Comments are Welcome

WORKING PAPER #237
INDUSTRIAL RELATIONS SECTION
PRINCETON UNIVERSITY
AUGUST 1988

Occupational Matching: A Test of Sorts*

by Brian P. McCall

Department of Economics

Princeton University

First Version: May 1988

This Version: August 1988

* I would like to thank David Card for helpful comments on an earlier draft and Bruce Meyer for use of his Semi-parametric Hazard Estimation program. I am grateful to the Industrial Relations Section of Princeton University for financial support.

OCCUPATIONAL MATCHING: A TEST OF SORTS

Abstract

This paper develops a model of occupational matching where, within an occupation, information at one job may be useful for predicting the match at other jobs. Recent developments in the theory of superprocesses are used to derive the optimal sampling policy which predicts that those currently working their second job within an occupation are less likely to separate from this job then those working their first job. Also, this difference should increase with tenure in the previous job since, for those with long tenures, it is more likely that occupational sorting has taken place. These predictions are tested using weekly tenure data from the National Longitudinal Survey: Youth Cohort. Controlling for unobserved heterogeniety and employing semi-parametric estimation techniques, it is found that one's previous job tenure significantly lowers the likelihood of leaving the current job only if both jobs are of the same occupation. However, overall, occupational switchers are more likely to leave the current job only if the tenure in the previous job is greater than one year. Similar results are found for job quitters when the data is analyzed using a competing risks framework.

Brian P. McCall
Department of Economics
Princeton University
AFTER September 1988:
University of Minnesota

1. Introduction

Job 'shopping' has long been given as an explanation for job turnover (especially for youths)[1]. People usually begin a job without full knowledge of its characteristics, knowing that if things turn out poorly they can quit. Recently, a number of models of job mobility have tried to formalize this notion of job matching.[2] Most of these studies, however, have implicitly assumed that matching is done only at a job level.[3] It seems likely too that matching takes place at an occupational level. This is suggested by the significant fraction of people who switch occupations when switching jobs.[4] The purpose of this paper is to see whether there is any empirical evidence to support this notion of occupational matching.[5]

To facilitate this goal, a theoretical model of job matching is developed here that incorporates the possibility that matching information has an occupation specific component. Thus, within an occupation, matching information obtained at one job may be useful for predicting the match at others. Using recent developments in the statistical theory of superprocesses, the workers optimal sampling strategy is derived. One empirical implication gleaned from the optimal strategy is that those working their first job in an occupation should be more likely to quit than those who are working their second (or any subsequent) job in the occupation. This is because, if occupation specific information is significant, workers in these jobs have already undergone some occupational sorting, with the poorly matched being (voluntarily) weeded out. So, for these workers, job departures would occur only for matching reasons which are job specific.

One might believe that occupation switching is in of itself evidence that occupational matching takes place. However, switches may occur for other reasons. It may be that one occupation is a natural training ground for another. It is thus possible that occupation switching could be entirely a 'stepping stone' phenomena. However, the stepping stone hypothesis implies that individuals who continue in a given occupation are more likely to move on to the next one rather than less likely, as the occupational sorting model implies.[6]

Using 6 years (1979-1984) of data from the National Longitudinal Survey:Youth cohort, several 'job separation' hazard models are estimated using a proportional hazards approach. The various models make different assumptions about unobserved heterogeniety and the form of the baseline hazard. I find that, for those who switch occupations, tenure in the previous job has no significant effects on the separation hazard for the current job. However, for those who switched jobs but not occupation, individuals with longer tenure in the previous job are less likely to leave the current job . Interestingly, when unobserved heterogeniety is accounted for, the hazard rate of leaving the second job is actually higher for occupation 'stayers' with low levels of tenure on the first job than for occupation 'switchers'. For tenures in excess of 50-60 weeks on the first job however, hazard rates on the second job for occupation stayers are lower than those of occupation switchers.

Only under very stringent assumptions will the theoretical model developed here be a model of overall job separations. More generally, the model can only be interpreted as a model of quits. So, to concentrate on quitting behavior, a competing risks model is estimated where job separations are divided into three 'risks'; Quits, Fires and Other reasons. The effect of tenure in the previous job on the quitting hazard for the current job is estimated separately for those who quit their previous job. The estimated effect for these quitters is similar to the estimate for overall job separations, however a tenure of roughly two years is now needed in the first job before occupation switchers are less likely to quit then those who remain in the same occupation for their first two jobs. For those who quit their previous job, I found no significant differences between occupation switchers and stayers in their risk of being fired.

Looking at workers fired from their previous job, I found that occupational switchers are less likely to be fired from their new job but are also more likely to quit. Long tenures in the previous job for fired workers reduces the likelihood of either quitting or being fired from the current job, with the effect not being significantly different for occupation switchers and stayers.

The estimates of the competing risks model also reveal that college and high school graduates are no more likely to quit then high school dropouts but are significantly less likely to be fired. Those who switch jobs directly are both less likely to quit or be fired than those experiencing some unemployment. High starting wages also have significantly negative impacts on ones chances of quitting or being fired. Finally, I found that although Blacks are less likely to quit their job than either Whites or Hispanics, the risk of they run of being fired is no different.

The structure of the remainder of this paper is as follows. Section 2 will develop the theoretical model of the paper. Assuming that there is no job search (ie no wage uncertainty) and that job and occupation specific information arrives once in some random period (which can differ between the two), the structural form of the job separation hazard is derived for those working their first job in an occupation and for those working their second job in an occupation. The differences between these two hazards is then explored.

After describing the data used for the empirical analysis in Section 3, Section 4 presents the empirical results . Several specifications of the proportional hazards model are presented. Estimates are obtained using a Weibull baseline as well with non-parametric techniques developed by Cox (1975). Cox's partial likelihood method, however, is only strictly valid when data is continuous. This method may give poor approximations when the data is discrete. So, estimates are also obtained using discrete, semi-parametric, methods developed by Meyer(1986). The Cox and semi-parametric estimates are quite similar. Their estimated baseline distributions suggest that the Weibull distribution is inappropriate. These estimates suggest that the likelihood of a job separation at first increases and then tends to decrease with job tenure. This pattern continues when unobserved heterogeniety is controlled for using a Gamma mixing distribution.

Some tests of the proportionality assumption are also performed. These tests are similar in spirit to Chow's (1960) test for the time consistency of structural parameters in a linear regression model. If the model is truly proportional then the estimated coefficients for the entire sample should not differ appreciably from estimates obtained from a sub-sample of individuals with tenure greater than say T, where tenure for the ith individual in this sub-sample is measured by $T_i - T$.

Although the tests are not exhaustive, the evidence indicates that the proportionality assumption is reasonable for all covariates except the one-digit occupational dummy variables. So, the empirical model was also estimated separately for the two largest occupations: Service and Clerical workers[7]. The results for Service workers are quite favorable to the predictions of the theoretical model. The model's performance is less impressive when Clerical workers are considered.

Finally, Section 5 gives a summary and conclusion.

2. Model

This section builds a job matching model where matching information is split into job and occupational components. The model is similar in spirit to that of McCall(1987). Here, within an occupation, information obtained at one job may be useful in predicting the outcome at another. After formulating a simple model, a brief description of the techniques used to solve these sorts of optimization problems will be given. Next, these techniques will be used to analyze the workers optimal decision strategy. Finally, some testable implications for the 'separation from employment' hazard will be established.

i) Assumptions

To keep things at a manageable level it is assumed that initial wages are known with certainty and that there is no intra-occupational variation in wages. Let w_i denote the initial wage for the ith occupation, i=1,...,N. It is also assumed that it is at least as costly to switch jobs if that switch also entails a change in occupation. This could arise if costly training is needed to 'qualify' one to work in an occupation. Formally, assume that the cost of working the first job in the ith occupation is c_{1i} and that subsequent job switches in the ith occupation cost c_i where $c_{1i} \geq c_i$,i=1,...,N. Since there is no wage uncertainty, job switches result only in the loss of one period's wages.

After work has commenced at the first job within a particular occupation, say the ith, the worker receives two types of matching information. This information takes the form of random variables with randomly-distributed arrival times which add to or subtract from the net wage received on the job. Thus, before any information is received, the worker continues to receive w_i for any job in the ith occupation. After either form of information arrives the wage is higher or lower than w_i by the realized value of the particular random variable.

Job-specific information is that which pertains only to the current job and is independent across all jobs (both within and across occupations). The job -specific information for the j^{th} job in the i^{th} occupation is represented by a random variable ζ_{ij} . I will assume that job-specific information is identically distributed across all jobs within an occupation, $\zeta_{ij} = \zeta_i$ and that ζ_i has a cumulative distribution function F_i with bounded support [b,B]and $E(\zeta_i)=0$. The arrival time of this information at the jth job, T_{ij}, is assumed to follow a geometric distribution with parameter r_i.[8]

It is also assumed that there is an occupation-specific component of net wages. For the ith occupation (i=1,...N) this is represented by a random variable ω_i with $E(\omega_i)=0$. Assume that ω_i is distributed with c.d.f. G_i with bounded support [c,C], and arrives according to a geometrically distributed random variable T_i with parameter p_i . For occupation-specific information, the arrival time is measured as the total time worked in the occupation.

I will assume that all random variables are mutually independent. Thus, the random variables (ω_i, ζ_{ik}, T_{ik} k=1,2,..., and T_i) are mutually independent i=1,...,N and that for all $i \neq j$ the (ω_i , ζ_{ik}, T_{ik} k=1,2,..., and T_i) is independent of (ω_j, ζ_{jk}, T_{jk} k=1,2,..., and T_j). The first independence assumption is merely for simplicity, the latter is needed to employ the solution concept to be discussed next.[9]

Finally, I assume that individuals are risk neutral and evaluate future income streams using a constant discount rate β.

ii) Solution Concept[10]:

The model just specified turns out to be a special case of an optimal decision problem referred to in the statistics literature as a superprocess. These problems are a generalization of the more familiar Multi-Armed Bandit (MAB) problem which has been used in economics as a modeling tool to some extent.[11]

In short, the MAB problem deals with how to optimally 'play' N bandits sequentially. Each period one bandit is played, a reward is earned, and more information is received about the reward structure of the particular bandit played. At the outset, prior beliefs may distinguish bandits. Intuitively, one might conjecture that the optimal policy involves some sort of ordering of the bandits. We shall see shortly that this is the case.

A superprocess generalizes the MAB by additionally assuming that decisions must be made 'within' each bandit (subsequently I will refer to these as superbandits). These decision, in turn, ultimately affect bandit rankings.

Define an index policy as one that assigns each period a number (index) to every bandit and plays that bandit with the highest number. Gittins and Jones (1974) showed for the MAB problem that if i) only one bandit can be played each period and ii) information is independent across bandits, then the optimal solution involves an index policy[12]. For the superprocess, Whittle (1981) showed that the optimal solution involves an index policy if one additional assumption is satisfied. Briefly, the extra condition is iii) for every bandit, in all states, the optimal decision policy of a decision problem which considers only working the individual superbandit or 'retiring' and receiving some fixed payment Z, must be independent of this retirement payment (for a specified range).

I will not consider this condition further since in the sequel I simply assume that it is satisfied. It is important to remember, however, that this assumption is not innocuous and may in general place restrictions on the model. Below, I will give some indication of the extent of these restrictions.

The primary benefit of an index policy is that it reduces a complicated decision problem into N much simpler ones. Provided that an index policy is optimal, the index for each superbandit depends only on its information set and reward structure. The general form of the index, $Z_i(0)$, for the ith superbandit in its initial state (0) is:

$$Z_i(0) = \sup_{s \in S_i}\{\sup_T\{E_0(\Sigma_{t=1,\ldots T}\beta^t R_i(\phi,s) / \Sigma_{t=1,\ldots T}\beta^t)|F_i(0)))\quad (2.1)$$

where s is an element of the strategy space, S_i, of the ith superbandit, T is a stopping time, ϕ is an element of the state space Φ_i of the i^{th} superbandit, $R_i(\phi,s)$ is the payoff in state ϕ when following strategy s, $F_i(0)$ is the information set at 0, and expectations are taken with respect to this information set. The optimal policy at the outset is to work the ith superbandit if $Z_i(0) = \max_{j=1,\ldots,N}\{Z_j(0)\}$.

iii) Optimal Decision Policy

In this subsection, I will apply the results from superprocess theory to analyze the worker's optimal decision in the matching model set out in i). Here, each occupation is a superbandit. So, playing a new superbandit involves switching occupations. The decisions made 'within' the superbandit involves whether or not to switch jobs within the occupation. Thus, the 'within' bandit decision structure is particularly simple, involving two possible actions ('stop' or 'continue')

Since the goal is to derive testable implications, I shall not completely characterize the optimal policy for this problem but only those parts which will help accomplish this goal.

In general the index attached to the ith occupation at the outset (denoted as state 0) will depend upon all the parameters associated with it:

$$Z_i(0) = Z_i(c_{1i}, c_i, F_i, r_i, G_i, p_i) \qquad (2.2)$$

It is possible for condition iii) not to be satisfied in the states in which occupation-specific information as not been received. When occupation-specific information has been obtained, one can appeal to sufficient conditions established by Glazebrook (1982) to ensure that condition iii) is satisfied. Specifically, for condition iii) to be satisfied, the optimal decision (or in our case stopping) rule must be unaffected as the alternative reward (Z) is increased from zero to $Z_i(0)$. But if one is indifferent between switching jobs and staying at the current job (within an occupation) at a low level of Z, then will actually prefer to stay as Z is raised. Thus, the 'reservation' value of job-specific information, within the i^{th} occupation, will change with Z.

