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CENTER DISCUSSION PAPER NO. 689

DOES JOB MATCHING DIFFER BY SEX?

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May 1993

Note: Center Discussion Papers are preliminary materials circulated to stimulate discussions and critical comments. Anne Beeson Royalty is a Ph.D. candidate in the Economics Department at Yale University.

Research for this paper was supported by the Alfred P. Sloan Dissertation Fellowship and the Rockefeller Foundation Dissertation Fellowship.

Many thanks for helpful comments and good advice on this and previous drafts go to Ricardo Barros, Lori Bollinger, Moshe Buchinsky, Vassilis Hajivassiliou, James Heckman, Jennifer Hunt, Paul Schultz, Joe Tracy and Joel Waldfogel. Fellow graduate students Gerwin Bell, Susan Parker and Deborah Reed have also provided supportive criticism and review. Workshop participants at the California Institute of Technology, University of Chicago Graduate School of Business, University of Pennsylvania, Southern Methodist University, Stanford University, Vanderbilt University and Yale University also merit recognition for their useful comments and constructive criticism.

Job matching models provide a framework that connects turnover decisions to wages. These models therefore provide a possible explanation for the gender wage gap through the effect on wages of differences in turnover behavior by sex. But if job matching is to be an explanation of the wage gap then matching must differ by sex. This paper investigates patterns of job matching by sex and education level. Multinomial probit estimates of the probability of job-to-job and job-to-nonemployment turnover are obtained using a recently developed simulated maximum likelihood method. These estimates are in turn used to estimate implied reservation wages by sex and education group. Tests for equality of the turnover probabilities and reservation wages of men and women are conducted. It is found that differences between women's and men's turnover is primarily accounted for by the behavior of less educated women. The equality of the job turnover patterns of men and women with greater than a high school education cannot be rejected.

Keywords: Turnover, Job Matching, Male-Female Wage Gap, Reservation Wage, Multinomial Probit, Simulated Maximum Likelihood

Subject Index: Economic Demography and Labor Economics

DOES JOB MATCHING DIFFER BY SEX?

I. INTRODUCTION

The average wage of women has been between 60% and 70% of that of men for much of the 20th century (Goldin [1990], Marini [1989]) although recent evidence has pointed to a narrowing of the wage gap by the early 1980's (Blau and Beller [1988], Smith and Ward [1984]). In the sample of young people in the 1980's that is used in this paper, this gender wage gap has still not been eliminated.

Several ways that the labor market behavior of men and women may differ are often proposed in studies of the labor market experiences of men and women and are often pointed to as the most likely sources of the unexplained wage gap. For instance, such studies emphasize maternity leaves, the current societal expectation that women are primarily responsible for child-raising, and the traditional status of wives as secondary earners in the household. These observations have prompted several "turnover explanations" of the gender wage gap. For example, investigations have been made into the effect of intermittent labor force participation on wages through its effect on human capital investment. This research has resulted in no consensus on the size or significance of these effects (Mincer and Polachek [1974], Corcoran and Duncan [1979], Corcoran [1979], Gronau [1988]). A second "turnover explanation" of the wage gap suggests that lower expected tenure might cause lower female wages if employers face fixed training or other personnel costs (Donohue

[1988]). In this paper, I suggest job matching as yet a third "turnover explanation" of the male-female wage gap.

Observed levels of job tenure and labor market experience are the result of an individual's decisions about whether or not to work and whether or not to stay at the same job. Recent theoretical and empirical work on job matching and search explores the labor market mechanisms that generate observed levels of tenure and experience. These matching models describe an optimal job turnover process and a consequent positive impact on wages. These models provide a framework that connects turnover decisions to wages. They therefore also provide a possible explanation for wage differences between men and women due to differences in turnover behavior and a framework with which to analyze these differences.

Concentrating on the process of job matching for men and women may help identify to what extent matching differs by sex, whether any such differences affect wages, and whether or not women are compensated equally for similar labor market behaviors as men. Or more succinctly, "Can differences in job matching behavior help explain the male-female wage gap?" In this paper, rather than trying to estimate directly the effect of matching decisions on wages, I will look at the question at hand in a more indirect way. If job matching is to help explain the wage gap, then matching behavior must differ by sex. The question asked here, therefore, is more simply "Are there differences in the job matching behavior of men and women?"

I will address this question by looking at men and women by education level.

Education is an important determinant of wages and the size of the gender wage gap varies by education level. Additionally, studies of the turnover of women have obtained contradictory results on the effect of education on women's job turnover. These points suggest that looking at turnover and job matching for men and women by education level may provide evidence on the extent to which any of the "turnover explanations" described above may indeed explain the male-female wage gap.

Dividing the sample along this dimension also allows some criterion for how well these "turnover explanations" do in explaining the wage gap. The education levels I use in the analysis are less than or equal to high school (LHS) and greater than high school (GHS). A wage gap exists for both groups. In my sample the ratio of the mean wage of less educated females (LHSF) to that of less educated males (LHSM) is 0.79. This ratio for the more highly educated group is 0.86. If turnover is to account for a large portion of the wage gap, then differences in turnover for men and women should be found for both education groups. However, the wage gap between more highly educated men and women is smaller than that of less educated men and women. Therefore it is expected that job matching or other differences in job turnover will vary more for less educated men and women than for the more highly educated groups if turnover plays an important role in explaining the wage gap.

A general test of wage gap "turnover explanations" is accomplished by testing for the equality of job-to-job and job-to-nonemployment turnover probabilities for men and women. Estimated probabilities are generated from multinomial probit (MNP) estimations of job

turnover. A MNP framework with unrestricted correlation structures is made feasible through recent work in simulated estimation methods. A more specific test of the job matching "turnover explanation" of the wage gap is conducted by testing for the equality by sex of estimated job-to-job and job-to-nonemployment reservation wages. The job matching explanation for the wage gap is described in more detail in the following section (Section II) and the method used to obtain reservation wages estimates is described briefly in Section III and in more detail in Section VII. Average turnover patterns are documented in Section IV. A model of turnover is presented in Section V and the results of estimating this model are reported in Section VI. Section VIII discusses possible bias in the estimates and conclusions are found in Section IX.

II. MATCHING, MEN, and WOMEN

Matching and search are related aspects of the process by which workers locate a good job match through time on the job (matching) or time in the labor market (search). Both on-the-job search and matching are based on a worker's opportunities to change jobs in his or her quest for higher wages. The implications of both theories for wages grow out of optimal turnover behavior (Johnson [1978], Burdett [1978], Jovanovic [1979, 1984], Viscusi [1980a]). Previous studies of the wages of men and women, in focussing on tenure and experience profiles and returns to other human capital investments such as training, have acknowledged the importance of the decisions and labor market moves made early in a worker's career. Work on matching has also emphasized early career "job shopping" in relation to wage growth (Johnson [1978], Viscusi [1980a]). Such considerations suggest

exploring the importance of matching for men and women, especially young men and women.

Differences in the labor market behavior of men and women may occur for many reasons, with women's traditional home and family responsibilities primary among these reasons. Such differences can be interpreted in terms of job matching models and in this way the importance of possible differences in the labor market behavior of men and women can be measured. The frequency of the untested attribution of the unexplained wage gap to these reasons, combined with a policy interest in closing the wage gap if it is due to labor market discrimination, make it a useful task to determine whether these reasons are indeed a primary determinant of the gender wage gap.

How might these possible differences in the behavior of men and women be understood in the matching framework? The optimal turnover behavior used in these models is assumed to be unconstrained and unaffected by any individual heterogeneity in the value of non-market time. The wage gains due to matching that are predicted are based on unconstrained workers who have no reason to be in the nonemployment state other than to search for a good job. If the job turnover of a woman is constrained, for example, by her husband's location, she may not achieve equal wage gains due to matching as a similar man. A woman who leaves the labor force temporarily to have children may stop the job matching or on-the-job search process at the economically "wrong" time thereby losing out on some of the potential gains to matching.¹ Matching models therefore provide an appropriate

¹"Right" and "wrong" are here used in relation to the optimal separation strategy as defined by traditional matching and search models. As stated above, these models assume no mobility constraints and do not account for the value of non-market time. If workers do have constraints on mobility then these models are incorrectly specified, and the decision predicted as "right" is not the correct one for that individual. Women may have more of such

framework with which to tackle these issues. With these possible interpretations of the models in mind, I now turn to a discussion of how to test for differences in the job matching behavior of men and women.

III. TESTING THE JOB MATCHING BEHAVIOR OF MEN AND WOMEN

The defining feature of job matching models is the reservation wage property that a worker leaves the firm if the wage falls below some reservation value and stays on the job otherwise. The existence of a reservation wage gives the model its predictive power. Tests for differences in the matching behavior of men and women must therefore look to the reservation wage profile as the definitive aspect of such behavior. This paper uses observed turnover behavior to estimate reservation wage profiles for men and women by education level and, by testing for the equality of reservation wages, tests whether or not matching differs by sex and education level.

First, I will provide a brief overview of the theory of matching with particular emphasis on the importance of the reservation wage.² The prototypical job-matching model is developed in Jovanovic [1979] and is summarized in Mortensen [1986]. Each worker-firm match is assumed to be unique and the productivity of the worker at one job is independent of that worker's productivity at any other job. Noisy measures of this match-specific productivity are observed during each period on the job. Through these observations, the

constraints and therefore estimation of the model for women may produce estimates that are different from those for men.

²The discussion here will center on job matching as opposed to job search but the empirical work is formulated to encompass on-the-job search behavior as well. For an overview of search models, see Devine and Kiefer [1991].

worker and firm learn about the productivity of their match. Because of the assumptions of an infinite horizon, risk neutrality, and independent productivity draws from a common distribution across job matches, the value of quitting the current job and taking a new job offer is constant over time. Because of the Bayesian learning framework used and the assumption that the wage paid to the worker will be the current conditional expectation of productivity based on all past productivity observations on this job, the problem becomes an optimal stopping problem. The worker decides whether and when to stop working at the current job. Since the value of quitting is constant while the value of staying increases with the wage, this problem has the reservation wage property -- that is, the worker leaves the firm if the wage falls below the reservation value for that level of tenure and stays otherwise.³

The empirical implications of the model result from this reservation wage property. The distribution of wages given tenure on the job becomes a conditional distribution, the condition being that the wage in each previous period on the job exceeded the reservation wage for that period. The prediction of the model for the effect of wages and tenure on the probability of quitting the job are also based on this reservation wage property. For example, the probability of leaving the current job is predicted to decrease with higher current wages. The learning structure of the model implies autocorrelation of a worker's wages at a particular job. Therefore, if the current wage is high, future wages are less likely to fall below the reservation wage and the worker is less likely to leave that job.⁴

³See Flinn [1986] for a clear illustration of these results.

⁴For a more detailed summary of this and other matching and search models see Mortensen [1986] .

Matching models predict wage growth with job tenure and search models predict wage growth with labor market experience -- tenure and experience being accumulated according to the matching and search decisions made by the individual. Therefore, if there are differences in the matching and on-the-job search processes by sex, these processes could contribute to the male-female wage gap. In this paper I look at job matching behavior by sex and education level in order to explore the question of whether or not job matching contributes to the gender wage gap. If matching is to play a major role in explaining the male-female wage gap, I would expect to find differences in job matching by sex for both education groups analyzed since there exists a gender wage gap for both groups. As discussed in the Introduction, the wage gap is greater for less educated women. Therefore, a matching explanation of the wage gap implies larger differences in job matching for less educated men and women than for more highly educated men and women.

Taking optimal matching behavior as given, observed turnover behavior implies a reservation wage profile. I proceed by assuming three possible states: leaving the current job for a new job; leaving the current job for nonemployment; and staying on the current job. A worker will leave the job for a new job if the new wage offer exceeds the reservation offer and the value of nonemployment. A worker will leave the job for nonemployment if the current wage falls below the reservation wage for the current level of tenure and experience and no acceptable alternative job offer is available. By definition, the reservation wage is the wage at which the worker is indifferent between staying on the job and leaving the job for nonemployment. Also by definition, the reservation offer is the offer at which the worker is indifferent between staying at the current job and taking a new job offer. My

goal is to estimate the reservation wages and offers of men and women but reservation wages and offers are not directly observed. I have only discrete information on which state is chosen. As will be described in detail in Section VII, for the purposes of estimation the indifference concept can be alternatively expressed in terms of turnover probabilities. The estimated reservation wage (offer) is the wage (offer) at which the probability of staying on the job is equal to the probability of leaving the job for nonemployment (a new job).

The estimation strategy of this paper is as follows. Multinomial probit estimates of turnover equations are first used to generate predicted probabilities of job-to-job (JJ) and job-to-nonemployment (JNE) turnover holding constant the wage, job tenure, labor market experience, and other variables expected to influence the reservation wage and the reservation offer. These estimates are obtained using a recently developed simulated maximum likelihood method. The model and its estimates are presented in Section V. Given the estimated parameters of the turnover equations, calculating turnover probabilities at a series of wage levels allows identification of the wage at which the probability of staying on the job equals that of leaving to a new job (JJ reservation wage or w_J^R) and the wage at which the probability of staying on the job equals the probability of moving into nonemployment (the JNE reservation wage or w_N^R). These equalizing wages are the estimates of the JJ and JNE reservation wages. Section VII describes this procedure and the estimates it generates.

If matching models are appropriate models of turnover behavior, then observed job turnover will imply a reservation wage profile as described above. If these models do not adequately describe the turnover behavior of either men or women, then the implied

reservation wage profile will differ from the optimal path that arises from matching theory. These implied reservation wage and offer profiles will be estimated for men and women by education group. If differences by group are found in these profiles, the approach used here does not explain what causes the differences. Different preferences on the part of men and women would cause different reservation wages by sex. Differences in firm demand for workers by sex that affects alternative job offers would be reflected in the reservation wage estimated with this method. Any differences in the matching process by sex, be they caused by individual choices, institutional constraints, or discrimination, will affect the reservation wage profiles estimated by this method. Only if the matching process is as defined in the prototypical models will these estimates be true estimates of the reservation wage profile. As the goal of this paper is to test whether or not the matching processes of men and women are the same, this shortcoming is not a problem. What is needed is simply a method for summarizing the implications of matching theory in order to perform such a test. The reservation wage is the most appropriate summary of the behavior described in matching models.

IV. AVERAGE TURNOVER BY SEX AND EDUCATION

Before turning to this model and its estimation, it will be useful to summarize average turnover probabilities and to survey previous findings on male and female turnover. Figures A1-A12 in Appendix A are graphs of turnover profiles for a subsample of the National Longitudinal Survey of Youth (NLSY) young men and women. Included in this subsample are men and women from the random sample who were at least 22 years old at the time of

the interview. Interview years 1980-1987 are pooled. The subsample consists of 10,354 observations on men and 9856 on women. The data are described in more detail in Appendix D. Figures A1-A4 illustrate job-to-job turnover against age, experience, tenure, and the real wage on the current job.⁵ Similarly, Figures A5-A8 and A9-A12 illustrate job-to-nonemployment transitions and the percentage staying at the same job. Some of the most interesting graphs are also pictured in the text.

These figures show that when plotted against age, experience, or the wage level, men have higher job-to-job (JJ) turnover than do women. JJ turnover ranges from about 12% to about 25% when plotted by age, with men's turnover generally about 2-4 points above women's. When plotted against tenure, JJ turnover does not differ significantly by sex. Average JJ turnover at a tenure level of less than one year is approximately 25% but falls to less than 10% by the time a worker reaches six years of tenure. Keep in mind that the differential turnover rates that are observed by age affect the distribution of tenure by sex.

The turnover patterns illustrated in these figures conform generally to theory. JJ turnover is monotonically declining with age, tenure, and the wage for both men and women. Both human capital and job matching models predict declining turnover with job tenure.⁶ Matching models also predict that turnover will decrease with higher wages if the wage is a

⁵Age is the individual's age on January 1 of the given interview year. Experience is actual labor market experience calculated from detailed work history data of the individual up to the interview date. Tenure is the number of years spent with the current employer. For the graphs, both tenure and experience are rounded down. The real wage is the worker's reported wage adjusted by the CPI index so that all wages are in terms of 1979 dollars. For the graphs, the real wage is rounded to the nearest dollar.

⁶The matching theory of Jovanovic [1979] actually predicts that turnover will first increase and then will decrease with tenure as learning occurs. The length of time of the initial increase may be so short that it cannot be captured in this data.

good proxy for the value of the current job match. These patterns are reflected in the tenure-turnover and wage-turnover graphs. It is also interesting to note in Figure 1 the inverted-U shape of the experience-turnover profile for both men and women. An inverted-U shape for the tenure profile in JJ turnover is predicted

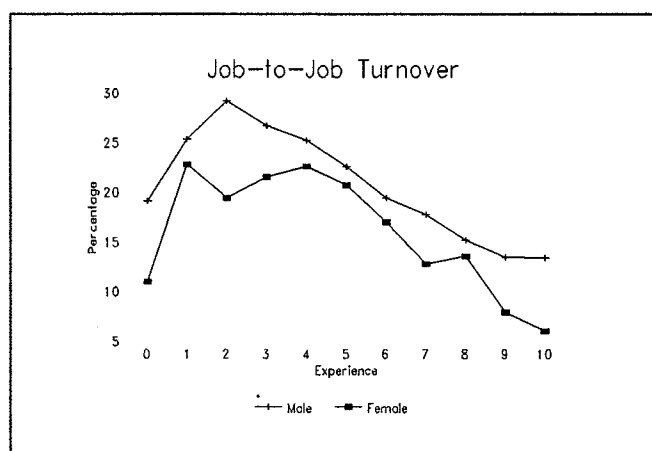


Figure 1

by Jovanovic's learning model of job matching. Jovanovic's model does not address general learning with time in the labor market. This JJ turnover by experience graph (Figure 1) may suggest that learning is affecting job turnover in a manner similar to that predicted in Jovanovic's model but that the effect is stronger in the experience than in the tenure dimension.

