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A COMPARISON OF THE EFFECTS OF MATCHING AND SEARCH ON THE WAGES OF MEN AND WOMEN

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In this paper, I compare the effects of job matching and job search on the wages of men and women by education level. I find that matching and search exert a strong influence on the wages of young men and women, providing support for matching theories that emphasize "job shopping" early in a worker's career. The matching-related differences in wage determination documented appear to be strongest across education groups -- not by sex. I find that numerous facets of the labor market process that I study look remarkably similar for more highly educated young men and women. My results indicate that though job matching and turnover are important in wage determination, they do not provide an explanation of the male-female wage gap that exists for more highly educated men and women.

Keywords: Job Matching, Job Search, Male-Female Wage Gap

Subject Index: Economic Demography and Labor Economics

I. INTRODUCTION

I have shown in previous work (Royalty [1993]) that the turnover of women with a high school education or less differs significantly from the turnover of more highly educated women as well from the turnover of men of both education levels. It was shown that the turnover probabilities generated in multinomial probit estimations could be used to estimate the reservation wage profiles that form the basis of job matching and search models. That investigation of matching and search centered on the implications of these models for turnover patterns, but the problem was more generally formulated in terms of the possible contribution of differences in matching and search behavior to the gender wage gap. The finding that less educated (LHS) women differ from all others in their job matching behavior left on the table the question of whether or not this difference in labor market behavior was a contributor to the wage gap between less educated men and women. In this paper, I address this question.

Specifically, the question to be answered is: "Can differences in matching and search behavior help explain the male-female wage gap?" It is difficult to quantify the effects of matching and search on wages since there exists no quantifiable variable "matching" or "search". There are observable variables, however that are correlated with the process of matching and search. By definition the process of matching and search occurs only through the accumulation of job tenure and labor market experience. Job matching models such as those of Jovanovic (Jovanovic [1979a], [1979b], [1984]) focus on the learning and wage growth that occurs with tenure on the job. On-the-job search models such as Burdett [1978] concentrate on the location of high wage job matches with time in the labor market. By the very nature of the models, the wage gains that are predicted due to matching and search are correlated with tenure or experience since these gains cannot be realized without the accumulation of job tenure and labor market experience.

Recent empirical work on matching and search has emphasized the bias in OLS wage equation coefficients on tenure and experience due to the correlation between these variables and unobserved match-specific productivity (Altonji and Shakotko [1987], Abraham and Farber [1987], and Topel [1991]). The notion of bias employed in these papers is implicitly based on some concept of a "pure" tenure or experience effect on wages, an effect due solely to the accumulation of experience or tenure and unaffected by any relationship between these variables and the unobservable components of the wage.

The wage growth due to matching and search is attained by making optimal job and labor market turnover decisions. These turnover decisions produce the actual levels of job tenure and labor market experience that workers are observed to have accrued. Consequently, tenure and experience are inherently a part of the outcome of the matching and search process. It might be argued that the "bias" of OLS tenure and experience coefficients is really not a bias at all but merely another component of tenure and experience returns. Nonetheless, the formulation of the problem used by these authors -- correcting for the bias in OLS wage estimates due to job matching and search -- can be used to provide evidence about the relative importance of matching and search in wage determination for men and women. As Topel points out, what these authors have defined as the OLS bias is also the extent to which experience and tenure are correlated with the unobservable matching and search component of wages. The size of these biases can be taken as indicative of the importance of matching and search in wage determination.

I use the framework of Topel [1991] to estimate this bias, comparing the results for men and women. Briefly, the idea is first to obtain a consistent estimate of within job wage growth -- that is, an estimate of the total returns to experience and tenure during a job, purged of the effects of any correlation of experience and tenure with the unobservables. As will be described in detail below, a second stage estimation then provides an estimate of the correlation of tenure and experience with the unobservable component of wages that theory suggests is attained through matching and search. This is possible since the "pure" effect of these variables on the wage has been accounted for in the first stage of the estimation. This two-stage method yields a measure of the returns to matching and search through this estimate of the correlation of tenure and experience with the job match component of the wage. In this paper, I will compare the matching and search returns for men and women by education level and explore various mechanisms that might explain the differences that are found.

II. ESTIMATION METHOD

Following Topel [1991], I now describe the two-stage estimation procedure used to obtain estimates of the returns to matching and search. The wage equation is specified as follows:

$$w_{ijt}=\beta_0+\beta_X X_{it}+\beta_T T_{ijt}+\beta_Q Q_{ijt}+\phi_{ijt}+\epsilon_{ijt} \tag{1}$$

where w_{ijt} is the wage of person i at firm j at time t; X_{it} is the labor market experience of person i at time t; T_{ijt} is the tenure of person i at firm j at time t; ϕ_{ijt} is the match-specific productivity of person i at job j at time t; and ϵ_{ijt} is an iid error. Q_{ijt} is a vector of other observable variables, such as education, that are expected to enter the wage equation and that are included in empirical work.

Due to the job matching and search processes, tenure and experience will be correlated with match-specific productivity, ϕ. The learning theory of matching implies that a match with a high value of ϕ, ϕ_{high}, will tend to last longer than a match with a low value of ϕ, ϕ_{low}, because it is less likely that the wage based on the expected value of ϕ_{high} will fall below the reservation value that would indicate that the worker should quit or that an alternative offer would exceed the reservation offer. This implies that tenure and ϕ will be positively correlated.[1] Search theory indicates that as individuals spend more time in the labor market searching they will tend to find better matches. Therefore there will also be a positive correlation between

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[1]Topel (Topel [1991]) points out that on-the-job search theory indicates that tenure and ϕ may be correlated for a different reason. Since searching workers take new jobs with higher average wages than the old, workers with short tenure may have recently found a high ϕ match, resulting in a negative correlation between tenure and ϕ. Empirical evidence of positive correlation between tenure and ϕ indicates this phenomenon to be less important than that described by the matching model.

experience and ϕ. Due to the correlation between the explanatory variables and the unobservables, OLS estimates of the returns to experience and tenure will include the effects of this correlation and will be biased estimates of the "pure" effect of tenure and experience on wages, measured by β_T and β_X respectively.

In the first stage of this two-stage method, wage growth between consecutive years for people who have not changed jobs during that year is regressed on the change in the explanatory variables over that year. The first stage regression equation is then:

$$w_{ij(t+1)}-w_{ijt}=\beta_X+\beta_T+\beta_{Q'}(Q'_{ij(t+1)}-Q'_{ijt})+\omega_{ij(t+1)}-\omega_{ijt} \tag{2}$$

where $\omega_{ijt}=\phi_{ijt}+\epsilon_{ijt}$ and Q'_{ijt} includes those variables of Q_{ijt} that vary with t. If $E[\omega_{t+1} - \omega_t] = 0$, OLS on equation (2) will provide consistent estimates of within job wage growth, $B = \beta_X + \beta_T$, the combined effect of the accumulation of one year of tenure and experience during the course of a job.[2] Only the combined effects of tenure and experience are identified here because tenure and experience are both incremented by one in each year. The first stage does identify separate effects of the higher order tenure and experience terms that are included in the empirical work.

