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Discussion Paper

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NLS Discussion Papers

Gender Differences in the Quit Behavior of Young Workers

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FINAL REPORT

Gender Differences in the Quit Behavior of Young Workers

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Executive Summary

Objectives

In this study, we examine the cohorts of young men and women in the National Longitudinal Surveys of Labor Market Experience. Our broad objective is to address the following questions about early-career mobility:

1. Overall, which gender undergoes the most turnover during the early career?

2. What observable factors influence the turnover of each gender? In particular, is there evidence that women, as well as men, quit their jobs because they are "shopping" for a durable employment relationship? How is turnover influenced by such measures of family responsibilities as marital status and the birth of a child? Do unemployment rates and other measures of market conditions have differential effects on men and women?

3. Do unobservable or unmeasured factors account for a significant amount of turnover? Are these factors relatively more important for women than for men?

4. Is the turnover behavior of men and women changing with successive birth cohorts or labor market entry cohorts? Do continuously employed workers exhibit a different pattern of turnover than workers who interrupt their careers?

5. Are voluntary or job-to-job transitions caused by a different set of factors than other types of job separations?

Methodology

Although we begin with descriptive analyses of the samples, most of our conclusions are based on estimates of discrete time proportional hazard models. A hazard model describes the instantaneous rate of job "failure" at a particular level of tenure conditional upon survival to that level. In a proportional hazard model, a vector of covariates is assumed to act multiplicatively on a baseline hazard. After some experimentation, we settled on the assumption that the baseline hazard arises from a Gompertz distribution.

By estimating a discrete time model, we can readily allow for the presence of time-varying covariates. That is, we estimate the effects on the hazard rate of factors that evolve over time, such as wages, unemployment rates and marital status. We also correct for the presence of unobserved heterogeneity. Although we control for a wide array of person-, job-, and market-specific characteristics, there are likely to be unobserved or unmeasured factors that also influence turnover. By correcting for these factors, we ensure that our other estimates are unbiased. In addition, we can estimate the proportion of men and women who are "movers" and "stayers" for unobserved reasons.

Findings

1. When we look at all workers whose careers had not started or whose first jobs began or were in progress during the year of the first interview (the "full sample"), we find that women have a higher hazard rate than men. Furthermore, we find that 58 percent of the women and only 46 percent of the men are movers for unobserved reasons.

2. Men and women respond very differently to family characteristics. Among the full sample of men, being married, becoming married, and the birth of a child all lower the hazard of job separation. The hazard rate of women falls when they get married, but it is otherwise unaffected by their marital status. The hazard rate increases if they have a newborn child, but not if they have older children.

3. Both men and women appear to engage in job shopping. Among the full sample, the hazards of both genders fall with increased prior experience, increases in the proportion of time that is spent working, increased tenure, and increased wages.

4. For women, there are large differences between an early birth cohort and a late birth cohort. The differences among men are considerably less pronounced. Unobserved heterogeneity becomes an insignificant factor among the late cohort of women, and the only important

determinant of women's turnover that may not be known at the time of hire are the presence of a newborn child and the act of becoming married. Overall, we find that women appear to be converging toward the turnover behavior of men over time.

5. There are also important differences among successive labor market entry cohorts. For men, marital status, becoming married, and becoming divorced appear to be growing increasingly important. For women, the effect of a newborn child is becoming increasingly important, as are the effects of prior experience and wages.

6. Among continuously employed workers, family characteristics are less important in explaining turnover. Furthermore, only 16 percent of the men and 28 percent of the women are movers for unobserved reasons.

7. Many variables that are important determinants of job separations do not explain voluntary and job-to-job transitions. In general, these transitions are less influenced by personal and family characteristics such as educational attainment, becoming married, and prior experience.

Implications

The study provides a wealth of detailed information about the turnover behavior of young men and women, but we wish to highlight four key implications.

1. When we look at all transitions undergone by the full sample of workers, we conclude that it is more difficult for employers to identify non-quitters among a pool of women than among a pool of men. This is because a larger proportion of women are movers for reasons that cannot be observed, and because female turnover is influenced by two important factors that are generally not observed by employers at the time of hire—namely, becoming married and the presence of a newborn child.

2. This conclusion is reversed when we focus on separate birth cohorts, since unobserved heterogeneity is unimportant among the younger women. In general, we conclude that younger women look very much like men in their turnover behavior.

3. Family responsibilities (especially the birth of a child) are not primary causes of job separations among women. In fact, the hazard rate of continuously employed women and of women in the late birth cohort are the only ones that increase with the birth of a child. Women are more likely to leave their jobs when they get married and when they have a newborn child, but both of these factors are short-lived by their very nature.

4. We find that both men and women exhibit signs of job shopping. That is, they locate increasingly high quality job matches as they gain experience, and they lock into those jobs by investing in job-specific skills.

Section 1: Introduction

The days when women automatically withdrew from the labor force upon marrying or having a child are long gone. Although it remains common for women with young children to interrupt their careers, increasing numbers work continuously throughout their adult lives. There is concern, however, that young women who are not planning career interruptions are unable to signal their intentions to potential employers. Employers may simply equate "female" with "quitter" because women have higher average turnover rates than men. Such statistical discrimination would be costly to women, since training, promotions, and even the jobs themselves are often unavailable to workers who are expected to quit.

At issue is whether young women are denied valuable opportunities because employers assume they are quitters. Not only would employers be wrong to take such a view, but they would be wrong to assume that young men are *not* quitters. Early in their careers, men are extremely likely to quit their jobs—not necessarily to withdraw from the labor force, but because they are "shopping" for a durable employment relationship. They may quit upon discovering a better job or upon realizing that their current job is not as good as had been hoped. While women are more prone than men to leave the labor force, the fact is that young workers are likely to quit their jobs regardless of their gender.[1]

Although we can dismiss the notion that women quit and men do not, a number of questions remain. Do young women quit more often than men? Do young women quit primarily to have babies, or do they also engage in job shopping? Given that employers can only observe a handful of characteristics at the time of hire, is it more difficult for them to identify the female non-quitters than the male non-quitters? To answer these questions, we use data from the National Longitudinal Surveys of Labor Market Experience (NLS) to estimate proportional hazard models for all job separations, regardless of whether the worker is subsequently employed, unemployed,

[1]Of course, young men also leave the labor force, primarily to return to school or because they are discouraged about their employment prospects.

or out of the labor force.[2] In other words, we view the data from the employer's perspective. We estimate separate models for men and women in order to compare each gender's determinants of turnover. We also estimate separate models for an "early" and a "late" birth cohort within each gender. This enables us to identify whether later cohorts exhibit different turnover patterns, and whether cohort effects are gender-specific. Finally, we analyze the behavior of four additional sub-samples: five cohorts by their year of entry into the labor force, jobs that were left voluntarily, jobs left to start a new job, and sub-samples of continuously employed workers.

The notion that women comprise a homogeneous group characterized by sporadic labor force participation has been refuted by Heckman and Willis (1977) as well as others. While many women continue to withdraw from the labor force either temporarily or permanently to fulfill household responsibilities, a large number of women work continuously. Available data do not always permit us to distinguish such women from those who experience short and infrequent interruptions, but the evidence suggests that even married women of child bearing age have grown increasingly committed to the labor force. Smith and Ward (1985), for example, find that 25 to 34 year old women increased their participation rate by over 20 percent during the 1970s.

If women who plan to remain in the labor force also plan to keep their jobs, then it is important that employers be able to identify them as non-quitters. Women who plan to interrupt their careers are unwilling to invest in skills that will depreciate during their absence. Since skill investments are associated with wage growth, these women are essentially opting for relatively flat wage profiles (Sandell and Shapiro, 1978; Mincer and Ofek, 1982; Cox, 1984). Job-specific investments are beneficial to workers who do not plan to quit, but such investments require that the firm shares the worker's belief that the employment relationship will last (Becker, 1975; Hashimoto, 1981). Women who plan to keep their jobs will be denied investment opportunities if their employers assume they are planning career interruptions.

The question, of course, is whether young women who remain in the labor force are actually non-quitters. If they are, then they differ dramatically from their male counterparts. A number of

[2]Although we have in mind worker-initiated separations, we realize that quits, fires, and layoffs are not clearly distinguishable conceptually or empirically. Our only recourse is to make use of workers' reported reasons for leaving their jobs.

studies (Bartel and Borjas, 1981; Topel and Ward, 1985; Topel, 1986; Light, 1987, 1988) document the rapid mobility that men typically undergo early in their careers as they search for a durable job match. These workers also enjoy tremendous wage growth, but the evidence suggests that they invest primarily in skills that are portable across jobs (Light, 1988). If young women prove to exhibit similar job matching behavior, then the quitter label can be construed as an accurate reference to their age rather than a discriminatory inference about their gender. Furthermore, accusations that women are denied training in job-specific skills would be unfounded, since such investments would be nonoptimal for both the worker and the employer.