So, the solution concept will not be applicable for certain parameterizations. However, if c_{1i} is high relative to c_i, F_i is such that $P(-d < \zeta_i < d) = 0$ for d sufficiently large, and p_i is sufficiently low then condition iii) will be satisfied.[13] The large c_{1i} will drive down $Z_i(0)$ so that retirement is less of a factor. If ζ_i must be either larger than d or smaller than -d then one will not likely be on the margin between switching jobs and staying (ie the reservation value will not be unique and so variations in Z may still leave the decision policy unchanged). Finally, a small p_i lowers the chance that occupation-specific information will arrive in the near future if it hasn't already arrived.

When condition iii) is satisfied for all states then an intraoccupational job switch will occur, assuming occupation-specific information hasn't arrived, if $\zeta_i < \underline{\zeta}_i$ where $\underline{\zeta}_i$ satisfies:

$$(w_i + \underline{\zeta}_i) = \frac{[(-c_i(1 - \beta s_i) + \beta w_i)(1 - \beta) + \beta w_i(1 - F_i(\underline{\zeta}_i)) + \int_{\underline{\zeta}_i}^{B} \zeta_i dF_i(\zeta_i)]}{[1 - \beta s_i - \beta r_i F(\underline{\zeta}_i)]} \tag{2.3}$$

The proof of this result follows from noting that the when condition iii) is satisfied, the optimal intraoccupational switching policy in occupation i is identical to that when only occupation i is available. Equation (2.3) then follows from noting that the optimal value function for this problem satisfies:

$$V^c_i(w_i + \zeta_i) = -c_i + \beta\, r_i \int_b^B V_i(w_i + \zeta_i) dF(\zeta_i) + \beta s_i\, V_i(w_i)\}$$

and

$$V^s_i(w_i + \zeta_i) = (w_i + \zeta_i)/(1-\beta)$$

where $V^c_i(w_i + \zeta_i)$ represents the (optimal) value of switching when the current job has matching value ζ_i, $V^s_i(w_i + \zeta_i)$ is the value of stopping, $V_i(w_i + \zeta_i) = \max\{V^s_i(w + \zeta_i), V^c_i(w_i + \zeta_i)\}$, $V_i(w_i)$ is the value of working in the job before job-specific matching information has arrived and $s_i = 1 - r_i$.

If occupation-specific information, ω_i, has arrived (and an occupation switch has not occured) then a job switch will occur when $\zeta_i < \underline{\underline{\zeta}}_i(\omega_i)$, where $\underline{\underline{\zeta}}_i$ satisfies

$$(w_i+\underline{\underline{\zeta}}_i+\omega_i)=\frac{[(-c_i(1-\beta s_i)+\beta(w_i+\omega_i)(1-\beta)+\beta(w_i+\omega_i)(1-F_i(\underline{\underline{\zeta}}_i))+\int_{\underline{\underline{\zeta}}_i}^{B}\zeta_i dF_i(\zeta_i)]}{[1-\beta s_i-\beta r_i F(\underline{\underline{\zeta}}_i)]} \qquad (2.4)$$
[14]

It can easily be established that $\partial \underline{\underline{\zeta}}_i/\partial \omega_i < 0$. This follows because the higher ω_i, the more costly a job switch becomes, since an individual who changes jobs will lose $w_i + \omega_i$ for one period. One can also show from equation (2.4) that, $\underline{\zeta}_i > \underline{\underline{\zeta}}_i$ as $\omega_i > 0$.

Even though I won't solve for $Z_i(0)$ explicitly, I will derive the form of the index when occupation but not job-specific information is known ($Z_i(\omega_i)$) and when both occupation and job-specific information are known and an intraoccupational job switch is not optimal ($Z_i(\omega_i, \zeta_i)$).

Suppose that a job within the ith occupation is currently being worked and neither job nor occupation-specific information has yet arrived. Let $Z^* = \max_{j\neq i}\{Z_j\}$. So, Z^* represents the the value of the next best alternative occupation.[15] If $c_{1i} \geq c_i$, an occupation switch will occur only when occupation-specific information arrives. This is because, under my assumptions, if 'bad' job-specific information arrives before occupation-specific information, then, if $c_{1i} \geq c_i$ the index for the ith occupation can not drop below its initial value (and hence Z^*). This is a result of the fact that the individual will be in essentially in the same position as that when he/she first entered the occupation except that now the cost of sampling a new job is c_i.

If occupation-specific information arrives before job-specific information, on the other hand, then an occupational switch will occur when $Z_i(\omega_i) < Z^*$. It is shown in Appendix A that

$$Z_i(\omega_i) = (w_i + \omega_i)/(1-\beta) + [r_i\beta(1-F_i(\underline{\zeta}_i))\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i/(1-\beta + r_i\beta(1-F_i(\underline{\zeta}_i)))]$$

There I also show that $\partial Z_i/\partial r_i > 0$ and $\partial Z_i/\partial \underline{\zeta}_i \leq 0$. Intuitively, the higher r_i the more probable that job-specific information will arrive in the near future with possibly large positive gains, any 'negative gains' being attenuated by the option of switching jobs. The higher $\underline{\zeta}_i$, the more likely the arrival of job-specific information will result in a job switch, or in other words, the less likely its arrival will make one better off (ie less likely that Z_i increases) . Since we have $\partial \underline{\zeta}_i(\omega_i)/\partial \omega_i < 0$,

$$dZ_i(\omega_i)/d\omega_i = \partial Z_i/\partial \omega_i + \partial Z_i/\partial \underline{\zeta}_i \; \partial \underline{\zeta}_i(\omega_i)/\partial \omega_i > 0.$$

Since $Z_i(\omega_i)$ is strictly increasing in ω_i, we can implicitly solve $Z_i(\underline{\omega}_i) = Z^*$ for $\underline{\omega}_i$. So if $\omega_i < \underline{\omega}_i$, an occupational switch occurs. The probability this event occurring, conditional on occupation-specific information arriving before job-specific information, is $G(\underline{\omega}_i)$.

Assuming occupation-specific information arrives after job-specific information, three possibilities arise:[16] a) the worker may decide to remain in the current job , b) the worker may switch occupations or c) he/she may switch jobs but remain in the same occupation. The reason a person who has, at least, 'temporarily' settled in a job may resume intraoccupational search after occupation-specific information arrives is that if ω_i is less than zero (but not sufficient to induce an occupation switch) then the 'costs' of a job switch are reduced. Recall that when $\omega_i < 0$ that $\underline{\zeta}_i(\omega_i) < \zeta_i$. Thus, there is some chance that ζ_i falls in this gap. This chance, however, is reduced given my assumption that $P[-d \leq \zeta_i \leq d] = 0$ and for simplicity I shall assume that this interval is sufficient so that $P[\, \underline{\underline{\zeta}}_i(\omega_i) < \zeta_i < \underline{\zeta}_i \mid \omega_i < 0$ and $Z_i(\omega_i) > Z^*] = 0$.

Under this assumption, the arrival of occupation-specific information will not result in a 'within occupation' search for those who have already received job-specific information. So, the index for occupation i, after occupation-specific information arrives when a suitable job match has already been found within the occupation, therefore satisfies:

$$Z_i(\zeta_i, \omega_i) = (w_i + \zeta_i + \omega_i)/(1 - \beta).$$

Thus, an occupation switch will occur if

$$(w_i + \zeta_i + \omega_i)/(1 - \beta) < Z^*$$

or

$$\omega_i < Z^*(1 - \beta) - w_i - \zeta_i \equiv \underline{\underline{\omega}}_i.$$

The likelihood of this is $G_i(\underline{\underline{\omega}}_i)$.

Next, I would like to derive expressions for the empirical job separation hazard for those whose current job is their first job worked in occupation i and for those working their second job in occupation i who had tenure T^* in their first job. If occupation-specific information is significant, then one might suspect that those working in their second job would be less likely to separate, especially if T^* is large. This is because 'occupational self-selection' is likely to have already occurred in job1.

Formally, let $h_{1i}(t)$ = P(separate from job1 in period t| haven't separated before t) and $h_{2i}(t|T^*)$ = P(separate from job2 in period t]|haven't separated before the t and had worked T* periods in job1). Theorem 2.1 derives these empirical hazards for my model.

Theorem 2.1 $h_{1i}(t) = P^*(t)$ and $h_{2i}(t|T^*) = z(T^*)P^*(t) + (1- z(t^*))Q^*(t)$ where

$$P^*(t) = q_i^{t-1}s_i^{t-1}[s_ip_iG_i(\underline{\omega}_i) + q_ir_iF_i(\underline{\zeta}_i) + o(\Delta t)] + (1- q_i^{t-1})s_i^{t-1}r_i\int_{\underline{\omega}_i}^{C} F_i(\underline{\underline{\zeta}}_i(\omega_i))$$

$$dG_i/(1-G(\underline{\omega}_i)) + (1- s_i^{t-1})q_i^{t-1}p_i\int_{\zeta_i}^{B} G_i(\underline{\omega}_i(\zeta_i))dF_i/(1-F_i(\underline{\zeta}_i)),$$

$$Q^*(t) = s_i^{t-1}r_i\int_{\underline{\omega}_i}^{C} F_i(\underline{\underline{\zeta}}_i)dG_i/(1-G(\underline{\omega}_i)),$$

and

$$z(T^*) = q_i^{T^*}/ (q_i^{T^*} + (1 - G_i(\underline{\omega}_i))(1 - q_i^{T^*}))$$

with $q_i = 1 - p_i$, $s_i = 1 - r_i$, and $o(\Delta t)$ consisting of terms of 'second order'.

Proof: See Appendix B

It is easy to show that, under the assumptions of the model, $P^*(t) > Q^*(t)$ for all t.[17] Thus, $h_{2i}(t|T^*)$ is a weighted average of $h_{1i}(t)$ and something less than $h_{1i}(t)$. Also, the weight on $h_{1i}(t)$ decreases with T*. So, as suspected, those who are working their second job in an occupation are less likely to leave it in any interval then those working their first job and this difference increases with T* [18]. It is also easy to show that $\partial P^*(t)/\partial t$ is less than zero for t sufficiently large and that $\partial Q^*(t)/\partial t < 0$ for all t. If $s_i < q_i$ then a sufficient condition for $\partial P^*(t)/\partial t < 0$ is that $t > \log\{\log q_i/(\log s_i - \log q_i)\}$.[19]

Figure 2.1 displays $h_{1i}(t)$, $h_{2i}(t|10)$, and $h_{2i}(t|20)$ for the case where both occupation and job-specific information are of the 'good' news 'bad' news type (each occurring with equal probability), with 'bad' occupation-specific information always resulting in an occupation switch , 'bad' job-specific information always resulting in a job switch, and $r_i = p_i = .05$.

3. Data

The data used for the empirical analysis of this paper was derived from the National Longitudinal Survey (N.L.S.): Youth Cohort. This panel data set follows 12681 youths aged 14-22 as of 1979. At the time of this study the survey contained 7 years of data; years 1979-1985.

My data set was actually derived from the N.L.S. Work History Tape with some additional variables added from the Cohort tapes. The WHT builds a 'Job Array' from the retrospective information included on the Cohort Tapes. This Job Array gives a week by week accounting of the respondent's work history over the 1979-1985 period. The WHT, however, omits some variables, included in the Cohort tapes, which are essential for the analysis that follows. Specifically, no education nor marital status variables were included on this tape. In addition, the WHT doesn't classify job separations into quits,layoffs ect. So this information was taken from the Cohort tape and merged to the WHT as described below.

The goal of the empirical work will be to look for differences in behavior between those switching jobs (employers) but not occupations and those switching both jobs (employers) and occupations[20]. Because of this only respondents who have worked at least two jobs were included in the data set[21]. The two jobs used for this purpose are the first two jobs worked after school has been left. I use these jobs because I would like to pick up workers early in their job histories, while as much occupation specific matching uncertainty as possible remains. Although some occupation specific information may be revealed through schooltime employment, jobs held concurrently with school attendance are not analyzed in this study since many of these jobs involve summer employment which necessarily terminates after 2 or 3 months. It is unlikely that many of these jobs are related to an individual's ultimate career plans.

To accomplish this sample selection, I first restricted my sample to those individuals in the N.L.S, sample who were recorded as fulltime students as of the survey date in 1979. Then, using the Cohort tapes, I determined the date at which the respondents were no longer fulltime students ("Date Zero"). I searched from this date forward for the first job worked. This will be called Job1. It happened that some of the respondents were currently working a job at "Date Zero". Since the date of leaving school is likely to be a crude approximation, for these people a backward search was performed to locate the starting date of this job. If the job started within 15 weeks of "Date Zero", then it was labelled Job1. For those who started working this job more than 15 weeks before "Date Zero" two possibilities arose: a) if this job was part-time (< 30 hours/week) then it assumed that it was part-time job worked during school and unlikely to be related to ones' career plans. So, the next job worked (if any) was labelled Job1 b) if the job was a fulltime job then the respondent were dropped from my sample. This ommision could result in some bias. Five percent of the sample was deleted for this reason.

The N.L.S. Youth Job Array, described above, lists only the most recent job. When a new job is started the old job is dropped from the array even though that job need not have been left. A DualJob array contains information on those respondents holding multiple jobs. Since the program which constructed Jobs 1 and 2 and determined whether a switch had occurred used only the information in the Job Array, those holding dualjobs at the time of a 'switch' were deleted unless the those jobs designated as Job1 and Job2 were worked 40 hours or more. This was to preclude the pcssibility of designating as a job switch those who merely take on a part-time second job. 2% of the original number of respondents were deleted for this reason.