Since experience at time t is equal to initial experience upon entering this job ($X0_{ij}$) plus tenure on this job, the tenure and experience terms on the right-hand-side of equation (1) can be rewritten as $\beta_X X0_{ij} + (\beta_X + \beta_T)T_{ijt}$. In the second stage of the

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[2]Notice that this specification does not allow for the learning about ϕ inherent in the full matching model since it requires that $E[\omega_{t+1} - \omega_t] = 0$. However, Topel [1991] and Topel and Ward [1992] present evidence that wage innovations are serially independent, thereby justifying this first-stage estimator.

estimation, $\hat{B} * T$, the consistent estimate of the effect on the wage of tenure and experience during this job is subtracted from both sides of equation (1). The second stage dependent variable is then the current wage purged of the "pure" effects of tenure and experience since the start of this job. Therefore, subtracting $\hat{B} * T$ from both sides of equation (1) leaves:

$$w^*_{ijt} = \beta_0 + \beta_X X0_{ij} + \beta_{Q''} Q''_{ijt} + \phi_{ijt} + \epsilon_{ijt} \tag{3}$$

where w^*_{ijt} is the log wage of person i at firm j at time t less the effect of tenure and experience ($\hat{B} * T$) on this job and other time-varying variables (Q'_{ijt}) as estimated in the first stage; $X0_{ij}$ is the labor market experience of person i when s/he entered job j; and Q''_{ijt} are the variables in Q_{ijt} that do not vary over time. According to the search and matching theory employed in this paper, the OLS estimated coefficient on β_X from equation (3) provides an upper bound on the return to experience. It is an upper bound because search theory suggests that initial experience will be positively correlated with ϕ since people with a longer time in the labor market will be more likely to have found better matches.[3] A lower bound on the return to tenure is then

[3]The consistency of the other second stage estimates depends on the assumption that the other explanatory variables are independent of ϕ_{ijt}.

obtained by subtracting the second-stage estimate of the return to experience from the consistent first-stage estimate of the return to tenure and experience.[4]

A measure of the importance of matching in wage formation, which is the primary focus of this paper, can be found by considering the following auxiliary equation:

$$\phi_{ijt}=a+(m_{ten} * T_{ijt})+(m_{\exp} * X_{it})+\tau_{ijt}. \quad \textbf{(4)}$$

Equation (4) incorporates matching and search notions by specifying that job-specific productivity, ϕ_{ijt}, will be correlated with both tenure and experience. Search theory suggests that $m_{exp} > 0$ since a longer time in the market yields better job matches. Matching theory implies that $m_{ten} > 0$ since higher productivity, higher wage matches will tend to have longer tenures.[5] Substituting equation (4) into equation (1) shows that m_{ten} and m_{exp} are equal to the bias of OLS coefficient estimates on tenure and experience respectively. Although the two cannot be separately identified, their sum, $m = m_{ten} + m_{exp}$, can be estimated. This estimate of m can be understood to be the total return to matching and job search since it represents the extent to which matching and search contribute to the unobservable match-specific component of the wage through tenure and experience.

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[4]The primary focus of this paper is on the returns to matching and search reported in the text below but the full tables of first and second stage estimates and a discussion of these results can be found in Appendix C.

[5]As mentioned above, under certain conditions on-the-job search theory also has a different implication for the sign of m_{ten}. As workers search for better matches they tend to gain from changing jobs. Workers who have recently changed jobs have on average higher wages and lower tenures, implying $m_{ten} < 0$. Therefore, technically, m_{ten} is unsigned, although the literature on job matching has generally assumed it to be positive for the reasons stated in the text. The available evidence also supports this assumption (Topel [1991], Topel and Ward [1992]).

Substituting the right-hand-side of equation (4) for the ϕ in equation (3) leaves:

$$w^{*}_{ijt}=(\beta_0+a)+(\beta_X+m_{\exp})XO_{ij}+(m_{ten}+m_{\exp})T_{ijt}+\beta_{Q''}Q''_{ijt}+\tau_{ijt}. \tag{5}$$

Therefore, an estimate of wage growth bias due to matching and search, $m = m_{ten} + m_{exp}$, can be obtained by including tenure as a regressor in the second stage estimation.

III. ESTIMATES OF RETURNS TO MATCHING & SEARCH

The results on turnover from previous work (Royalty [1993]) suggest that it is important to divide the sample by education level when attempting to analyze possible differences in the matching and search behavior of men and women. The following table summarizes the results for men and women by education group. (The data are described in Appendix A.) Education levels here and elsewhere in the paper are abbreviated as education less than or equal to high school (LHS) and education greater than high school (GHS).[6] These estimates imply increases in wages due to matching and search ranging from 2.6% to 7.5% per year for these young men and young women. These estimates stand in contrast to Topel's estimate of this same parameter for men of 0.002. The much larger estimates of m found here suggest that in this sample of young people, matching and search are much more important than in Topel's older PSID sample. These results provide support for matching theories that

[6]At other points the abbreviations LHSF, GHSF, LHSM, and GHSM are used for females with less than or equal to a high school education, females with education greater than high school, males with less than or equal to a high school education, and males with education greater than high school.

emphasize the importance of "job shopping" early in a worker's career (Johnson [1978], Viscusi [1980]).

Table I
Estimates of Return to Job Search Plus Matching*
$m = m_{ten} + m_{exp}$
Standard Errors in Parentheses**

	Men	Women
LHS (Less than or Equal to High School)	0.047 (0.010)	0.073 (0.010)
GHS (Greater than High School)	0.038 (0.015)	0.026 (0.012)

* See Appendix B, Table B-1 for the complete list of estimated coefficients.
** Standard errors are corrected for two-stage estimation with the method of Newey [1984]. See Appendix D for details of the covariance correction.

Table I shows that matching and search are of highest value to less educated women, increasing their wages by over 7.5% per year.[7] Hypothesis tests of the equality of m for LHS women versus the other groups are rejected at a significance level of 0.01 for LHSF versus GHSF, and 0.10 for LHSF versus LHSM and LHSF versus GHSM. Tests at standard significance levels cannot reject the equality of m for more highly educated men and women or for LHS men versus GHS men or women.

The similarity of these results with those obtained in the investigations of turnover is marked. Once again, less educated women experience different outcomes than all other groups. In this case, it appears that their returns to matching and

[7]The estimated coefficients reflect the effect of an explanatory variable on the log wage. Therefore an estimated coefficient of 0.073 increases wages by over 7.5% per year since $(e^{0.073} - 1) = 0.0757$.

search are higher than those of the other groups examined. Also, more highly educated women do not differ significantly from more highly educated men. In the remainder of this paper, I will explore possible reasons for these findings in the context of matching and search models and especially in light of the previous findings of differences in turnover patterns among groups.

IV. WHY DO RETURNS TO MATCHING AND SEARCH DIFFER BY SEX AND EDUCATION?

In the previous section, I found that the returns to matching and search as estimated by $\hat{m}$ were significantly greater for less educated women than for GHS women and men of both education groups. In previous work (Royalty [1993]), I have also found that LHS women have a significantly higher probability of job-to-nonemployment (JNE) turnover. This finding of higher JNE turnover for LHS females suggests that, depending on their average length of time spent in nonemployment, LHS women may have lower levels of actual labor market experience than do the other groups. This speculation is confirmed by the following table of the means of actual labor market experience and job tenure by sex and education group.