Existing gender-related turnover studies (Barnes and Jones, 1974; Viscusi, 1980; Blau and Kahn, 1981; Waite and Berryman, 1985; Donohue, 1986a, 1986b; Meitzen, 1986) provide hints that women who change jobs are indeed attempting to improve their match. For example, better educated women are found to have higher quit probabilities, and quits are shown to improve the wages of women as well as men. These studies do not share the focus of the proposed research, however, so the issue of job shopping among women is left largely unexplored. Furthermore, many conclusions about determinants of men's and women's quit probabilities are suspect because the studies pre-date or fail to utilize state-of-the art econometric techniques.

In the next section, we discuss our econometric model. Section 3 describes the data set and summarizes differences in male and female turnover behavior. Sections 4 and 5 present estimates of hazard models, and Section 6 contains our conclusions.

Section 2: The Statistical Model

Most of the earlier turnover studies cited in Section 1 estimated logit models. We use the approach that has become standard for the analysis of turnover, which is to estimate hazard functions. Three recent studies (Meitzen, 1986; Donohue, 1986a, 1986b) also estimate hazard models, but our approach differs from theirs in two important respects. First, we estimate a discrete time model (obtained from aggregating an underlying continuous time model) to allow for the presence of time-varying regressors. The theoretical literature on turnover describes workers' efforts to maximize their lifetime earnings by searching for optimal "matches" of their skills with jobs. In this context, a worker observes the stream of wages paid to him or her on the current job and the stream of outside wage offers; whenever either wage path changes, the worker reevaluates the benefit of continued employment. Not only can both wages change many times within employment spells, but those changes play a key role in determining the spell's duration.[3] Models that do not allow for the presence of time varying regressors fail to capture the essential ingredients of modern theories of job matching. The second methodological difference is that we include corrections for unobserved heterogeneity, since it is well known that failure to do so may yield biased estimates of duration dependence. The type of correction that we perform is described below.

The aggregation of a continuous time model to a discrete time model is readily performed—and computations are greatly simplified—when the hazard function is restricted to the family of proportional hazards. The proportional hazards model (in continuous time) can be expressed as

$$\lambda(t;\mathbf{x}) = \lambda_0(t)\exp(\mathbf{x}\beta)$$

where t denotes time, $\lambda_0(t)$ is an arbitrary baseline hazard function, $\mathbf{x}$ is a row vector of covariates, and β is a column vector of parameters. As noted in Kalbfleisch and Prentice (1980), a model of discrete survival data is appropriate when the survival time is subject to interval grouping—that is, when we do not observe the exact survival time (arising from an underlying continuous

[3]Since we analyze job-to-nonemployment transitions as well as job-to-job movement, we capture changes in the value of nonemployment by letting marital and child-bearing status change with time.

distribution) but rather the interval A_j in which it falls, where $A_j = [a_{j-1}, a_j)$, $j = 1, ..., k+1$ are $k+1$ disjoint intervals, and $a_0 = 0$, and $a_{k+1} = \infty$. In the discrete time model, the hazard at interval A_j is defined as

$$P(T \in A_j | T > a_{j-1}) = 1 - \lambda_{A_j}^{\exp(\mathbf{x}_{j-1}\beta)}$$

where T represents the completed duration of an employment spell,

$$\lambda_{A_j} = \exp\left(-\int_{a_{j-1}}^{a_j} \lambda_0(u)du\right),$$

and $\mathbf{x}_{j-1}$ is the value of the vector $\mathbf{x}$ at time a_{j-1}.

In principle, we could estimate the set of λ_{A_j}, together with β but it would involve an unusually large number of parameters. One alternative is to condense the likelihood function and estimate β with no reference to the set of incidental parameters, λ_{A_j} (a procedure made possible because of the assumption of proportional hazards). There are two reasons why we chose not to proceed along these lines. First, we want to examine the effect of current job tenure on the likelihood that a spell will end. By maximizing a partial likelihood function we ignore the (possible) tenure dependence of the underlying baseline hazard. Second, we want to correct our estimates for the potential presence of unobserved heterogeneity across individuals in the sample. This second issue prevents us from performing a simple condensation of the likelihood function (Ward and Tan, 1985). Therefore, we chose to reduce the number of parameters to be estimated by further constraining the baseline hazard. We assume that the baseline hazard arises from a Gompertz distribution with parameters δ and γ:[4]

$$\lambda_0(t) = \delta e^{\gamma t}, \quad \delta > 0.$$

The discrete time model allows us to handle time varying covariates in a convenient way. By assuming that the vector $\mathbf{x}$ is constant within a time interval A_j, but that it varies from one interval to another, time varying covariates can be readily incorporated into the model. That is, at time a_{j-1} the vector $\mathbf{x}$ takes on the values $\mathbf{x}_{j-1}$, assumed to remain constant within the interval A_j. We define the intervals to be three months—a time period in which virtually all aspects of a

[4]This choice of hazard is discussed at length in Section 4.

job match are likely to be constant.[5]

In duration models where unobserved individual heterogeneity is assumed to follow a known, parametric distribution, estimates have been shown to be sensitive to the specified distribution (Heckman and Singer, 1984a, 1984b; Trussell and Richards, 1983). One alternative is to use nonparametric methods. Heckman and Singer (1984b) prove the consistency of a nonparametric maximum likelihood estimator (NPMLE) and find—from limited Monte Carlo experiments—that the NPMLE estimates structural parameters rather well, but it does not yield acceptable estimates of the underlying mixing distribution of unobserved individual heterogeneity components.

We have chosen to follow the strategy used in Lillard and Waite (1987) where a finite mixing distribution is specified to have two support points. We believe this is a reasonable compromise. Estimation of the model using the NPMLE estimator developed by Heckman and Singer—in which the number of support points is determined during estimation—is computationally quite burdensome. On the other hand, preliminary findings reported in Taubman, Behrman, and Sickels (1988) indicate that when a very rich set of measures of individual heterogeneity is available, a relatively parsimonious specification for the finite mixture will do the job. The NLS provides such a wealth of information on observed individual heterogeneity that we expect that a finite mixture with two support points should provide the required flexibility to avoid biases in the estimates of structural parameters.

Consequently, we allow for the presence of unobserved individual heterogeneity by specifying a distribution of proportional shifts in the hazard function in the form of a finite mixture. The "shift factor" of the baseline hazard is expanded to include an error term, θ_q, that takes Q values. That is, the shift factor is now equal to $\exp(x\beta + \theta_q)$, where θ_q occurs with probability P_q, such that $\sum_q P_q = 1$. In particular, we set $q = 1, 2$, and since a normalization of the values of the residuals is required, we set $\theta_1 = 0$. Since $P_2 = 1 - P_1$, estimation of the parameters of the finite mixture involves the estimation of two parameters only, θ_2 and P_1. To assist numerical convergence, the likelihood function is maximized with respect to α, where $P_1 = \exp(-\exp(\alpha))$.

[5] Although the data permit us to define intervals as short as one month, we found that one-month and three-month intervals yield virtually identical estimates. We have opted to use three-month intervals because they lower computation costs considerably.

We now describe the likelihood function that emerges from this hazard model. To minimize the problem of initial conditions discussed by Heckman and Singer (1984a), we restrict the "full sample" to individuals whose careers have not started or whose first jobs begin or are in progress during the year of the first interview. Because some workers' first employment spells are in progress at the time of the first interview, the data set has left truncation (*i.e.*, workers whose first job begins and ends before the first survey are excluded from the sample, but those whose first job is still in progress are included). The data set is not left censored, since we observe current tenure for employment spells that are in progress at the time of the first survey. Consequently, the contribution to the likelihood function of a spell that had been in progress for m months at the time of the first survey, and that lasts to time t in interval A_τ, is

$$\sum_{q=1}^{Q} P_q \left(\prod_{j>m}^{\tau-1} \lambda_{A_j}^{\exp(\mathbf{x}_{j-1}\beta+\theta_q)} (1 - \lambda_{A_\tau}^{\exp(\mathbf{x}_{\tau-1}\beta+\theta_q)}) \right).$$

The contribution to the likelihood function of an employment spell that starts at the initial survey date or later, and ends at time t in interval A_τ is given by

$$\sum_{q=1}^{Q} P_q \left(\prod_{j=1}^{\tau-1} \lambda_{A_j}^{\exp(\mathbf{x}_{j-1}\beta+\theta_q)} (1 - \lambda_{A_\tau}^{\exp(\mathbf{x}_{\tau-1}\beta+\theta_q)}) \right).$$

Finally, the contribution to the likelihood of an employment spell that begins at the initial survey date or later and is in progress at the time of the last survey (*i.e.* of a censored spell), say at time a_k, is

$$\sum_{q=1}^{Q} P_q \left(\prod_{j=1}^{k} \lambda_{A_j}^{\exp(\mathbf{x}_{j-1}\beta+\theta_q)} \right).$$

When an individual is included in the sample, all his or her observed employment spells, in addition to the first job, contribute to the likelihood function. The contribution corresponds to the second or the third case just discussed, depending on whether the ending time of the spell is known or the spell is censored.