Job-to-Nonemployment (JNE) turnover looks very different than JJ turnover.⁷ JNE turnover graphed against age stands out as illustrating large differences in turnover by sex. As seen in Figure 2, men show a definite declining pattern with age: 18% at age 22 to about 10% by age 29. Women's JNE turnover on the other hand shows only a modest decline: from 21% at age 22 to 17% at age 29. The

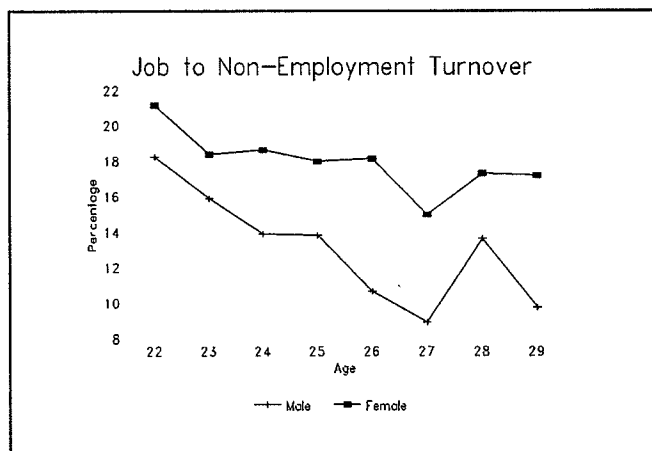


Figure 2

difference by sex is attenuated when graphed against tenure but the lower turnover to nonemployment for men continues to be significant. When plotted against experience and the wage, however, these sex differences are erased. Again it should be noted that the higher JNE turnover of women causes a different distribution of men and women by experience level. The experience, tenure, and wage profiles illustrate monotonic declines in turnover although diminishing precision at higher ages and wages make it impossible to rule out upturns.

The higher JJ turnover of men and the higher JNE turnover of women are offsetting influences, causing differences in the average percentage of male and female workers staying

⁷Nonemployment includes observations on both those individuals who report themselves as unemployed and those who report themselves to be out of the labor force (OLF). The NLSY work history data define such a distinction but when a nonemployed spell includes time both unemployed and OLF, the exact time period assigned to each is arbitrary. Therefore it is difficult to identify with confidence the destination -- unemployed or OLF -- of a person leaving employment. In this paper both are therefore included in the larger category called nonemployed.

on the job at any given age, experience, or tenure to be insignificant.⁸ Indeed, these profiles look remarkably similar by sex. For example, as shown in Figure 3, during their first year of labor market experience 39% of women and 41% of men will stay at the same job. By the time they reach 8 years of experience the

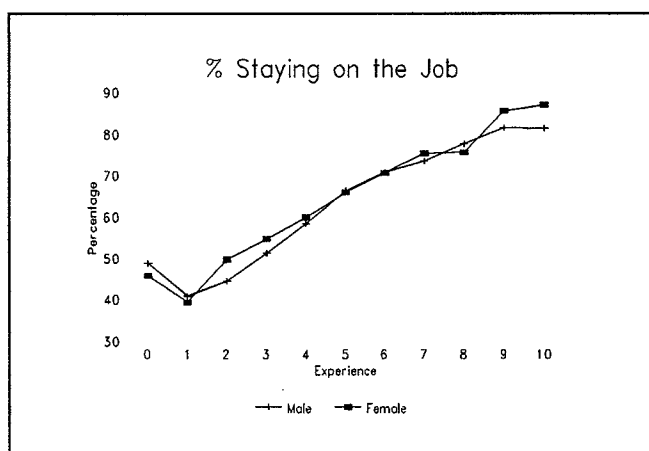


Figure 3

percentages are 76% of women and 78% of men. The stay-wage profile (Figure A12) on the other hand shows a slightly higher but usually significant percentage of women staying on the job than men for a given wage.

These results are not at odds with other comparisons of male and female job quit rates although other studies have not distinguished between the type of quit -- job-to-job or job-to-nonemployment -- and therefore do not illustrate some of the outcomes shown here. For example, declining turnover with tenure is usually found for both men and women just as these figures show. On the other hand, Donohue [1988] finds a U-shaped job quit hazard for women in his early (1968-71) cohort and in a low-tenure sample from the Equal Employment Opportunities Pilot Program Survey, Meitzen [1986] finds that the probability of a woman's quitting the job increases with tenure. Several of these studies (for example, Light and Ureta [1992] and Donohue [1988]) find that the negative tenure effect is stronger for men than for women.

⁸See Figures A9-A12 in Appendix A.

Some of the previous studies also examine the effect of wages on turnover and find a negative effect of the wage on turnover for both men and women. In his logit analysis, Viscusi [1980b] finds the marginal effect of the wage on the probability of quitting the job to be equal for men and women, while Light and Ureta [1992] in a discrete-time hazard study find the negative wage effect to be stronger for women than for men.

Studies of men's mobility (see, for example, Mincer and Jovanovic [1981]) have found that education is negatively correlated with turnover. Comparisons of men and women have differed in their findings. Donohue [1988] and Light and Ureta [1992] find that education has a negative effect on the quit rate of both men and women. Blau and Kahn [1981] and Viscusi [1980b] find an insignificant effect for education on the quit rate of men and a positive effect for that of women. These conflicting results suggest the need for further inquiry into the relationship between education and women's turnover patterns.

When I divide my sample of young men and women by education level, it becomes apparent that the average turnover patterns reported above are masking some potentially important differences among women. Figures A13-A24 report the same turnover profiles discussed above broken down by education level.⁹ The education levels used are less than or equal to high school (LHS) and greater than high school (GHS). Abbreviations used throughout the text are LHSM (males with education of high school or less), GHSM (males with greater than high school education), LHSF (females with education of high school or

⁹The sample sizes are as follows: LHS-Female 4792 observations, GHS-Female 5064 observations, LHS-Male 6018 observations, and GHS-Male 4336 observations.

less), and GHSF (females with greater than high school education). Again, the most interesting of the figures are reproduced in the text.

These graphs by education level illustrate that the differences in male and female job-to-job turnover discussed above are accounted for mainly by differences in the JJ turnover of less educated women. Less educated

women (LHSF) have lower average levels

of JJ turnover than more highly educated

women (GHSF) by age, experience, tenure, and the wage. These differences are

generally significant by women's

education group at the 95% level except

in the case of tenure. Figure 4 illustrates

JJ turnover by age for these groups. The

JJ turnover of LHS women is about 4 percentage points lower than GHS women at each age level. Women with greater than a high school education, on the other hand, look very much like men in their JJ turnover patterns.

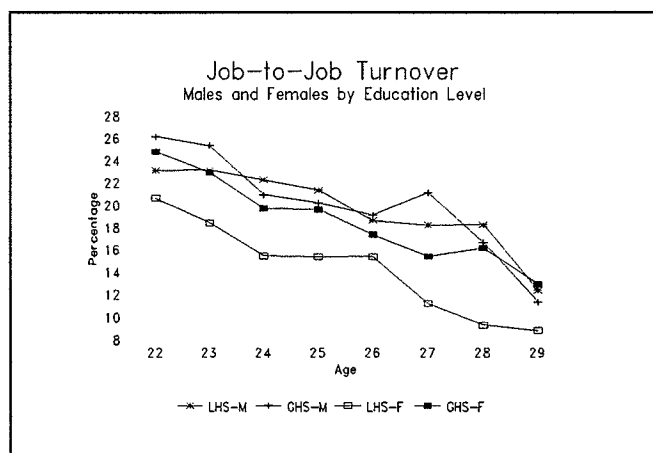


Figure 4

The job-to-nonemployment turnover graphs again highlight differences between less educated women and all others. In particular, Figure 5 shows that LHS women have a JNE turnover rate that is approximately 7 percentage points higher than GHS women at each age level. In other words, the JNE average transition rate of less educated women is 40-85% higher, depending on the age level, than that of higher educated women. The differences between LHS women and all others are smaller but still significant in the tenure, experience,

and wage profiles. Once again, more highly educated women look very similar to men of both education levels in all four graphs.¹⁰

Lower JJ turnover and higher JNE turnover of LHS women relative to all others balance one another to just about equalize their overall quit rates with those

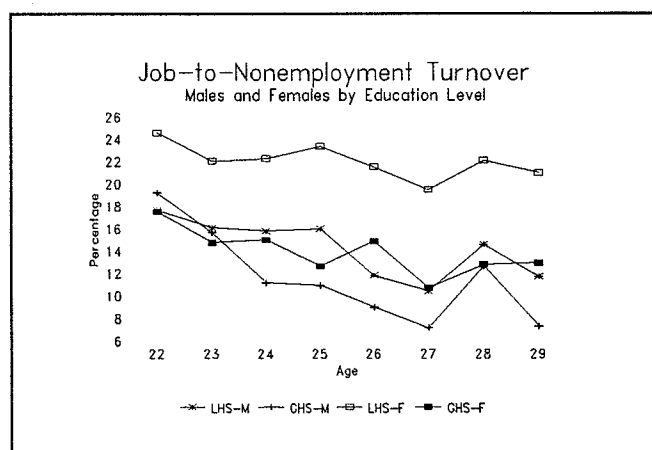


Figure 5

of the other three groups. The average percentage of each group who stay at the same job is very similar for men and women of all education levels. By age level, the lower "stay" rate for LHS women as compared to GHS women is marginally significant at the 95% level for some age levels. By experience and tenure the differences in "stay" rates for women by education level are generally insignificant. At low wage levels LHS women have higher "stay" probabilities while at higher wage levels the differences are insignificant.¹¹

The fact that average turnover by education for women looks so different for the different types of transition might explain why previous studies have obtained conflicting results on the effect of education on the turnover of women. When the type of turnover is not accounted for, the result is ambiguous depending on whether the higher turnover to nonemployment of lower educated women outweighs the higher job-to-job turnover of more highly educated women, or vice-versa. Again, these figures represent only simple averages

¹⁰See Appendix A, Figures A17-A20 for these graphs.

¹¹See Appendix A, Figures A21-A24.

but the large differences between women of different education levels for different types of job transitions suggest that there may be some important unexplored differences in job matching behavior among women.

V. MODEL OF TURNOVER

The model is based on the job-to-job and job-to-nonemployment turnover equations that follow from the extended matching model as set forth in Jovanovic [1984].¹² The wage of worker i at time t on the current job j is w_{ijt} . The new wage offer of firm k to worker i at time t is:

$$w_{ikt} = \beta_0 + \beta_x X_{it} + \phi_{ikt}. \quad (1)$$

The wage offer is assumed to depend on labor market experience, X , both due to job search and due to general human capital accumulation with experience. I assume that worker-firm matches differ in their productivity and that the true productivity of the match is unknown when a worker begins a new job. Workers and firms observe some measure of productivity each period but this measure is only a noisy signal of the true productivity of the match.

Workers and firms update their assessments of the true value of their match using the imperfect observations that are available. Therefore workers and firms are learning about the true value of match-specific productivity as tenure on the job increases. Wages are based on the current assessment of productivity. The wage offer of firm k includes a random factor, ϕ_{ikt} that represents the initial assessment of the value of match ik (worker i to firm k). This

¹²See Topel [1986] for an implementation of a matching model that includes only job-to-job turnover.

draw of ϕ_{ikt} is assumed to be independent of previous draws of ϕ implying that alternative offers for the same individual are independent of one another.

The reservation offer of worker i at time t is:¹³

$$R_{it}^O = \gamma_0^J + \gamma_w^J w_{ijt} + \gamma_T^J T_{it} + \alpha_{it}^J, \quad (2)$$

where w_{ijt} is the current wage and T_{it} is tenure on the current job.¹⁴ α_{it}^J is an unobservable shock that is (for now) assumed to be iid and normal across individuals and time. The matching model predicts that the reservation offer will be increasing in the current wage, so γ_w^J should be positive. Clearly it is expected that a worker with a relatively high current wage would require a relatively high outside offer in order to change jobs. The matching model also suggests that the reservation offer is negatively related to tenure on the job. This result follows from the Bayesian learning structure of the model which allows greater potential for wage growth early in a job. As tenure on the job increases, more is known about true match-specific productivity and therefore less chance remains for wage growth. The same current wage at a higher level of tenure therefore represents a less valuable potential future wage stream. The offer at which the worker is indifferent between the current job and a new job (the JJ reservation offer) will therefore decrease with tenure holding constant the wage on the current job. Equations (1) and (2) imply that a worker will leave the current job for a new job if

¹³Note that "J" superscripts indicate a reference to the job-changing equation as opposed to "N" superscripts which will indicate the job-to-nonemployment equation.

¹⁴Other variables expected to influence the reservation offer such as union status and bad health are included in the empirical work.

$$(\beta_0 - \gamma'_0) + \beta_x X_{it} - \gamma'_w w_{ijt} - \gamma'_T T_{it} + (\phi_{ikt} - \alpha'_{it}) > 0. \quad (3)$$

Additionally, a worker will leave the job for nonemployment if the value of the current job falls below some reservation value. If the current wage is an accurate reflection of the value of the current job,¹⁵ this reservation value can be called the reservation wage and is expressed as follows:

$$w_{it}^R = Z_{it} \gamma^N + \alpha^N_{it}. \quad (4)$$

The vector Z_{it} includes variables such as asset income and health status that are thought to affect the value of nonemployment. α^N_{it} is analogous to α'_{it} above. Equation (4) implies that the worker will leave the job for nonemployment if

$$Z_{it}^N \gamma^N - w_{ijt} + \alpha^N_{it} > 0. \quad (5)$$

Equations (3) and (5) summarize the turnover behavior of workers.¹⁶

Previous studies of the labor market outcomes of men and women have suggested several reasons that the turnover of men and women may differ. In particular, men and women have traditionally adopted different roles on the job and at home. If such traditional

¹⁵The empirical work includes other variables such as union status and job tenure which may contribute to the value of the job.

¹⁶In Jovanovic's [1984] three state matching model (Jovanovic [1984]) nonemployment is used only as a vehicle for generating a higher offer arrival rate. Therefore, with an acceptable offer in hand, a worker would never choose to leave the job for nonemployment and theoretically we need only specify two equations describing turnover, equations (3) and (5). This paper, however, acknowledges additional reasons for leaving the job to nonemployment and therefore includes in the vector Z variables such as asset income which are thought to affect this choice. Given the choice of nonemployment for reasons other than search, a second inequality for each possible type of transition will be specified. For example, a new job must be preferred both to staying on the current job and to leaving the job for nonemployment. These restrictions are included when the estimations are described below in terms of the standard discrete choice framework with three alternatives.

roles are still valid descriptions of the behavior of men and women in the 1980's, we would expect to find different preferences for work versus nonemployment for men and women. These preferences will be expressed in terms of the model most explicitly in equation (5) describing JNE turnover. A second major difference that historically has been ascribed to men and women is a wife's customary status as a secondary earner in the married household. This, combined with greater home work responsibilities for women, may mean that there are omitted variables such as a spouse's job transfer or the presence of disabled family members that should appear in the women's turnover equation but that are unimportant for men. If so, the parameters estimated for women will suffer from an omitted variable bias that does not exist for men. Therefore, if these types of differences between men and women are important, the estimated parameters of this model should differ for males and females when estimations are carried out separately by group.

The differences in male and female labor force behavior just described are often cited as possible causes of the unexplained male-female wage gap through the effects of turnover differences on the expected length of a job. It is speculated that lower expected tenure might cause lower female wages if employers face fixed training or other personnel costs (Donohue [1988]). The literature on job matching suggests that there are other avenues by which turnover may affect wages. These models tie wages to turnover in ways other than simply through expected job duration. In these models optimal turnover leads directly to higher expected wages. In either case, the relationship between turnover and the wage gap is dependent on assumed turnover differences between men and women. I seek to test whether or not those differences are significant for young people in the 1980's.