Job information was obtained from the WHT for both the beginning and end (or for Job2 possibly, right censored) dates of both jobs. Personal information on the respondents may change if the job overlaps two interview periods. This information was supplemented with marriage and schooling information from the Cohort Tapes. Specifically, the marital status and completed grade of the respondent, for the same year as the start dates of jobs 1 and 2, was added to the information already obtained from the WHT. Also, information regarding the 'reason for leaving' Job1 and Job2 was appended. Finally,all respondents with missing values for any variables (except the 'Reason for Leaving Job' variables) used in the empirical analysis were deleted.

The final sample contains 1667 respondents. Table 3.1 summarizes the data. The N.L.S. oversamples minorities, and this oversampling remains, as is seen by the 42% percent of my sample who are non-white.

A one-digit occupational transition matrix is given in Table 3.2. This shows the percentage of respondents in occupation i at of the end of job 1 who are in occupation j as of the start of job2. Looking along the diagonal gives the percentage who remain in the same occupation from Job1 to Job2. As can be seen there is a lot of variation in this percentage, from a low of 38.4% in Sales to a high of 100% in Private Household Services. Overall, 40.3% switch occupations when moving to Job2.

It may also be of some interest to search for any 'asymmetries' in the transition matrix. This might give some rough indication of the existence of 'stepping stone' occupations. One might expect that if occupation i is a stepping stone for occupation j then one would observe a high percentage of movement from i to j (the (i,j) cell in Table 3.2 would be large) but relatively little movement from j to i. Only one notable asymmetry presents itself in my sample and that is between Clerical and Sales. 21.8% of people working in the Sales occupation as of Job1 switch to a Clerical occupation in Job2. However, only 5.9% move from Clerical to Sales. In the Laborers, Operatives, and Craftsman occupations, where one might suspect transitions from Laborers and Operatives to Craftsman to be larger than movements in the reverse direction, we see from Table 3.2 that no clear asymmetries present themselves. So, at this aggregate level, at least, occupational switching seems less of a 'stepping stone' phenomena.

4.RESULTS

i) No Unobserved Heterogeniety

This section will review the empirical results of the paper. The main focus will be to test for the presence of occupation-specific information. This will proceed by looking for empirical differences in tenure behavior on the second job between those who have switched jobs but not occupations and those who have switched both jobs and occupations between their first and second jobs.

Before moving on, it is worthwhile to discuss the definition of a switch used throughout most of this section. Here, an occupation switch will be taken to mean a switch at the one digit level using 1970 Census occupation classifications. This broader definition is better suited to this section's objective since it is more likely that the informational assumptions of Section 2 will be satisfied using this broad definition and, as noted in Section 3, 'stepping' stone switches are less likely to be observed at this level of definition.

It is nevertheless possible that more than two occupations can be worked in the first job. So, a switch will said to have taken place if the occupation worked in Job2 at the start of the job is different from either that occupation worked at the start of Job1 or that worked at the end (if it should differ). At the end of this section, I will briefly consider how my results change when occupation switches are defined at the 3-digit level.

As predicted by the theory of Section 2, the hazard of separating from Job2 ought to be less for those who have switched occupations between Job1 and Job2. Recall that the hazard of leaving Job2 is defined as

$$\lambda_2(t) = P(\text{leave job 2 in period } t \mid \text{haven't left before } t)$$

Figure 4.1 presents non-parametric estimates of this hazard, using life table methods. The data is stratified into those who have switched occupations between Job1 and Job2 and those who haven't. As can be seen, no clear differences present themselves between the two groups. The bottom of Figure 4.1 present the results of tests of equality between the two strata. As can be seen the the null hypothesis of equality cannot be rejected.

Though these results are counter to what the theory predicts, they shouldn't be taken as conclusive on two accounts. First, these two groups may differ along some other characteristics and that could confound the results. Ideally, one should control for other characteristics that might affect the likelihood of separation. Secondly, recall that the theory predicts that more significant differences in job separation should be observed for those with longer tenures in Job1. If the assumptions of the theory are satisfied then tenure in Job1 should not have any effect on the Job2 separation hazard for those who switch occupations. For those who remain in the same occupation, however, the Job 2 separation hazard should decrease with tenure in Job1.

Restricting the sample to those workers with over 40 weeks tenure in Job 1, Figure 4.2 presents re-estimates of the Job 2 separation hazard for switchers and non-switchers. Here we see that some differences emerge. Those who switch occupation are consistently more likely to leave Job2 for the first five months of tenure. The tests of equality vary in significance, with the Wilcoxon test rejecting the null hypothesis at the 6% level. Thus, we have some weak confirmation of the predictions of Section2. Again however, other covariates need to be controlled for. This is done next.

In what follows, I shall assume that the hazard of separating from Job2 takes the following form

$$\lambda_2(t|x_i,\theta) = \lambda^0_2(t)\exp\{x_i'\beta\}\theta \qquad (4.1)$$

where $\lambda^0_2(t)$ is the baseline hazard, x_i is a k-vector of covariates for the ith individual, and θ represents unobserved heterogeneity. Here, the usual proportionality assumptions are made: the observed and unobserved covariates affect the baseline hazard through proportionate shifts. We shall normalize θ so that $E(\theta)=1$.

A list of the covariates used in the estimation of (4.1) is given in Appendix C. These include: the length of tenure in the previous job, whether the respondent switched occupations between Job1 and Job2, the starting wage for Job2, whether Job2 was a union or government job, the number of weeks the individual was out of work between jobs 1 and 2, one-digit occupation and industry dummy variables for Job2, and dummy variables for race, sex, schooling, and marital status. Five different estimates of β were obtained corresponding to different assumptions about $\lambda^0{}_2(t)$ and θ. In this subsection I will review the results when it is assumed that the distribution of θ is concentrated at its mean. Then (4.1) reduces to

$$\lambda_2(t|x_i) = \lambda^0{}_2(t)\exp\{x_i'\beta\} \qquad (4.2)$$

This form of the hazard is appropriate if the covariates of Appendix C properly account for all heterogeneity in the sample (and are measured without error). To estimate (4.2) one can either assume a functional form for $\lambda^0{}_2(t)$ or use non parametric techniques. One popular functional form used for $\lambda^0{}_2(t)$ is the Weibull distribution.

$$\lambda^0{}_2(t) = \lambda p(\lambda t)^{p-1}$$

In this case estimates of β, β, are obtained by maximizing the log likelihood

$$\text{Log } L = \sum_{i=1,N}\{\log\lambda+\log p+(p-1)\log\lambda t_i+x_i'\beta\}\delta_i - \sum_{i=1,N}\exp[x_i'\beta - (\lambda t_i)^p]$$

with respect to λ, p, and β, where δ_i is an indicator variable which equals 1 if the ith (i=1,...,N) individual separates from his/her job at t_i and equals 0 if the ith individual is censored at t_i.

Techniques developed by Cox(1975) allow one to estimate β without having to assume any particular parametric form for $\lambda^0{}_2(t)$. Cox's partial likelihood method estimating β is obtained by maximizing

$$\text{Log } L = \sum_{t=1,T}[\{\sum_{i\varepsilon D(t)}x_i\}'\beta - d_t\log\{\sum_{i\varepsilon R(t)}\exp(x_i\beta)\}]$$

with respect to β, where there are T failure times (or periods) indexed by t, and D(t) is the set of individuals who fail at t, d_t is the number of individuals in D(t), and R(t) is the number of individual who remain 'just before' time t. Columns (1) and (5) of Table 4.1 present the parameter estimates for the Weibull and Cox models

As pointed out in Kalbfleish and Prentice(1980) however, the Cox estimator is only exact when there are no 'ties' in the data (d_t=1 for all failure times, t). This is because Cox's model is a continuous time model. The NLS Work history data, however, is weekly (my estimates, given in Table 4.1, further group 'failures' into 4 week intervals). Since over 100 failures can occur in one interval (for example 132 people leave Job2 between weeks 5 and 8; interval 2) the approximations of the Cox partial likelihood may be poor. Therefore, it would be nice to use techniques which were discrete in nature but retained the non-parametric flavor of Cox's partial likelihood. Meyer (1986) (see also Kalbfleish and Prentice(1980), pg) has developed general techniques for estimating failure time models when the data is discrete. With no unobserved heterogeniety, Meyer's Semiparametric Estimator (SE) jointly estimates the β's and the baseline hazard (the baseline isn't 'partialled out' as in Cox's method). The estimates of β and the baseline hazard, represented by the parameters $\gamma(t)$, $t=1,...,T$, where T periods of failures can occur, is obtained by maximizing the likelihood

$$\text{Log } L = \sum_{i=1,N}\{\delta_i \log[1-\exp\{-\exp[\gamma(t_i)+x_i'\beta]\}]-\sum_{t=0,t_i}\exp[\gamma(t)+x_i'\beta]\}$$

with respect to β and γ, where t_i is the failure time of the ith individual. Column (3) of Table 4.1 provides the estimates β using this method where the dimension of γ is 62 (ie 62 4-week periods of failure)[22].

The first thing to notice about the estimates in Table 4.1 is that the Cox and SE estimates are very similar. Figure 4.3a graphs the estimated baseline hazard from both techniques. Here, the estimates are very close, especially in the early periods. Thus, even when ties are abundant the Cox estimator performs quite reasonably.

The Weibull estimates do less well. In particular, has can be seen in Figure 4.3a, the estimated baseline hazard using the Weibull model doesn't closely approximate either the Cox or SE estimates. Using the Weibull, one finds negative duration dependence in the data. Thus, the longer one has been at a job the less likely they are to leave. This result has been found by others (see Burdett,Kiefer and Sharma(1985) for example). However, the Cox and SE estimates suggest that the likelihood at first increase and then decreases over time. Perhaps a better parametric specification would not restrict the baseline hazard to be monotonic throughout as does the Weibull[23].

The estimated coefficients for the SWITCH, TENURE1, and TENURE1*SWITCH, variables are of primary interest to this study. The model developed in Section 2, predicts that the coefficient for TENURE1 be negative, that for TENURE*SWITCH be positive, and that for SWITCH be zero. As one can see from Table 4.1 columns (1),(3), and (5) the empirical results lend some support to the model. A long tenure in the previous job significantly lowers the likelihood of a job separation in the current job only when both jobs are of the same occupation. TENURE*SWITCH provides evidence of whether the effect of tenure in the previous job for those who switch occupations between jobs 1 and 2 is greater then the tenure coefficient of those who don't. That is, due to other factors not included in the model of Section 2, tenure in the previous job may affect the likelihood of leaving the current job. The model predicts only that the tenure effect is less for occupation stayers. For all three specifications TENURE*SWITCH is significantly positive at the 10% level.[24] On the other hand, the SWITCH dummy is insignificantly different from zero over the three specifications. So, switching occupations between Job1 and Job2 in of itself does not seem to influence an individual's tenure behavior in Job2.

Examining the effects of the other covariates we see that workers with higher initial hourly wages in Job2 are less likely to separate from their jobs whereas fulltime workers (> 30 hours) are insignificantly different from parttime workers. College graduates (≥ 16 years education) and High school graduates (≥ 12 years but < 16 years of education) are less likely to leave Job2, though the coefficient for high school graduates is insignificant. People who switch jobs directly with no intervening 'out of work' spell are also less likely to leave Job2.

Married females are more likely to leave their Job2 then unmarried males whereas married males and unmarried females are insignificantly different from unmarried males. Whether a job is unionized or not doesn't affect the overall job separation hazard. Government jobs, on the other hand, significantly increase the likelihood of leaving Job2. Finally, at least in the Cox specification, both industry and occupation dummies are jointly significant at the 5% level.

ii) Unobserved Heterogeniety

So far I have neglected to account for possible unobserved heterogeniety. Lancaster (1979) and others have shown that such neglect could seriously bias the estimates of β.[25] To incorporate it, I return to the more general specification of (4.1). The likelihood function for the SE estimator with a 'mixing' c.d.f. $\mu(\theta)$ is:

$$\text{Log } L(\gamma,\beta,\mu) = \sum_{i=1,N} \log \{\int \exp[\theta[\sum_{t=0,t_i-1} \exp\{\gamma(t)+x_i'\beta\} d\mu(\theta) - \delta_i \int \exp[-\theta \sum_{t=0,t_i} \exp\{\gamma(t)+x_i'\beta\}] d\mu(\theta)\}$$

The likelihood for the Weibull model is modified in a similar manner

We shall assume that θ has a Gamma distribution. Heckman and Singer (1984a,1984b) have shown that the estimated β can vary considerably depending on the assumed functional form of the unobserved heterogeniety. Though this result may be a problem for the Weibull model (Heckman and Singer's results assumed a Weibull model) it is likely that the SE estimates of β will be more robust to the functional form assumed for the mixing distribution since part of the variability in β may be a result of misspecification of the baseline hazard. Han and Hausman (1986) have also conjectured that misspecification of the mixing distribution will be less of a problem when the baseline is semiparametrically estimated. However, the Heckman & Singer critique should be kept in mind when viewing my results.

It can be seen from Table 4.1 (columns (2) and (4)) that some of conclusions are strengthened when unobserved heterogeniety is modeled. The coefficient for TENURE*SWITCH is now significantly positive at the 5% level for the specifications of columns (2) and (4). The coefficient for TENURE1 still remains significantly negative at the 1% level. However, when controlling for unobserved heterogeniety, the coefficient for SWITCH becomes significantly negative.