We specify the unobserved individual heterogeneity component to be the same for each individual within and across spells, but independently distributed across individuals. Alternatively, we could assume that unobserved heterogeneity components are independent across spells for a given individual (Tuma, Hannan, and Groeneveld, 1979). The suitability of each approach depends on what is being captured by the unobserved components. If the source of heterogeneity is time-invariant factors that make some workers movers and others stayers (holding everything else constant), then our formulation is appropriate. If, on the other hand, unobserved heterogeneity reflects the quality of the job match, then a specification that allows for independent components across spells for a given worker is a better choice.

To test for the source of unobserved heterogeneity, we estimated hazard models (by gender) for first employment spells, making no corrections for unobserved heterogeneity and including the length of future jobs as a covariate. Future job length was measured as the length of the second observed job and, alternatively, as the average length of all subsequent jobs. If the hazard of job separation for the first jobs is independent of the length of subsequent jobs, then we can infer that match quality is the source of unobserved heterogeneity (see Flinn and Heckman, 1982). On the other hand, a significant coefficient on the length of future jobs would suggest that the source of heterogeneity is time-invariant factors that make some workers movers and others stayers.

We find the latter case to apply to the women: both measures of future job length have negative coefficients. Since longer future jobs result in a lower hazard, we conclude that the sample of women consists of "movers" and "stayers"—*i.e.*, the same workers who have long future jobs also have low hazards of job separation on their first jobs. For the men, the length of the second job has no effect on the hazard rate of the first job and the average length of all subsequent jobs has a positive, but marginally significant effect.[6] Clearly, a short panel introduces a bias toward finding that a longer than average first job must be followed by a shorter than average second job, and the maximum panel length for men is two years shorter than it is for women. This may explain why we find a positive coefficient on subsequent job duration for the men, which suggests that the duration of first jobs and subsequent jobs are negatively correlated. Therefore, we conclude that there is weak evidence (at best) that match quality is the source of unobserved heterogeneity among the men. In light of the very strong evidence that time-invariant factors are the source of

[6]The coefficient on "average length" is 0.019 and the normal statistic is 1.69; the coefficient on "length of the second job" is 0.009 and the normal statistic is 0.899. For the women, the coefficients (normal statistics) are -0.023 (-1.80) and -0.041 (-3.34), respectively.

unobserved heterogeneity among the women, however, we believe that our choice of specification of the unobserved components is justified.

Section 3: Characteristics of the Data

We analyze all available years of data from the young men and young women cohorts of the National Longitudinal Surveys. The men were followed from 1966 to 1981; although the young women's survey is still in progress, only 1968 to 1985 data are analyzed in this study. We began by identifying the date when each participant entered the labor force. To avoid analyzing short-term jobs that are followed by a return to school, we did not start the clock on a worker's career until he or she began a period of labor force participation that would last at least 18 months. If that date occurred while the survey was in progress or no earlier than six years prior to its inception, the worker remains in our sample.[7] In addition, the worker must hold at least one job for which an hourly wage is reported. These criteria yield a sample of 17,361 jobs held by 4,600 men and a sample of 15,372 jobs held by 4,490 women.

In subsequent sections, we present hazard model estimates for (a) all transitions undergone by the workers in these two samples whose careers have not started or whose first jobs begin or are in progress at the time of the first survey, (b) only those transitions which are reported as voluntary, (c) only job-to-job transitions and (d) all transitions undergone by workers who have been continuously employed. In this section, we summarize each of these samples.

Table 1, which compares workers' characteristics at their first and last interviews, suggests that men are more successful than women in locating high paying jobs during the early career. When the average man is first interviewed, he is 20.6 years old, has 1.7 years of experience, and earns \$6.29 per hour (in 1982 dollars). When the typical woman is first observed, she is almost a year older than her male counterpart, but she has only 0.3 years of additional experience and she earns a lower wage. Job seniority is equal, so the difference in experience means that the woman began her current job with more prior experience than did the man. On average, women are observed over a slightly longer period of time (9.7 versus 9.1 years), but they receive substantially less wage

[7] Although two-thirds of the participants began their careers after the NLS began, 622 men and 612 women had been working for more than one year when they were first interviewed. We deleted the small number of workers who had been working for over six years because it is difficult to determine when they first entered the labor force.

Table 1: Characteristics at First and Last Interview

	MEN		WOMEN	
	Beginning of Panel	End of Panel	Beginning of Panel	End of Panel
Age	20.6	29.6	21.4	31.0
Potential experience	1.7	10.8	2.0	11.7
Tenure	0.7	4.1	0.7	3.7
Real hourly wage [a]	6.29	9.77	4.86	6.32
Jobs per worker		3.8		3.4
Number of jobs		17,361		15,372
Number of workers		4,600		4,490

[a] In 1982 dollars.

growth: men's wages increase by an average annual rate of 6.1 percent, while women's increase by only 3.1 percent per year. Furthermore, the average man has an additional 0.4 years of tenure at the last interview despite being a year younger and less experienced than his female counterpart. These numbers suggest that while men move into durable, high paying jobs, women either fail to locate equally good matches or do so much later in their careers.

Table 1 indicates that men receive a higher return to their early labor force activities and that they also undergo more turnover. Men are observed holding an average of 3.8 jobs over a nine year period, while women average 3.4 jobs in 9.7 years. As an alternative to this simple comparison, Table 2 shows the number of jobs held per year by workers in various demographic groups, occupations, and industries. The first row indicates that the sample of 4,600 men holds an average of 0.46 jobs per year, while the 4,490 women hold 0.43 jobs per year; these numbers refer to *observed* jobs divided by the sum of job durations, so they understate actual turnover.[8] Sub-samples of married and white men average far fewer jobs per year, but women in these categories are indistinguishable from the full sample. Among both men and women, education beyond the high school level appears to reduce turnover and living in the South or in an SMSA has no effect. Men who are unionized also hold fewer jobs per year while, surprisingly, unionized

[8] "Observed" jobs are simply jobs that appear in the sample—i.e., jobs for which starting and ending dates are reported or inferred and at least one wage is reported. The measures of average jobs per year reported in Table 1 also refer to observed jobs, so they understate turnover as well.

women hold far more than average. Among the industries, the greatest amount of turnover occurs in construction and agriculture, although women are rarely observed in these categories. This finding is unsurprising, since the cyclic and seasonal nature of these industries leads to a great deal of short-term employment. The occupational groupings reveal another unexpected result: both male and female professional and technical workers hold fewer jobs than average, yet managerial work has opposite effects on female and male turnover.

In addition to examining the effects of observable characteristics on turnover, we also consider self-reported reasons for job separations. The NLS repeatedly asked participants why they left their last job. Although non-coding is unusually prevalent, we can associate a response with roughly 27 percent of the jobs in each sample; 45 percent of the men and 40 percent of the women provide a response for at least one job. Table 3 reports the frequency distribution of these responses. Men and women do not differ appreciably in the frequency with which they are fired or laid off, but they differ dramatically in their reported reasons for quitting. Women attribute 23.7 percent of their separations to their family or health, while this reason accounts for only four percent of separations among men.[9] By the same token, men are far more likely than women to report the discovery of a better job as the reason for their last job separation. Job dissatisfaction, which encompasses wages, hours, location, working conditions, and co-workers, is the most common reported reason for both men and women.

When men and women change jobs for the same reason, we wish to learn whether they are at similar levels of experience and tenure, and whether the transitions lead to more durable jobs. The panel nature of our data enables us to classify a limited number of jobs according to why they *will* end, in addition to why they began (i.e., why the last job ended).[10] Table 4 presents mean completed durations and mean experience at the time of transition for jobs classified in both these ways. The first row of the top panel indicates that the typical man's job that *will* end in a fire or layoff began when he had five years of experience. Since it will last 1.15 years, that is the worker's

[9]Because pregnancy is alternatively coded as "family" and "health", these categories are aggregated.