Table II Means of Labor Market Experience and Tenure by Sex and Education Group		
	Actual Labor Market Experience Mean	Tenure Mean
Males	5.565	1.766
LHS	5.625	1.868
GHS	5.482	1.623
Females	5.127	1.715
LHS	4.885	1.770
GHS	5.373	1.660

Perhaps the simplest explanation for the higher returns to matching and search for LHS women is that at low levels of experience the marginal return to search is higher. This explanation is in accordance with the job shopping models cited above that emphasize the importance of job search when workers are young. Since less educated women are more likely to leave the labor force for nonemployment, perhaps they remain in the early stages of job shopping longer in calendar time than the other groups who participate in the market more continuously. Constraining the returns to matching and search to be linear in experience and tenure might therefore produce higher estimated returns for less educated women.

This proposition of non-linearities is easily tested by allowing equation (4) to include higher terms of tenure and/or experience. For example, including a quadratic in both tenure and experience, equation (4) can be rewritten as:

$$\phi_{ijt}=a+(m_{ten} * T_{ijt})+(m_{\exp} * X_{it})+(m_{ten2} * T^2)+(m_{exp2} * X^2)+\tau_{ijt}. \tag{6}$$

This addition implies that higher order terms of tenure and experience should be included in the second stage estimations.[8] Rewriting the second stage estimating equation (5) we have in this case

$$w^*_{ijt}=(\beta_0+a)+(\beta_X+m_{\exp})XO_{ij}+(m_{ten}+m_{\exp})T_{ijt}+m_{ten2}T^2+m_{exp2}X^2+\beta_{Q''}Q''_{ijt}+\tau_{ijt}. \tag{7}$$

Returns to matching and search will in this case be composed of the coefficients on tenure and these higher order terms. Three additional second stage estimations were performed. Model 1 included tenure and tenure-squared. Model 2 included tenure and experience-squared. And Model 3 included tenure, tenure-squared, and experience-squared. The relevant results from Model 3 are presented below and the full model results are included in Table B-2 in Appendix B.[9]

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[8]Higher order terms of tenure and experience are included in the first stage and the within job wage growth implied by these first-stage estimates is subtracted from the log wage to create w^*. Therefore, the second stage estimated coefficients on tenure-squared and experience-squared should capture only the non-linearities in the returns to matching and search.

[9]The results from Models 1 and 2 are not included since the test results are qualitatively similar to those described below from Model 3, the most general of the three models.

Table III
Estimates of $m_1 = m_{ten} + m_{exp}$, m_{ten2}, and m_{exp2}
Second Stage Estimations
Standard Errors in Parentheses*

	LHS MEN	GHS MEN	LHS WOMEN	GHS WOMEN
Tenure (Coefficient is $\hat{m}_1 = \hat{m}_{ten} + \hat{m}_{exp}$)	0.139 (0.034)	0.034 (0.048)	0.213 (0.031)	0.083 (0.035)
Tenure^2 (Coefficient is $\hat{m}_{ten2}$)	-0.006 (0.003)	-0.006 (0.005)	0.000 (0.000)	-0.011 (0.004)
Experience^2 (Coefficient is $\hat{m}_{exp2}$)	-0.005 (0.003)	0.004 (0.004)	-0.014 (0.003)	0.000 (0.000)

* Standard errors are corrected for two-stage estimation with the method of Newey [1984]. See Appendix D for details of the covariance correction.

Although some support is found for the proposition that non-linearities exist in the relationship between wages and time spent in matching and search, these results indicate that the higher return to matching and search for less educated women relative to the other groups is not due merely to their lower levels of experience. Each of the three models that included higher order terms of tenure and/or experience in the second stage estimations showed that LHS women have higher estimated returns to matching as estimated by m_1, m_{ten2}, and m_{exp2}. Evaluating the returns for each group at the mean level of tenure and experience for GHS men, Model 1, which included tenure and tenure-squared, implies a cumulative return to matching and search to be 0.83 for LHS women, 0.60 for GHS women, 0.68 for LHS men, and

0.45 for GHS men. Model 2 implies this cumulative return to be 1.08 (LHSF), 0.25 (GHSF), 0.84 (LHSM), and 0.09 (GHSM). These cumulative returns as estimated in Model 3 are 1.08 (LHSF), 0.56 (GHSF), 0.99 (LHSM), and 0.25 (GHSM). In the case of Model 3, the most general of the three models of non-linearity, Chi-squared tests reject the joint hypothesis of equality of the coefficients on tenure, tenure-squared, and experience-squared for LHSF vs GHSF and LHSF vs GHSM at the 0.01 significance level. The only change from the previous results is that the equality of returns for less educated men and women now cannot be rejected at a significance level of 0.10.[10] These findings indicate that I cannot attribute the higher returns for less educated women reported in Table I simply to higher marginal returns at lower levels of experience or tenure.

A second possible explanation for the higher estimated returns to matching and search for less educated women involves adopting one concept from dual labor market theory. Dual labor market theories describe a labor market comprised of a secondary sector made up of low-paying, dead-end jobs and a primary sector made up of higher paying, career-oriented jobs. If two such sectors do exist, matching and search may play a role in movement by workers between sectors.[11] For example, workers might

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[10]Tests of Model 1 and Model 2 produce similar test results.

[11]Dual labor market theories emphasize labor market segmentation and the lack of movement by secondary workers from the secondary sector to the primary sector. The lack of movement between sectors is, in fact, a critical aspect of the formal segmented labor market theory making a matching and search interpretation of the dual sectors questionable within this framework. Note, however, that one weakness of dual labor market theory is its failure to explain adequately the source of this immobility of workers. My empirical investigation therefore adopts only the concept that there might exist "good" and "bad" jobs within the labor market and then explores the extent to which matching and search might contribute to movements from "bad" to "good" jobs. See Taubman and Wachter [1986] for a review of the segmented labor market literature.

more easily first find jobs in the secondary sector but continue to search on-the-job, looking for a better job in the primary sector. It might be conjectured that the movement from secondary jobs to primary jobs is more important to the wages of less educated workers if higher education allows easier access to primary jobs. Less educated workers might have to acquire work experience or skills in the secondary sector before gaining access to primary jobs while more highly educated workers do not.

To investigate this issue, I first present two tables illustrating the distribution of this sample by occupational category.[12] Table IV shows that, as expected, the occupational distribution differs substantially by sex and education group. Men are more highly represented in the blue collar occupations and more educated men and women are more likely to be in skilled, white collar occupations.[13]

Some important differences are seen more clearly when the table is aggregated into the categories "skilled" and "unskilled". Table V indicates that as with many other labor market phenomena described and analyzed in this paper, more highly educated men and women look very much the same, while less educated women differ

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[12]One problem associated with dual labor market theory is identifying which jobs are primary and which are secondary. Dickens and Lang [1985] present evidence that occupational breakdowns are more descriptive of the dual labor market concept than are industry breakdowns.