These results taken together imply a 'crossing time'. This is defined as the tenure in Job1 where the total effects are equal (see Figure 4.4).[26] This time varies between 55 and 65 weeks for the two specifications (57.7 weeks for the semi-parametric specification with a Gamma mixing distribution and 63.3 for the Weibull specification with Gamma mixing distribution. So, roughly, one year of tenure is needed in JOB1 before those who switch occupations are more likely to leave JOB2 then those who don't.[27]

One possible explanation for this result could be that the occupation-specific information process is more complex than that assumed in Section 2. For example, if occupation-specific information came in two pieces, with both having to come out 'bad' to induce an occupation switch, then those respondents who have switched jobs (but not occupations) with very little tenure in the first job might consist mainly of those who have received just one piece of information. So, at least initially, they may be more likely to quit Job2 because of an occupational mismatch. However, as tenure in the first job increases it becomes more likely that all occupation-specific information is known. Thus, for sufficiently long tenure in job1, the likelihood of leaving Job2 for non-switchers would be less.

Another result of interest is that when unobserved heterogeniety is added to the Weibull model, the estimated duration dependence switches from negative to positive. Now,according to the Weibull estimates, the longer one works in Job2 the more likely they are to leave. But as can be seen from Figure 4.3b the Weibull model continues to fit the data poorly so one can't draw much from this result. As can be seen from the SE/Gamma estimates the baseline still rises at first and then tends to fall which was the general pattern observed for SE estimates with no mixing distribution (though it tends to fall more slowly with the mixing distribution).

Comparing some of the other estimated coefficients of (3) and (4), we see that none of the variables which were significant in (3) change sign in (4). MARRIED*FEMALE and COLLEGEGRD, however, lose significance whereas the coefficient for FULLTIME is now significantly negative in column (4) at the 10% level. Finally, unobserved heterogeniety does seem to be present as the significant estimate of σ^2 suggests.

iii) Tests of Proportionality

Up to this point, I have not examined the question of whether the proportionality assumption is reasonable. This subsection will describe the results of some initial attempts to address this question.

The techniques which I will use here to test the proportionality assumption are similar to those used to test for time consistency of sets of regression coefficients in linear regressions; the Chow Test.[28] If the proportionality assumption is true then re-estimating the model, using only those who work Job2 longer than T and redefining tenure as T_i - T, should not yield significantly different parameter estimates.

One way to perform this test is to introduce time varying covariates $z_i(t)$ with

$$z_i(t) = \begin{cases} 0 & \text{for } T_i \leq T \\ x_i & \text{for } T_i > T \end{cases}$$

Using the Cox regression model, the log likelihood becomes

$$\text{Log } L = \sum_{t \leq T} [\{\sum_{i \varepsilon D(t)} x_i\}'\beta - d_t \log\{\sum_{i \varepsilon R(t)} \exp(x_i \beta)\}] + \sum_{t > T} [\{\sum_{i \varepsilon D(t)} x_i\}'(\beta + \gamma) - d_t \log\{\sum_{i \varepsilon R(t)} \exp(x_i'(\beta + \gamma))\}].$$

The test then reduces to testing $\gamma = 0$. This test is similar to tests proposed by Anderson and Senthilselvan (1982) and Moreau et al (1985).[29]

Due to the large number of covariates used in the analysis above I have performed test of proportionality on three different groups of covariates: the industry dummy variables (IND), the occupation dummy variables (OCC) and all other covariates (OTHERCOV). Also, to reduce computations, failure times were grouped into four week intervals. Since no T clearly presents itself, two different values were tried (T = 3 and T = 4). The results are presented in Table 4.2

As is seen in this table, the proportionality assumption seems reasonable for both the IND and OTHERCOV variables. The null hypothesis, $\gamma = 0$, cannot be rejected at the 10% level using the likelihood ratio, score, or Wald test for either T . However, the proportionality assumption appears to be violated for the occupational dummy variables. At T = 4, the null hypothesis is rejected at the 10% level with all three tests.

iv) Individual Occupations

The results of the preceding subsection suggest that the job tenure process should be handled differently within occupations. One might try to re-estimate the model by stratifying the sample by occupation, allowing the baseline hazard to differ across occupation but not the effects of the covariates. However, the theoretical results of section 2 do not really imply such restrictions. Since the arrival rates of information, along with their possible effect on net wages, can differ across occupation, the effects of TENURE1,SWITCH, and SWITCH*TENURE1 may vary across occupation. So, instead of stratifying by occupation, the entire model was re-estimated occupation by occupation. Due to data limitations, however, results are presented for only the two largest occupations in the sample, Clericals and Services.

Table 4.3 gives the results of estimating the Cox model separately for these two occupations. As can be seen, for both occupations the estimated coefficient of SWITCH*TENURE1 continues to be positive but is only significant for Services. The estimated coefficients for TENURE1 is significantly negative for both Clericals and Services. The effect of SWITCH on tenure in Job2 is significantly negative for Clericals but insignificantly different from zero for Services. So, the results for Services are much more in line with the predictions of the model of Section 2.

There also are some other interesting differences between the two occupations. For Clerical workers, switching jobs directly with no intervening out of work spell significantly lowers the likelihood of a Job2 separation but for Services it has no significant effect. Married females are significantly more likely to leave Job2 in Services but not in Clericals. Blacks and Hispanics job separation rates in Clericals are not significantly different from those of Wihtes. However, in Services, Hispanics are significantly more likely to leave Job2 than Whites, and there is some weak evidence that Blacks are less likely than Whites to leave Job2. The hourly initial wage significantly lowers the likelihood of leaving Job2 for Clericals but has no effect on the separation rate for Services. Finally, in Services, unionized workers are significantly (at the 10% level) more likely to leave Job2 than non-unionized workers. Union status,however, has no effect on the Job2 separation rate of Clerical workers.

So, we see that considerable differences do exist between the two occupations. When testing jointly for the equality of β between the two occupations, while still letting the baseline hazards vary across occupations, one can reject the null hypothesis of equality at the 0.5% level.

iv) Competing Risks Model[30]

The results of the preceding subsection implicitly have assumed that all types of job separations are alike. This assumption would be reasonable if a worker's value to an employer, as well as the job's value to the worker, is determined solely by the worker's (expected) productivity, if there are no informational asymmetries between employee and employer, and re-negogiating costs are negligible. In this case a job separation would occur when the value (expected productivity plus information value) of an alternative is higher than the total value of the current job.[31] Under these circumstances quits and fires should be observationally equivalent. However, when these assumptions are violated, quitting and firing behavior may differ. One indication of this is given by the fact that when the SWITCH, TENURE1, and TENURE1*SWITCH covariates are interacted with the type of job separation in Job1 (quit, fire or other reasons), one rejects the null hypothesis that the effects of these covariates on the overall Job2 separation hazard is independent of the type of separation in Job1 (at the 5% level).

To account for the possible differences between quits and fires, a competing risks model will be estimated with three alternative risks: Quits, Fires, and Other (reasons). Quits include only those who quit their job for other than family or pregnancy reasons. Fires include layoffs, and those who were fired for cause or left their job due to a plant closing (this last reason for job separation was only distinguished in the 1984 and 1985 interviews). Finally Other is a catch all category which includes: missing values, quit for pregnancy or family reasons, left due to program ending, and separated due to end of temporary or seasonal job.

For simplicity, I will assume that all heterogeneity is accounted for by the covariates and that the three risks described above are independent. These assumptions lead to a simple decomposition of the likelihood. Generally, if there are M competing risks and letting $\lambda_j(t,x_i)$ denote the hazard for the jth risk, the likelihood function can be written as:

$$L = \prod_{i=1,N}\{[\lambda_j(t_i,x_i)]^{\delta_i} \prod_{j=1,M}\exp[-\int \lambda_j(u,x_i)du]\}$$

where t_i is the failure time of the individual i, who 'fails' due to cause j. This can be rewritten as

$$L = \prod_{i=1,N} \prod_{j=1,M}\{[\lambda_j(t_i,x_i)]^{\delta_i \cap \sigma_{ij}} \exp[-\int \lambda_j(u,x_i)du]\}$$

or

$$L = \prod_{j=1,M} \prod_{i=1,N}\{[\lambda_j(t_i,x_i)]^{\delta_i \cap \sigma_{ij}} \exp[-\int \lambda_j(u,x_i)du]\}$$

and σ_{ij} is an indicator variable that is 1 if the ith individual fails because from the jth risk. So the log likelihood can be written as

$$\text{Log } L = \sum_{j=1,M} \log L_j$$

where $\text{Log } L_j = \sum_{i=1,N} \{[\log\lambda_j(t_i,x_i)]\phi_j - \int \lambda_j(u,x_i)du\}$

where $\phi_i = \delta_i \cap \sigma_{ij}$.

Again, we will assume that $\lambda_j(t,x_i) = \lambda_j(t)\exp\{x_i'\beta\}$. So, the competing risks model can be estimated by performing three estimations, one for each risk, where those who 'fail' from other causes are treated (along with those who are truly censored) as censored.

The results from estimating this competing risks model, using both Cox and Semi-parametric techniques, are presented in Table 4.4 and Figure 4.5. Estimates were obtained only for the quit and fire risks since any interpretation of the results for the other risk would be difficult given its 'catch all' nature.

Since the model of Section 2 is really a model of quits (when quits and fires aren't equivalent), I will concentrate on the differences in the effects of tenure in Job1 on the likelihood of quitting Job2 between those who both quit Job1 and switched occupations and those who quit Job1 but didn't switch occupations. As can be seen from columns (1) and (3) of Table 4.4 the results are similar to those obtained with all types of job separations. The effect of tenure in Job1 on the likelihood of quitting Job2 is significantly negative, for those who quit Job1, only if they did not switch occupations between jobs 1 and 2. One can reject the null hypothesis that $\beta_{TENURE1*SWITCH*QUITJOB1} \leq \beta_{TENURE1*NSWITCH*QUITJOB1}$ in favor of the alternative $\beta_{TENURE1*SWITCH*QUITJOB1} > \beta_{TENURE1*NSWITCH*QUITJOB1}$ at the 10% level. However, as with the estimates obtained in columns (2) and (4) of Table 4.1 which control for unobserved heterogeneity,

$\beta_{SWITCH*QUITJOB1}$ is significantly less than $\beta_{NSWITCH*QUITJOB1}$. The 'crossing time' implied by the estimated coefficients of Table 4.4 increases to 120 weeks. Thus, occupational switchers are less likely to quit Job2 than those who don't switch only when tenure in Job1 exceeds two years. Columns (2) and (4) of Table 4.4 show that SWITCH*QUITJOB1, NSWITCH*QUITJOB1, TENURE1*SWITCH*QUITJOB1, and TENURE1*NSWITCH*QUITJOB1 effects on the firing risk for Job2 are similar to that of the quit risk. However, for those who quit Job1, occupational switchers and stayers are not statistically different in the firing risk they face for Job2.

Looking at those who were fired from Job1, we see that although the effect of tenure in Job1 on the likelihood of quitting Job2 is (significantly) negative for those who switched occupations between Job1 and Job2, one cannot reject the null hypothesis that this effect is equal to that of non-switchers. This is also true for the fire risk. However, those who are fired from Job1 and switch occupations are significantly more likely to quit and are less likely to be fired Job2 then those who don't switch occupations.

We also see from Table 4.4 that switching jobs directly with no intervening 'out of work' spell significantly lowers the likelihood of quitting. This result is similar to that of Antel(1988). Though the model developed above precluded both the possibility of both on and off the job search, this result is consistent with the notion that workers searching on the job have higher reservation wages and find better jobs then those who search while unemployed. That the match is also better for the employer is seen by the significantly negative coefficient on the dummy variable for no intervening unemployment spell.

A high initial wage in Job2 lowers the likelihood of quitting. This result is consistent with what others have found (See Pencavel (1970) for example). However, the results in columns (2) and (4) also show that a high initial wage lowers the chances of being fired. These two results in conjunction are consistent with high initial wages being the result of good initial matching.

We also see from Table 4.2 that `Blacks are less likely to quit then either Whites or Hispanics, although all three races are equally likely to be fired. Both High School and College graduates appear no more likely to quit then those with less than a High School's education. However, more education does appear to decrease one's chance of being fired.

Both quitting and firing behavior seems to be independent of sex or marital status. The result obtained in Table 4.1 that married women are more likely to leave their jobs seems to be a result of the fact that married women are more likely to leave because of family or pregnancy reasons.

Long 'out of work' spells between Job1 and Job2 tends to lower the risk of being fired from Job2. Interpretation of this result is made hard by the fact that these spells do not necessarily coincide with the amount of time spent looking for work. The amount of time spent out of work though has no effect on the likelihood of quitting Job2.

Unionized workers are no more likely to either quit or be fired then are Non-union workers. However, government workers, while having identical quitting behavior, appear to run a greater risk of being fired than those working in the private sector. This is probably a result of the fact that in the early 1980's many government jobs (other than military jobs which were excluded from my sample) were eliminated as social programs were cut. Also, it is interesting to note that at the one-digit level, industry but not occupational dummies were jointly significant in determining the firing risk whereas the opposite result held for risk of quitting.