For the purposes of estimation, the two turnover equations ((3) and (5)) can be written in a standard multinomial discrete choice framework as follows:

$$\begin{aligned} y_1 &= Q\delta^1 + \epsilon_1 \\ y_2 &= Q\delta^2 + \epsilon_2 \\ y_3 &= Q\delta^3 + \epsilon_3 \end{aligned} \tag{6}$$

where the first equation in (6) represents the value of a new job, the second equation is the value of nonemployment, and the third equation in (6) represents the value of staying at the current job. If $(y_1 > y_2)$ and $(y_1 > y_3)$, the worker moves from the current job to a new job, referred to here as a JJ transition. If $(y_2 > y_1)$ and $(y_2 > y_3)$, the worker moves from the current job to nonemployment, a JNE transition. If $(y_3 > y_1)$ and $(y_3 > y_2)$, then the worker stays at the current job. Since the alternatives are judged relative to each other, the problem reduces to two equations:

$$\begin{aligned} y_1 - y_3 &= Q(\delta^1 - \delta^3) + (\epsilon_1 - \epsilon_3) \\ y_2 - y_3 &= Q(\delta^2 - \delta^3) + (\epsilon_2 - \epsilon_3). \end{aligned} \tag{7}$$

Written in this way, the relationship between the estimating equations and the model described above becomes clearer. For example, $(\delta^1_0 - \delta^3_0) = (\beta_0 - \gamma'_0)$, and $(\delta^1_w - \delta^3_w) = -\gamma'_w$.

The error term relationships are $(\epsilon_1 - \epsilon_3) = (\phi_{ikt} - \alpha'_{it})$ and $(\epsilon_2 - \epsilon_3) = \alpha^N_{it}$. An assumption of joint normality on the errors in (6) implies a multinomial probit (MNP) for the estimation of these turnover equations. A multinomial probit specification allows for flexible correlation structures across alternatives, unlike the restrictive assumptions necessitated by, for example, multinomial logit. More specifically, possible correlation structures of the MNP include correlation between pairs of alternatives and, with panel data, individual random effects by

alternative or first order autoregressive processes in the errors. The smooth simulated maximum likelihood estimation method developed by Boersch-Supan and Hajivassiliou [1990] overcomes the computational difficulties caused by the high dimensional integrals called for in multinomial probit estimation, difficulties which until recently seriously deterred the use of these models in practice. Other simulation estimation methods for limited dependent variable models are reviewed in Hajivassiliou [1992].

The dependent variable for each observation is whether the worker left the job for a new job, left the job for nonemployment, or stayed on the current job during the time period under consideration.¹⁷ The turnover transition probabilities being estimated are, therefore, only transitions that begin with a job. This definition of job turnover necessitates that a person be working in order to be included in the sample. Possible sample selection problems raised by this sample definition are discussed below.

¹⁷Estimations have been carried out using samples defined over two different time intervals. The results discussed in the main body of the text use all the data available on the turnover of each individual. This sample definition allows an individual worker to have more than one observation per year if s/he held more than one job during this year. For example, worker *i* in year *t* might be observed to leave Job #1 for Job #2 (JJ decision) and to stay on Job #2 for the rest of that year (a decision to stay on the current job). The advantage of this sample definition is that it uses all the data on turnover available from the NLSY survey. The disadvantage of this sample definition is that each decision of each individual is not taking place within the same time interval since some workers (those who change jobs) are allowed more than one decision per year while other workers (those who do not change jobs) are allowed only one decision per year. The alternative sample definition used allows only one observation per year per individual. In the above example, only the JJ transition from Job #1 to Job #2 would be recorded for worker *i* in year *t*. The advantage of this sample definition is that all turnover decisions in the sample occur within time intervals of the same length. The disadvantage is that some known turnover data must be thrown away. The two sample definitions produce similar results and no differences occur in the tests for equality of turnover behavior across groups. Graphs of the results from the alternative sample definition are included in Appendix C. A sample definition that would combine the advantages of both of the two definitions just described is possible only if data on all variables is available at the same frequency as the data on job turnover. In the NLSY, after creating a job history as described in Appendix D, turnover data is available at a weekly frequency. It is not possible, however, to track other variables this closely since survey participants were asked about other job information only at yearly intervals.

Explanatory variables included in Q are tenure on the current job and its square, actual labor market experience and its square, health status, union status, the real wage on the current job and its square, asset income, marital status, and number of children. Note, however, that fertility and marriage decisions, particularly of women, may be related to unobservable components of the reservation wage, making the number of children and marital status endogenous.¹⁸ Estimations were therefore run with and without number of children and marital status as explanatory variables. Although the coefficients on these variables are significant, the effects of other variables and the test results for these two specifications were qualitatively the same. Estimations with marital status and number of children included are discussed and graphed. Both sets of coefficients are reported in Appendix E.

An alternative econometric approach that has been used in models of job turnover is duration analysis. I have chosen to use MNP instead for two main reasons. First, the discrete choice framework conforms more closely to the structural model presented above than does the actual implementation of a duration model. Since my estimates of the reservation wage (see Section VII) depend upon a structural interpretation of this model, the more easily interpretable MNP framework is preferable to the reduced form duration model. Second, the MNP allows more flexibility in estimating the error structure, both contemporaneous and temporal, of the discrete alternatives than duration analysis can handle in relation to the possible destination states in a competing risks model. Additionally, the most

¹⁸See Rosenzweig and Schultz [1985] for a joint analysis of women's labor supply and fertility decisions and Browning [1992] for an overview of the effects of children on various aspects of household behavior.

often cited advantage of duration models over discrete choice models is that the estimated parameters do not change depending on the length of the time interval chosen for discrete analysis. This result depends on the assumption that the econometrician has continuous data on all variables. Since the NLSY data, like most other large panel surveys, include observations on most variables only at yearly intervals, the duration framework is not superior to MNP in this respect.

Before turning to the estimation results, note that the first estimates reported do not take account of possible persistent unobservable individual heterogeneity. That is, the vector ϵ in (6) is assumed to be independent across individuals and time. If instead $\epsilon_{3it} = \mu_{3i} + \eta_{3it}$ where μ_{3i} represents the worker's preference for staying at the same job and η_{3it} is iid, then one would expect ϵ_3 to be positively correlated with tenure, since a preference for staying at the same job will have affected previous job-to-job turnover and therefore current tenure. A similar argument can be made for a negative correlation between ϵ_2 and experience. Let δ^3_T be the coefficient on tenure in the third equation of (6). If ϵ_3 is positively correlated with tenure, it is expected that δ^3_T will be biased upward.¹⁹ This problem and its affect on the group comparisons conducted here is discussed in more detail in Section VIII below.

Further estimates are presented that attempt to correct for this problem by estimating the MNP model with unobservable random effects that are constant for the individual over time. Random effects can be used to represent the preference of the individual for staying at

¹⁹This is the problem of "spurious state dependence" caused by "temporally persistent unobservables" analyzed by Heckman [1981b].

the same job or for staying in the labor market thereby taking into account unobserved heterogeneity that is persistent for the same individual over time. When the possible correlation of these random effects with the explanatory variables is also taken into account, this procedure should eliminate the bias that might be caused by correlation of tenure or experience with the unobservables.

VI. MNP ESTIMATION RESULTS

Figures B1-B9 in Appendix B summarize the first set of MNP estimates obtained by sex and education group. The coefficients estimated by MNP for JJ and JNE turnover relative to staying on the current job are presented in Tables E1-E4 in Appendix E.²⁰ It should be noted, however, that because the scale of the coefficients is not identified in MNP models and because, unlike in linear models, the effect of the coefficients on the probabilities depends on the levels of the explanatory variables, the probabilities graphed and reported in the text are the correct comparison across groups as opposed to the coefficients reported in these tables.

The estimated probabilities graphed and discussed here are based on estimations that impose the restrictions that the variance of each error is fixed at unity and no correlation is allowed across alternatives. This independent probit assumption was imposed, however, only after tests could not reject this assumption. Although the independent probit assumption could not be rejected in this case, allowing for the possibility of correlation across

²⁰Two different specifications are presented. The first includes both number of children and marital status as explanatory variables. The second excludes these variables from the estimation.

alternatives is an important feature of the MNP specification used in this paper. The MNP framework allows that testing of the independence assumption rather than the forced imposition of this assumption required by the multinomial logit.

Estimations are carried out separately for each of the four sex and education groups. Based on the average turnover rates reported above, only estimates by sex and education group will be discussed. The data are from the National Longitudinal Survey of Youth (NLSY). The sample used here includes interview years 1980-1987 of workers who were at least 22 years old at the time of the interview.²¹ The data are described in more detail in Appendix D.

MNP estimations point to the importance of the wage in both types of turnover for all sex and education groups. This finding is in accordance with studies of the turnover of men such as Topel and Ward [1992]. Tenure and experience are also found to be important in determining turnover. The turnover probabilities graphed by the wage level, by tenure, and by experience will be graphed and described below. As shown in Table I and Table II, the MNP estimations also show that asset income increases the probability of both JJ and JNE turnover for all groups although these differences are significant only in the case of JNE turnover for both groups of women. The results shown in these two tables indicate that the inclusion of demand indicators in the form of dummy variables for the range of local unemployment rates also serves the purpose of providing a distinction between the two subcategories of nonemployment -- unemployment and out of the labor force. It is found that

²¹This age cut off was used in order to avoid the endogenous sample selection of samples by education level that would result from letting a worker enter the sample as soon as he or she left school and entered the labor force.

high local unemployment rates significantly decrease the probability of JJ turnover for all four groups. However, while high unemployment increases the probability of JNE turnover for both groups of men, the effect for women is either insignificant or negative. I interpret this variation between men and women to be caused by a higher proportion of women's JNE turnover being a choice to leave the labor force with more men becoming unemployed.

Table I
Estimated Job-to-Job Turnover Probabilities
Evaluated at Different Levels of Selected
Explanatory Variables
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Asset Income = 0	0.177 (0.005)	0.186 (0.006)	0.134 (0.005)	0.167 (0.006)
Asset Income = 5000	0.179 (0.020)	0.197 (0.010)	0.145 (0.017)	0.184 (0.015)
Dummy for Local UE rate $\leq 6\% = 1$	0.216 (0.010)	0.219 (0.011)	0.169 (0.011)	0.198 (0.010)
Dummy for Local UE rate $> 12\%$ $= 1$	0.135 (0.012)	0.156 (0.017)	0.097 (0.012)	0.125 (0.014)
Marital Status = 0	0.175 (0.007)	0.174 (0.007)	0.152 (0.009)	0.176 (0.007)
Marital Status = 1	0.171 (0.008)	0.205 (0.013)	0.117 (0.007)	0.147 (0.009)
Number of Children = 0	0.182 (0.007)	0.196 (0.007)	0.154 (0.007)	0.187 (0.006)
Number of Children = 1	0.180 (0.006)	0.195 (0.012)	0.133 (0.005)	0.143 (0.010)

*Other variables held constant at group means.

LHSM: Males, less than or equal to high school education

GHSM: Males, greater high school education

LHSF: Females, less than or equal to high school education

GHSF: Females, greater high school education

Table II
Estimated Job-to-Nonemployment Turnover Probabilities
Evaluated at Different Levels of Selected
Explanatory Variables
Standard Errors in Parentheses

	LHSM	GHSM	LHSF	GHSF
Asset Income = 0	0.131 (0.005)	0.106 (0.006)	0.185 (0.006)	0.118 (0.005)
Asset Income = 5000	0.139 (0.014)	0.118 (0.008)	0.226 (0.021)	0.144 (0.015)
Dummy for Local UE rate $\leq 6\% = 1$	0.107 (0.008)	0.091 (0.007)	0.183 (0.011)	0.134 (0.008)
Dummy for Local UE rate $> 12\%$ $= 1$	0.167 (0.013)	0.120 (0.015)	0.191 (0.016)	0.112 (0.013)
Marital Status = 0	0.157 (0.007)	0.122 (0.007)	0.174 (0.009)	0.115 (0.006)
Marital Status = 1	0.104 (0.007)	0.081 (0.009)	0.198 (0.008)	0.132 (0.009)
Number of Children = 0	0.105 (0.005)	0.100 (0.006)	0.160 (0.007)	0.105 (0.005)
Number of Children = 1	0.141 (0.005)	0.112 (0.010)	0.184 (0.006)	0.146 (0.009)

*Other variables held constant at group means.

LHSM: Males, less than or equal to high school education

GHSM: Males, greater high school education

LHSF: Females, less than or equal to high school education

GHSF: Females, greater high school education

Comparing the MNP turnover profiles by tenure, experience and the wage to the simple averages, I find that most of the patterns previously reported are reproduced with this multivariate approach. In particular, less educated women have lower JJ turnover and higher JNE turnover than the other groups when graphed against experience, tenure, and the wage. Graphs of these two types of turnover against tenure are found in Figure 6 and Figure 7.

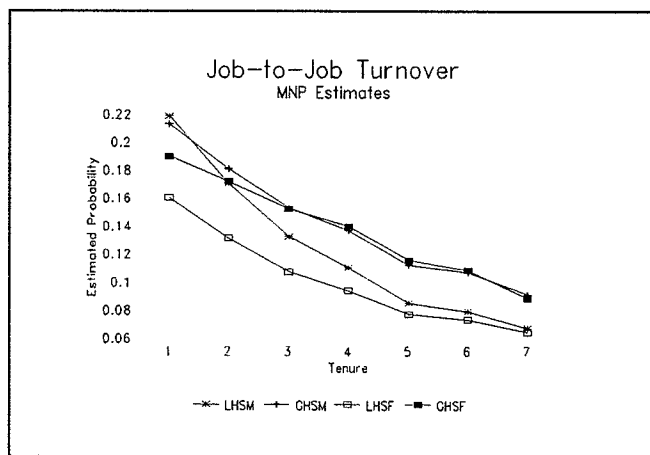


Figure 6

The most notable difference between the simple averages and the MNP results occurs in the JNE versus tenure profile for LHS women. The MNP results show that holding constant other variables such as labor market experience, the JNE turnover probability of LHS women first decreases, but then increases with tenure on the job (Figure 7). This stands in contrast to the JNE probability by tenure of the other groups, each of which shows a monotonically declining probability of turnover to nonemployment as tenure increases. The same result shows up less dramatically in the stay-tenure profile (Figure B8)

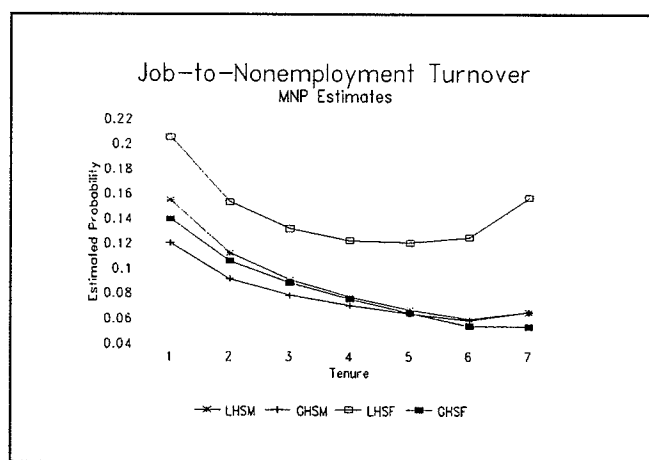


Figure 7

where a downturn in the probability of staying on the job for LHS women occurs at about five years of tenure. The MNP estimates confirm the initial observation that less educated women differ significantly in their turnover decisions from more highly educated women.

This observation as well as the similarity of the turnover patterns of higher educated women to those of men of both education levels can be confirmed by tests for the equality of the estimated turnover probabilities. Probabilities are calculated by group and the tested probabilities are evaluated at the group means.²² As shown in Table III, with one exception, the equality of all three turnover probabilities for LHS women with all other groups is rejected. In the case of JJ turnover and the probability of staying on the job, equality cannot be rejected for the three other groups. Lastly, the equality of turnover probabilities for GHS men and women cannot be rejected for JJ turnover, JNE turnover, or for the probability of staying at the same job.

Estimations were also conducted allowing for random effects (RE) for the same individual over time. That is, in (6) I let $\epsilon_{kit} = \mu_{ki} + \eta_{kit}$ for each alternative k , where the random effect μ is normal and iid across individuals and η is normal and iid across individuals and time.²³ Both μ and η are assumed to have a mean of zero. The variances of two of the three random effects can be identified.

²²Since the probabilities are between 0 and 1, they are differentiable and their variances can be computed using the "delta method."

²³Due to the estimation program used, a balanced panel was necessary in order to perform these estimations. My sample is not a balanced panel. It was therefore artificially balanced by dropping observations on some individuals. The resulting balanced panel included four time periods with observations on 767 LHSM, 556 GHSM, 597 LHSF, and 650 GHSF. Note that the process of creating a balanced panel is exogenous to the sample.

Table III
Two-Tailed Tests for Equality of Turnover Probabilities
Significance Level = 0.05
Normal Test Statistic in Parentheses

	Job-to-Job Probability*	Job-to- Nonemployment Probability*	Stay on the Job Probability*
LHS-M vs GHS-M	Do Not Reject (0.317)	Reject (3.406)	Do Not Reject (1.421)
LHS-M vs LHS-F	Reject (5.696)	Reject (6.326)	Do Not Reject (1.277)
LHS-M vs GHS-F	Do Not Reject (0.270)	Do Not Reject (1.832)	Do Not Reject (2.469)
GHS-M vs LHS-F	Reject (5.418)	Reject (9.132)	Reject (2.538)
GHS-M vs GHS-F	Do Not Reject (0.555)	Do Not Reject (1.580)	Do Not Reject (0.887)
LHS-F vs GHS-F	Reject (5.322)	Reject (7.835)	Reject (3.583)

*Evaluated at group means.