[13]The skilled blue collar category includes construction and protective service supervisors, firefighters, craft and precision workers, mechanics, repairers and farm managers. The blue collar unskilled category includes private household workers, guards, food servers, farm non-managers, machine operators (not included as skilled), movers, laborers, and apprentices. The white collar skilled category includes executives, administrators, accountants, architects, engineers, scientists, health professionals, teachers, clergy, lawyers, artists, technicians, and retail sales supervisors. The unskilled white collar category includes non-supervisor retail sales workers, recreation workers, non-clergy religious workers, typists, clerks, receptionists, and messengers.

from the other groups. For example, 45% of GHS men and women are in skilled occupations while only 24% of LHS women fall into that category.

Table IV
Percentage of Men and Women
in each Occupational Category*

	White Collar Skilled	White Collar Unskilled	Blue Collar Skilled	Blue Collar Unskilled	Total %
Males					
LHS	8.5	9.3	28.5	53.7	100.0
GHS	38.9	21.9	12.2	27.1	100.0
Females					
LHS	24.1	29.5	2.6	43.8	100.0
GHS	48.5	28.6	1.3	21.6	100.0

*See footnote 13 for a breakdown of these categories.

Table V Percentage of Men and Women in Skilled and Unskilled Occupations*			
	Unskilled	Skilled	Total %
Males			
LHS	66.8	33.2	100.0
GHS	54.8	45.2	100.0
Females			
LHS	76.0	24.0	100.0
GHS	55.4	44.6	100.0
*See footnote 13 for a breakdown of these categories.			

In terms of matching and search behavior, the issue is not the static picture of the occupational distribution for men and women but rather whether or not that distribution changes differentially by group with experience in the labor market and whether or not less educated women benefit more from movement to different types of jobs. In order to examine this point, Table VI presents one simple measure of the movement between skilled and unskilled jobs by group at different levels of labor market experience. In each cell, the number to the left of the arrow is the proportion of the group (LHSM, GHSM, LHSF, or GHSF) in the category (unskilled or skilled) for workers with actual labor market experience of two years or less. The number to the right of the arrow is the same proportion for workers with experience of five years or more.[14] This table indicates that there is substantial movement between

[14]Five years is approximately the sample mean of experience for each group. Experience of less than two years is used to represent the very early career years where occupational matching may not yet have occurred.

occupational categories in the early career years for each group. Only 10% of less educated women with less than two years of experience hold jobs in skilled occupations. Of those same women once they have attained at least five years of experience, 33% hold skilled jobs. While this is a noticeable increase, the other groups also increased their ranks in skilled jobs as they spent more time in the labor market. This table cannot therefore answer the question as to whether the occupational distribution changes differentially by group in such a way as that increases the wages of one group relative to the others. To address that question, I now present results from OLS and two-stage wage regressions that include occupational dummy variables. In particular, I will examine whether or not the estimated returns to matching and search are affected by the inclusion of these occupational dummies. It is expected that, if occupational movement is largely responsible for matching and search wage gains, inclusion of occupational dummy variables in the second stage estimations will reduce the estimated returns to matching and search since the included occupational dummies will now pick up those effects.

Before presenting those results, however, it should be noted that Table VI once again shows a remarkable similarity of GHS men and women. 35% GHS men with less than two years of experience are found in skilled jobs as compared to 33% of GHS women. For GHS men with at least five years of experience the percentage is 51% while that for GHS women is 50%.

Table VI
Percentage of Men and Women
at Different Levels of Experience
Working in Skilled and Unskilled Occupations*

Proportion in Category, Sample: Experience $\leq$ 2
$\rightarrow$
Proportion in Category, Sample: Experience $\geq$ 5
(Number of Observations Represented by Each
Percentage in Parentheses)

	Unskilled $Exp\leq2 \rightarrow Exp\geq5$	Skilled $Exp\leq2 \rightarrow Exp\geq5$
Males		
LHS	77% $\rightarrow$ 62% (221) (1892)	23% $\rightarrow$ 38% (65 1174)
GHS	65% $\rightarrow$ 49% (129) (997)	35% $\rightarrow$ 51% (70) (1054)
Females		
LHS	90% $\rightarrow$ 67% (507) (1334)	10% $\rightarrow$ 33% (54) (666)
GHS	67% $\rightarrow$ 50% (175) (1151)	33% $\rightarrow$ 50% (87) (1145)

*See footnote 13 for a breakdown of these categories.

As stated above, if movement across occupations plays a substantial role in the matching and search process, a process proxied by tenure and experience, then it is expected that the inclusion of the occupational dummies would affect the estimated returns to experience and tenure. Before proceeding to the second stage estimations of the returns to matching and search, occupational dummy variables were added to OLS wage regressions. The results are reported in Table B-6 in Appendix B. For each group these dummy variables are significant. It is generally found that workers in white collar skilled jobs and in blue collar skilled jobs receive higher wages than those in blue collar unskilled jobs. However, the premium to workers in white collar unskilled jobs relative to blue collar unskilled jobs is significant only for women. When I compare the coefficients on tenure and experience when occupational dummies are included in the estimation to those estimated without the occupational dummies (reported in Table B-5 in Appendix B) I find insignificant changes in the estimates. It is also interesting to note that the improvement in the R^2 with the inclusion of the occupation dummies is greater for higher education men and women than for their less educated counterparts. These two findings make it seem improbable that occupational movement explains the previously reported finding that less educated women receive the highest returns to matching and search.

Exploration of this issue continues by the addition of occupational dummies to the two-stage estimations described above. Estimates of m, the return to matching and search, with these variables included are reported in Table VII below. Other coefficient estimates from this regression are reported in Table B-3 in Appendix B.

Table VII
Estimate of Return to Job Search Plus Matching*
$m = m_{ten} + m_{exp}$
Occupational Dummy Variables Included in Estimation
Standard Errors in Parentheses**

	Men	Women
LHS	0.042 (0.010)	0.059 (0.010)
GHS	0.030 (0.015)	0.018 (0.012)

* See Appendix B, Table B-3 for the complete list of estimated coefficients.
** Standard errors are corrected for two-stage estimation with the method of Newey [1984]. See Appendix D for details of the covariance correction.

As compared to the original estimates reported in Table I above, these estimates of the return to matching and search are smaller for each education and sex group. Although this finding provides some evidence that occupational movement may play a part in generating returns to matching and search, tests cannot reject the equality of the estimates reported in Table VII with the original estimates of Table I for any of the four groups. Also these results cannot provide an explanation for the higher returns to matching and search for less educated women since this group continues to receive higher returns than the other groups even once the occupational dummies are included in the estimation. It appears from this examination that movement across occupations may be related to the gains to labor market search but that this movement and its associated wage gains are not substantially related to education nor are they the only source of the returns to matching and search.[15]

Less educated women have very different job and labor market turnover patterns than do more highly educated women and men of both education groups (Royalty [1993]). This fact seems crucial in the continuing search for an understanding of the reasons behind the higher estimated returns to matching and search found thus far for LHS women. The most prominent difference in turnover patterns for this group is their higher job-to-nonemployment turnover.