Finally, Figure 4.5 shows the pattern of the estimated baseline hazard for quits and fires to be very similar through the first ten months of tenure on

Job2. Both baseline hazards tend to increase for the first four or five months, then decrease for the next couple of months and then once again increase. However, the level of the estimated baseline hazard for fires is only about 1/2 the estimated baseline hazard for quits.

v) 3-Digit Occupational Switching

Before concluding I would like to discuss briefly how my results change when occupational switches are defined at the 3-digit level.Using this definition approximately 61% of workers switch occupations between Job1 and Job2 where only 42% switched using the one-digit definition. Re-estimation using this definition produced noticeably different results for the SWITCH and SWITCH*TENURE1 variables. Using the Cox partial likelihood method and using weekly data for tenure in Job2, estimated values for both β_{SWITCH} and $\beta_{SWITCH*TENURE1}$ are not significantly different from zero.[32] Thus, when using this definition of switching, occupational switchers and stayers appear identical.

These results, at first glance, seem to contradict the theory of Section 2. However, one must remember that the theory of Section 2 explicitly assumed the inter-occupational independence of information. It is much more likely that this assumption is violated when occupations are defined narrowly at the three digit level. Secondly, it is plausible that occupational switching is more a 'stepping stone' phenomena at the 3-digit level. Thirdly, many of the recorded changes in occupation at the three digit level may actually represent miscodes. In summary then, it may not be surprising that the distinction between stayers and switchers breaks down when occupations are defined at a highly disaggregated level.

5.Summary and Conclusions.

This paper has built a model of occupational matching where, within an occupation, matching information obtained at one job may be useful in predicting matches at subsequent jobs. If this 'occupation-specific' information is significant then the model predicts that those working their second job in an occupation are less likely to leave then those working their first. This difference becomes more pronounced the longer the tenure in their first job of those currently working their second job.

The National Longitudinal Survey; Youth Cohort was used to tests these predictions. Youths were followed through their first two jobs worked after leaving school and differences in separation rates in the second job were sought between those who switched occupations between their first and second jobs and those who didn't. Using a proportional hazard approach, it was seen that differences do exist between the two groups. Though tenure in the first job did significantly lower the likelihood of leaving the second job for non-switchers, and was insignificant for occupation switchers, for some specifications, the total difference between the two groups was characterized by a 'crossing time'. This 'crossing time' was defined as the amount of tenure in the first job where occupational switchers and stayers rate of separation in the second job was equal. Occupational switchers were more likely to leave their second job than non-switchers only when the tenure in the first job exceeded this crossing time. It typically ranged between 50 and 60 weeks. These results were robust to different specifications of the baseline hazard and when unobserved heterogeniety was controlled for. Finally, there was some evidence that the proportionality assumption was not an appropriate assumption for occupational effects.

The model of occupational matching analyzed, however, was generally only a model of quits since it was developed in a partial equilibrium framework. To control for other causes of leaving, a competing risks model was estimated with three 'risks'; Quits, Fires, and Other reasons. The crossing time phenomena continued to persist when analyzing quitters, but increased to approximately two years.

The competing risks framework used in this study assumed that the risks were independent. But Berninghaus et al (1986), among others have shown that , in equilibrium, quits and fires can be related. Thus, the quitting and firing risks of job separation may be highly correlated. Arguments by Borjas and Rosen (1980) suggest that quits and fires in fact could be perfectly correlated. One fruitful avenue of research would be to relax the independence assumption maintained here. This could be accomplished using techniques developed by Han and Hausman (1986).

The estimation techniques used in this paper was non-structural. However, the 'structural' hazard was derived in Section 2. Research is currently under way to structurally estimate the model developed in this paper. Identification issues aside, the results of this paper suggest a more complex occupation-specific matching process since the simple model developed here cannot capture the 'crossing' phenomena observed in the data. Structural estimation might best proceed by employing simulation techniques (See for example Pakes (1986)).

Finally, the results of this paper suggest that, in modeling the job matching process, informational dependencies should not be neglected. Of course, to get anywhere, independence assumptions must ultimately be invoked. Whether this is done at the occupational, or possibly the industry or regional, level, the data clearly indicate that invoking them at job level is inappropriate.

Notes

1. See Reynolds (1951).

2. See, for example, Johnson(1978), Jovanovic(1979a,1979b,1984), Lippman and McCall(1981), McCall and McCall (1981), McCall(1987), Miller(1984), Viscusi(1979,1980), and Wilde (1979).

3. McCall(1987) and Miller(1984) are exceptions .

4. See Miller(1984), and Shaw(1988).

5. See Flynn(1985) and Miller(1984) for empirical tests of the job matching hypothesis.

6. Shaw (1988) has found some evidence bearing on this point. Using a Polychotomous Logit Choice model she found that, at the 3-digit occupational level, occupation tenure had a significantly positive effect on a 'within employer' occupational change whereas it had a significantly negative impact on 'cross employer' occupational change.

7. Estimates were obtained only for these two occupations due to lack of sufficient data for the other occupations.

8. Note that under these assumptions jobs within an occupation are indistinguishable.

9. Formally, the latter assumption means that the σ-algebras generated by random variables associated with each occupation are independent.

10. For a more in depth discussion either McCall(1987), Ross (1983) or Whittle (1982).

11. See McCall(1987), McCall and McCall (1981,1987) and Miller (1984). Rothschild(1974) and Viscusi(1979,1980) analyze economic problems using a two-armed bandit approach.

12. See Varaiya et al (1985) for a more general proof.

13. If, alternatively, we assume that intraoccupational job switches are costless and are done instantaneously, then the Whittle condition will be satisfied.

14. The proof of this is similar to that for (2.3)

15. One can view $Z^*(1-\beta)$ has the alternative 'wage'.

16. By job specific information 'arriving' I mean that a, at least temporarily , suitable match has been found and no further job switching will occur before occupation specific information arrives.

17. Since $P[\ \underline{\underline{\zeta}}_i(\omega_i) < \zeta_i < \underline{\zeta}_i \mid \omega_i < 0 \text{ and } Z_i(\omega_i) > Z^*] = 0$ we have $P[\ F(\underline{\zeta}_i) \geq$

$F(\underline{\zeta}_i) \mid Z_i(\omega_i) > Z^*] = 1$ or

$$F(\underline{\zeta}_i) \geq \int_{\underline{\omega}_i}^{C} F(\underline{\zeta}_i(\omega_i))dG(\omega_i)/(1-G(\underline{\omega}_i))$$

Also it is easy to show that $o(\Delta t) \geq rpF(\underline{\zeta}_i)$. Hence,

$$P^* > \{q_i^{t-1}s_i^{t-1}r_iq_i + q_i^{t-1}s_i^{t-1}r_ip_i + (1-q_i^{t-1})s_i^{t-1}r_i\}\int_{\underline{\omega}_i}^{C} F(\underline{\zeta}_i(\omega_i))dG(\omega_i)/(1-G(\underline{\omega}_i))$$

$$= s_i^{t-1}r_i\int_{\underline{\omega}_i}^{C} F(\underline{\zeta}_i(\omega_i))dG(\omega_i)/(1-G(\underline{\omega}_i)) = Q^*.$$

18. Note that if $P[\,\underline{\zeta}_i(\omega_i) < \zeta_i < \underline{\zeta}_i \mid \omega_i < 0$ and $Z_i(\omega_i) > Z^*] > 0$, then it may be possible for Q* to exceed P*. This is because those who have received 'poor' occupation specific information but have decided not to switch occupations, are more likely to switch jobs then those who haven't because the 'costs' of a switch are lower.

19 For $s_i < q_i$, the condition becomes $t > \log\{\log s_i/(\log q_i - \log s_i)\}$ and for $s_i < q_i$, P* is strictly decreasing for all t.

20. Since job information is updated yearly for those who don't switch, it is possible to get information on occupation switching within a job. This information wasn't exploited for two reasons. First, most jobs didn't overlap two survey periods and so occupation status was observed only once. Secondly, it seems likely these switches are because one occupation is a training ground or 'stepping stone' for the next.

21. Since this may bias the sample towards movers, the estimated effects of other covariates on tenure should be viewed with caution.

22. I would like to thank Bruce Meyer for making available his Semi Parametric Hazard Estimation Program (SHE). The estimates in columns (1) - (4) of Table 4.1 were computed using SHE. The estimates in column (5) of Table 4.1 were computed using BMDP as were all subsequent estimates.

23. For example, one might use a Gamma or Inverse Gauss distribution for the baseline.

24. When the null hypothesis is that $\beta_{TENURE*SWITCH} \leq 0$.

25. Also see Elber and Ridder (mimeo).

26. More formally, the crossing time t is defined as the t such that

$\beta_{TENURE*SWITCH}t + \beta_{SWITCH} = 0$.

27. One alternative explanation for these results is that there are 'low cost'

switchers and 'high cost' switchers. Low cost switchers would be more likely to switch occupations and also jobs in general, So, those who switch occupations from Job1 to Job2 could consist mainly of these low cost switchers and hence would be more likely to leave Job2. However, the crossing time result obtained when controlling for unobserved heterogeniety suggest that self-selection is due more to matching reasons since those who switch occupations with little tenure in the previous job are actually less likely to leave than those who didn't switch occupations.

28. See Chow(1960)

29. Also see Arjas (1988) for a graphical method for assessing the fit of the Cox proportional hazard model.

30. See Kalbfleish and Prentice(1980) or Elandt-Johnson and Johnson(1979) for a complete discussion of competing risks models.

31.See Borjas and Rosen (1980).

32. A full presentation of these estimates has been ommited from this paper.

Gittins,J.C. and D.M. Jones, " A Dynamic Allocation Index for the Sequential Design of Experiments," in Progress in Statistics, J. Gani (ed.), North Holland, 1974, 241-266.

Glazebrook, K.D.,"On a Sufficient Condition For Superprocesses Due to Whittle," Journal of Applied Probability, 19 (1982), 99-110.

Han A., and J. Hausman, "Semiparametric Estimation of Duration and Competing Risk Models," mimeo, 1986.

Heckman J., and B. Singer, " A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," Econometrica, 52 (1984a), 271-320.

__________________, "Econometric Duration Analysis," Journal of Econometrics, 24 (1984b), 63-132.

Johnson, W., "A Theory of Job Shopping," Quarterly Journal of Economics, 92 (1978), 261-278.

Jovanovic, B., "Job Matching and the Theory of Turnover," Journal of the Politica Economy, 87 (1979a), 972-90.

__________, "Firm Specific Capital and Turnover," Journal of the Political Economy,87 (1979b), 1246-60.

__________, "Matching, Turnover, and Unemployment," Journal of the Political Economy, 92 (1984), 108-122.

Kalbfleish, J.D. and R.L. Prentice, The Statistical Analysis of Failure Time Data, John Wiley and Sons, 1980.

Lancaster,T. "Econometric Methods for the Duration of Unemployment", Econometrica, Vol 47 No. 4, July 1979, 939-956.

References

Anderson, J., and A. Senthilselvan, "A Two-step Regression Model for Hazard Functions," Applied Statistics, Vol. 31 No. 1, 1982, 44-51.

Antel,J. J., "Interrelated Quits: An Empirical Analysis of the Utitlty Maximizing Mobility Hypothesis," The Review of Economics and Statistics, March 1988, 17-22.

Arjas, E., "A Graphical Method for Assessing the Goodness of Fit in a Cox's Proportional Hazard Model," Journal of the American Statistical Society, Vol. 83, 1988, 204-212.

Berninghaus, S., S. Lippman, and J. McCall, "An Equilibrium Model of Job Turnover with Belated Information," Information Economics and Policy, Vol. 2 No 3, 1986, 212-229.

Borjas, G. and S. Rosen, "Income Prospects and Job Mobiliity of Young Men," in Research in Labor Economics, R. Ehrenberg ed., Vol. 3, 1980.

Burdett,K., N. Kiefer, and S. Sharma, " Layoffs and Duration Dependence in a model of Turnover," Journal of Econometrics, 28 (1985), 51-69

Chow, G., " Tests for Equality between Sets of Coefficients in Two Linear Regressions," Econometrica, 32, 532-553.

Cox, D.R. "Partial Likelihood," Biometrika, 62, 1975, 269-276.

Elandt-Johnson, R. and N. Johnson, Survival Models and Data Analysis, John Wiley and Sons, 1979.

Elbers, C. and G. Ridder, "The Sensitivity of Duration Models to Misspecified Unobserved Heterogeniety and Duration Dependence," mimeo.

Flinn, C.J., " Wages and Job Mobility of Young Workers", Journal of the Political Economy, Vol. 94 No. 3 pt. 2, 1986, s88-s110.

Lippman,S.A. and J.J. McCall, "The Economics of Belated Information," InternationalEconomic Review, 22 (1981), 135-46.

McCall B.P., "A Sequential Analysis of Occupational Mobilty," mimeo, 1987.

___________, and J.J. McCall, "Systematic Search, Belated Information and the Gittins Index," Economic Letters, 8 (1981), 327-33.

Meyer, B., "SemiParamemetric Estimation of Hazard Models," M.I.T., mimeo, 1986.

Miller, R.A., "Job Matching and Occupational Choice," Journal of the Political Economy, 92 (1984), 1086-120.

Moreau ,T., J. O'Quigley and M. Mesbah, " A Global Goodness-of-Fit Statistic for the Proportional Hazards Regression Model," Applied Statistics, Vol. 34 No. 3, 1985, 212-218.

Pakes, A., " Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," Econometrica, 54 (1986) 755-784.

Pencavel, J.H., An Analysis of the Quit Rate in American Manufacturing Industry, Industrial Relations Section, Princeton University 1970.

Reynolds, L., The Structure of Labor Markets, (New York: Harper, 1951).

Ross, S.M., Introduction to Stochastic Dynamic Programming, Academic Press, 1983.