[10]For a job to be assigned a reason for its eventual dissolution, three criteria must be met: a worker must report a reason for leaving his or her last job, the last job must be in our sample— i.e., its starting and ending dates are known, at least one hourly wage is reported, and no other job intervened between the two—and no more than 18 months can have elapsed between jobs.

Table 2: Number of Jobs Held Per Year by Workers with Selected Personal and Job Characteristics

	MEN		WOMEN	
	Jobs Per Year[a]	Percent of Time Spent in Category[b]	Jobs Per Year[a]	Percent of Time Spent in Category[b]
Full Sample	0.46	100	0.43	100
Married	0.40	57	0.45	56
Nonwhite	0.53	25	0.44	30
≤ 12 years of school	0.49	61	0.46	66
> 12 years of school	0.42	39	0.38	34
Live in South	0.49	40	0.44	40
Live in SMSA	0.45	73	0.43	73
Wages set by union	0.36	14	0.57	14
Industry				
Agriculture, forestry, fishing	0.70	2.5	0.61*	1.8*
Mining	0.39	1.4		
Construction	0.75	9.0		
Manufacturing	0.38	35	0.41	20
Transp., communication, utilities	0.34	8.7	0.27	5.5
Trade	0.57	16	0.64	15
Finance, insurance, real estate	0.42	3.7	0.34	8.6
Services	0.50	17	0.43	42
Public administration	0.28	6.4	0.29	6.5
Occupation				
Clerical	0.42	9.1	0.39	40
Sales	0.45	5.4	0.71	3.8
Professional, technical	0.34	17	0.34	19
Managerial	0.38	7.5	0.44	2.5
Craftsmen, foremen	0.46	17	0.41	1.0
Operatives, laborers, service	0.55	43	0.54	31

[a] $\Sigma k / \Sigma D_{jk}$, where $k = 1$ if job j is in category k, 0 otherwise.
[b] $\Sigma D_{jk} / \Sigma D_j$, where D_{jk} is duration if job j is in category k, 0 otherwise.
* Includes mining and construction.

Table 3: Distribution of Reasons for Job Separations

Reported Reason	MEN	WOMEN
Fired	3.2	2.8
Laid off	26.1	22.6
Quit due to		
Health/family	4.3	23.7
Job dissatisfaction	29.9	26.8
Found better job	24.4	7.6
School	3.2	3.5
Other	8.9	12.9
Number of jobs	4,836	3,930
Number of workers	2,049	1,813

tenure when he is discharged. According to the first row of the bottom panel, men who have been fired or laid off acquire new jobs that last 0.96 years, on average.

A number of interesting contrasts emerge from Table 4. First, women tend to have slightly more tenure than men when they are fired or laid off (1.31 years versus 1.15 years), and their subsequent jobs last longer (1.13 years versus 0.96 years). The former comparison suggests that women invest less intensively in job-specific skills, while the latter suggests that they find relatively better (i.e., longer) jobs after an involuntary discharge. Second, jobs that are entered into because they are "better" are much longer than average for both men and women, although women tend to make such transitions later in their careers. Just the opposite is true for job changes caused by health problems and family obligations. Men have an average of 5.4 years of experience when they make such transitions, while women have only four. Of course, the likelihood of poor health—which, for men, is likely to be a more important factor than family obligations—increases with age, while pregnancy and family obligations are likely to occur early in the careers of women.

The turnover described thus far includes transitions from jobs to new jobs, unemployment, non-employment, and spells that cannot be identified. Since one of our goals is to compare the job shopping behavior of men and women, we wish to focus on those transitions which are job-to-job.

Given the spotty nature of the timelines, it is not always easy to identify a job-to-job transition. For each job, we measured the length of time that elapsed between its termination date and the

Table 4: Job Duration and Prior Experience, by Reason for Leaving Current Job and by Reason for Leaving Last Job

	MEN			WOMEN		
Reason for Leaving Current Job	Number of Jobs	Mean Duration	Mean Prior Exp.	Number of Jobs	Mean Duration	Mean Prior Exp.
Fired/laid off	1,496	1.15	5.00	1,161	1.31	4.63
Quit due to						
Health/family	201	1.67	5.39	1,018	1.42	3.95
Job dissatisfaction	1,403	1.44	4.27	1,186	1.31	4.13
Found better job	1,138	1.72	4.42	351	1.96	4.66
School	185	1.06	2.73	159	1.31	2.96
Other	476	1.61	5.21	551	1.82	4.20
All quits	3,403	1.55	4.43	3,418	1.51	6.80
Reason for Leaving Last Job	Number of Jobs	Mean Duration	Mean Prior Exp.	Number of Jobs	Mean Duration	Mean Prior Exp.
Fired/laid off	1,418	0.96	6.85	1,000	1.13	6.58
Quit due to						
Health/family	207	1.30	7.80	931	1.05	5.96
Job dissatisfaction	1,444	1.41	6.48	1,054	1.28	6.13
Found better job	1,179	1.82	6.98	299	3.76	7.32
School	157	0.91	4.62	138	1.13	4.89
Other	431	1.28	7.68	508	2.06	6.95
All quits	3,265	1.50	4.09	2,930	1.59	6.28

starting date of the next observed job. For men, the mean "gap" is 11.07 months, with a standard deviation of 14.47; for women, the mean is 15.70 months and the standard deviation is 23.34. Jobs that are followed by a gap may in fact be immediately succeeded by a new job that is not in our sample. However, in an effort to select jobs that are *known* to be followed by another job, we require that the gap be less than three months.

This selection criterion yields a sample of 2,974 jobs for the men and 1,630 jobs for the women that end with job-to-job transitions. The average man's job ends when it is 0.87 years old and the average woman's ends after 1.03 years. In our subsequent analysis, we will determine whether the factors that cause these jobs to end differ from the factors that cause the full sample of jobs to end.

The final sub-sample that we examine consists of workers who are "continuously employed." To construct these samples, we used information on the number of weeks during the last year (or since the last interview) that respondents spent working, unemployed, or out of the labor force. Again, we are not able to account for all the weeks in each worker's career. In particular, we invariably lose sight of a large number of weeks when interviews are conducted biannually. In order to skirt this problem, we focus on those weeks that *can* be accounted for and calculate the percentage of time that is known to be spent working. For the men, an average of 85.6 percent of the entire panel is accounted for, and an average 81.1 percent of this time is known to be spent working. The corresponding numbers for the women are 68.5 and 62.1. We use the median of the men's time-spent-working distribution—89 percent—as the cutoff point in defining continuously employed workers. That is, anyone who spends more than 88 percent of their time working is considered to be continuously employed. Gaps in the data, rather than unemployment or non-employment, account for most of the time spent not working.

Table 5 duplicates the information contained in Table 1 for the samples of continuously employed workers. It reveals that, among continuously employed workers, women appear to be more successful than men at transiting into durable jobs. At the end of the panel, men and women have roughly the same amount of labor market experience, but women have almost 15 months of additional tenure. However, continuously employed women appear to be getting lower returns to

Table 5: Characteristics at First and Last Interview
(SAMPLE: Continuously Employed Workers)

	MEN		WOMEN	
	Beginning of Panel	End of Panel	Beginning of Panel	End of Panel
Age	21.1	30.2	21.6	31.1
Potential experience	2.0	11.1	1.6	11.2
Tenure	1.0	5.3	1.0	6.5
Real hourly wage [a]	6.70	10.23	5.52	7.79
Jobs per worker		3.2		2.5
Number of jobs		7,433		2,812
Number of workers		2,343		1,142

[a] In 1982 dollars.

tenure than their male counterparts: the ratio of female to male wages at the end of the panel is 0.76, which is exactly the same as the ratio for the full sample.

Section 4: Estimates for the Full Sample

Prior to adopting a unique specification for the baseline hazard, we estimated models in which the baseline hazard was alternatively specified to be Gompertz, Weibull, and Box-Cox. The baseline hazard under a Gompertz specification was described in Section 2. Under a Weibull specification, it is

$$\lambda_0(t) = \rho k(\rho t)^{k-1}$$

with ρ, $k > 0$. The baseline hazard under a Box-Cox specification is defined as

$$\lambda_0(t) = \exp(\gamma_1 \frac{t^{\lambda_1} - 1}{\lambda_1} + \gamma_2 \frac{t^{\lambda_2} - 1}{\lambda_2}),$$

with $\lambda_2 > \lambda_1 \geq 0$. The Box-Cox hazard is quite general in that it contains both the Gompertz and the Weibull hazards as special cases. It is readily verified that setting $\lambda_1 = 0$ and $\gamma_2 = 0$ in the above expression yields a Weibull hazard, while setting $\lambda_1 = 1$ and $\gamma_2 = 0$ yields a Gompertz hazard.