Higher than average job-to-nonemployment turnover could imply that a worker is not operating within the framework assumed by the prototypical search and matching models. These models assume that a worker's job mobility is unconstrained and unaffected by any individual heterogeneity in the value of non-market time. The wage gains due to matching and search that are predicted by these models are based on unconstrained workers who have no reason to be in the nonemployment state other than to search for a good job. High job-to-nonemployment turnover due to reasons not taken into account in these models, such as leaving the labor force temporarily to have children, could lower the returns to time spent in the matching and search process. The returns to matching and search estimated in the two-stage procedure used in this paper rely on years of tenure and experience to proxy the matching and search processes. Workers who stop these processes in mid-stream by leaving the

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[15]Note that this analysis of wage gains due to occupational mobility does not take into account the possible endogeneity of the occupational choice of the worker.

labor force may not receive the same returns to matching and search per year as other workers. It may therefore be necessary to control for previous job-to-nonemployment decisions in order to estimate correctly the returns to matching and search. This may be particularly important in the comparisons by group since the rate of turnover to nonemployment for less educated women is significantly different than that rate for the other three groups (Royalty [1993]).

In order to test for the importance of differences in turnover patterns to the wage gains due to matching and search, I include in the two-stage estimations a variable intended to capture the intensity of the worker's matching and search history. To proxy the intensity of the worker's matching and search history I use a ratio that represents the time spent working full-time relative to time available since age 18.[16] I will call this variable the full-time work ratio. By counting only jobs where hours worked were greater than fifteen per week, I control for one aspect of the intensity of the search and matching process.[17] By using a ratio of actual to potential experience, I control for previous job-to-nonemployment decisions. Since actual labor market experience is already included in the estimations, the addition of this new variable should give some indication of the importance to wages of a worker's history of previous labor market turnover decisions.

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[16] More precisely, this ratio is the number of weeks when the individual worked at least fifteen hours a week since age 18 to number of weeks since the individual turned 18. Means of this variable by groups are as follows: 0.83 (LHSM), 0.74 (GHSM), 0.73 (LHSF), 0.71 (GHSF).

[17] The use of this variable in the numerator of the ratio also avoids colinearity problems that could be caused by using the same actual experience variable used to define initial experience at the beginning of the job.

The following table illustrates that previous turnover behavior is closely related to the estimated returns to matching and search.

Table VIII
Estimates of $m_1=m_{ten}+m_{exp}$
Includes Full-time Work Ratio
Standard Errors in Parentheses*

	LHS MEN	GHS MEN	LHS WOMEN	GHS WOMEN
Tenure (Coefficient is $\hat{m}_1=\hat{m}_{ten}+\hat{m}_{exp}$)	0.029 (0.010)	0.032 (0.015)	0.027 (0.010)	0.023 (0.012)
Full-time Work Ratio	0.259 (0.058)	0.075 (0.058)	0.457 (0.054)	0.033 (0.050)

* Standard errors are corrected for two-stage estimation with the method of Newey [1984]. See Appendix D for details of the covariance correction.

First notice that the full-time work ratio has a positive and significant effect on the wages of LHS men and women. In contrast, the effect of this variable on the wages of GHS men and women is positive but insignificant. More importantly, the inclusion of this variable in the two-stage estimations has the predicted effect on the estimated returns to matching and search. Comparing these estimates (Table VIII) to those of Table I, one sees that the estimates of m for GHS men and women are almost unchanged while those for LHS men and women are substantially lower when the full-time work ratio is included in the regression. When this dummy variable is included, equality of the returns to matching and search cannot be rejected for any pair of the four groups. In fact, the estimates, $\hat{m}$, are now remarkably similar for each sex and education group.

It should be noted, however, that the fact that the full-time work ratio does not significantly affect the wages of more educated men and women may be a result of the definition of this variable. This variable is defined relative to the worker's age. More highly educated men and women have spent time since age 18 in school and therefore the amount of full-time work since age 18 may be less important to their current wages than it is for less educated men and women. This definition was chosen, however, in order to avoid other problems in the interpretation of the coefficients that were deemed more serious than this one. Definitions of potential experience based on years since the end of schooling made it impossible to distinguish between the effect of education on the wages of GHS men and women and the effect of this alternate definition of the ratio of actual to potential experience. Nonetheless, I argue that the inclusion of this full-time work ratio serves the intended purpose -- providing a measure of the intensity of the search and matching process -- especially for the two less educated groups for whom the amount of time in the nonemployment state appears to be exceptionally important. The similar estimated returns to matching and search found for each group when this full-time work ratio is included lends support to the contention that this variable is a useful indicator for the intensity of the matching and search process. The fact that the returns to matching and search are not statistically different for the four groups when this proxy for the intensity of the matching and search process is included in the estimation indicates that turnover out of the labor market plays an important role in the wage growth process under study.

V. CONCLUSION

In this paper I find returns to matching and search that are significant and positive for all four sex and education groups. The effect of high job-to-nonemployment turnover, and more generally the intensity of the search and matching process, has a significant effect on the wages of the less educated men and women. The inclusion of the full-time work ratio, used to proxy the intensity of the matching and search process, also lowers the estimated returns to matching and search for these two groups. Once this variable is included in the two-stage estimation, similar returns to matching and search are found for all four sex and education groups. In general the results are similar for less educated men and women and for more educated men and women but differ across education groups.

The matching-related differences in wage determination documented appear to be strongest across education groups -- not by sex. The effect of matching and search on the wages of less educated men and women is similar. But the strong effect on wages of the full-time work ratio, especially for less educated women, indicates that matching and search may indeed play a role in explaining the wage gap between this group of men and women. On the other hand, I have found that numerous facets of the labor market process that I study -- turnover probabilities, estimated returns to matching and search, occupational movement, the effect on wages of the full-time work ratio -- look strikingly similar for more highly educated young men and women. It appears that though job matching and turnover are important in wage determination, they do not provide an explanation of the male-female wage gap that exists for more highly educated men and women.

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APPENDIX A - DATA APPENDIX

The sample used in this thesis is the National Longitudinal Survey Youth (NLSY) cohort, a panel survey of 12,686 young men and women. The survey began in 1979 and continues annually. The 12,686 individuals of the NLSY are divided into three samples: a random sample, a poverty sample, and a military sample. Estimations were performed on the sample of NLSY young men and women over age 21 from the random sample for interview years 1980-1987.

In addition to the usual demographic, family, and education data collected in such surveys, the NLSY records information on up to five jobs per year held by the individual. Detailed information including wage, hours worked, union status, industry, and occupation is available for each job. For each worker, I have tracked employers across interviews thereby creating a job history as well as a record of job turnover for each individual.

This created job history assures that job-specific variables such as the wage and union status are correctly identified with the particular job. It avoids the problems that can be created by multiple job holders or job changers if the survey records only current information on one job or if no identification of the employer is available. The NLSY supplies the necessary information to track job-specific data. It should be noted, however, that the work history data supplied directly by the NLSY does not automatically track job-specific data with its categorization of jobs as Job #1, Job #2, etc. Job #1 in year t may be recorded as Job #2 in year t+1. Therefore, with the employer identification provided, I have tracked job-specific data across interview years.

In order to create a history of job turnover, it is also necessary to identify the "main job" for multiple job holders. The main job was identified as being that job on which the worker earned the most during that week. This classification of the main job suffers from the disadvantage that a temporary fluctuation in hours worked on a secondary job may cause that job to be temporarily classified as the main job. This would make it appear that the worker changed jobs during this period when he or she did not. Therefore, if a main job was interrupted for a period of one quarter or less, it is considered to be the main job throughout the period. A worker's recorded real wage in 1979 dollars must also be at least 70% of the minimum wage in 1979 in order to be included in the sample. This sample restriction and definition of job turnover follow closely that used in Topel [1986].