Rothschild, M., "A Two Armed Bandit Theory of Market Pricing," Journal of EconomicTheory, 9 (1974), 185-202.

Shaw, K.L. "Occupational Change, Employer Change, and the Transferabilty of Skills," Southern Economic Journal, 53 (1987), 702-719.

Varaiya, P., J. Walrand, and C. Buyukkoc, "Extensions of the Multi-armed Bandit Problem: The Discounted Case," I.E.E.E Trans. and Auto. Control, AC-30, 1985, 426-439.

Viscusi,W.K., Employment Hazards: An Investigation of Market Performance, Harvard University Press, (1979b).

________, "A Theory of Job Shopping: A Bayesian Perspective," Quarterly Journal of Economics, 94 (1980), 609-614.

Whittle, P., "Multi-Armed Bandits and the Gittins Index," Journal of the Royal Statistical Society, B 42, 14 (1980).

________, Optimization Over Time, vol. 1, Wiley, 1982.

Wilde, L., "An Information Theoretic Approach to Job Quits," in S.A. Lippman and J.J. McCall (eds.), Studies in the Economics of Search, North Holland 1979, 35-52.

Appendix A

In this appendix I shall show that

$$Z_i(\omega_i)=(w_i+\omega_i)/(1-\beta)+[r_i\beta(1-F_i(\underline{\zeta}_i))\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i/(1-\beta+ r_i\beta(1-F_i(\underline{\zeta}_i))]$$

and that $\partial Z_i(\omega_i)/\partial\underline{\zeta}_i \leq 0$ and $\partial Z_i(\omega_i)/\partial r_i > 0$.

Let $V_i(\omega_i, Z)$ be the optimal value function of working at least one more period in the ith occupation when occupation specific information has been received and a retirement reward of Z is available (each period thereafter). Whittle (1981) has shown that the index associated with the ith occupation in this case is the value of Z which makes one indifferent between continuing and retiring. Thus $Z_i(\omega_i)$ satisfies the recursive relation

$$Z_i(\omega_i) = V_i(\omega_i, Z_i(\omega_i)).$$

Writing out V_i we have

$$Z_i(\omega_i) = \omega_i + w_i + \beta r_i F(\underline{\zeta}_i) Z_i(\omega_i) + [\beta r_i(1-F(\underline{\zeta}_i))(w_i + \omega_i + \int_{\underline{\zeta}}^{B}\zeta_i dF_i)/(1-\beta)]$$
$$+ \beta(1-r_i)Z_i(\omega_i)$$

Solving for $Z_i(\omega_i)$ and simplifying gives the desired result.

Differentiating $Z_i(\omega_i)$ with respect to r_i yeilds

$$\partial Z_i(\omega_i)/\partial r_i = \frac{\{(1-\beta+ r_i\beta(1-F_i(\underline{\zeta}_i))\beta(1-F_i(\underline{\zeta}_i)\int_{\underline{\zeta}}^{B}\zeta_i dF_i - r_i\beta^2(1-F_i(\underline{\zeta}_i))^2\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i\}}{\{1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i)\}^2}$$

which simplifies to

$$\partial Z_i(\omega_i)/\partial r_i = \beta(1-F_i(\underline{\zeta}_i)\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i/ \{1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i)\}^2 > 0.$$

Assuming that F_i is continuously differentiable with density f_i, in the relevant ranges, we have:

$$\partial z_i/\partial \zeta_i = \{[-r_i\beta f_i(\underline{\zeta}_i)\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i - r_i\beta(1-F_i(\underline{\zeta}_i)f_i(\underline{\zeta}_i)][1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i)] +$$

$$r_i\beta f_i(\underline{\zeta}_i)r_i\beta(1-F_i(\underline{\zeta}_i)\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i\}/\ \{1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i))\}^2.$$

This reduces to

$$\partial z_i/\partial \zeta_i = \frac{\{-r_i\beta(1-F_i(\underline{\zeta}_i)f_i(\underline{\zeta}_i)[1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i))] - (1-\beta)r_i\beta f_i(\underline{\zeta}_i)\int_{\underline{\zeta}_i}^{B}\zeta_i dF_i\}}{\{1-\beta+r_i\beta(1-F_i(\underline{\zeta}_i))\}^2} \leq 0.$$

Appendix B

Theorem 2.1 of the paper will be proved in this Appendix. Before proving the theorem some notation will be introduced.

As defined in the paper:

Job1 - the first job worked in the occupation

Job2 - the second job worked in the occupation

$h_{1i}(t)$ - P(quit 1st job in period t | haven't quit Job1 up to t}

$h_{2i}(t|T^*)$ - P(quit 2nd job in period t | haven't quit Job2 up to t and had tenure T* in Job1}

Also define:

oi(t-1) - denotes that occupation-specific information has been received by the start of the t^{th} interval

ji(t-1) - denotes that job-specific information has been received by the start of the t^{th} interval

Bad - denotes the case that the information was sufficiently bad to induce a quit

Q(t) - denotes that a person quits in period t

oi(t) - denotes that a person receives occupation-specific information in period t

js(t) - denotes that a person has received job specifc information in period t

Δt - denotes the period length

t - indicates that the person has survived up to the beginning of period t.

Given this notation I shall no prove:

__Theorem 2.1__ $h_{1i}(t) = P^*(t)$ and $h_{2i}(t|T^*) = z(T^*)P^*(t) + (1- z(t^*))Q^*(t)$ where

$$P^*(t) = q_i^{t-1}s_i^{t-1}[s_ip_iG_i(\underline{\omega}_i) + q_ir_iF_i(\underline{\zeta}_i) + o(\Delta t)] + (1- q_i^{t-1})s_i^{t-1}r_i\int_{\underline{\omega}_i}^{\zeta}F_i(\underline{\zeta}_i(\omega_i))$$

$$dG_i/(1-G(\underline{\omega}_i)) + (1- s_i^{t-1})q_i^{t-1}p_i\int_{\underline{\zeta}_i}^{\beta}G_i(\ \underline{\omega}_i(\zeta_i))dF_i/(1-F_i(\underline{\zeta}_i)),$$

$$Q^*(t) = s_i^{t-1}r_i\int_{\underline{\omega}_i}^{\zeta}F_i(\underline{\zeta}_i)dG_i/(1-G(\underline{\omega}_i)),$$

and

$$z(T^*) = q_i^{T^*}/\ (q_i^{T^*} + (1 - G_i(\underline{\omega}_i))(1 - q_i^{T^*}))$$

with $q_i = 1 - p_i$, $s_i = 1 - r_i$, and $o(\Delta t)$ consisting of terms of 'second order'.

__Proof:__ The proof will follow from applying the law of iterated expectations and noting that the probabilty of an event is just the expectation of the indicator function of that event. Finally, the events conditioned on at time t are just whether the individual has not received job nor occupation-specific information, has received one but not the other, or has received both. From this we have

$$h_{1i}(t)= P(\sim oi(t-1)\cap\sim ji(t-1)\,|t)\{P(oi(t)\cap\sim ji(t)\cap Bad|t\cap \sim oi(t-1)\cap\sim ji(t-1)) +$$

$$P(ji(t)\cap\sim oi(t)\cap Bad|t\cap \sim oi(t-1)\cap\sim ji(t-1)) + P(oi(t)\cap ji(t)\cap Bad|t\cap$$

$$\sim oi(t-1)\cap\sim ji(t-1))\} + P(\sim oi(t-1)\cap ji(t-1)\,|t)P(oi(t)\cap Bad|\sim oi(t-1)\cap ji(t-1)) +$$

$$P(oi(t-1)\cap\sim ji(t-1)\,|t)\ P(ji(t)\cap Bad|t\cap oi(t-1)\cap\sim ji(t-1)) \qquad \text{(B1)}$$

Now the probabilty of not receiving occupation-specific information by the start of the t^{th} interval is q_i^{t-1}. Similarly, the probability of not receiving job-specific information by the start of the t^{th} interval is s_i^{t-1}. If job-specific information arrives before occupation-specific information then a quit will result with probability $F_i(\underline{\zeta}_i)$ whereas if occupation-specific information arrives before job-specific information a quit will occur with probabilty $G_i(\underline{\omega}_i)$. When it is known that occupation-specific information has arrived at some earlier date and that a quit has not resulted then the (unconditional) probability that the arrival of job-specific information in period t will result in a quit is $\int_{\underline{\omega}}^{C} F_i(\underline{\zeta}_i(\omega_i))dG_i/(1-G(\underline{\omega}_i))$. Similarily, in the reverse case we have $\int_{\underline{\zeta}_i}^{B} G_i(\underline{\omega}_i(\zeta_i))dF_i/(1-F_i(\underline{\zeta}_i))$. Finally, if we assume that both p_i and r_i become 'small' with Δt (with both $p_i/\Delta t$ and $r_i/\Delta t$ approaching a constant) then the term $P(Q(t)\cap oi(t)\cap ji(t)|t\cap \sim oi(t-1)\cap\sim ji(t-1))$ is of order $o(\Delta t)$. Substituting into (B1) gives P^*.

The expression for $h_{2i}(t|T^*)$ is derived by noting that if a person has worked in the occupation for T* periods in Job1 then the probabilty of not receiving occupation-specific infomation in that time is $q_i^{T^*}$. The probability of a person receiving 'good' occupation-specific information before T* is $(1 - q_i^{T^*})*(1- G_i(\underline{\omega}_i))$. Due to the memoryless property of the geometric distribution, those who don't receive occupation-specific information and stay in the same occupation when switching jobs behave identically to those first entering the occupation. Those who have received good occupation specifc information, however, will only leave the new job if they receive bad job-specific information. $h_{2i}(t|T^*)$ results from the fact that the econometrician cannot observe which type of 'stayer' the individual is. Q.E.D.

Appendix C

This apppendix describes the variables used in the empirical analysis of Section 4.

Variable	Definition
INITIALWAGE	Initial hourly wage for Job2
FULLTIME	Dummy variable that equals 1 if hours/week worked in Job2 were greater than 30.
QUITJOB1	Dummy variable that equals 1 if the respondent quit Job1.
FIREJOB1	Dummy variable that equals 1 if the respondent was fired from Job1.
OTHERJOB1	Dummy variable that equals 1 if the respondent left Job1 for reasons other than for being fired or quitting or if the reason for leaving was not known.
SWITCH	Dummy variable that equals one if the respondent switched occupations between Job1 and Job2
NSWITCH	Dummy variable that equals one if the respondent didn't switch occupations between Job1 and Job2.
TENURE1	Weeks of tenure in Job1
HSHGRD	Dummy variable that equals 1 if the respondent completed 12-15 years of schooling as of Job2.
COLLEGEGRD	Dummy variable that equals one if the respondent completed 16 years (or more) of schooling as of Job2
WKSOUTWK	Measures the number of weeks out of work between Job1 and Job2.
NOOUTWORKSPELL	Dummy variable that equals 1 if there were no weeks spent out of work between Job1 and Job2.
MARRIED	Dummy variable that equals 1 if the respondent was married as of the start of Job2.
NMARRIED	Dummy variable that equals 1 if the respondent was not married as of the start of Job2.
MALE	Dummy variable that equals 1 if the respondent was a male.
FEMALE	Dummy variable that equals 1 if the respondent was female.
HISPANIC	Dummy variable that equals one if the respondent was Hispanic.
BLACK	Dummy variable that equals one if the respondent was Black.
UNIONJOB2	Dummy variable that equals 1 if Job2 was unionized
GOVTJOB2	Dummy variable that equals 1 if Job2 was a government job.

The following dummy variables are Industry and Occupation dummies which were set to one if the respondents classification number fell within the specified range for Job2. The numbers represent the 1970 Census Industry and Occupation Classification codes.*

INDUSTRY	
MINING	047-057

CONSTRUCTION	067-077
MANUFACTURING	107-398
TRANS/COMM/PUBUT	407-479
TRADE	507-698
FIN/INSUR/RLEST	707-718
BUS/REPR SERVICES	727-759
PERSONAL SERVICES	769-798
ENT/RECR SERVICES	807-809
PROF SERVICES	828-897
PUB ADMIN	907-937

<u>OCCUPATION</u>

MANAGERS	201-245
SALES	260-284
CLERICAL	301-395
CRAFTSMAN	401-575
OPERATIVES	601-715
LABORERS	740-765
FARMERS	801-824
SERVICES	901-965
HOUSEHOLD	980-984

* The excluded industry in the empirical analysis of the paper was Agriculture/Forestries/Fisheries 017-028. The excluded occupation was Professionals 001-195.

Figure 2.1 *

Theoretical Predictions for Job Separation Hazard

* These predictions are derived from a 'good' news 'bad' news model where either 'bad' occupation specific or job specific news causes one to leave their job. The probabilty that occupation specifc and/or job specific news arrives in a period is .05. The three hazards are for someone working their first job in an occupation (Hz Job1), working their second job with a tenure of 10 periods in their first job (Hz Job2,10), and working their second job with a tenure of 20 periods in their first job (Hz Job2,20).

Table 3.1*

Summary of Data

Whites (%)	58.1
Blacks (%)	26.3
Hispanics (%)	15.6
Female (%)	52.3
High School Graduates (%)	85.4
College Graduates (%)	15.6
Average Age at Start of Job1 (yrs)	19.9
Average Tenure in Job1 (wks)	38.2
Reasons for Leaving Job1:	
a) Quit (%)	41.4
b) Fired (%)	23.1
c) Other Reasons (%)	35.5
Occupation Switchers Job1 to Job2 (%)	40.3
Unionized in Job2 (%)	14.9
Government in Job2 (%)	3.7

* High School graduates are defined as those who have completed 12 or more years of education by the year Job2 began. College graduates are defined as those who have completed 16 or more years of education by the year Job2 began.