The extra flexibility afforded by the Box-Cox hazard comes at a price. To write the likelihood function for our discrete time model we follow the standard approach of expressing the discrete hazard as a function of the integrated (continuous) baseline hazard. Since there is no analytical solution for the integral of a Box-Cox hazard, numerical integration is required. Numerical integration is also required to compute the gradient vector at each iteration. Of course this can be avoided if numerical derivatives are used—a practice we avoided because of the large number of parameters and sample sizes involved.

In preliminary tests, we found that numerical integration increased estimation time by an order of magnitude, so we obtained estimates for a sample of workers whose first jobs began or were in progress in the first year of the survey. This selection criterion, which eliminates the problem of initial conditions and likely minimizes the problem of time inhomogeneity of the environment, yields fairly large samples anyway. For both men and women, about 35 percent of the "full samples" described earlier are contained in the restricted samples: the sample of men has 31,948 observations for 6,191 workers, and the figures for women are 27,025 observations for 5,313 workers.

We report our estimates for the three models in Tables 6 and 7. The Box-Cox hazard has four parameters to capture the tenure dependency of the hazard of job separation; the Weibull and Gompertz hazards have only one parameter each. Thus, it is unsurprising that the Box-Cox model yields the largest value of the likelihood function for the samples of men and women. The estimates for women show that the Box-Cox hazard fits the data only marginally better than the Gompertz; the Weibull hazard results in a considerably worse fit. Comparing the parameter estimates that obtain from the Gompertz and from the Box-Cox models we find no sign reversals. Indeed, the estimates are so close that there is no apparent benefit to be gained from using the Box-Cox specification in subsequent analysis.

The results for the sample of men parallel those for women, though in this case the Box-Cox model yields a value of the likelihood function equal to -10011.8 versus a value of -10045.8 from the Gompertz model. Again, we find no sign reversals in the parameter estimates, and the estimates are very close in magnitude. The one exception is the estimate of the fraction of men who are "movers" for unobserved reasons and, therefore, the estimate of θ_2 (the difference in the intercept term for "stayers" and "movers"). The fraction of stayers is estimated at 86 percent in the Box-Cox model, compared with 74 percent in the Gompertz model. Given that the remaining parameter estimates appear to be unaffected by the choice of baseline hazard (ignoring the Weibull model estimates), and given the high cost of obtaining estimates for the Box-Cox model, we chose to specify a Gompertz hazard for the remaining analysis.

We estimated a Weibull model for the full samples of men and women to determine whether our findings on the relative merits of alternative baseline hazard specifications are sample specific. We find the same pattern found for the restricted samples: the Gompertz model fits the data considerably better. The estimates are reported in Table A1 in the Appendix.

To avoid the problem of initial conditions mentioned in Section 2, we begin by estimating hazard models for samples of workers whose careers had not started or whose first jobs began or were in progress during the year of the first interview. The first interview for the men was in 1966 (generally in November) and, for the women, it was in January or February, 1968. These selection criteria yield samples of 2,594 men and 2,552 women.

Table 6: Estimates for Gompertz, Weibull, and Box-Cox Hazard Models
Correction for Unobserved Heterogeneity
(SAMPLE: Women Whose First Jobs Begin or Are in Progress in the First Year of the Survey)

	GOMPERTZ		WEIBULL		BOX-COX	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	-.093	-1.68	-.065	-.97	-.084	-1.30
MARRIED	.182	3.09	.124	2.16	.169	2.86
WEDS	.138	1.50	.122	1.28	.144	1.47
DIVORCES	-.125	-1.08	-.082	-.54	-.114	-.91
BIRTH	.243	3.74	.267	3.76	.252	3.66
NEWBORN	.287	3.89	.319	2.96	.288	2.85
PRESCHOOL	.238	4.50	.204	3.44	.225	3.93
SCHOOL	.007	.41	.004	.29	.008	.49
PRIOREXP	-.206	-9.71	-.051	-4.05	-.202	-8.54
TIMEWORKING	-.051	-.96	-.185	-2.02	-.089	-.99
INVOLUNTARY	.388	6.81	.409	6.24	.370	5.01
WAGE	-.511	-9.42	-.545	-9.94	-.500	-9.09
PARTTIME	.334	7.06	.320	5.34	.325	6.05
UNION	.341	5.74	.309	4.82	.315	4.51
CONSTRUCTION	.059	.38	.051	.29	.067	.46
TRANSPORTATION	-.383	-5.32	-.397	-3.26	-.376	-3.41
TRADE	.426	7.36	.396	6.60	.409	7.57
PUBADMIN	-.481	-5.94	-.524	-4.10	-.473	-4.61
SMSA	.013	.22	.026	.44	.023	.38
SOUTH	.059	1.15	.029	.52	.053	.88
UNEMPLOYMENT	.001	.11	.014	1.13	.002	.26
Y6869	-.453	-4.57	-.700	-6.00	-.437	-4.41
Y7071	-.106	-.76	-.672	-4.94	-.098	-.72
Y7273	-.051	-.33	-.871	-5.89	-.033	-.20
Y7475	-.614	-3.03	-1.803	-9.77	-.598	-2.90
Y7677	.278	1.20	-1.209	-6.35	.290	1.13
Y7879	-.123	-.43	-1.912	-9.17	-.114	-.38
Y8081	.607	1.89	-1.562	-6.76	.605	1.76
Y8283	1.246	3.31	-1.378	-5.45	1.220	3.06
γ	-.021	-12.47	—	—	—	—
$\log(k)$	—	—	-.182	-7.18	—	—
γ_1	—	—	—	—	-.114	-3.25
γ_2	—	—	—	—	-.009	-1.86
$\log(\lambda_1)$	—	—	—	—	-17.315	-.27
$\log(\lambda_2)$	—	—	—	—	.150	1.41
$\log(\delta)^*$	-2.220	-9.00	-1.948	-8.44	-2.167	-8.75
α	-.286	-3.64	-.182	-1.55	-.219	-1.65
θ_2	1.193	22.02	1.316	16.59	1.173	14.92
Log likelihood	-8490.837		-8529.557		-8486.012	

* For the Weibull model, this is the estimate of $k \log(\rho)$; it is the estimate of the constant term in the Box-Cox model.

Table 8 summarizes the variables we consider, which include characteristics of the individual, the job match, and the environment. In the first category are dummy variables indicating race and marital status; since *changes* in marital status are likely to be important determinants of turnover, we also include dummy variables indicating whether the worker marries or divorces during the interval. To control for the effects of children, we include a dummy indicating whether a child is born during the interval; for women, we also include indicators of whether she has a newborn child or preschool children.[11] In addition, we include a measure of years of completed schooling. We measure past job shopping activity by including years of potential prior experience (PRIOREXP), the fraction of potential prior experience that is accounted for by *observed* jobs (TIMEWORKING), and a dummy variable indicating whether the last job was left involuntarily. To measure characteristics of the current job match, we include the (log of the) hourly wage, dummy variables indicating union status, part-time status, and industry of employment. Since most industries proved to have no effect on the hazard, we include only construction, transportation, trade, and public administration.[12] We account for market characteristics with monthly unemployment rates and dummy variables indicating calendar years, residence in an SMSA, and residence in the South.

Table 9 reports estimates for a Gompertz hazard model with corrections for unobserved heterogeneity. The first thing to note is that personal characteristics do not effect the hazards as one might have expected. Being married lowers the hazard rate for men but has no effect for women. Becoming married (WEDS) lowers the hazard rate for men and women, but the effect of a divorce is not statistically significant for either gender. The birth of a child lowers the hazard rate for men but, surprisingly, it has an insignificant effect for women. Nevertheless, women are more likely to separate from their jobs if they have a newborn child, although the presence of a preschooler has no effect on their hazard. Race is not an important predictor of turnover behavior for either men or women, while increased educational attainment lowers both hazards, although the effect is far more pronounced for men.

[11]The number of children age 18 or under proved to have no effect on the hazard for either gender. Since male respondents were not asked their children's ages, we cannot include the NEWBORN and PRESCHOOL dummies in their hazards.

[12]For the women, the construction dummy also includes agriculture and mining. We formed this composite industry because only a handful of women appear in each category.