Means of the data are presented in the table below. Tenure is the number of years spent with the current employer. Experience is actual labor market experience calculated from detailed work history data of the individual up to the interview date. The real wage is the worker's wage adjusted by the CPI index so that all wages are in terms of 1979 dollars.

NLSY Random Sample Age ≥ 22, 1980-87 Means by Sex and Education Level				
	LHSM	GHSM	LHSF	GHSF
Tenure	1.98	1.67	1.94	1.75
Experience	5.68	5.58	5.10	5.46
Bad Health Dummy	0.03	0.02	0.05	0.03
Union Dummy	0.24	0.13	0.17	0.14
Real Wage	4.81	5.58	3.81	4.80
Asset Income	0.20	0.57	0.21	0.37
Marital Status Dummy	0.43	0.29	0.56	0.36
Number of Children	0.61	0.19	0.85	0.23
Local Unemployment Rate > 6% and ≤ 12%	0.56	0.51	0.59	0.52
Local Unemployment Rate > 12%	0.16	0.10	0.14	0.11
Number of Observations	6018	4336	4792	5064

TABLES - APPENDIX B

Table B-1
Second Stage Estimates
Estimates of $m=m_{ten}+m_{exp}$
Dependent Variable ln(real wage) - estimated wage growth from 1st stage
Standard Errors in Parentheses*

	LHS MEN	GHS MEN	LHS WOMEN	GHS WOMEN
Intercept	0.624 (0.089)	0.342 (0.129)	0.638 (0.091)	0.085 (0.109)
Initial Experience	0.025 (0.029)	0.073 (0.041)	-0.035 (0.026)	0.025 (0.031)
Education	0.031 (0.005)	0.035 (0.006)	0.021 (0.007)	0.058 (0.005)
Bad Health Dummy	-0.046 (0.042)	-0.218 (0.050)	-0.171 (0.048)	-0.156 (0.046)
Married Dummy	0.105 (0.014)	0.115 (0.020)	-0.048 (0.015)	0.007 (0.016)
Union Dummy	0.218 (0.017)	0.138 (0.023)	0.130 (0.019)	0.158 (0.021)
Northeast Region Dummy	0.013 (0.019)	0.107 (0.026)	0.109 (0.023)	0.100 (0.021)
South Region Dummy	-0.048 (0.016)	0.050 (0.024)	0.007 (0.019)	0.027 (0.019)
West Region Dummy	0.099 (0.023)	0.153 (0.027)	0.150 (0.023)	0.081 (0.025)
SMSA Dummy	0.120 (0.016)	0.194 (0.023)	0.076 (0.019)	0.121 (0.020)
Tenure (Coefficient is $m=m_{ten}+m_{exp}$)	0.047 (0.010)	0.038 (0.015)	0.073 (0.010)	0.026 (0.012)

* Standard errors are corrected for two-stage estimation method with the method of Newey [1984]. See Appendix D for details of covariance correction.

Table B-2
Second Stage Estimates
Includes Second Order Effects
Dependent Variable ln(real wage) - estimated wage growth from 1st stage
Standard Errors in Parentheses*

	LHSM	GHSM	LHSF	GHSF
Intercept	0.475 (0.072)	0.400 (0.112)	0.466 (0.086)	0.060 (0.089)
Initial Experience	0.079 (0.014)	0.035 (0.022)	0.099 (0.015)	0.022 (0.016)
Education	0.029 (0.005)	0.035 (0.006)	0.012 (0.007)	0.057 (0.005)
Bad Health Dummy	-0.038 (0.042)	-0.219 (0.051)	-0.176 (0.048)	-0.154 (0.046)
Married Dummy	0.104 (0.014)	0.112 (0.020)	-0.043 (0.015)	0.004 (0.016)
Union Dummy	0.216 (0.017)	0.141 (0.023)	0.119 (0.019)	0.154 (0.020)
Northeast Region Dummy	0.013 (0.019)	0.107 (0.026)	0.099 (0.022)	0.096 (0.021)
South Region Dummy	-0.044 (0.016)	0.051 (0.024)	0.007 (0.019)	0.026 (0.019)
West Region Dummy	0.101 (0.023)	0.153 (0.027)	0.142 (0.023)	0.079 (0.025)
SMSA	0.123 (0.016)	0.194 (0.023)	0.080 (0.018)	0.123 (0.020)
Tenure (Coefficient is $m=m_{ten}+m_{exp}$)	0.138 (0.034)	0.034 (0.048)	0.212 (0.031)	0.083 (0.035)
Tenure^2 (Coefficient is m_{ten2})	-0.006 (0.003)	-0.006 (0.005)	0.000 (0.003)	-0.011 (0.004)
Experience^2 (Coefficient is m_{exp2})	-0.005 (0.003)	0.004 (0.004)	-0.014 (0.003)	0.000 (0.003)

* Standard errors are corrected for two-stage estimation method with the method of Newey [1984]. See Appendix D for details of covariance correction.

Table B-3
Second Stage Estimates
Including Occupational Dummy Variables
Dependent Variable ln(real wage) - estimated wage growth from 1st stage
Standard Errors in Parentheses*

	LHS MEN	GHS MEN	LHS WOMEN	GHS WOMEN
Intercept	0.619 (0.088)	0.553 (0.129)	0.770 (0.091)	0.228 (0.108)
Initial Experience	0.022 (0.029)	0.068 (0.041)	-0.042 (0.026)	0.020 (0.031)
Education	0.030 (0.005)	0.017 (0.006)	0.005 (0.007)	0.041 (0.005)
Bad Health Dummy	-0.055 (0.041)	-0.212 (0.052)	-0.154 (0.046)	-0.161 (0.046)
Married Dummy	0.095 (0.013)	0.105 (0.020)	-0.047 (0.015)	-0.006 (0.016)
Union Dummy	0.225 (0.017)	0.142 (0.023)	0.163 (0.019)	0.140 (0.021)
Northeast Region Dummy	0.008 (0.019)	0.104 (0.025)	0.100 (0.022)	0.111 (0.021)
South Region Dummy	-0.048 (0.016)	0.049 (0.023)	0.002 (0.019)	0.026 (0.019)
West Region Dummy	0.089 (0.023)	0.149 (0.026)	0.148 (0.023)	0.097 (0.025)
SMSA Dummy	0.109 (0.016)	0.166 (0.023)	0.051 (0.018)	0.113 (0.020)
Tenure (Coefficient is $m=m_{ten}+m_{\exp}$)	0.042 (0.010)	0.030 (0.015)	0.059 (0.010)	0.018 (0.012)
White Collar, Skilled	0.146 (0.027)	0.232 (0.024)	0.251 (0.019)	0.257 (0.022)
White Collar, Unskilled	-0.033 (0.022)	0.019 (0.025)	0.140 (0.018)	0.070 (0.022)
Blue Collar, Skilled	0.157 (0.015)	0.140 (0.031)	0.287 (0.038)	0.377 (0.069)

* Standard errors are corrected for two-stage estimation method with the method of Newey [1984]. See Appendix D for details of covariance correction.