LHS-M: Males, less than or equal to high school education

GHS-M: Males, greater high school education

LHS-F: Females, less than or equal to high school education

GHS-F: Females, greater high school education

Table IV Estimates of the Standard Deviations of Individual Random Effects (T-Statistics for Null Hypothesis that Standard Deviation Equals One in Parentheses)				
	Estimated Standard Deviation of RE		Estimated Standard Deviation of RE Means of Tenure & Experience Included in Estimation	
	JJ Equation	JNE Equation	JJ Equation	JNE Equation
LHSM	1.125 (0.819)	1.149 (1.134)	1.111 (0.637)	1.163 (1.240)
GHSM	1.008 (0.045)	1.244 (8.571)	1.015 (0.914)	1.241 (3.084)
LHSF	1.016 (0.118)	1.241 (4.921)	1.021 (0.156)	1.239 (5.437)
GHSF	1.017 (0.199)	1.240 (5.246)	1.001 (0.005)	1.246 (13.898)

As illustrated in the second column of Table IV, for all groups except LHSM, the estimated standard deviation of the random effect in the JNE equation is significantly different from one. In contrast, the null hypothesis of $\sigma_{\eta JJ}=1$ in the JJ equation cannot be rejected for any of the four groups.

In order to compare the RE specification with the previously reported results, one-period probabilities were calculated by evaluating the probabilities at the mean of the random effects and adjusting the one-period standard deviation to account for the additional variance

term allowed in the random effect specification.²⁴ Comparing the RE model with the first set of results, I find first that the JJ turnover by tenure profile for LHSF changes with the addition of the random effects. Figure 8 shows that when random effects are included, the JJ turnover of this group turns up at about five years of tenure.

More interestingly, I also find that the JNE turnover of LHSF looks more like that of the other three groups when RE's are included in the estimation. For example, Figure 9 shows that the JNE turnover by the real wage looks very similar for less educated men and women in this specification.

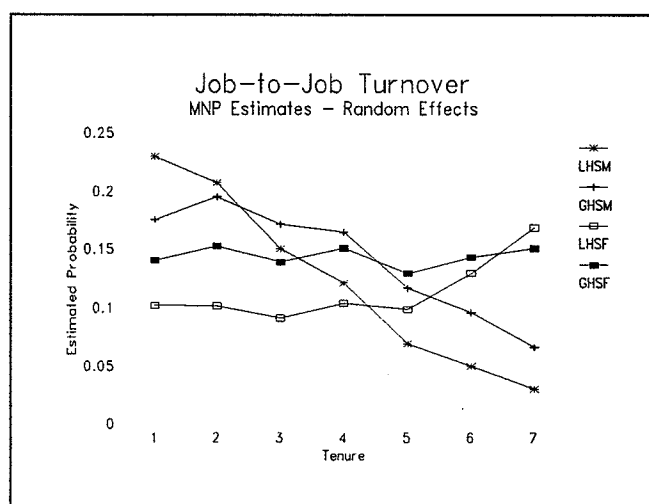


Figure 8

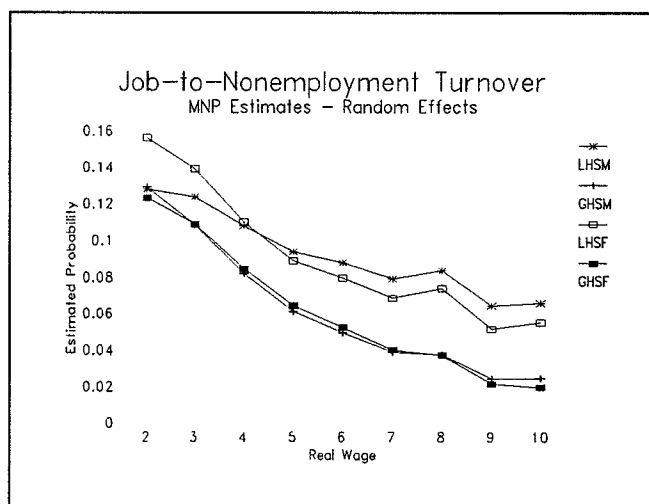


Figure 9

When tests of a sequence of turnover choices are performed, however, the equality of the turnover behavior of less educated women compared to the other groups can still be rejected in the RE model. Three sequences of choices were considered. P_{JJ4} is the four

²⁴The joint probability in a model that allows correlation in the unobservables over time is the probability of a sequence of choices. Tests across groups for different choice sequences are presented below.

period sequence defined as stay on the current job for three periods and leave for a new job in the fourth period. P_{JNE4} is defined as stay on the job for three periods and leave for nonemployment in the fourth period. P_{s4} is the sequence where the worker stays at the current job for all four periods. Tests for the equality of P_{JJ4} , P_{JNE4} , and P_{s4} across groups were conducted. The equality of P_{JJ4} and P_{JNE4} for LHSF versus GHSM and GHSF is rejected at a significance level of 0.05. Equality is rejected for LHSF versus LHSM at a significance level of 0.10. The equality of these turnover probabilities for less educated men, more educated men, and more educated women cannot be rejected.

As described in Section V, the unobservable random effects, μ_{ki} , may be correlated with tenure on the job and labor market experience since tenure and experience result from previous turnover decisions. Such correlation between the unobservables and the explanatory variables causes biased estimates. One way to correct for this problem is to put some structure on the form of this correlation. I proceed by assuming that this correlation can be represented as follows:

$$\begin{aligned}\mu_{JJi} &= \alpha_{JJ} \bar{T}_i + \mu'_{JJi} \\ \mu_{JNEi} &= \alpha_{JNE} \bar{X}_i + \mu'_{JNEi}\end{aligned}\tag{8}$$

where μ_{JJ} is the random effect in the JJ equation, μ_{JNE} is the random effect in the JNE equation, and μ'_{JJ} and μ'_{JNE} are random effects that are uncorrelated with the explanatory variables. $\bar{T}_i$ is the average tenure over the panel for worker i and $\bar{X}_i$ is the average level of experience for worker i over the panel. A second set of RE estimations were performed that included average tenure as an explanatory variable in the JJ equation and average experience as an explanatory variable in the JNE equation. Likelihood ratio tests rejected the

specification without these two variables in favor of their inclusion for all sex and education groups. As shown in Table IV, the estimates of the standard deviations of the random effects are similar in size to the estimates when the average values of tenure and experience are not included in the estimation. The estimated coefficient on average tenure is negative and significant as predicted for GHSM and GHSF but is insignificant for both LHSM and LHSF. The estimated coefficient on average experience is not significant for any group.

The major difference between the estimates obtained in this model and those previously reported shows up in the JJ-tenure profile.²⁵ As can be seen in Figure 10, for three of the groups, I now find rising job-to-job turnover with tenure, conditional on the wage and the individual's average level of job tenure

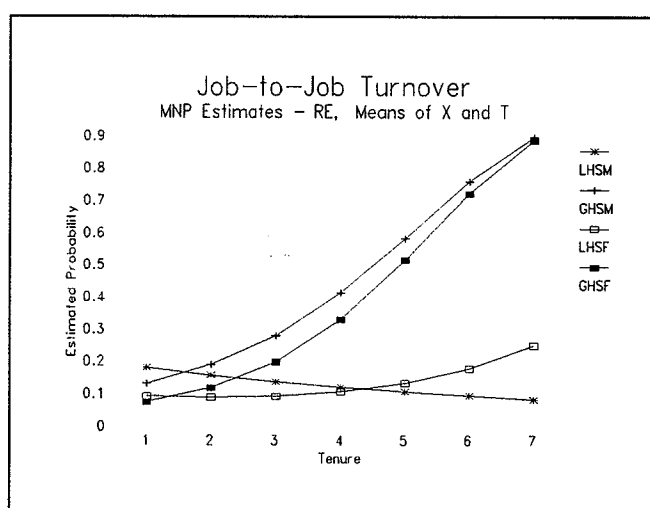


Figure 10

over the panel. This is in accordance with the predictions of the matching model.

Figure 11 illustrates that this RE specification also produces estimates for LHSF and LHSM that imply that the JNE turnover of these two groups is more similar than it looks in the models previously discussed. Hypothesis tests indicate that the equality of the P_{JJ4} (stay, stay, stay, JJ transition) probability sequence is still rejected for less educated women and the three other groups. However, P_{JNE4} (stay, stay, stay, JNE transition) for LHSF is estimated

²⁵One-period probabilities were again calculated by evaluating the probabilities at the mean of the random effects and adjusting the one-period standard deviation to account for the additional variance term allowed in the RE specification.

with much less precision in this specification²⁶ making it impossible to reject equality for any pairwise comparison of the JNE probability sequence for LHSF with the other groups. Nonetheless, as a whole the RE estimations do not change the conclusions reached previously. Less educated

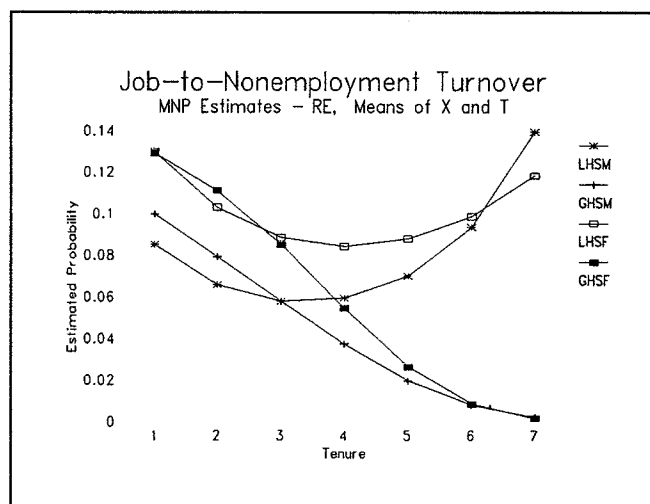


Figure 11

women stand out as having different turnover patterns than more educated women or either group of men while the three other groups look substantially the same.

VII. ESTIMATING THE RESERVATION WAGE

In this section, I present an additional test of the equality of men's and women's turnover that focusses the analysis more precisely on job matching behavior. This is accomplished by testing whether or not the reservation wages and offers of the four groups are equal. As previously discussed, the job-to-job reservation offer and job-to-nonemployment reservation wage are "trigger" wages. At a current wage below the JNE reservation wage the worker leaves the job for nonemployment. At or above that wage, he or she does not leave for nonemployment. The decision is made in the same way with the JJ reservation offer except that the transition under consideration is to a new job. In this

²⁶In this specification its standard error is 0.0211 versus a standard error of 0.0061 in the previous RE model.

section, I develop a method for estimating these reservation wages using the parameters estimated by multinomial probit.

Before describing this estimation procedure in more detail some terms must be clarified. For simplicity, first consider an individual worker's problem in a deterministic setting with no unobserved heterogeneity. The JNE reservation wage (w_{Nt}^R) is the wage that triggers a decision to leave the current job for nonemployment. From equation (5), this trigger wage can be defined by setting the wage of individual i equal to that worker's reservation wage given that the two best of the three alternatives is either staying or moving to nonemployment:²⁷

$$Z_{it}^N \gamma_{Nt}^N = w_{Nt}^R. \quad (9)$$

Holding constant all other variables, w_{Nt}^R is the wage at which individual i at time t would be indifferent between leaving employment and staying at the same job.

The JJ reservation wage (w_J^R) requires somewhat more clarification. The JJ turnover equation (3) is specified in terms of a reservation offer. The reservation offer is the offer at which the worker is just indifferent between taking a new job and staying on the old job. Clearly, however, as shown in equation (2), the reservation offer depends on the current wage. The JJ reservation wage is defined to be the value of the current wage that would shift the reservation offer to the point where the worker is indifferent between staying on the

²⁷This condition is a result of the increase in complexity associated with a three state search and matching model as opposed to the two-state case. In the two-state case the JNE reservation wage is defined simply by equation (9) without the condition on the value of an alternative offer. A similar condition, which is described below, must be imposed when defining the JJ reservation wage.

job and taking a new job offer. The JJ reservation wage is simply a transformation of the reservation offer that allows one to consider the current wage, the JNE reservation wage, and the JJ reservation wage in the same dimension. Again considering the deterministic problem, the JJ reservation wage for individual i is defined by the following two equations. Setting the wage offer of individual i equal to the reservation offer of that individual (see equations (1) and (2)) yields the following:

$$\beta_0 + \beta_x X_{it} = \gamma'_0 + \gamma'_w w_{ijt} + \gamma'_T T_{it}. \quad (10)$$

A simple transformation to a JJ reservation wage as described above is obtained by rewriting equation (10) as

$$\frac{(\beta_0 - \gamma'_0) + \beta_x X_{it} - \gamma'_T T_{it}}{\gamma'_w} = w_{jit}^R. \quad (11)$$

Holding all other variables constant and given that a new job and staying on the job rank above the nonemployment option, w_{jit}^R is the trigger wage for a JJ transition for individual i at time t .

Equation (9) and equation (11) and the stated conditions define the JNE and JJ reservation wages for individual i if no unobservable heterogeneity affects this worker's reservation offer or reservation wage. Incorporating such unobservable heterogeneity changes these definitions only slightly. Each of these reservation wages will now include a component that is known to the individual but unobservable to the econometrician. In this case equations (9) and (11) can be rewritten as

$$Z_{it}^N \gamma^N + \alpha_{it}^N = w_{Nit}^R \quad (12)$$

for the job-to-nonemployment reservation wage and

$$\frac{(\beta_0 - \gamma_0') + \beta_x' X_{it} - \gamma_T' T_{it} + (\phi_{ikt} - \alpha_{it}')}{\gamma_w'} = w_{Jit}^R \quad (13)$$

for the job-to-job reservation wage. Allowing for a distribution of unobserved heterogeneity in the turnover equations across individuals generates a distribution of JJ and JNE reservation wages across individuals.

If consistent estimates of the β and γ vectors were available and if $E[\phi - \alpha'] = 0$ and $E[\alpha^N] = 0$, then consistent estimates of w_{Nit}^R and w_{Jit}^R could be obtained by substituting the consistent estimates of β and γ into equations (9) and (11). As is well known, however, discrete choice models are identified only up to a scale parameter. Since this is a discrete choice problem, the scale of the multinomial probit estimates of β and γ is unidentified and an estimate of the two reservation wages cannot be obtained in the way just described.

The scale problem associated with discrete choice models results from having data only on the alternative chosen and not on the level of the underlying utilities of the various alternatives. In terms of the discrete choice framework specified above in equation (6), this means knowing only that, say, $(y_1 > y_2)$ and $(y_1 > y_3)$ but not the levels of y_1 , y_2 , or y_3 . The likelihood function of a discrete choice model must therefore be written in terms of the

probability of a particular alternative being chosen.²⁸ The resulting estimates cannot therefore be used to predict the levels of y_1 , y_2 , or y_3 but can be used to predict the probability of a given alternative.

Because of the discrete nature of the problem, in order to obtain estimates of the JJ and JNE reservation wages, these reservation wages must be interpreted in terms of turnover probabilities. In a manner somewhat analogous to the probit likelihood function, estimates of the two reservation wages can be expressed implicitly in terms of the turnover probabilities. To clarify this concept, let $V_s(Q)$ be the value of staying at the current job, $V_{JJ}(Q)$ the value of leaving the job for a new job, and $V_{JNE}(Q)$ the value of leaving the current job for nonemployment for an individual with known characteristics Q . Equations (9) and (11) describe the deterministic world where, in order to solve for the reservation wages, we set $V_s(Q) = V_{JJ}(Q)$ and $V_s(Q) = V_{JNE}(Q)$. Equations (12) and (13) describe a world with uncertainty where, in order to solve for the reservation wages, we set $V_s(Q) + \xi_s = V_{JJ}(Q) + \xi_{JJ}$ and $V_s(Q) + \xi_s = V_{JNE}(Q) + \xi_{JNE}$ where ξ_k is the unobservable component of the value of alternative k to the individual. As just described, due to the nature of the problem, it is not possible simply to solve these two equations for the reservation wages. Therefore I solve this problem by moving to probability space. Since the ξ 's are continuous random variables, $P(V_s(Q) + \xi_s = V_{JJ}(Q) + \xi_{JJ}) = 0$ and

²⁸For example, take a discrete choice problem with two alternatives. Worker i chooses the first alternative if $y_i = X_i\beta + \epsilon_i > 0$. In this case define an index variable $D_i = 1$. If the second alternative is chosen the inequality is reversed and $D_i = 0$. Let the sample consist of N individuals. Then the probit likelihood function for this problem is:
$$\prod_{i=1}^N [1 - \Phi(\frac{-X_i\beta}{\sigma})]^{D_i} [\Phi(\frac{-X_i\beta}{\sigma})]^{(1-D_i)}$$
 Where Φ is the standard normal cumulative distribution function and σ is the standard deviation of ϵ .

$P(V_s(Q) + \xi_s = V_{JNE}(Q) + \xi_{JNE}) = 0$. However, I can reexpress this concept by setting

$P(V_s(Q) + \xi_s > V_{JJ}(Q) + \xi_{JJ}) = P(V_s(Q) + \xi_s < V_{JJ}(Q) + \xi_{JJ})$ and $P(V_s(Q) + \xi_s >$

$V_{JNE}(Q) + \xi_{JNE}) = P(V_s(Q) + \xi_s < V_{JNE}(Q) + \xi_{JNE})$.