Table 3.2*

Occupation Transition Matrix

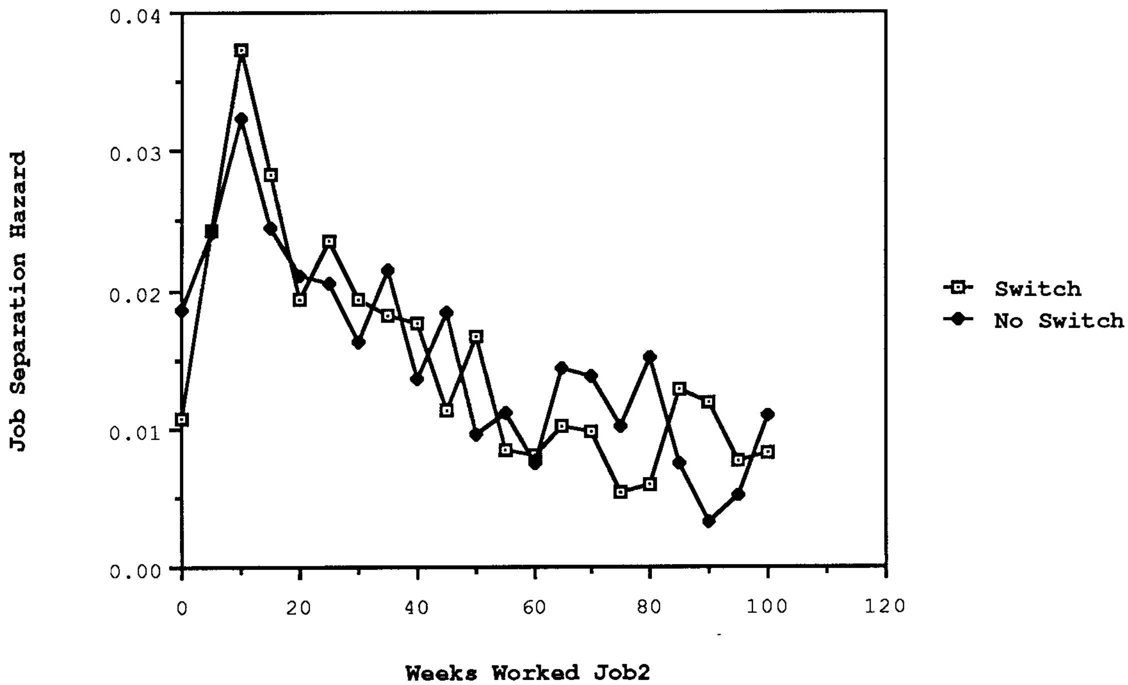
Job1 bY Job2

	PROF.	MAN.	SALES	CLER.	CRAFT.	OPER.	LABOR	FARM	SERV.	HOUSE.
PROF.	**69.0**	4.1	4.7	9.4	1.8	3.5	1.8	0.6	5.3	0.0
MAN.	4.6	**56.9**	11.4	15.9	2.3	0.0	0.0	0.0	9.1	0.0
SALES	8.1	7.0	**38.4**	22.2	4.0	3.0	4.0	0.0	13.1	0.0
CLER.	6.1	2.2	5.9	**62.7**	2.8	4.2	2.5	0.8	12.8	0.0
CRAFT.	1.5	0.7	3.0	8.2	**51.9**	10.4	14.1	1.5	8.9	0.0
OPER.	4.1	1.8	3.6	10.4	4.5	**54.8**	9.5	2.3	9.1	0.0
LABOR	3.6	0.0	1.2	12.7	8.5	12.1	**46.1**	1.8	13.9	0.0
FARM	2.6	0.0	2.6	0.0	5.3	26.3	5.3	**50.0**	7.9	0.0
SERV.	6.0	2.1	4.2	13.3	3.1	7.6	6.0	0.5	**57.3**	0.0
HOUSE.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**100.0**

* This transition matrix is read as the percentage of workers in occupation i as of Job1 that are in occupation j as of Job2. Along the diagonal gives the percentage of workers who remain in the same occupation. The total number of workers is 1709.

Figure 4.1*

Non Parametric Hazard Estimates
For Leaving Job2
Switched Occupations vs Not Switched Occupations



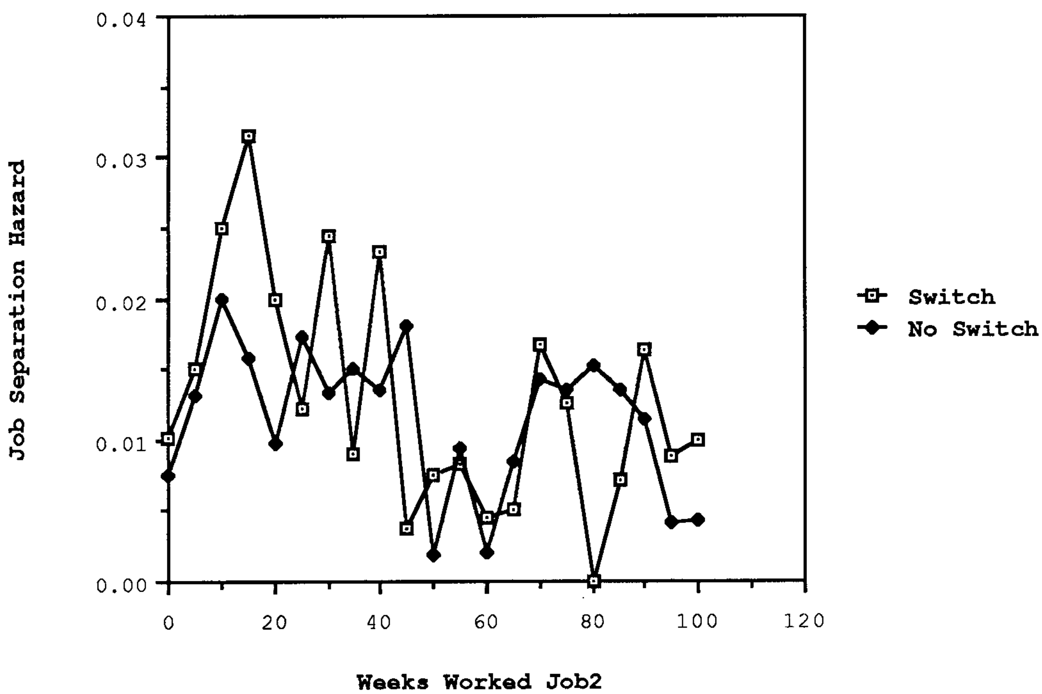
Tests of Equality Over Strata

Test	Chi-Square	Approx. P-Value
Log Rank	.1108	.7392
Wilcoxon	.4442	.5051
-2*LN(L)	.0088	.9252

* The number of observations is 1667. Of these 672 or 40.3 % switched occupations.

<u>Figure 4.2</u>*

Non Parametric Hazard Estimates
For Leaving Job2
Switched Occupations vs Not Switched Occupations
Tenure in Job1 at Least 40 Weeks



Tests of Equality Over Strata

Test	Chi-Square	Approx. P-Value
Log Rank	1.426	.2324
Wilcoxon	3.698	.0545
-2*LN(L)	.9537	.3288

* Of the 1667 respondents, 492 had a tenure in their first job of at least 40 weeks. Of these 165 or 33.5% switched occupations.

Table 4.1*
Parameter Estimates for Hazard of Leaving Job2

Bsline/Mx	Wbl/None	Wbl/Gamma	S.P./None	S.P./Gamma	Cox/None
Parameters	(1)	(2)	(3)	(4)	(5)
INITIALWAGE	-.0471***	-.0554**	-.0451***	-.0544***	-.0436***
	(.0124)	(.0197)	(.0135)	(.0166)	(.0152)
FULLTIME	.0750	-.2610**	-.0683	-.1519*	-.0616
	(.0593)	(.1187)	(.0640)	(.0895)	(.0644)
BLACK	-.0555	-.1921	-.0776	-.1414	-.0759
	(.0661)	(.1313)	(.0726)	(.1009)	(.0708)
HISPANIC	.0808	.0789	.0612	.0686	.0582
	(.0798)	(.1578)	(.0823)	(.1193)	(.0836)
SWITCH	-.0949	-.3482**	-.1193	-.2194*	-.1148
	(.0787)	(.1559)	(.0852)	(.1177)	(.0844)
TENURE1	-.0069***	-.0101***	-.0071***	-.0086***	-.0069***
	(.0010)	(.0017)	(.0011)	(.0014)	(.0012)
TENURE1*SWITCH	.0025	.0055**	.0026	.0038*	.0025
	(.0016)	(.0025)	(.0017)	(.0021)	(.0018)
UNIONJOB2	-.0728	-.0402	-.0610	-.0545	-.0531
	(.0761)	(.1476)	(.0851)	(.1145)	(.0839)
GOVTJOB2	.7197***	.9723***	.6725***	.8898***	.6252***
	(.1437)	(.3507)	(.1415)	(.2456)	(.1441)
WEEKSOUTWORK	.0005	.0014	.0002	.0011	.0000
	(.0010)	(.0021)	(.0011)	(.0016)	(.0011)
NOOUTWORKSPELL	-.3919***	-.7604***	-.3722***	-.5370***	-.3551***
	(.1116)	(.2095)	(.1235)	(.1668)	(.1113)
HSCHGRD	-.1184	-.0774	-.1014	-.0768	-.0992
	(.0781)	(.1606)	(.1264)	(.1194)	(.0824)
COLLEGEGRD	-.3303***	-.3280	-.2932**	-.2841	-.2859**
	(.1198)	(.2282)	(.1289)	(.1747)	(.1316)
MARRIED*MALE	-.1571	-.3018	-.1459	-.2427	-.1489
	(.1321)	(.2303)	(.1434)	(.1843)	(.1428)
MARRIED*FEMALE	.2689***	.1198	.2175**	-.1546	.2028**
	(.0980)	(.1792)	(.1063)	(.1403)	(.0972)
NONMAR*FEMALE	.0683	-.0654	.0354	-.0286	.0330
	(.0681)	(.1352)	(.0750)	(.1028)	(.0739)
INDUSTRY					
MINING	-.0098	-.2320	-.0340	-.1724	-.0395
	(.3600)	(.5992)	(.3743)	(.4683)	(.3937)
CONSTRUCTION	.6961***	1.0616***	.6598***	.8651***	.6407***
	(.1715)	(.3838)	(.1858)	(.2762)	(.2019)
MANUFACTURING	.0927	-.1802	.0634	-.0620	.0588
	(.1613)	(.3285)	(.1744)	(.2397)	(.1822)
TRANS/COMM/PUBUT	-.0083	-.4469	.0130	-.1959	.0175
	(.2219)	(.4389)	(.2484)	(.3379)	(.2435)
TRADE	-.0154	-.2736	-.0142	-.1502	-.0147
	(.1545)	(.3139)	(.1670)	(.2294)	(.1736)
FIN/INSUR/RLEST	-.2611	-.7490*	-.2271	-.4574	-.2204
	(.2108)	(.4049)	(.2306)	(.3080)	(.2325)
BUS/REPR SERVICES	.3131*	.2345	.2864	.2551	.2718
	(.1841)	(.3708)	(.1978)	(.2715)	(.1984)
PERSONAL SERVICES	.3866*	.1558	.3062	.2169	.2984
	(.1996)	(.4086)	(.2073)	(.2965)	(.2084)
ENT/RECR SERVICES	.3154	.1482	.3362	.2433	.3251
	(.2480)	(.5054)	(.2742)	(.3836)	(.2518)

Table 4.1(cont.)

Parameter Estimates for Hazard of Leaving Job2

	(1)	(2)	(3)	(4)	(5)
PROF SERVICES	.0848	-.1667	.0832	-.0527	.0780
	(.1669)	(.3340)	(.1808)	(.2458)	(.1833)
PUB ADMIN	.1013	.1138	.1664	.1134	.1503
	(.2265)	(.4505)	(.2450)	(.3315)	(.2553)
OCCUPATION					
MANAGER	-.1744	-.3539	-.1464	-.2295	-.1468
	(.2172)	(.3505)	(.2354)	(.2943)	(.2047)
SALES	.2630*	1.0173***	.3323**	.6194***	.3129*
	(.1515)	(.3004)	(.1703)	(.2310)	(.1715)
CLERICAL	-.1028	.1077	-.0653	-.0091	-.0609
	(.1241)	(.2243)	(.1384)	(.1791)	(.1310)
CRAFTSMAN	-.0190	.0632	.0235	.0089	.0222
	(.1546)	(.2957)	(.1731)	(.2301)	(.1680)
OPERATIVES	.0829	.4049	.1161	.2361	.1141
	(.1421)	(.2684)	(.1591)	(.2110)	(.1536)
LABORERS	.1678	.5105*	.2045	.3174	.1918
	(.1467)	(.2779)	(.1640)	(.2182)	(.1581)
FARMERS	.8948***	2.0542***	.9442***	1.5635***	.8900***
	(.2185)	(.4934)	(.2337)	(.3651)	(.2629)
SERVICES	.1703	.5332**	.1826	.3189	.1785
	(.1254)	(.2253)	(.1399)	(.1817)	(.1316)
HOUSEHOLD	.1435	.7726*	.2443	.5145	.2213
	(.2203)	(.4675)	(.2324)	(.3439)	(.2328)
μ	.0990***	.0508***	-	-	-
	(.0075)	(.0054)			
ϕ	.8706***	1.5860***	-	_	-
	(.0231)	(.0860)			
σ^2	-	1.6103***	-	.6331***	-
		(.1927)		(.1890)	
LnL	-4304.4	-4226.3	-4194.5	-4188.1	-8079.5

* Job2 is the second job worked since school has been left. The number of observations is 1667.Tenure in the Job2 is measured in four week intervals. Standard errors are in parenthesis. One,two and three astericks indicate signifcance levels of 10,5 and 1 percent respectively. Both Occupation and Industry dummies were jointly significant at the 1% level.