Table 7: Estimates for Gompertz, Weibull, and Box-Cox Hazard Models
Correction for Unobserved Heterogeneity
(SAMPLE: Men Whose First Jobs Begin or Are in Progress in the First Year of the Survey)

	GOMPERTZ		WEIBULL		BOX-COX	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	.036	.66	.032	.55	.031	.55
MARRIED	-.142	-2.76	-.237	-4.68	-.139	-2.46
WEDS	-.295	-3.79	-.337	-3.52	-.294	-3.21
DIVORCES	.133	.76	.115	.63	.143	.84
BIRTH	-.277	-6.12	-.248	-3.74	-.262	-3.92
SCHOOL	-.023	-2.27	-.035	-3.88	-.017	-1.11
PRIOREXP	-.206	-8.66	-.014	-1.08	-.199	-7.01
TIMEWORKING	-.326	-4.53	-.551	-6.43	-.397	-4.73
INVOLUNTARY	.423	7.38	.333	4.96	.394	6.45
WAGE	-.124	-2.64	-.203	-4.17	-.140	-2.10
PARTTIME	.678	17.56	.693	10.25	.658	7.77
UNION	-.448	-7.61	-.477	-6.50	-.428	-6.40
CONSTRUCTION	.419	7.21	.443	6.52	.419	5.42
TRANSPORTATION	-.399	-9.96	-.293	-2.86	-.377	-3.44
TRADE	.066	1.21	.017	.30	.047	.80
PUBADMIN	-.271	-3.05	-.260	-2.35	-.275	-2.55
SMSA	-.099	-2.18	-.074	-1.41	-.092	-1.64
SOUTH	-.055	-1.10	-.084	-1.63	-.064	-1.26
UNEMPLOYMENT	-.035	-3.36	-.037	-2.66	-.035	-3.20
Y6869	.748	10.85	.517	7.25	.795	9.63
Y7071	1.396	13.17	.766	7.17	1.412	9.45
Y7273	1.004	6.74	.056	.46	1.076	4.93
Y7475	1.417	7.54	.113	.71	1.500	5.51
Y7677	2.124	8.99	.373	2.18	2.162	6.46
Y7879	2.387	8.85	.229	1.33	2.381	6.44
Y8081	2.502	7.85	-.030	-.13	2.479	5.65
γ	-.030	-14.55	—	—	—	—
$\log(k)$	—	—	-.033	-13.12	—	—
γ_1	—	—	—	—	-.023	-.52
γ_2	—	—	—	—	-.096	-3.84
$\log(\lambda_1)$	—	—	—	—	-16.866	-.02
$\log(\lambda_2)$	—	—	—	—	-.387	-4.95
$\log(\delta)$*	-2.108	-14.87	-1.997	-9.45	-1.781	-7.93
α	-1.209	-2.68	.186	1.26	-1.903	-.82
θ_2	.870	12.77	1.209	8.79	.819	1.89
Log likelihood	-10045.896		-10079.701		-10011.867	

* For the Weibull model, this is the estimate of $k \log(\rho)$; it is the estimate of the constant term in the Box-Cox model.

Table 8: Sample Means and Standard Deviations
(SAMPLE: Workers Whose Careers Have Not Started or Whose First Jobs Begin or Are in Progress in the First Year of the Survey)

Variable	Definition	MEN Mean	MEN Std. Dev.	WOMEN Mean	WOMEN Std. Dev.
NONWHITE	1 if nonwhite	0.247	0.431	0.274	0.446
MARRIED	1 if married	0.589	0.492	0.593	0.491
WEDS	1 if marries during interval[a]	0.059	0.235	0.059	0.235
DIVORCES	1 if divorces during interval[a]	0.018	0.134	0.026	0.159
BIRTH	1 if child is born during interval[a]	0.150	0.357	0.120	0.325
NEWBORN	1 if child age one or under	—	—	0.037	0.188
PRESCHOOL	1 if child age six or under	—	—	0.220	0.414
SCHOOL	Years of schooling	12.989	2.821	13.034	2.347
AGE		25.537	4.611	26.694	4.940
PRIOREXP	Years of potential prior experience	3.644	3.604	4.031	4.182
TIMEWORKING	Ratio of actual to potential experience	0.488	0.348	0.415	0.337
INVOLUNTARY	1 if left last job involuntarily	0.094	0.292	0.085	0.279
TENURE	Years of tenure	2.542	3.010	2.651	3.026
PARTTIME	1 if works less than 35 hours/week	0.061	0.240	0.161	0.367
WAGE	Log of real hourly wage[b]	2.015	0.500	1.702	0.476
UNION	1 if wages set by union	0.175	0.380	0.195	0.396
	1 if industry is				
CONSTRUCTION	Construction	0.101	0.301	0.019[c]	0.137
TRANSPORTATION	Transp., communication, utilities	0.072	0.258	0.052	0.222
TRADE	Trade	0.167	0.373	0.152	0.359
PUBADMIN	Public administration	0.058	0.234	0.060	0.237
UNEMPLOYMENT	Unemployment rate[d]	9.213	2.951	11.247	3.399
SOUTH	1 if living in the South	0.417	0.493	0.377	0.485
SMSA	1 if living in an SMSA	0.730	0.444	0.747	0.435
	1 if year is				
Y6869	1968-69	0.118	0.323	0.061	0.239
Y7071	1970-71	0.166	0.372	0.111	0.314
Y7273	1972-73	0.130	0.336	0.127	0.333
Y7475	1974-75	0.143	0.350	0.134	0.341
Y7677	1976-77	0.141	0.348	0.136	0.343
Y7879	1978-79	0.131	0.337	0.127	0.333
Y8081	1980-81	0.118	0.322	0.125	0.330
Y8283	1982-83	0.000	0.016	0.174	0.379
Number of individuals		2594		2552	
Number of observations		50,167		48,570	

[a] Since we only know that a change occurs between successive interviews, the variable equals one for every six-month interval falling between the two interview dates.
[b] In 1982 dollars.
[c] Includes mining and agriculture.
[d] Unemployment rate during first month of the interval.

The effects of prior experience, tenure, and wages suggest that both men and women engage in job shopping although, as we saw in Section 3, men appear to do so more vigorously. PRIOREXP and TIMEWORKING (the ratio of observed to potential experience) have a negative effect on the hazard rate for both genders. The hazard rate also declines in tenure for both genders, but especially for men (*i.e.*, γ is greater in absolute value). This is consistent with the notion that workers lock into good matches, presumably by investing in match-specific skills. We also find that an increase in the current wage—which is considered to be a good indication of match quality—lowers the hazard rate for both genders, but especially for women. The effect for men may be dampened by the fact that they are relatively more successful in parlaying a high current wage into an even higher outside wage offer.

The coefficients on UNION and the industry dummies suggest that some of the observed, unconditional difference in male and female turnover is attributable to the types of jobs favored by each gender. About 19 percent of the observations for both men and women refer to union jobs, but UNION lowers the hazard for men and raises it for women. Apparently, women who are unionized are concentrated in service professions (*e.g.*, teaching) and do not gain job stability from their union status. The coefficients on the industry dummies have the same signs and are of comparable magnitudes for men and women. The hazard of job separation is higher for workers in the construction and trade industries, and is lower for workers in transportation and public administration. Residence in a SMSA and in the south lowers the hazard for men, but has no effect for women. Higher unemployment rates, on the other hand, lower the hazard for women, but do not have a statistically significant effect on the hazard rate for men.

The list of regressors includes dummy variables for calendar years, with the years prior to 1968 corresponding to the "omitted" period for both men and women. The coefficients on the year dummies reveal a pronounced secular increase in the hazard for men and a secular decrease in the hazard for women. The sample period was characterized by declining labor force participation rates of men and increasing rates for women. Although increased participation rates can result from larger numbers of women in the labor force with no accompanying change in behavior, our estimates suggest that an increased commitment to the labor force may have also been a factor.

To summarize, the estimates suggest that the early turnover behavior of men and women differ, but not dramatically. In particular, job shopping appears to be an important determinant of mobility for both genders. Although we have identified a number of variables that employers can use to predict turnover behavior for each gender, we have also shown that female turnover is increased by an important factor that is often unknown at the time of hire—namely, the presence of a newborn child. For this reason alone, it may be more difficult to screen for non-quitters among women than among men.