Or in terms of the previous notation, the JJ reservation wage estimate will be defined by setting the probability of staying on the job equal to the probability of leaving for a new job:

$$\begin{aligned} P\left(\frac{(\beta_0 - \gamma'_0) + \beta_x X - \gamma'_T T + (\phi - \alpha')}{\gamma'_w} > \hat{w}_{JJ}^R, \beta_0 + \beta_x X + \phi \geq Z\gamma^N + \alpha^N\right) = \\ P\left(\frac{(\beta_0 - \gamma'_0) + \beta_x X - \gamma'_T T + (\phi - \alpha')}{\gamma'_w} \leq \hat{w}_{JJ}^R, \hat{w}_{JJ}^R \geq Z\gamma^N + \alpha^N\right). \end{aligned} \quad (14)$$

And the JNE reservation wage estimate is defined by setting the probability of staying at the current job equal to leaving that job for nonemployment:

$$\begin{aligned} P(Z\gamma^N + \alpha > \hat{w}_{JNE}^R, Z\gamma^N + \alpha > \beta_0 + \beta_x X + \phi) = \\ P(Z\gamma^N + \alpha \leq \hat{w}_{JNE}^R, \hat{w}_{JNE}^R \geq \frac{(\beta_0 - \gamma'_0) + \beta_x X - \gamma'_T T + (\phi - \alpha')}{\gamma'_w}). \end{aligned} \quad (15)$$

More concisely, equations (14) and (15) are written

$$\begin{aligned} \hat{P}_{stay}(\hat{w}_{JJ}^R, T, X, A) &= \hat{P}_{JJ}(\hat{w}_{JJ}^R, T, X, A) \\ \hat{P}_{stay}(\hat{w}_{JNE}^R, T, X, A) &= \hat{P}_{JNE}(\hat{w}_{JNE}^R, T, X, A) \end{aligned} \quad (16)$$

where P_{stay} , P_{JJ} , and P_{JNE} are defined as the probability of staying at the current job, the probability of leaving the job for a new job, and the probability of leaving the job for non-employment and where A is a matrix of all explanatory variables except the wage (w), tenure

(T), and experience (X). Given the estimated parameters from the MNP estimations, the probabilities that form these two equations can be calculated. This provides a mechanism for estimating the implied reservation wages.²⁹

Actual estimates of w_J^R and w_N^R were obtained by a grid search procedure. Given the mean levels of the explanatory variables other than the wage, the three predicted probabilities $\hat{P}_{stay}(w, T, X, A)$, $\hat{P}_{JJ}(w, T, X, A)$, and $\hat{P}_{JNE}(w, T, X, A)$ were calculated for each trial wage and a search procedure produced the two wages that most closely satisfied (16).³⁰ It can be seen from (16) that these estimates can be calculated for a series of tenure or experience levels, thereby creating estimated reservation wage-tenure or wage-experience profiles. All variables other than the wage and either tenure or experience were held constant at the group averages in the calculations of the estimated probabilities. This procedure produces an estimated reservation wage or wage profile for the average individual in each group. I use these estimates to test the equality of the job matching behavior of men and women by education level.

²⁹This procedure depends crucially on the time interval during which offers are received and decisions made for identification of the levels of the reservation wages. If, for example, the time interval considered was one month rather than one year, it would take a smaller wage to equate the probability of staying on the job to the probability of leaving the job for a new job or for nonemployment. Nonetheless, the levels of the reservation wages that are implied are the same for the four groups. Therefore, tests of the equality of the reservation wage across groups remain valid despite this caveat. This procedure also depends on the assumption that the parameters of the model do not depend on wages -- an assumption that is also implicit in the maximum likelihood method used to obtain the MNP estimates.

³⁰Defined as equal to at least three decimal places.

Table V Estimated Reservation Wages by Sex and Education Group Standard Errors in Parentheses*		
	Job-to-Job Reservation Wage**	Job-to- Nonemployment Reservation Wage**
Males - LHS	-4.89 (0.29)	-8.90 (0.32)
Males - GHS	-2.06 (0.22)	-2.93 (0.12)
Females - LHS	-16.53 (0.35)	-18.45 (1.76)
Females - GHS	-1.91 (0.09)	-2.30 (0.11)
*The calculation of the variance of the estimated reservation wage is described in footnote 32. **Adjusted by mean and standard deviation of the real wage by group.		

The estimated reservation wage and standard errors for the average member of each of the four groups is presented in Table V.³¹ These estimates partially confirm the results outlined above that men and women with more than a high school education are similar in their turnover patterns.³² The equality of the JJ reservation wage for GHS men and GHS

³¹The following section will discuss a possible source of bias which may cause these estimates of the reservation wage to be negative. I show in that section that despite this possible bias these estimates can be used to test for equality of the matching behavior of men and women. Because of this possible bias, however, I will not discuss the size of these estimates. The estimates of the reservation wage will be used solely to test for whether or not matching behavior is equivalent for the four groups.

³²The variances of the reservation wage estimates were obtained using the "delta method." The expressions for the necessary derivatives of the reservation wage with respect to the MNP parameters were obtained by differentiation of the equations in (16).

women cannot be rejected while the equality of the JNE reservation wage for the two groups is rejected. Equality of the JJ and JNE reservation wages of less educated women with all other groups is strongly rejected. The same is true for less educated men. Once again, LHS women show the strongest differences from the other groups. In fact, at tenure levels of greater than three years no JJ reservation wage can even be calculated for this group. Given the MNP estimates for less educated women, there is no wage that equalizes the probability of staying on the job and the probability of leaving for a new job. This result might be interpreted to mean that one or more of the assumptions of the matching model that assure that the reservation wage property will hold are violated in the case of LHS women.

VIII. POSSIBLE BIASES AND EFFECTS ON COMPARISONS BY GROUP

A. SAMPLE SELECTION BIAS

Through their neglect of sample selection, turnover studies implicitly assume that turnover from a job is independent of the probability of being in the sample. Since being in the sample is defined by a person's having a job, this assumption may not be very plausible. The assumption just described is harder to justify once individual random effects are introduced. In a 3-state case with random effects, the econometrician acknowledges the possibility of the persistence of unobservable individual heterogeneity over time in a worker's preferences for changing jobs, leaving for nonemployment, or staying on the same job. In order to avoid sample selection problems, however, no correlation can be allowed between

labor market entry or reentry decisions and current job turnover decisions.³³ In order to be confident that any differences in sample selection bias across groups do not change the conclusions put forward in this paper, I now present some evidence on the possible effects of such sample selection.

The sample selection problem is that the JJ or JNE turnover probability conditional on a worker's being in the sample may not be equal to the unconditional JJ or JNE probability. This possibility seems particularly likely in the case of the JNE probability since one might expect that a person who is currently not employed has a higher propensity for choosing nonemployment than a person who is currently employed. Therefore, I will focus on possible sample selection bias in the estimated probability of JNE turnover.

In the context of the comparison of men and women by education group undertaken in this paper, the most relevant aspect of the sample selection problem is whether or not sample selection bias differs by group. Although I cannot quantify the size of these possible biases, I can show the extent to which sample selection bias would have to differ by group in order to change the hypothesis test results presented above.

By the laws of probability,

³³Also, with the introduction of such time-persistent unobservables the initial conditions problem will arise (Heckman [1981a]). It may be possible to solve the initial conditions problem in my case since this sample includes men and women who are young enough that I observe their entry into the labor market in which case the initial condition could be assumed to be exogenous. Initializing the process at this point, however, raises questions about endogenous sample selection when comparing workers of different education levels.

$$P_{JNE} = P_{JNE|A} * P(A) + P_{JNE|B} * P(B) \quad (17)$$

when A and B are two mutually exclusive and exhaustive events. Let A be the event of being in the sample and B be the event of not being in the sample. Ideally, I would test for the equality of P_{JNE} across groups. Instead I am able only to obtain group estimates of $P_{JNE|A}$ for each group. A sample selection bias in my group comparisons may occur if the difference between $P_{JNE|A}$ and $P_{JNE|B}$ varies across groups or if the probability of being in the sample differs across groups. For example, one might speculate that $P_{JNE|B}$ is larger for women than for men. Although I have no information on $P_{JNE|B}$, I do have data on the proportion of each sex and education group that is included in my sample of workers. These proportions can be used as estimates for P(A) and P(B). With estimates of $P_{JNE|A}$, P(A), and P(B),³⁴ I can calculate how large the discrepancies in $P_{JNE|B}$ would have to be by group in order to change the test results cited above.

The most marginal test result in the tests comparing men and women is that between GHSM and GHSF in their JNE probability. I have substituted possible alternative values for $P_{JNE|B}^{GHSM}$ and $P_{JNE|B}^{GHSF}$ into equation (17) to assess how strongly these unknown probabilities would have to differ in order to overturn the result that the JNE probability of more highly educated women is insignificantly different from that of more highly educated men. Such substitutions show that $P_{JNE|B}^{GHSF}$ would have to be approximately 25% larger than $P_{JNE|B}^{GHSM}$ in

³⁴Estimates of P(A) by group are as follows: LHSM 0.69; GHSM 0.81; LHSF 0.55; and GHSF 0.83.

order to reverse the hypothesis test results. Given the similarity of results found for these two groups throughout this paper, it seems unlikely that there exists a difference of this magnitude in the unknown $P_{JNE|B}$'s. Any modification in the results involving less educated women is even less likely since in this case the unknown $P_{JNE|B}^{LHSF}$ would have to be approximately 20% **smaller** than the unknown $P_{JNE|B}^{LHSM}$. I conclude, therefore, that it is unlikely that sample selection bias is causing incorrect results in my comparisons of the turnover probabilities of men and women.

B. NEGLECT OF TIME PERSISTENT UNOBSERVABLES

Two discrepancies with the formal matching model are found in the reservation wages reported in Table V and in reservation wage profiles that have been calculated as described above (but are not reported here). First, for most levels of tenure or experience the reservation wages by group are estimated to be negative. Second, as discussed in Section V, the prediction of the matching model is that the reservation wage path is increasing with tenure. The JJ reservation wage profiles implied by my estimates are found to be decreasing with tenure for each of the four groups. Both of these results may well be explained by the possible bias (discussed in Section V above) in the MNP parameter estimates used to generate these reservation wage profiles. In this section, I will discuss this possible source of bias, its potential affect on the reservation wage estimates, and, most importantly for the

goals of this paper, whether or not the possible bias is such that comparisons can still be made across groups.³⁵

As discussed above, if ϵ_3 is positively correlated with tenure, it is expected that the coefficient on tenure in the third equation in (6), δ^3_T , will be biased upward. Now consider how this would affect estimates of the JJ reservation wage. The JJ reservation wage estimate is implicitly defined by the first equality in (16). By the implicit function rule,

$$\frac{\partial \hat{w}^R_J}{\partial \delta^3_T} = \frac{\frac{\partial P_{stay}}{\partial \delta^3_T} - \frac{\partial P_{JJ}}{\partial \delta^3_T}}{\frac{\partial P_{JJ}}{\partial \hat{w}^R_J} - \frac{\partial P_{stay}}{\partial \hat{w}^R_J}}.$$

Since $\frac{\partial P_{JJ}}{\partial \hat{w}^R_J} < 0$, $\frac{\partial P_{stay}}{\partial \hat{w}^R_J} > 0$, $\frac{\partial P_{stay}}{\partial \delta^3_T} > 0$, and $\frac{\partial P_{JJ}}{\partial \delta^3_T} < 0$, $\frac{\partial \hat{w}^R_J}{\partial \delta^3_T}$ must be negative. The positive

correlation of tenure with the unobservable ϵ_3 could therefore explain the negative estimates of the JJ reservation wage.

An upward bias on the coefficient on tenure would also affect the prediction of the matching model that the reservation wage increases with tenure. Since δ^3_T is the coefficient on tenure, if δ^3_T is biased upward then the bias in the estimates of the reservation wage will

³⁵The negative estimates of the reservation wages may also result from the problem described in footnote 29 above. Since the level of the reservation wage estimates depends upon the time period of observation, the negative estimates may be caused by the level of detail available in the survey data. Note, however, that these reservation wage estimates are not unique in being affected by the time interval at which data are available. This is a pervasive problem in econometric estimation. Note also that, as stated in footnote 29, the levels of the reservation wages that are implied are the same for all four groups. Tests for equality of the reservation wages across groups are therefore not affected by this issue.

be a function of tenure. The direction of the possible bias is such that a reservation wage profile that is in fact upwardly sloping could be estimated to slope down with tenure.

The question now is whether the comparisons across groups attempted in this paper can still be made if the bias just described does exist. Under the null hypothesis that the reservation wage of each group is the same, comparisons across groups can be made as long as the extent of the correlation between tenure and the unobservable is the same for each group. Given that the null hypothesis is that all other parameters of the problem are equal across groups, this seems like a reasonable assumption. Therefore, if the null hypothesis of equal matching behavior across groups is not rejected, these group comparisons are valid since any possible bias affecting one group would affect the other equally. If, however, the null is rejected, there is no evidence about the relative size of this potential bias across groups. In this case, equality of the estimated reservation wage profiles can be rejected but further comparisons cannot be made.

The RE specification with the inclusion of average tenure and average experience discussed above is meant to correct the MNP estimates for the problem just described. It does not, however, fully solve the problem for the reservation wage estimates for the following reason. The method developed in this paper for estimating the reservation wages relies on one-period estimates of the probability of staying on the job, leaving for a new job and leaving the job for nonemployment. Yet the random effects model generates probabilities over a sequence of choices. In order to compare the reservation wage estimates under the RE specification to those without RE's, I again evaluated the probabilities at the mean level of the random effects and adjusted the (fixed) variance of the one-period errors to

account for the estimated variance of the random effects. I then calculated reservation wage estimates with these estimates. As predicted, these RE reservation wage estimates were, with two exceptions, greater than those reported in Table V above. The JJ reservation wages for GHSM and GHSF were in this case estimated to be positive.³⁶ Standard errors cannot be calculated for these estimates since the estimates are calculated without taking into account that the variances of the RE's are estimated and not fixed. No firm conclusions can therefore be drawn from this set of reservation wage estimates.³⁷

IX. CONCLUSION

In summary, I conclude that more educated men and women do not differ significantly in their turnover behavior. This result is striking. The sample is young and the data is recent but an often observed and often assumed difference between the labor market behavior of men and women does not hold for this subset of men and women. Less educated men and women, on the other hand, differ significantly in their turnover behavior both from each other and from more highly educated members of their own sex. The strong differences in the job matching process of less educated women and all others is also an important observation.

Interpretation of these results with respect to the unexplained gender wage gap poses a dilemma. Less educated women have the lowest median wages of the four groups under consideration. The wage gap between less educated men and women is also generally

³⁶The estimates were 1.27 and 0.23 for GHSM and GHSF respectively.

³⁷An alternative definition of the reservation wage might be devised based on the probability sequences relevant to the random effects model.

greater than that of more highly educated men and women. The results of this paper showing that the job matching behavior of less educated women differs significantly from all others might be taken as evidence that matching is an important contributor to this wage gap. On the other hand, the equality of the turnover patterns of women and men with greater than a high school education cannot be rejected. Yet the gender wage gap persists for this group as well. Job turnover cannot therefore provide an across-the-board explanation for the gender wage gap.