Table B-4
Second Stage Estimates
Including Full-time Work Ratio
Dependent Variable ln(real wage) - estimated wage growth from 1st stage
Standard Errors in Parentheses*

	LHSM	GHSM	LHSF	GHSF
Intercept	0.511 (0.080)	0.275 (0.120)	0.604 (0.090)	0.053 (0.100)
Initial Experience	0.009 (0.032)	0.068 (0.043)	-0.075 (0.029)	0.023 (0.033)
Education	0.029 (0.005)	0.037 (0.007)	0.013 (0.007)	0.059 (0.005)
Bad Health Dummy	-0.024 (0.042)	-0.212 (0.051)	-0.162 (0.046)	-0.155 (0.046)
Married Dummy	0.101 (0.014)	0.116 (0.020)	-0.032 (0.015)	0.008 (0.016)
Union Dummy	0.215 (0.017)	0.138 (0.023)	0.126 (0.019)	0.159 (0.021)
Northeast Region Dummy	0.016 (0.019)	0.108 (0.026)	0.105 (0.022)	0.100 (0.021)
South Region Dummy	-0.045 (0.016)	0.049 (0.024)	0.002 (0.019)	0.028 (0.019)
West Region Dummy	0.097 (0.023)	0.155 (0.027)	0.137 (0.023)	0.082 (0.025)
SMSA	0.126 (0.016)	0.196 (0.023)	0.070 (0.018)	0.122 (0.020)
Tenure (Coefficient is $m=m_{ten}+m_{\exp}$)	0.029 (0.010)	0.032 (0.015)	0.027 (0.010)	0.023 (0.012)
Full-time Work Ratio	0.259 (0.058)	0.075 (0.058)	0.457 (0.054)	0.033 (0.050)

* Standard errors are corrected for two-stage estimation method with the method of Newey [1984]. See Appendix D for details of covariance correction.

Table B-5
OLS
by Sex and Education Group
Dependent Variable = ln(real wage)
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Intercept	0.805 (0.039)	0.901 (0.054)	0.600 (0.036)	0.917 (0.047)
Tenure	0.098 (0.010)	0.086 (0.016)	0.084 (0.012)	0.126 (0.013)
Tenure-squared	-0.008 (0.002)	-0.007 (0.003)	-0.005 (0.002)	-0.016 (0.002)
Experience	0.081 (0.014)	0.043 (0.019)	0.102 (0.014)	0.021 (0.016)
Experience-squared	-0.003 (0.001)	0.001 (0.002)	-0.005 (0.001)	0.002 (0.002)
Union Dummy	0.224 (0.016)	0.127 (0.027)	0.122 (0.021)	0.160 (0.022)
Bad Health Dummy	-0.034 (0.037)	-0.230 (0.055)	-0.177 (0.034)	-0.166 (0.040)
Married Dummy	0.101 (0.013)	0.112 (0.021)	-0.042 (0.015)	-0.014 (0.016)
Northeast Region Dummy	0.007 (0.019)	0.100 (0.025)	0.099 (0.023)	0.106 (0.022)
South Region Dummy	-0.062 (0.016)	0.045 (0.024)	0.005 (0.019)	0.027 (0.020)
West Region Dummy	0.101 (0.020)	0.131 (0.026)	0.143 (0.023)	0.061 (0.023)
SMSA Dummy	0.125 (0.015)	0.208 (0.025)	0.078 (0.017)	0.124 (0.021)
R^2	0.205	0.148	0.189	0.115

Table B-6
OLS
by Sex and Education Group
Including Occupational Dummy Variables
Dependent Variable = ln(real wage)
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Intercept	0.791 (0.039)	0.853 (0.053)	0.577 (0.036)	0.816 (0.047)
Tenure	0.090 (0.010)	0.075 (0.016)	0.070 (0.012)	0.112 (0.013)
Tenure-squared	-0.007 (0.001)	-0.005 (0.003)	-0.003 (0.002)	-0.013 (0.002)
Experience	0.077 (0.013)	0.039 (0.018)	0.087 (0.014)	0.011 (0.016)
Experience-squared	-0.003 (0.001)	0.001 (0.002)	-0.004 (0.001)	0.003 (0.001)
Union Dummy	0.232 (0.016)	0.140 (0.026)	0.152 (0.020)	0.138 (0.022)
Bad Health Dummy	-0.044 (0.036)	-0.218 (0.054)	-0.160 (0.033)	-0.168 (0.039)
Married Dummy	0.092 (0.013)	0.102 (0.020)	-0.040 (0.014)	-0.022 (0.015)
Northeast Region Dummy	0.003 (0.019)	0.098 (0.025)	0.088 (0.022)	0.116 (0.021)
South Region Dummy	-0.062 (0.016)	0.048 (0.023)	0.002 (0.018)	0.024 (0.019)
West Region Dummy	0.090 (0.020)	0.138 (0.025)	0.141 (0.022)	0.083 (0.023)
SMSA Dummy	0.113 (0.015)	0.171 (0.024)	0.054 (0.017)	0.114 (0.020)
White Collar, Skilled	0.149 (0.024)	0.246 (0.022)	0.244 (0.019)	0.280 (0.019)
White Collar, Unskilled	-0.016 (0.022)	0.023 (0.025)	0.134 (0.017)	0.077 (0.021)
Blue Collar, Skilled	0.157 (0.015)	0.138 (0.030)	0.278 (0.049)	0.397 (0.069)
R^2	0.229	0.188	0.226	0.176

Table B-7
OLS
by Sex and Education Group
Including Full-time Work Ratio
Dependent Variable = ln(real wage)
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Intercept	0.798 (0.039)	0.898 (0.054)	0.622 (0.036)	0.923 (0.047)
Tenure	0.092 (0.010)	0.086 (0.016)	0.073 (0.012)	0.126 (0.013)
Tenure-squared	-0.008 (0.002)	-0.007 (0.003)	-0.004 (0.002)	-0.016 (0.002)
Experience	0.030 (0.017)	0.036 (0.021)	0.015 (0.018)	0.040 (0.018)
Experience-squared	0.000 (0.000)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Union Dummy	0.223 (0.016)	0.127 (0.027)	0.123 (0.020)	0.158 (0.022)
Bad Health Dummy	-0.020 (0.037)	-0.227 (0.055)	-0.169 (0.034)	-0.169 (0.040)
Married Dummy	0.097 (0.013)	0.113 (0.021)	-0.033 (0.015)	-0.016 (0.016)
Northeast Region Dummy	0.010 (0.019)	0.100 (0.025)	0.101 (0.023)	0.104 (0.022)
South Region Dummy	-0.061 (0.016)	0.044 (0.024)	0.001 (0.018)	0.026 (0.020)
West Region Dummy	0.099 (0.020)	0.131 (0.026)	0.136 (0.022)	0.058 (0.023)
SMSA Dummy	0.127 (0.015)	0.209 (0.025)	0.072 (0.017)	0.123 (0.021)
Full-time Work Ratio	0.207 (0.044)	0.036 (0.048)	0.341 (0.044)	-0.094 (0.040)
R^2	0.209	0.149	0.201	0.117

FIRST AND SECOND STAGE ESTIMATES - APPENDIX C

First stage estimates by sex and education group are reported in Table C-1 below while the second stage estimates are found in Table C-2. Greater detail is provided in the main text. Returns are much more similar in size for men and women who have greater than a high school education. In the case of tenure returns, all men and high education women look very similar, while low education women receive a notably lower return to tenure (Figure C-1). Note that my estimates for men are smaller and the returns flatten out faster than those of Topel [1991] but the estimates found here are closer to his than to the very small returns to tenure found by Altonji and Shakotko [1987] or Abraham and Farber [1987].