Furthermore, we must take into account the effect of unobserved heterogeneity. As Table 9 reveals, it plays an important role in explaining turnover, especially for women. The estimate of θ_2 is 1.02 for men and 1.22 for women. These numbers imply that unobserved heterogeneity increases the hazard rate by a factor of 2.8 for men ($e^{1.02}$) and by a factor of 3.4 for women. We can also identify what proportion of the sample changes jobs for reasons that are not captured by the observables. The value for α is -0.49 for the men and -0.13 for the women, which implies that 46 percent of the men and 58 percent of the women are "movers" for *unobserved* reasons.[13] These estimates indicate that there is a tremendous amount of unobserved heterogeneity within genders. However, factors that employers cannot control for are relatively more important for women than for men. This conclusion is reinforced by the results we obtained when we estimated the Box-Cox model.

To determine whether men and women who are deemed stayers differ in their quit behavior, we compute the implied probabilities of job separation in the following six months (conditional on various levels of current tenure) for both male and female stayers. These conditional probabilities were computed for the periods 1968-69, 1976-77, and 1980-81, for what roughly constitutes a modal worker: someone who is white and married, has twelve years of schooling, and lives in an SMSA. The probabilities were evaluated (separately for men and women) at the mean values of wages, unemployment rates, PRIOREXP, and TIMEWORKING. The top panel in Table 10 reports the probabilities of job separation for women and for men and the ratio of the former to the latter, for the period 1968-69. For the remaining periods, we only report the probabilities for men and

[13] $P_1 = exp(-exp(\alpha))$ is the percent that are "stayers," and $P_2 = 1 - P_1$ percent are "movers."

Table 9: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: Workers Whose Careers Have Not Started or Whose First Jobs Begin or Are in Progress in the First Year of the Survey)

	MEN		WOMEN	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	0.014	0.42	-0.051	-1.58
MARRIED	-0.205	-6.86	0.037	1.27
WEDS	-0.372	-7.20	-0.147	-2.83
DIVORCES	0.106	1.08	-0.121	-1.52
BIRTH	-0.334	-8.39	0.046	1.19
NEWBORN	—	—	0.379	6.43
PRESCHOOL	—	—	0.047	1.42
SCHOOL	-0.057	-10.39	-0.026	-3.95
PRIOREXP	-0.147	-20.33	-0.105	-16.02
TIMEWORKING	-0.364	-8.34	-0.329	-7.11
INVOLUNTARY	0.272	7.19	0.442	11.03
WAGE	-0.230	-8.00	-0.587	-19.37
PARTTIME	0.534	14.58	0.407	13.10
UNION	-0.591	-14.42	0.478	14.84
CONSTRUCTION	0.398	10.72	0.398	4.76
TRANSPORTATION	-0.300	-5.23	-0.575	-7.74
TRADE	0.128	4.12	0.334	10.58
PUBADMIN	-0.361	-5.39	-0.367	-5.58
SMSA	-0.105	-3.45	0.047	1.58
SOUTH	-0.099	-3.39	0.038	1.34
UNEMPLOYMENT	0.002	0.21	-0.021	3.49
Y6869	1.067	20.27	-0.375	-3.62
Y7071	1.441	22.14	-0.190	-1.81
Y7273	0.672	9.59	-0.509	-4.83
Y7475	0.961	10.99	-1.254	-10.94
Y7677	1.483	16.07	0.617	-5.30
Y7879	1.675	17.79	-1.313	-10.86
Y8081	1.780	15.06	-0.661	-5.06
Y8283	—	—	-0.220	-1.52
γ	-0.026	-33.99	-0.014	-17.23
$\log(\delta)$	-2.293	-23.32	-1.538	-10.81
α	-0.492	-4.47	-0.131	-1.63
θ_2	1.019	28.31	1.218	23.82
Log likelihood	-30275.431		-27176.867	

Table 10: Conditional Probability of Job Separation in the Next Six Months, Given Current Tenure of X Months, for Modal Workers[a].

By Gender, For Selected Periods.

Current tenure	1968-69 Women	1968-69 Men	1968-69 Women/Men	1976-77 Men	1976-77 Women/Men	1980-81 Men	1980-81 Women/Men
0	.107	.172	.621	.249	.341	.320	.254
6	.099	.149	.661	.217	.361	.281	.267
12	.091	.129	.706	.190	.382	.246	.282
24	.078	.097	.808	.143	.433	.188	.316
36	.067	.072	.927	.107	.493	.142	.358
48	.057	.054	1.067	.080	.564	.106	.407
60	.049	.040	1.146	.059	.647	.079	.465

By Gender, For Stayers and Movers, 1968-69.

Current tenure	Women Stayers	Women Movers	Men Stayers	Men Movers
0	.107	.318	.172	.407
6	.099	.297	.149	.361
12	.091	.276	.129	.318
24	.078	.240	.097	.246
36	.067	.209	.072	.187
48	.057	.180	.054	.143
60	.049	.156	.040	.107

[a]A modal worker is white, married, has 12 years of schooling, and lives in an SMSA.

the female-male ratio.

Glancing at the ratios of women's to men's job separation probabilities, it is apparent that women are generally less likely to leave their jobs in the next six months. The only exception is among workers with more than three years of current tenure during the period 1968-69. Table 10 also shows that men have undergone a rapid secular increase in the probability of job separation. For example, men faced a 17 percent chance of separation in the first six months of a new job in 1968-69 and a 32 percent chance in 1980-81—a two-fold increase. For women, the probability dropped from 11 percent to 8 percent during the same period.[14] In 1968-69, women faced a

[14]The secular decrease in the probabilities for women is slightly understated because the probabilities were evaluated at the average unemployment rate for the entire period. The estimated coefficient on the unemployment rate is -.021 for women, implying that the hazard decreases as the unemployment rate increases, and the latter was about four percentage points below (above) average in 1968-69 (1980-81). This is not a problem for men since their coefficient on the unemployment rate is very close to zero (0.002).

probability of job separation in the first six months of a new job that was only 62 percent as high as that of men. This ratio is 34 percent in 1976-77 and 25 percent in 1980-81.

To compare the behavior of movers to that of stayers, we compute analogous probabilities of job separation for movers for the period 1968-69. These are reported in the bottom panel of Table 10. The estimates reveal that, in the first two years of a new job, male movers face higher probabilities of job separation than female movers. Although the discrete hazard drops considerably faster with tenure for men than for women, it is unlikely that movers' jobs will survive long enough for this effect to take hold. For this reason, we conclude that jobs of male movers are somewhat more transitory than those of female movers.

Since female stayers generally have lower separation probabilities than their male counterparts, they may be a better bet from an employer's standpoint. Of course, the stayer designation refers to unobserved qualities, so it is not actually possible to identify such workers. If employers simply hire workers on the basis of observables and hope that they prove to be stayers, then they are more likely to be vindicated by their male employees; as we learned from Table 9, 54 percent of the men are stayers compared with only 42 percent of the women. Although this news may be discouraging to female non-quitters, they can take comfort in the knowledge that times are changing. Not only have successive cohorts of women increased their educational attainment and labor force participation rates, but they have altered their turnover behavior as well.

To demonstrate this, we present estimates of the hazard model for an "early" and a "late" birth cohort within each gender. Our early cohort consists of women who were born in the period 1944-46. The late cohort consists of women born in the period 1952-54. For the men, we use everyone born in 1942-44 and 1950-52. Three-year windows are used to maintain sufficiently large samples; for the same reason, we no longer require prior experience to be zero at the first observation. The samples contains observations on these workers while the respondents are between the ages of 24 and 31. There are 788 women in the early cohort and 1,019 in the late cohort; the corresponding samples sizes for the men are 853 and 1,438. Summary statistics for the four samples are presented in Tables A2 and A3 in the Appendix.