Appendix A: Average Turnover Probabilities

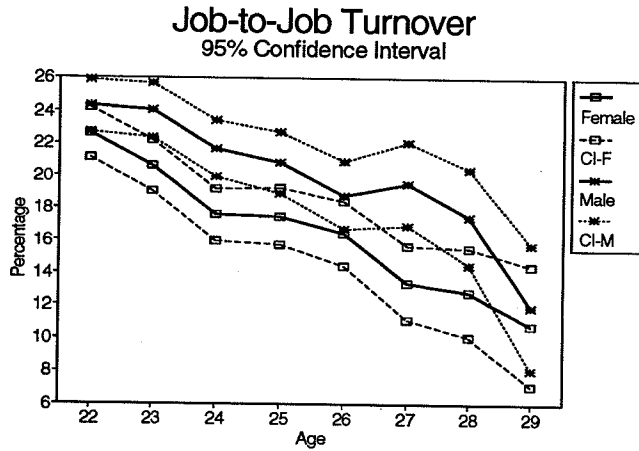


Figure A1

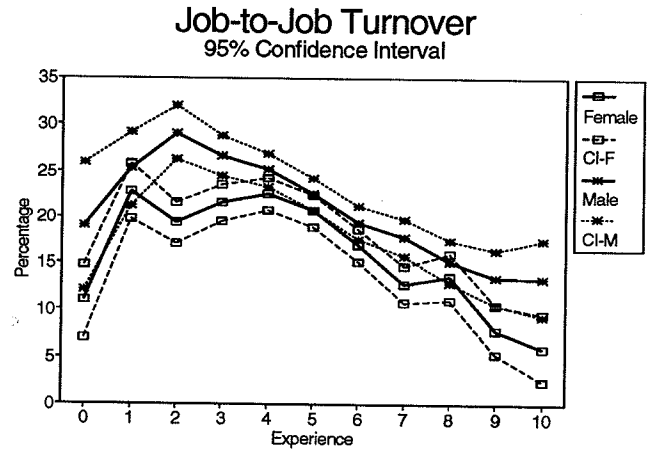


Figure A2

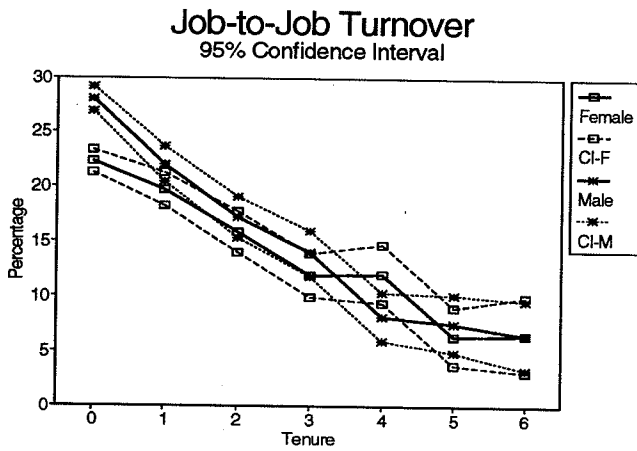


Figure A3

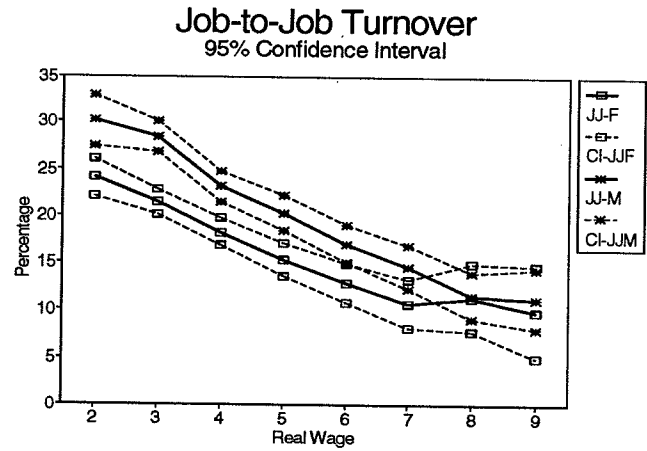


Figure A4

CI-M = Confidence Interval - Males
CI-F = Confidence Interval - Females

Appendix A: Average Turnover Probabilities

Job-to-Nonemployment Turnover
95% Confidence Interval

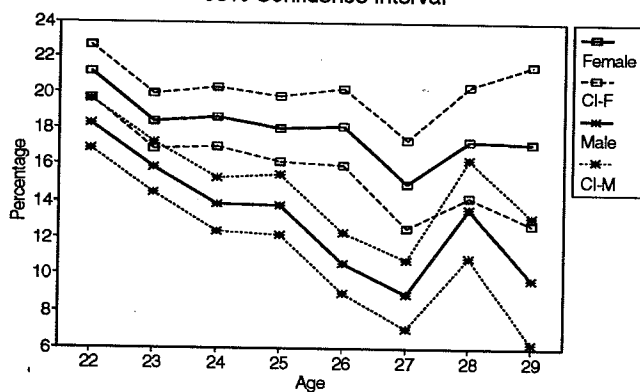


Figure A5

Job-to-Nonemployment Turnover
95% Confidence Interval

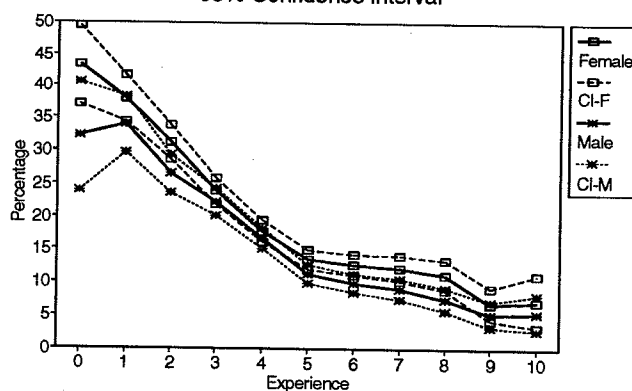


Figure A6

Job-to-Nonemployment Turnover
95% Confidence Interval

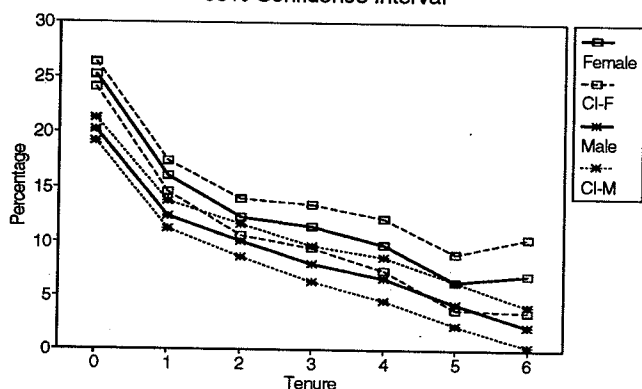


Figure A7

Job-to-Nonemployment Turnover
95% Confidence Interval

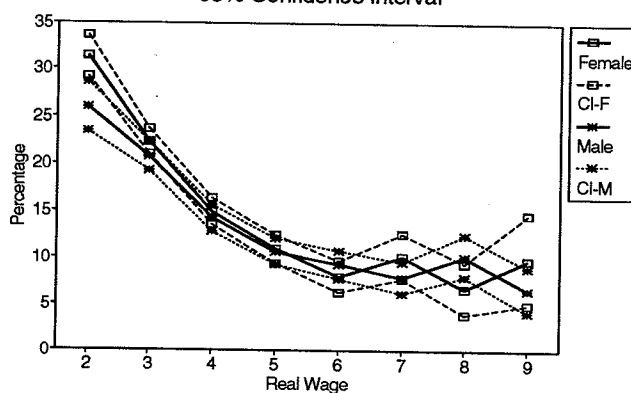


Figure A8

CI-M = Confidence Interval - Males
CI-F = Confidence Interval - Females

Appendix A: Average Turnover Probabilities

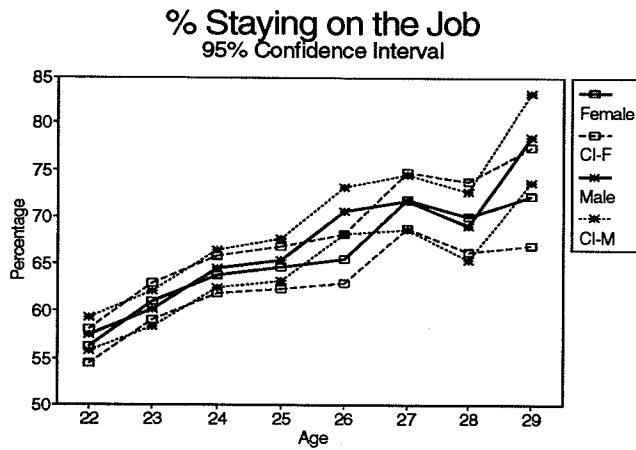


Figure A9



Figure A10

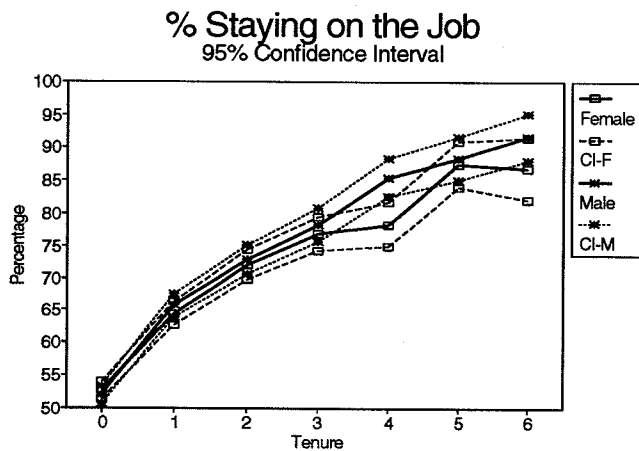


Figure A11

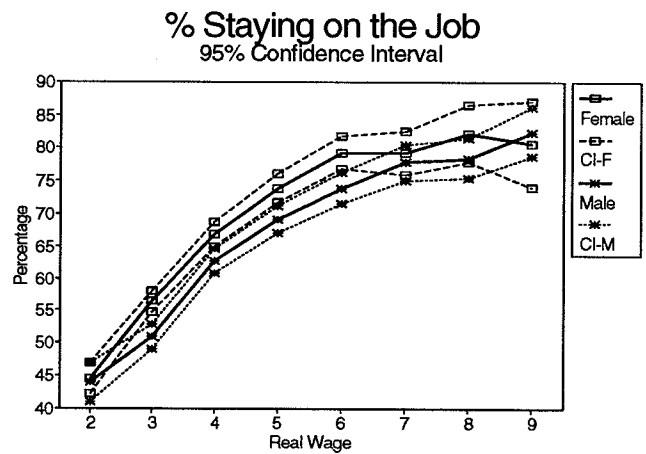


Figure A12

CI-M = Confidence Interval - Males
CI-F = Confidence Interval - Females

Appendix A: Average Turnover Probabilities

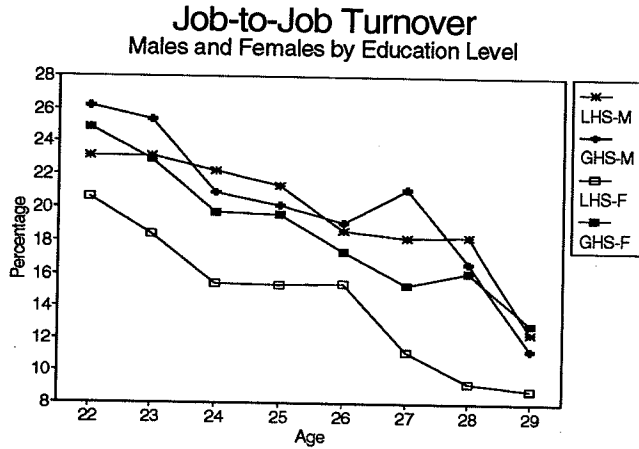


Figure A13

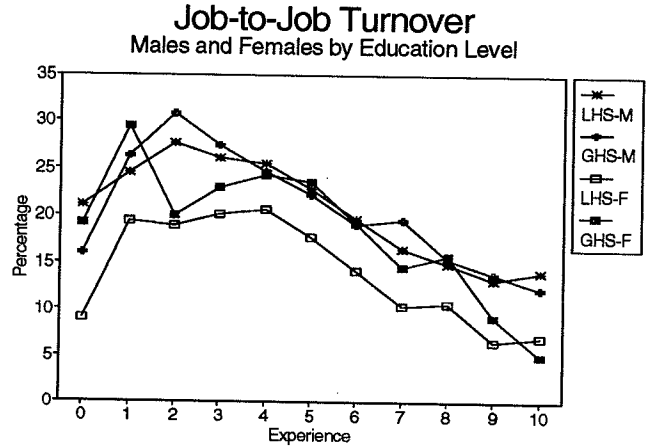


Figure A14

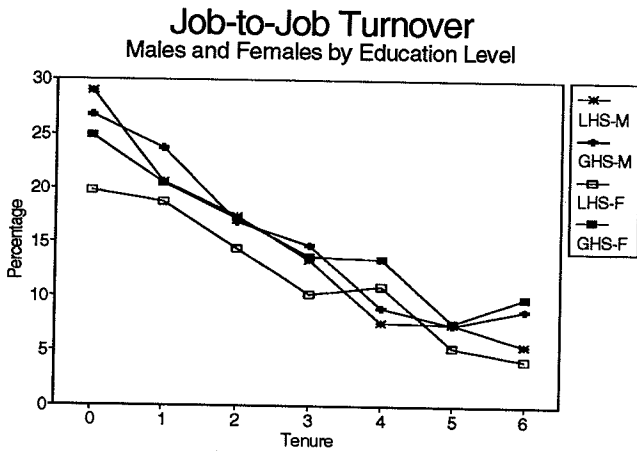


Figure A15

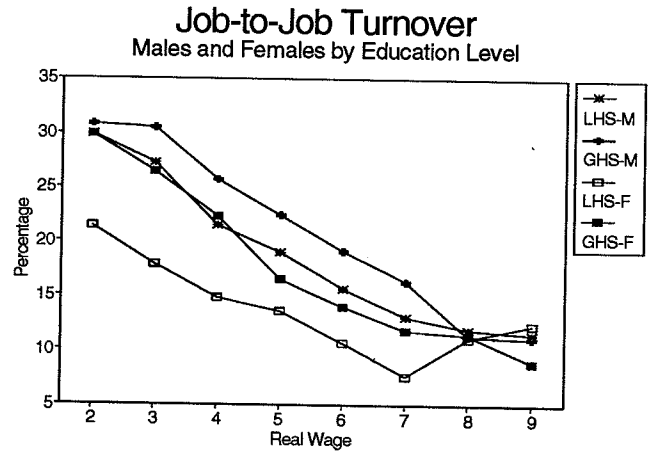


Figure A16

LHS-M = Males, Less than or equal to high school education
 GHS-M = Males, Greater than high school education
 LHS-F = Females, Less than or equal to high school education
 GHS-F = Females, Greater than high school education

Appendix A: Average Turnover Probabilities

Job-to-Nonemployment Turnover
Males and Females by Education Level

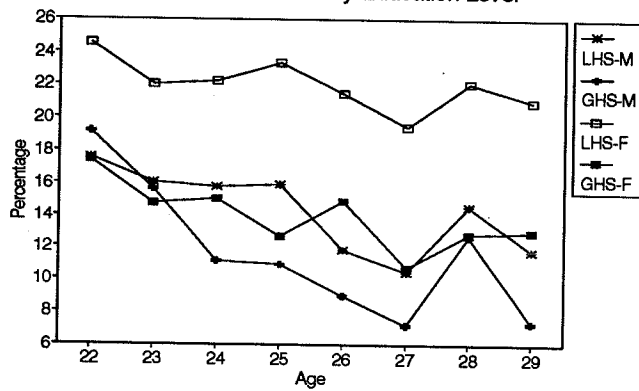


Figure A17

Job-to-Nonemployment Turnover
Males and Females by Education Level

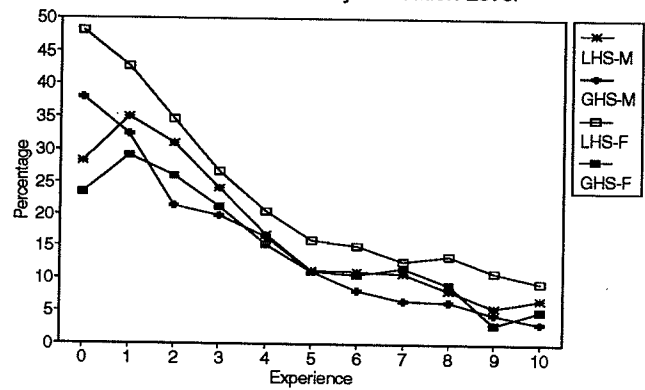


Figure A18

Job-to-Nonemployment Turnover
Males and Females by Education Level

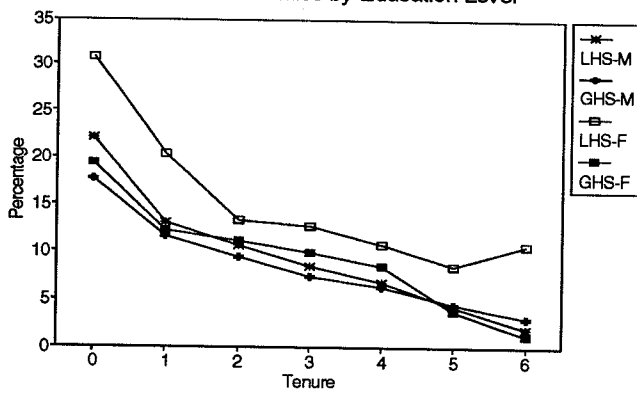


Figure A19

Job-to-Nonemployment Turnover
Males and Females by Education Level

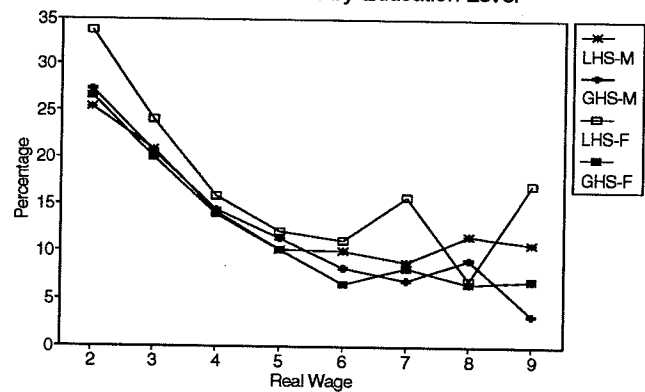


Figure A20

LHS-M = Males, Less than or equal to high school education
 GHS-M = Males, Greater than high school education
 LHS-F = Females, Less than or equal to high school education
 GHS-F = Females, Greater than high school education