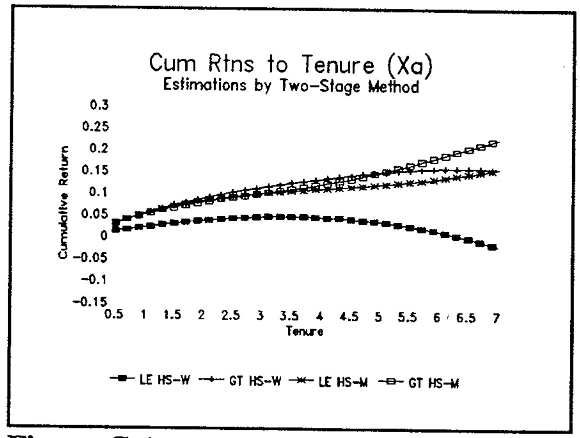

Figure C-1

Experience profiles differ more by education level than do tenure profiles, but it is again less educated women who differ the most from the other groups (Figure C-2). The tenure and experience returns depicted in these tables and figures is yet another illustration of the recurring theme of this paper that more highly educated men and

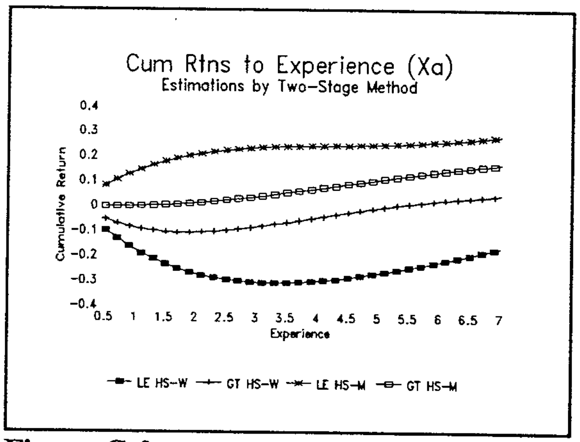

Figure C-2

women have very similar labor market outcomes while less educated women have very different labor experiences than the other groups.

Table C-1
First Stage Estimates of Within-Job Wage Growth
By Sex and Education Level
Dependent Variable=Differenced ln(real wage)
Sample: Age $\geq$ 22, 1979-1986
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Tenure*	0.036 (0.030)	0.089 (0.042)	-0.028 (0.027)	0.065 (0.031)
$Tenure^2$ (x 10)	-0.023 (0.024)	-0.013 (0.042)	-0.048 (0.028)	-0.043 (0.034)
$Experience^2$ (x 10)	0.014 (0.026)	-0.022 (0.037)	0.087 (0.027)	0.016 (0.029)
Weeks of Company Training**	-0.0004 (0.006)	0.003 (0.003)	-0.004 (0.005)	0.004 (0.003)
Weeks of Off-the-Job Training**	-0.0002 (0.002)	0.004 (0.003)	-0.004 (0.004)	0.004 (0.003)

* Includes returns to tenure and experience.
** Weeks of training include only training received during the course of the current job tenure.

Table C-2
Second Stage Estimates
By Sex and Education Group
Dependent Variable=
ln(real wage) - estimated wage growth from 1st stage
Sample: Age ≥ 22, 1979-1986
Standard Errors in Parentheses*

	LHSM	GHSM	LHSF	GHSF
Intercept	0.695 (0.093)	0.442 (0.140)	0.623 (0.095)	0.190 (0.120)
Initial Experience	0.006 (0.031)	0.061 (0.042)	-0.059 (0.027)	0.017 (0.032)
Education	0.037 (0.005)	0.034 (0.006)	0.039 (0.008)	0.055 (0.005)
Bad Health	-0.068 (0.043)	-0.223 (0.051)	-0.190 (0.048)	-0.164 (0.046)
Married Dummy	0.139 (0.015)	0.144 (0.022)	-0.036 (0.016)	0.020 (0.017)
Union Dummy	0.245 (0.017)	0.143 (0.024)	0.174 (0.021)	0.166 (0.021)
Northeast Dummy	0.015 (0.019)	0.111 (0.026)	0.110 (0.024)	0.100 (0.022)
South Dummy	-0.053 (0.017)	0.046 (0.024)	-0.009 (0.020)	0.026 (0.019)
West Dummy	0.084 (0.024)	0.148 (0.027)	0.130 (0.024)	0.079 (0.025)
SMSA Dummy	0.122 (0.016)	0.200 (0.023)	0.083 (0.019)	0.123 (0.020)

* Standard errors are corrected for two-stage estimation method with the method of Newey [1984]. See Appendix D for details of covariance correction.

COVARIANCE CORRECTION - APPENDIX D

The covariance matrix for the two-stage estimates reported in this paper were calculated using the method of Newey [1984]. Newey shows that the covariance matrix of such second stage estimates can be estimated with the method of moments.

Let Z be the matrix of first stage explanatory variables and X be the matrix of explanatory variables for the second stage. The first stage coefficients are contained in the [rx1] vector β and those for the second stage in the [sx1] vector λ. The second stage estimator for λ, $\tilde{\lambda}$, also uses one or more of the estimates obtained in the first stage, $\hat{\beta}$.

Let the first stage moment condition that defines $\hat{\beta}$ be:

$$\frac{1}{N}\sum_n g(Z_n,\hat{\beta})=0. \tag{D-1}$$

And the second stage moment condition defining $\tilde{\lambda}$:

$$\frac{1}{N}\sum_n h(X_n,\hat{\beta},\tilde{\lambda})=0. \tag{D-2}$$

Let $H_\lambda = E[\frac{\partial h_i}{\partial \lambda_k}]$, $i,k=1,\ldots,s$. H_β and G_β are analogous to H_λ. Let V_{hh} =

$E[h(X,\beta,\lambda) * h(X,B,\lambda)']$. V_{gg} and V_{gh} are analogous to V_{hh}. Let the variance-covariance matrix of $\tilde{\lambda}$ be Ω_λ. Newey shows that

$$\Omega_{\lambda} = H_{\lambda}^{-1} V_{hh} H_{\lambda}^{-1} + H_{\lambda}^{-1} H_{\beta} [G_{\beta}^{-1} V_{gg} G_{\beta}^{-1}] H_{\beta}' H_{\lambda}^{-1\prime} - H_{\lambda}^{-1} [H_{\beta} G_{\beta}^{-1} V_{gh} + V_{hg} G_{\beta}^{-1} H_{\beta}'] H_{\lambda}^{-1}. \tag{D-3}$$

Note that the first term, $H_{\lambda}^{-1} V_{hh} H_{\lambda}^{-1}$, is the variance of $\hat{\lambda}$, had β been known and not estimated in the first stage.

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