Figure 4.3a

Baseline Hazard Estimates

(No Mixing Distributions)

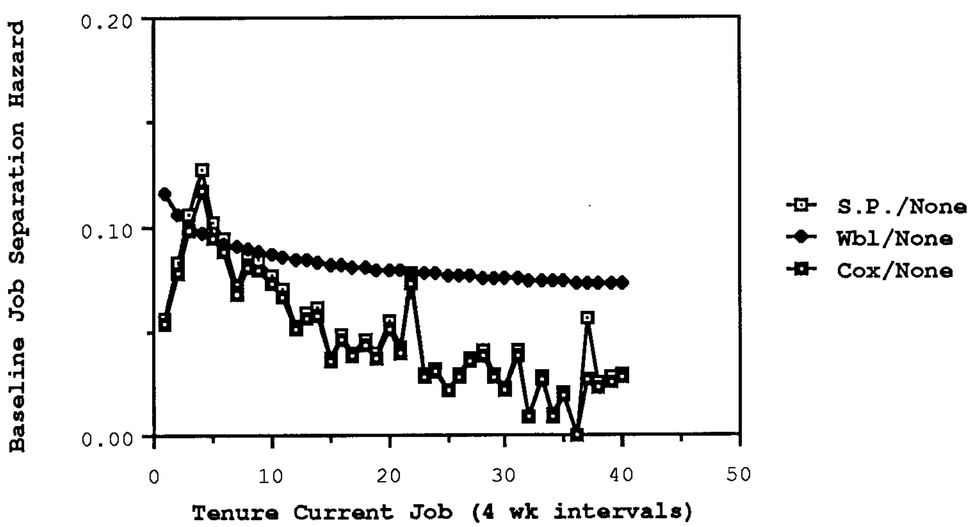


Figure 4.3b

Baseline Hazard Estimates

(with Gamma Mixing Distribution)

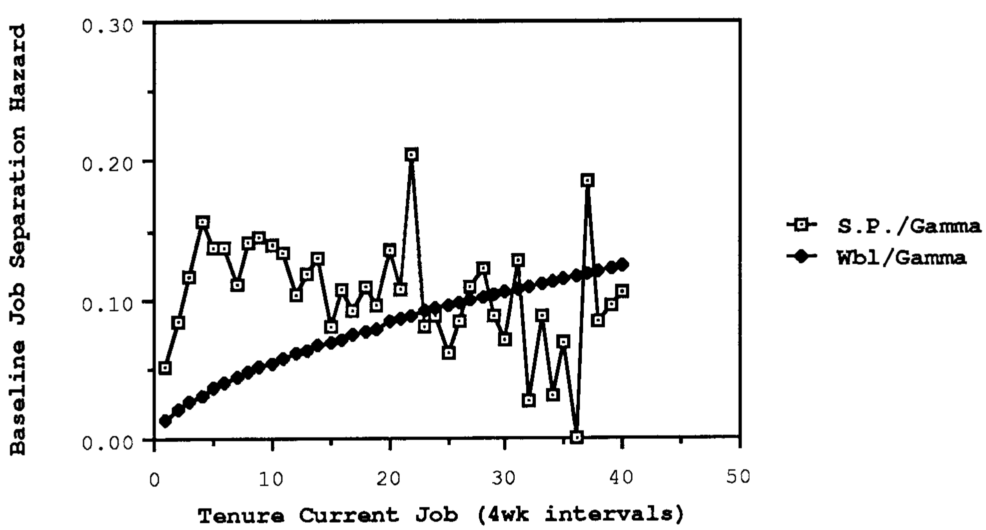
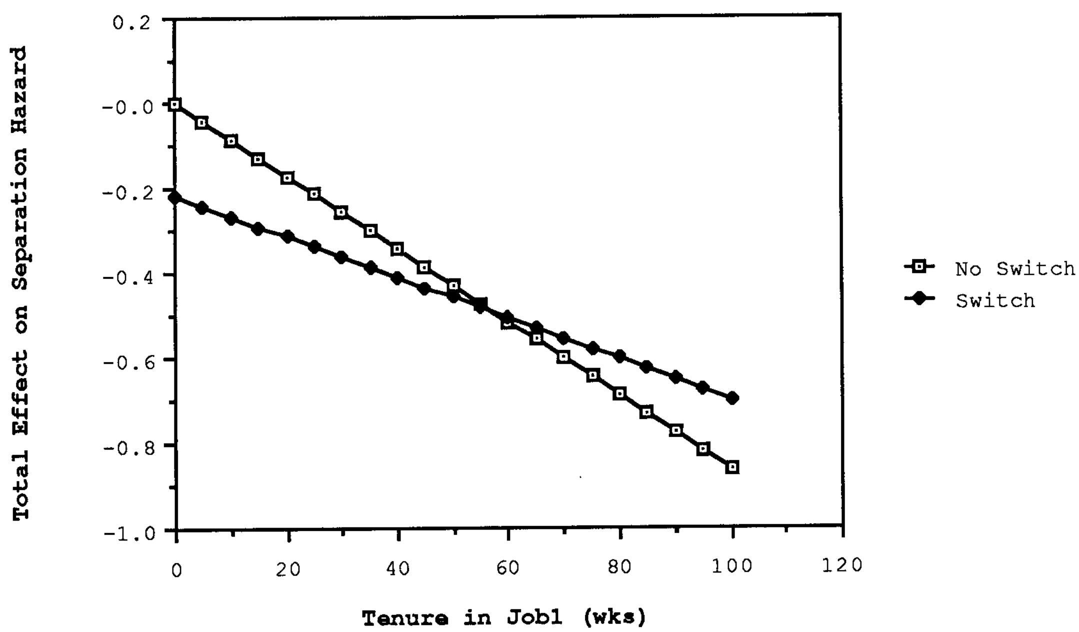


Figure 4.4*

Total Estimated Effect of Switching Occupations on Job2 Separation Hazard



* Estimates were taken from the Semi-parametric model with Gamma mixing distribution (see column 4 of Table 4.1).

Table 4.2*
Tests of Proportionality

T = 3

Test	**OCC**	**IND**	**OTHERCOV**
Lratio	8.99/.439	8.77/.643	21.74/.115
Score	8.96/.441	8.96/.626	21.63/.118
Wald	8.72/.461	8.78/.642	21.51/.121

T = 4

Test	**OCC**	**IND**	**OTHERCOV**
Lratio	16.46/.058	9.84/.545	19.88/.179
Score	15.98/.067	9.85/.544	19.82/.179
Wald	15.40/.081	9.72/.555	19.75/.182

* The Chi-square statistic is presented first and the associated P-value second. There were 9 occupation dummy variables (OCC), 11 industry dummy variables (IND), and 16 other variables (OTHER).

Table 4.3*

Parameter Estimates for the Hazard of Leaving Job2

Clerical & Services Occupations

Occupation	Clerical	Sevices
	(1)	(2)
Parameters		
INITIALWAGE	-.1408***	-.0324
	(.0511)	(.0426)
FULLTIME	.0969	-.0580
	(.1404)	(.1306)
BLACK	.2953	-.1911
	(.1664)	(.1426)
HISPANIC	.2240	.4016**
	(.1628)	(.1876)
SWITCH	-.4661**	-.0888
	(.1921)	(.1897)
TENURE1	-.0043*	-.0123***
	(.0025)	(.0034)
TENURE1*SWITCH	.0032	.0117**
	(.0039)	(.0052)
UNIONJOB2	-.0560	.3260*
	(.1833)	(.1939)
GOVTJOB2	1.6938***	.4650*
	(.3335)	(.2756)
WEEKSOUTWORK	-.0008	.0013
	(.0027)	(.0022)
NOOUTWORKSPELL	-.4380*	-.1863
	(.2538)	(.2828)
HSCHGRD	.0107	-.0026
	(.2635)	(.1677)
COLLEGEGRD	-.0712	.1689
	(.2191)	(.2714)
MARRIED*MALE	-.4511	.5292
	(.6638)	(.4223)
MARRIED*FEMALE	-.0712	.4738**
	(.2198)	(.1906)
NMARRRIED*FEMALE	-.0747	.0297
	(.1719)	(.2015)
LnL	-1303.4	-1435.2

* The parameter estimates are from a Cox regression where tenure in JOB2 was measured in weeks. Industries effects were controlled for at the 1-digit level but their estimates are not reported. There were 376 respondents in the Clerical during Job2. Of these 121 or 32.2 % were right censored. There were 350 respondents in the Service occupation during Job2. Of these 60 or 17.1% were right censored.

Table 4.4*

Parameter Estimates for Competing Risks Model

Cox vs Semi-Parametric Estimation

	Cox		S.P.	
	Quits	Fires	Quits	Fires
	(1)	(2)	(3)	(4)
Parameters				
INITIALWAGE	-.0789***	-.0720**	-.0843***	-.0721**
	(.0254)	(.0345)	(.0245)	(.0322)
FULLTIME	-.0084	.0522	-.0126	.0468
	(.1030)	(.1358)	(.0988)	(.1362)
BLACK	-.1657	-.0329	-.1737*	-.0444
	(.1154)	(.1393)	(.1118)	(.1464)
HISPANIC	.1274	.0491	.1212	.0561
	(.1288)	(.1705)	(.1250)	(.1777)
SWITCH*QUITJOB1	.3608*	.3711	.3568*	.3555
	(.1994)	(.2997)	(.1981)	(.3029)
NSWITCH*QUITJOB1	.9127***	.6163**	.9207***	.6364*
	(.1917)	(.3053)	(.1806)	(.3300)
TENURE1*SWITCH*QUITJOB1	-.0018	-.0011	-.0018	-.0012
	(.0029)	(.0037)	(.0025)	(.0029)
TENURE1*NSWITCH*QUITJOB1	-.0064**	-.0056	-.0065***	-.0059
	(.0028)	(.0046)	(.0023)	(.0052)
SWITCH*FIREJOB1	.4412*	.9316***	.4579*	.9381***
	(.2331)	(.2979)	(.2408)	(.3084)
NSWITCH*FIREJOB1	-.0334	1.5633***	-.0053	1.5464***
	(.2726)	(.2757)	(.2902)	(.2727)
TENURE1*SWITCH*FIREJOB1	-.0100**	-.0138***	-.0103**	-.0141**
	(.0044)	(.0050)	(.0046)	(.0060)
TENURE1*NSWITCH*FIREJOB1	-.0035	-.0072*	-.0035	-.0069*
	(.0047)	(.0038)	(.0049)	(.0036)
SWITCH*OTHERJOB1	.2478	.6519*	.2570	.6553
	(.2846)	(.3965)	(.2921)	(.4350)
TENURE1*SWITCH*OTHERJOB1	-.0075	-.0289*	-.0080	-.0291
	(.0073)	(.0173)	(.0080)	(.0235)
TENURE1*NSWITCH*OTHERJOB1	-.0063**	-.0167***	-.0065**	-.0172***
	(.0030)	(.0060)	(.0033)	(.0065)
UNIONJOB2	-.1045	.1648	-.1067	.1568
	(.1431)	(.1619)	(.1455)	(.1604)
GOVTJOB2	-.3435	.7175	-.3068	.7228*
	(.3459)	(.3038)	(.3113)	(.3751)
WEEKSOUTWORK	.0018	-.0063**	.0020	-.0061**
	(.0018)	(.0027)	(.0017)	(.0027)
NOOUTWORKSPELL	-.5155***	-.4814**	-.5338***	-.4991**
	(.1778)	(.2226)	(.1885)	(.2511)
HSCHGRD	.2129	-.2625*	.2115	-.2543*
	(.1432)	(.1508)	(.1395)	(.1567)
COLLEGEGRD	.1169	-1.0469***	.1064	-1.0568***
	(.2019)	(.3225)	(.2015)	(.3375)
MARRIED*MALE	-.1554	.0536	-.1511	.0583
	(.2343)	(.2625)	(.2387)	(.2795)
MARRIED*FEMALE	-.2356	.0200	-.2197	.0270
	(.1687)	(.2176)	(.1812)	(.2272)

Table 4.4*

Parameter Estimates for Competing Risks Model

Cox vs Semi-Parametric Estimation

	(1)	(2)	(3)	(4)
NMARRIED*FEMALE	-.0137	-.2117	-.0152	-.2021
	(.1144)	(.1533)	(.1096)	(.1592)
LN L	-3143.9	-1899.6	-2045.7	-1331.4

* Industry and Occupation effects were controlled for at the one-digit level but the results are omitted. The Cox regression was performed on weekly tenure data whereas, to limit computations, the semi-parametric model was estimated with tenure data grouped into 4-week intervals. 41.4% quit Job1, 23.0% were fired and 35.6% left for other reasons whereas, of those not censored in Job2, 39.8% quit, 24.9% were fired, and 35.3% left for other reasons.

Figure 4.5
Baseline Hazard Estimates for Competing Risks Model
Semi-Parametric Estimation