Appendix A: Average Turnover Probabilities



Figure A21

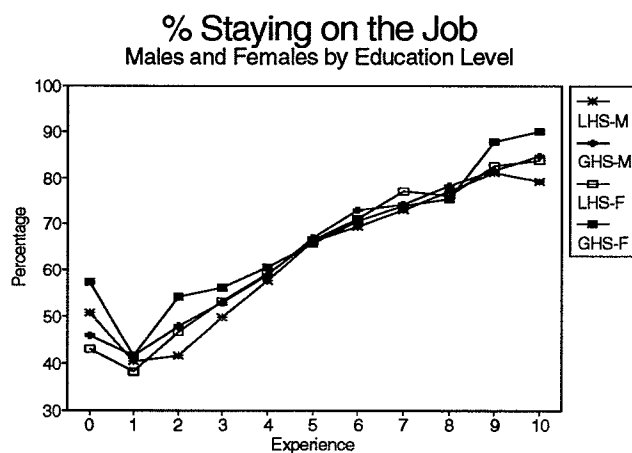


Figure A22

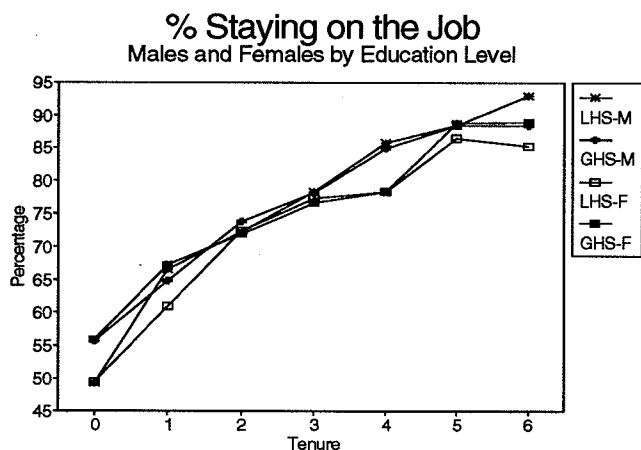


Figure A23

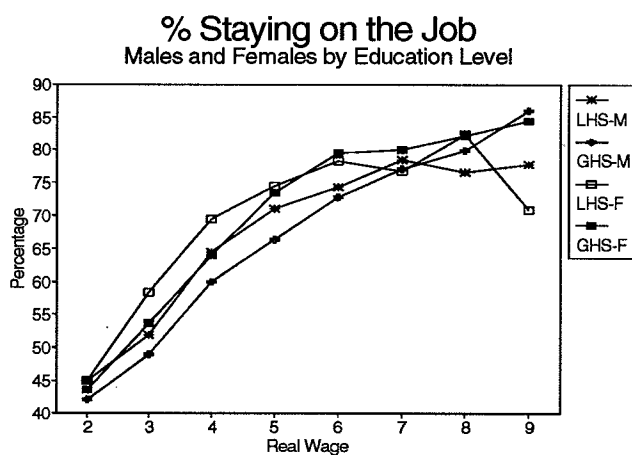


Figure A24

LHS-M = Males, Less than or equal to high school education
 GHS-M = Males, Greater than high school education
 LHS-F = Females, Less than or equal to high school education
 GHS-F = Females, Greater than high school education

Appendix B: MNP Estimated Turnover Probabilities

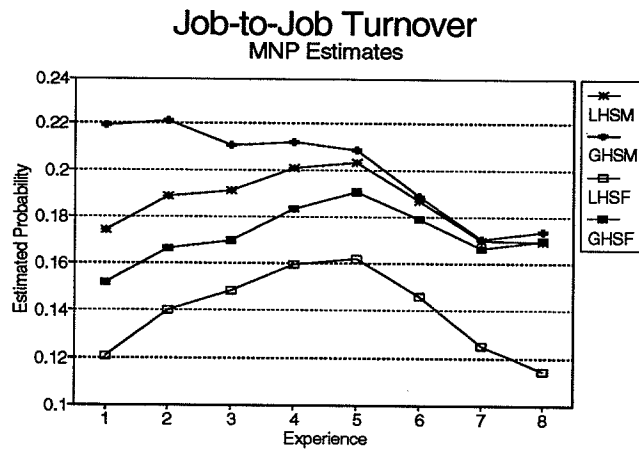


Figure B1

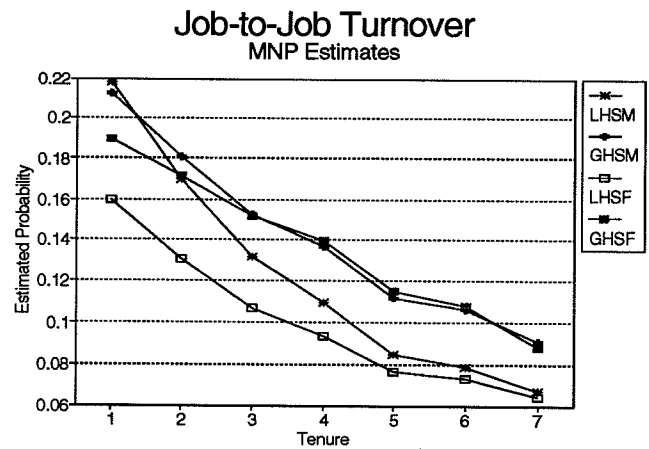


Figure B2

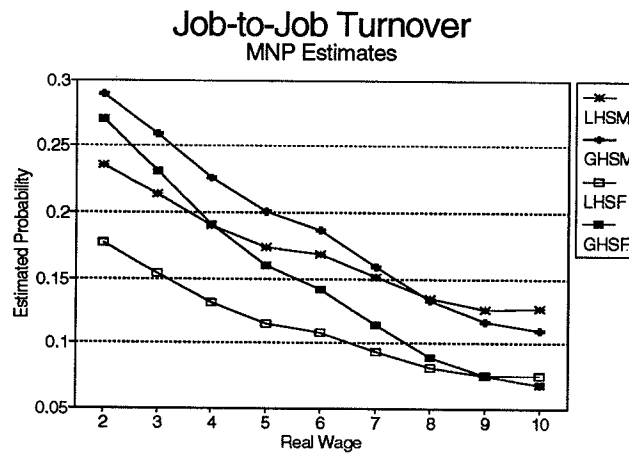


Figure B3

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

Appendix B: MNP Estimated Turnover Probabilities

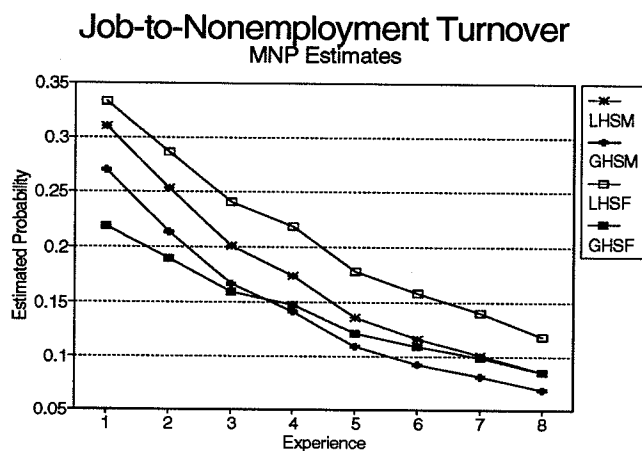


Figure B4

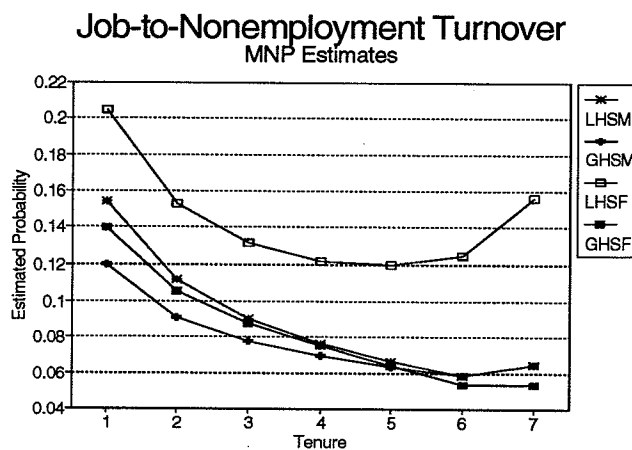


Figure B5

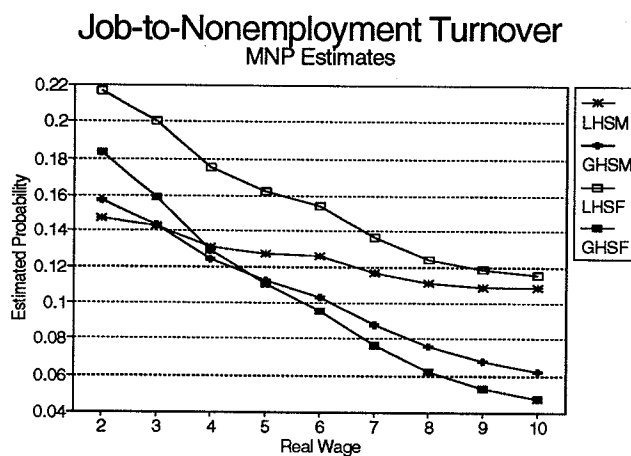


Figure B6

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

Appendix B: MNP Estimated Turnover Probabilities

Stay on the Job Probabilities
MNP Estimates

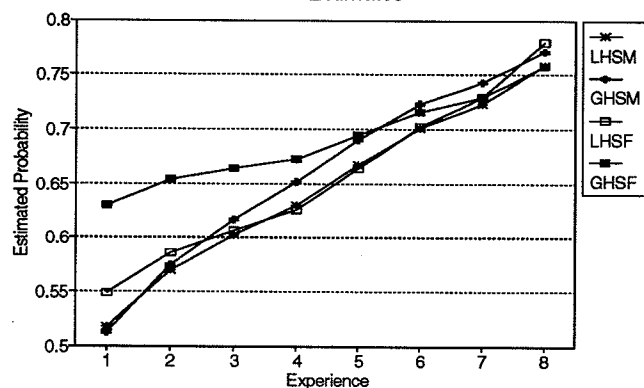


Figure B7

Stay on the Job Probabilities
MNP Estimates

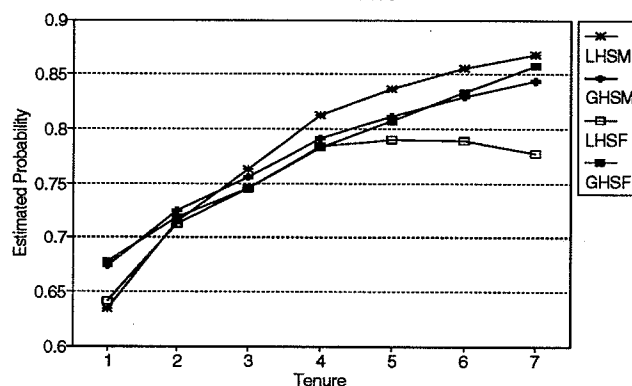


Figure B8

Stay on the Job Probabilities
MNP Estimates

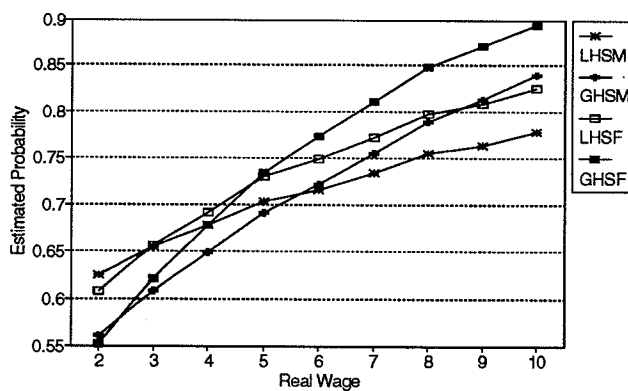


Figure B9

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

Appendix C: MNP Estimated Turnover Probabilities Yearly Observations per Individual

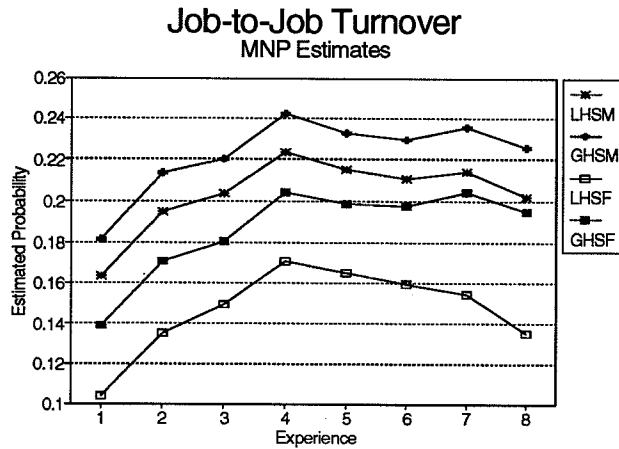


Figure C1

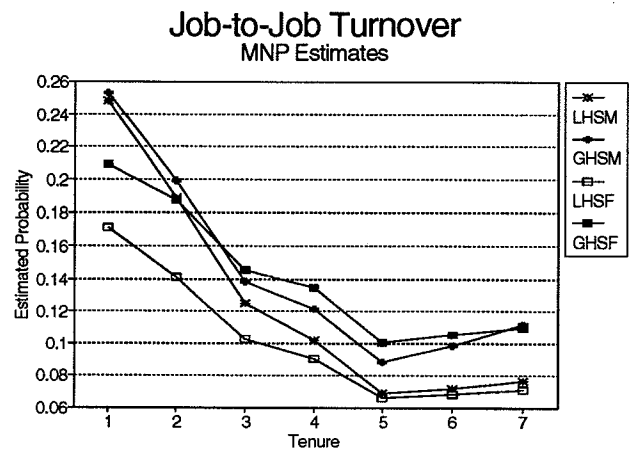


Figure C2

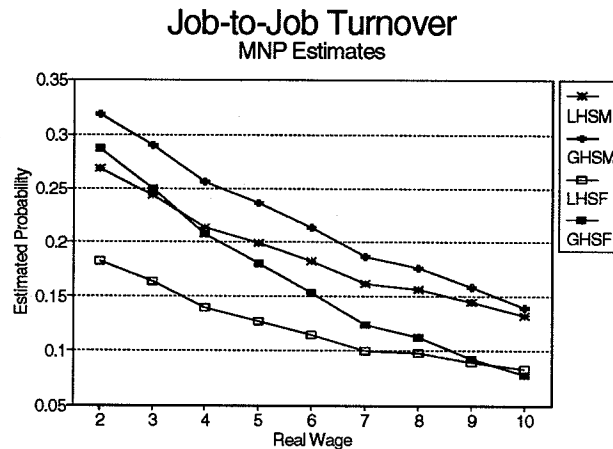


Figure C3

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

Appendix C: MNP Estimated Turnover Probabilities Yearly Observations per Individual

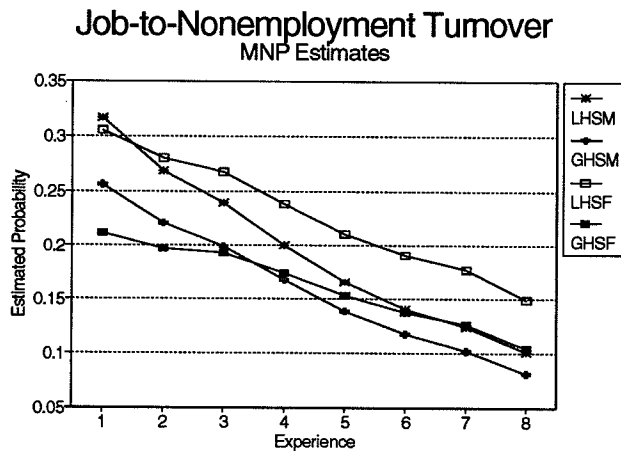


Figure C4

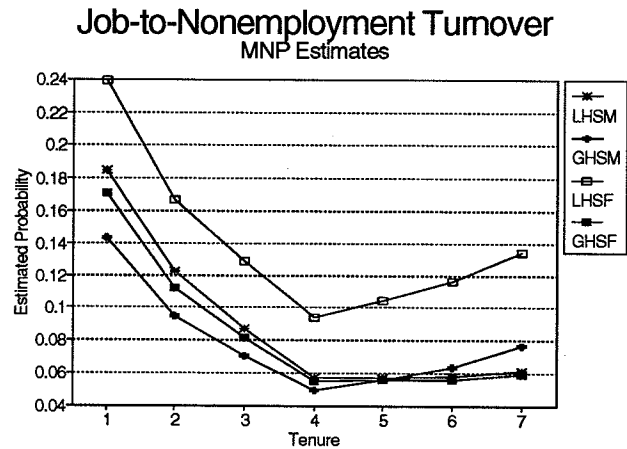


Figure C5

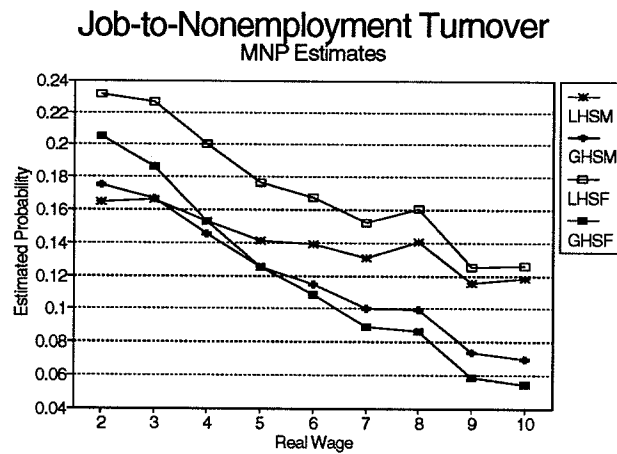


Figure C6

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

Appendix C: MNP Estimated Turnover Probabilities Yearly Observations per Individual

