntary Job Change		0.0318 (0.0086)	0.0517 (0.0119)
Voluntary Job Change \times Female			-0.0353 (0.0146)
Involuntary Job Change		-0.0279 (0.0132)	-0.0221 (0.0181)
Involuntary Job Change \times Female			-0.0107 (0.0254)
Age	-0.0014 (0.0019)	-0.0013 (0.0020)	-0.0014 (0.0020)
Years of Education	0.0008 (0.0023)	0.0009 (0.0023)	0.0013 (0.0023)
AFQT Percentile	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Sample Size	4,955	4,933	4,933

Standard errors in parentheses. Dependent variable is log hourly wage growth. Sample includes white men and women who are observed transitioning from one year of weak labor force attachment (LFA) to three consecutive years of strong LFA, and who had completed at least one year of college by the end of their first year of strong LFA. The definition of strong LFA is provided in section 4.1. Sample includes wages for the first three years following transition, and for any subsequent year of strong LFA, up to 10 years following transition. AFQT is a score received on a math and reading test administered to all NLSY respondents in 1980. Voluntary and involuntary job change refers to whether the last job that a worker ended did so for a voluntary or involuntary reason. All models include dummy variables for occupation, industry, year, and first year of strong LFA.