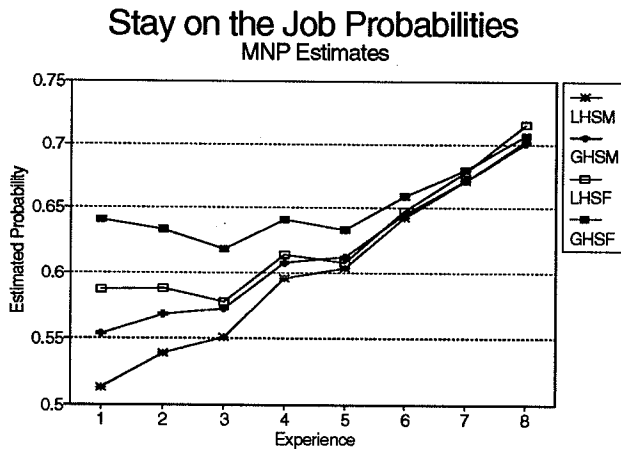


Figure C7

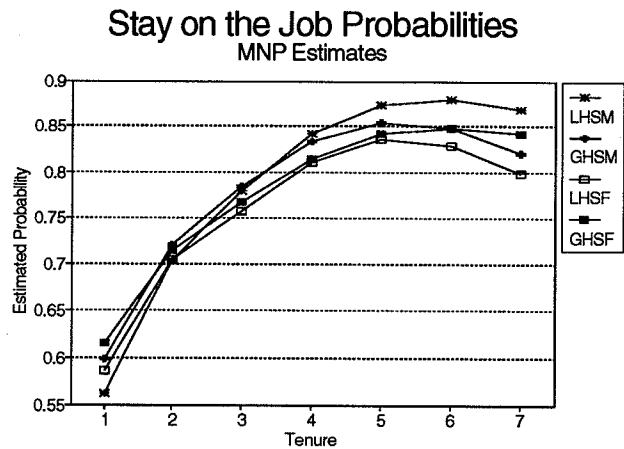


Figure C8

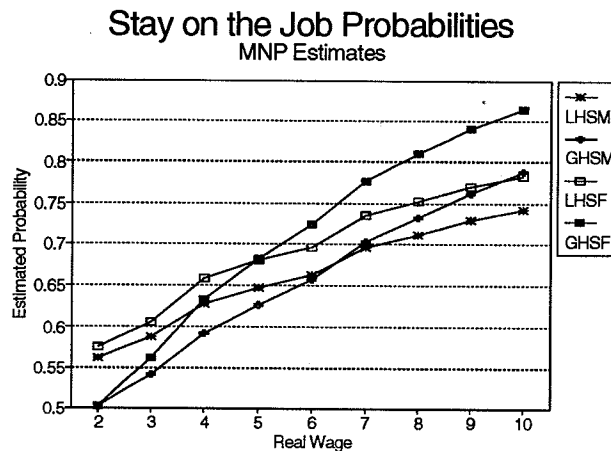


Figure C9

LHSM = Males, Less than or equal to high school education
 GHSM = Males, Greater than high school education
 LHSF = Females, Less than or equal to high school education
 GHSF = Females, Greater than high school education

APPENDIX D - 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.

APPENDIX D
DATA APPENDIX

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NLSY Random Sample Age $\geq$ 22, 1980-87 Means by Sex and Education Level				
	LHSM	GHSM	LHSF	GHSM
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 $\leq$ 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

TABLE E1 Estimated Coefficients - MNP Job-to-Job Turnover Equation Children and Marital Status Included (Standard Errors in Parentheses)				
	LHSM	GHSM	LHSF	GHSF
Wage	-0.120 (0.018)	-0.158 (0.015)	-0.191 (0.037)	-0.240 (0.020)
Wage-squared	0.003 (0.001)	0.002 (0.000)	0.007 (0.002)	0.005 (0.0004)
Tenure	-0.314 (0.041)	-0.172 (0.062)	-0.255 (0.050)	-0.083 (0.055)
Tenure-squared	0.016 (0.006)	0.005 (0.010)	0.016 (0.007)	-0.005 (0.009)
Experience	-0.004 (0.055)	-0.097 (0.067)	0.103 (0.062)	0.058 (0.061)
Experience-squared	-0.007 (0.005)	0.001 (0.006)	-0.018 (0.006)	-0.009 (0.005)
Bad Health Dummy	0.131 (0.162)	-0.053 (0.208)	0.105 (0.146)	-0.129 (0.181)
Union Dummy	-0.285 (0.072)	-0.185 (0.096)	-0.427 (0.095)	-0.471 (0.097)
Asset Income % 1000	0.006 (0.020)	0.016 (0.009)	0.029 (0.021)	0.026 (0.015)
Marital Status Dummy	-0.099 (0.062)	0.102 (0.078)	-0.200 (0.068)	-0.152 (0.069)
Number of Children	0.083 (0.034)	0.057 (0.065)	-0.066 (0.034)	-0.145 (0.062)
Local Unemployment Rate > 6% and ≤ 12%	-0.166 (0.061)	-0.164 (0.067)	-0.220 (0.073)	-0.206 (0.065)
Local Unemployment Rate > 12%	-0.348 (0.089)	-0.282 (0.112)	-0.454 (0.112)	-0.453 (0.108)
Constant	0.345 (0.156)	0.581 (0.189)	0.181 (0.194)	0.315 (0.185)

TABLE E2 Estimated Coefficients - MNP Job-to-Nonemployment Turnover Equation Children and Marital Status Included (Standard Errors in Parentheses)				
	LHSM	GHSM	LHSF	GHSF
Wage	-0.086 (0.026)	-0.152 (0.017)	-0.162 (0.041)	-0.241 (0.020)
Wage-squared	0.002 (0.001)	0.002 (0.000)	0.005 (0.003)	0.005 (0.000)
Tenure	-0.363 (0.048)	-0.259 (0.076)	-0.366 (0.049)	-0.223 (0.061)
Tenure-squared	0.027 (0.008)	0.020 (0.015)	0.038 (0.007)	0.010 (0.011)
Experience	-0.264 (0.056)	-0.311 (0.075)	-0.178 (0.056)	-0.146 (0.068)
Experience-squared	0.009 (0.005)	0.013 (0.007)	0.002 (0.006)	0.003 (0.006)
Bad Health Dummy	0.179 (0.174)	0.063 (0.206)	0.238 (0.134)	0.209 (0.173)
Union Dummy	-0.168 (0.075)	-0.095 (0.106)	-0.330 (0.087)	-0.333 (0.100)
Asset Income % 1000	0.018 (0.015)	0.027 (0.010)	0.053 (0.020)	0.046 (0.018)
Marital Status Dummy	-0.351 (0.067)	-0.272 (0.093)	0.072 (0.065)	0.070 (0.075)
Number of Children	0.227 (0.035)	0.076 (0.078)	0.083 (0.031)	0.197 (0.059)
Local Unemployment Rate > 6% and ≤ 12%	0.071 (0.069)	0.091 (0.079)	-0.096 (0.070)	-0.249 (0.071)
Local Unemployment Rate > 12%	0.298 (0.091)	0.155 (0.120)	-0.026 (0.099)	-0.218 (0.107)
Constant	0.649 (0.160)	0.880 (0.199)	0.696 (0.175)	0.720 (0.186)

TABLE E3 Estimated Coefficients - MNP Job-to-Job Turnover Equation Children and Marital Status Excluded (Standard Errors in Parentheses)				
	LHSM	GHSM	LHSF	GHSF
Wage	-0.122 (0.018)	-0.156 (0.015)	-0.179 (0.036)	-0.236 (0.020)
Wage-squared	0.003 (0.001)	0.002 (0.000)	0.006 (0.002)	0.005 (0.000)
Tenure	-0.320 (0.041)	-0.171 (0.062)	0.245 (0.049)	-0.089 (0.055)
Tenure-squared	0.017 (0.006)	0.005 (0.010)	0.014 (0.007)	-0.005 (0.009)
Experience	-0.009 (0.055)	-0.097 (0.067)	0.124 (0.061)	0.071 (0.060)
Experience-squared	-0.006 (0.005)	0.002 (0.006)	-0.020 (0.006)	-0.011 (0.005)
Bad Health Dummy	0.131 (0.162)	-0.062 (0.207)	0.099 (0.147)	-0.148 (0.181)
Union Dummy	-0.282 (0.072)	-0.180 (0.096)	-0.420 (0.094)	-0.474 (0.096)
Asset Income % 1000	0.006 (0.020)	0.016 (0.009)	0.022 (0.021)	0.022 (0.014)
Marital Status Dummy	---	---	---	---
Number of Children	---	---	---	---
Local Unemployment Rate > 6% and ≤ 12%	-0.161 (0.061)	-0.158 (0.067)	-0.233 (0.072)	-0.224 (0.065)
Local Unemployment Rate > 12%	-0.345 (0.088)	-0.276 (0.112)	-0.479 (0.112)	-0.477 (0.107)
Constant	0.370 (0.155)	0.584 (0.189)	-0.067 (0.184)	0.230 (0.183)

TABLE E4 Estimated Coefficients - MNP Job-to-Nonemployment Turnover Equation Children and Marital Status Excluded (Standard Errors in Parentheses)				
	LHSM	GHSM	LHSF	GHSF
Wage	-0.091 (0.026)	-0.157 (0.017)	-0.173 (0.040)	-0.246 (0.020)
Wage-squared	0.002 (0.001)	0.002 (0.000)	0.005 (0.003)	0.005 (0.000)
Tenure	-0.379 (0.048)	-0.264 (0.075)	-0.370 (0.049)	-0.222 (0.061)
Tenure-squared	0.028 (0.008)	0.020 (0.014)	0.039 (0.007)	0.012 (0.011)
Experience	-0.282 (0.055)	-0.313 (0.075)	-0.203 (0.055)	-0.161 (0.067)
Experience-squared	0.011 (0.005)	0.013 (0.007)	0.004 (0.005)	0.005 (0.006)
Bad Health Dummy	0.179 (0.171)	0.081 (0.206)	0.240 (0.134)	0.217 (0.171)
Union Dummy	-0.156 (0.075)	-0.088 (0.105)	-0.327 (0.086)	-0.323 (0.100)
Asset Income % 1000	0.016 (0.015)	0.026 (0.010)	0.056 (0.019)	0.048 (0.016)
Marital Status Dummy	---	---	---	---
Number of Children	---	---	---	---
Local Unemployment Rate > 6% and ≤ 12%	0.085 (0.068)	0.087 (0.078)	-0.097 (0.070)	-0.225 (0.070)
Local Unemployment Rate > 12%	0.295 (0.090)	0.151 (0.119)	-0.019 (0.098)	-0.204 (0.108)
Constant	0.713 (0.160)	0.887 (0.198)	0.919 (0.160)	0.817 (0.184)

BIBLIOGRAPHY

- Blau, Francine D., and Andrea H. Beller. July 1988. "Trends in Earnings Differentials by Gender, 1971-1981." *Industrial and Labor Relations Review* Vol. 41, No. 4. pp. 513-529.
- Blau, Francine D., and Lawrence M. Kahn. July 1981. "Race and Sex Differences in Quits by Young Workers." *Industrial and Labor Relations Review* Vol. 34, No. 4. pp. 563-577.
- Boersch-Supan, Axel and Vassilis Hajivassiliou. September 1990. "Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models." Cowles Foundation Discussion Paper No. 960, forthcoming *Journal of Econometrics*.
- Browning, Martin. September 1992. "Children and Household Economic Behavior." *Journal of Economic Literature* Vol. XXX, No. 3. pp. 1434-1475.
- Burdett, Kenneth. 1978. "A Theory of Employee Job Search and Quit Rates." *American Economic Review* Vol. 68, No. 1. pp. 212-220.
- Cain, Glen G. 1986. "The Economic Analysis of Labor Market Discrimination: A Survey." in Handbook of Labor Economics, Vol. I, (Orley Ashenfelter and Richard Layard, eds.). Amsterdam: North Holland. pp. 693-785.
- Corcoran, Mary E. 1979. "Work Experience, Labor Force Withdrawals, and Women's Wages: Empirical Results Using the 1976 Panel of Income Dynamics." in Women in the Labor Market, (Cynthia B. Lloyd, Emily S. Andrews, and Curtis L. Gilroy, eds.). New York: Columbia University Press. pp. 216-245.
- Corcoran, Mary and Greg J. Duncan. 1979. "Work History, Labor Force Attachment, and Earnings Differences Between the Races and Sexes." *Journal of Human Resources* Vol. 14. pp.3-20.
- Devine, Theresa J., and Nicholas M. Kiefer. 1991. Empirical Labor Economics: The Search Approach. Oxford: Oxford University Press.
- Donohue, John J. 1988. "Determinants of Job Turnover of Young Men and Women in the United States: A Hazard Rate Analysis." Volume 6. in Research in Population Economics, (T.P. Schultz, ed.). Greenwich, CT: JAI Press. pp. 257-301.

- Flinn, Christopher J. 1986. "Wages and Job Mobility of Young Workers." *Journal of Political Economy* Vol. 94, No. 3, Pt. 2. pp. S88-110.
- Goldin, Claudia. 1990. Understanding the Gender Wage Gap: An Economic History of American Women. New York: Oxford University Press.
- Gronau, Reuben. 1988. "Sex-related Wage Differentials and Women's Interrupted Labor Careers--the Chicken or the Egg." *Journal of Labor Economics* vol. 6, no. 3. pp. 277-301.
- Hajivassiliou, Vassilis. 1992. "Simulation Estimation Methods for Limited Dependent Variable Models." Forthcoming Handbook of Statistics, Vol. 11 (Econometrics), (G.S. Maddala, C.R. Rao, and H.D. Vinod, eds.).
- Heckman, James J. 1981a. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process." in Structural Analysis of Discrete Data with Econometric Applications, (Charles F. Manski and Daniel McFadden, eds.). Cambridge, MA: The MIT Press.
- Heckman, James J. 1981b. "Statistical Models for Discrete Panel Data." in Structural Analysis of Discrete Data with Econometric Applications, (Charles F. Manski and Daniel McFadden, eds.). Cambridge, MA: The MIT Press.
- Johnson, William R. 1978. "A Theory of Job Shopping." *Quarterly Journal of Economics* Vol. 92. pp. 261-278.
- Jovanovic, Boyan. 1979. "Job Matching and the Theory of Turnover." *Journal of Political Economy* Vol. 87, No.5. pp. 972-990.
- Jovanovic, Boyan. 1984. "Matching, Turnover, and Unemployment." *Journal of Political Economy* vol. 92, no. 1. pp. 108-122.
- Light, Audrey, and Manuelita Ureta. April 1992. "Panel Estimates of Male and Female Job Turnover Behavior: Can Female Nonquitters be Identified?" *Journal of Labor Economics* Vol. 10, No. 2. pp. 156-181.
- Marini, Margaret Mooney. 1989. "Sex Differences in Earnings in the United States." *Annual Review of Sociology* 15. pp. 343-380.
- Meitzen, Mark E. 1986. "Differences in Male and Female Job-quitting Behavior." *Journal of Labor Economics* Vol.4., No. 2. pp. 151-167.

- Mincer, Jacob, and Boyan Jovanovic. 1981. "Labor Mobility and Wages." in Studies in Labor Markets, (Sherwin Rosen, ed.). Chicago: University of Chicago Press. pp. 21-63.
- Mincer, Jacob, and Solomon Polachek. Mar/Apr 1974. "Family Investments in Human Capital: Earnings of Women." *Journal of Political Economy* 82. pp. S76-S108.
- Mortensen, Dale T. 1986. "Job Search and Labor Market Analysis." in Handbook of Labor Economics, Vol. 2, (Orley C. Ashenfelter and Richard Layard, eds.). Amsterdam: North Holland. pp. 849-919.
- Rosenzweig, Mark R., and T. Paul Schultz. December 1985. "The Demand and Supply of Births: Fertility and its Life Cycle Consequences." *American Economic Review* Vol. 75, No. 5. pp. 992-1015.
- Smith, James P., and Michael P. Ward. October 1984. *Women's Wages and Work in the Twentieth Century*. R-3119-NICHD. Santa Monica, CA: The Rand Corporation.
- Topel, Robert. 1986. "Job Mobility, Search, and Earnings Growth." Vol. 8 (part A). in Research in Labor Economics, (Ronald G. Ehrenberg, ed.). Greenwich, CT: JAI Press, Inc. pp. 199-233.
- Topel, Robert H. and Michael P. Ward. May 1992. "Job Mobility and the Careers of Young Men." *Quarterly Journal of Economics* pp. 439-479.
- Viscusi, W. Kip. May 1980. "A Theory of Job Shopping: A Bayesian Perspective." *Quarterly Journal of Economics* pp. 609-614.
- Viscusi, W. Kip. August 1980. "Sex Differences in Worker Quitting." *Review of Economics and Statistics* pp. 388-398.