Table 11: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: "Early" and "Late" Birth Cohorts of Men and Women, from Ages 24 to 31)

	MEN				WOMEN			
	1944-42		1950-52		1944-46		1952-54	
Variable	Coef.	Normal Stat.	Coef.	Normal Stat.	Coef.	Normal Stat.	Coef.	Normal Stat.
NONWHITE	.002	.02	-.049	-.87	-.111	-1.84	-.023	-.42
MARRIED	-.022	-.34	-.077	-1.28	.190	2.68	-.061	-1.05
WEDS	-.192	-1.23	-.191	-1.55	-.313	-1.80	-.020	-.14
DIVORCES	-.113	-.54	.119	.86	-.249	-1.33	.217	1.31
BIRTH	-.274	-3.65	-.150	-2.17	.249	2.72	.316	4.32
NEWBORN	—	—	—	—	.040	.19	.480	3.30
PRESCHOOL	—	—	—	—	.184	2.65	.028	.44
SCHOOL=12	-.002	-.02	-.204	-2.94	-.021	-.28	-.239	-3.77
SCHOOL=13-15	-.061	-.65	-.178	-2.29	-.156	-1.71	-.371	-4.39
SCHOOL=16+	-.391	-4.62	-.518	-5.31	-.159	-1.19	-.421	-4.24
PRIOREXP	-.043	-2.91	-.018	-1.40	-.098	-8.44	-.059	-4.61
TIMEWORKING	-.401	-3.55	-.491	-5.37	-1.152	-8.76	-.287	-3.24
INVOLUNTARY	.006	.11	.261	4.18	.451	6.42	.098	1.18
WAGE	-.230	-3.34	-.193	-2.84	-.432	-5.64	-.351	-5.74
PARTTIME	.901	9.49	.823	8.18	.278	3.60	.412	6.56
UNION	-.635	-7.05	-.492	-7.00	.549	5.88	-.087	-1.17
CONSTRUCTION	.486	5.80	.546	7.02	.515	3.10	.218	.96
TRANSPORTATION	-.320	-2.84	-.524	-4.76	-.263	-1.26	-.127	-.69
TRADE	.106	1.60	.215	3.61	.146	1.95	.242	3.61
PUBADMIN	-.464	-3.18	-.412	-3.54	-.372	-2.58	-.386	-2.46
SMSA	-.056	-.84	-.074	-1.33	.325	5.57	.004	.08
SOUTH	-.085	-1.41	-.126	-2.41	-.067	-1.05	.062	1.27
UNEMPLOYMENT	-.120	-3.57	-.220	-8.09	.242	7.21	.216	4.92
Y6667	-.613	-3.62	—	—	—	—	—	—
Y6869	-.300	-2.01	—	—	.852	5.01	—	—
Y7071	.228	2.02	—	—	.762	6.41	—	—
Y7273	-.424	-3.88	—	—	.699	5.32	—	—
Y7475	—	—	—	—	-.418	-3.87	—	—
Y7677	—	—	.535	7.52	—	—	—	—
Y7879	—	—	.053	.62	—	—	-.555	-5.75
Y8081	—	—	.407	3.54	—	—	-.192	-2.43
Y8283	—	—	—	—	—	—	.019	.17
Y8485	—	—	—	—	—	—	-2.707	-5.13
γ	-.024	-12.58	-.019	-13.00	-.018	-9.89	-.015	-10.85
$\ln(\delta)$	-1.748	-5.64	-.437	-1.31	-4.962	-14.71	-3.707	-9.81
α	-.777	-3.27	.586	1.22	-.054	-.41	—	—
θ_2	1.188	13.73	-.837	-4.54	1.587	11.42	—	—
Log likelihood	-6871.740		-7711.512		-5481.353		-5353.675	

The cohort comparisons are presented in Table 11. Although the early and late cohorts of women are separated by only eight years, the difference between them is quite remarkable. For the early cohort, the coefficients on MARRIED, BIRTH and PRESCHOOL are all positive and significant. For the late cohort, BIRTH is the only one of these three that remains significant, and NEWBORN also registers a very large, positive effect. These estimates reveal that family obligations have not ceased to affect women's quit rates, but they are confined to a much shorter period—after all, a preschooler is around for six years, but the combined events of BIRTH and NEWBORN last for only one year. The cohorts also differ in their response to schooling: the hazard of the early cohort is unaffected by the schooling dummies, but the late cohort's hazard falls sharply as educational attainment increases. Interestingly, the coefficients on PRIOREXP and TIMEWORKING are less negative for the late cohort than for the early cohort, while UNION goes from positive to negative (and insignificant). With these changes over time in the turnover behavior of women, the coefficients on only four variables—BIRTH, SMSA, SOUTH, and UNEMPLOYMENT—have different signs for men and women. The inter-cohort differences among men are considerably less pronounced. The biggest changes are in schooling and TIMEWORKING, which have larger (negative) effects on the late cohort than the early cohort, and in BIRTH and PRIOREXP, both of which become less negative over time.

While family obligations have a diminished impact on the younger women's hazard rate, unobserved heterogeneity has no impact whatsoever. This is in marked contrast to the early cohort. Among these women, 61 percent are movers and the hazard rate of the movers is 4.9 times as high as for the stayers. The effect of unobserved heterogeneity also virtually disappears over time for the men. Among the early cohort, 37 percent are movers and their hazard rate increases by a factor of 3.3, while only 17 percent of the late cohort can be deemed movers.

The message delivered by Table 11 is that employers should have no difficulty predicting who will quit when they look at a sample similar to the late cohort of women. The important determinants of these women's hazard rate are not only observable but, with the exception of BIRTH and NEWBORN, they are known at the time of hire. Furthermore, the two "unpredictable" factors are, by their very nature, short-lived events. This is in marked contrast to the family characteristics that raise the hazard of the early cohort (MARRIED, BIRTH and PRESCHOOL), some of which tend to endure for years at a time. From an employer's point of view, single women and women who are likely to give birth in the near future appear to be riskier prospects than their male counterparts. However, women who are likely to have completed their desired fertility appear to be safe bets, even when their children are still quite young.

In addition to claiming that non-quitters are identifiable in the late cohort of women, we can also conclude that employers would be unwise to favor men over women when attempting to pick the non-quitters from this pool of workers. A young worker of either gender is prone to future turnover, of course, but the ability to predict turnover does not increase when we confine our sample to men. In fact, it may actually decrease, since a small proportion of the men are movers for reasons that cannot be observed. Furthermore, we estimated the hazard model for a combined sample of men and women (using workers born in 1950-52) and controlled only for variables that employers observe at the time of hire, *i.e.*, we omitted WEDS, DIVORCES, BIRTH, NEWBORN, PRESCHOOL and the correction for unobserved heterogeneity. The estimated coefficient on a dummy variable equal to one for women is -0.19 with a normal statistic equal to .048. That is, after controlling for *observables*, the hazard rate of job separation is 17 percent lower for women than for men. By contrast, the gender effect is zero when we perform the same experiment on a sample of men and women born in 1944-46.

Section 5: Estimates for Selected Sub-Samples

In the previous section, we examined job separations without regard to the type of transition being undertaken. Jobs could end either voluntarily or involuntarily, and they could be followed by another job, unemployment, non-employment, or an unidentified spell. In addition, we ignored heterogeneity in individuals' commitments to the labor force. In order to augment our conclusions about the comparative job shopping behavior of men and women, we now re-estimate our hazard model for a variety of sub-samples. First, we look at five separate labor market entry cohorts. We then focus on a sample of jobs that end voluntarily, regardless of the type of spell that is entered into. We also examine a sample of jobs that are followed by another job, regardless of whether the transition is voluntary or involuntary. Finally, we restrict ourselves to the job-to-job transitions undergone by continuously employed workers.

Entry Cohorts

We focus on workers whose careers began in a specified calendar year in order to address two questions. The first is whether successive entry cohorts differ in their turnover behavior, and the second is whether the behavior of men and women converges over time. To accomplish this, we estimated our hazard model for five successive entry cohorts for each gender. For the men, we selected workers whose careers began in 1966-67, 68-69, 70-71, 72-73 and 74-75; for the women, the entry years are 1968-69, 70-71, 72-73, 74-75 and 75-76.[15] Workers in each cohort are followed for the first six years of their careers: workers whose careers began in 1966-67 are followed until 1971, etc.

Estimates for the five entry cohorts are presented in Tables 12 and 13. Unfortunately, the most dramatic numbers in these tables are in the bottom two rows, which indicate that the sample sizes shrink considerably with each successive cohort. The fourth and fifth male cohorts contain only 170 and 63 workers (2,373 and 833 observations), respectively. The third female cohort—which entered

[15] The first entry cohort for both genders also includes workers whose careers started prior to the first interview but who still were in their first jobs.

in 1972-73, the same years as the fourth male cohort—has only 419 workers (7,433 observations), while the next two cohorts contain 161 and 109 workers, respectively. These small samples compel us to discount the later cohorts—and, in fact, almost every secular pattern that we can detect stops abruptly with the fourth cohort.

Nevertheless, we do see that several variables become more important for each successive male cohort. The coefficients on MARRIED, WEDS and DIVORCE become increasingly negative for the first three cohorts. The coefficients on PRIOREXP display an even more pronounced pattern: they go from -0.023 for the 1966-67 cohort to -1.33 for the 1970-71 cohort. However, the effects of WAGE and TIMEWORKING evolve in a non-monotonic fashion.

For the women, we find that the coefficients on PRIOREXP, TIMEWORKING, and WAGE all become more negative with each of the first three cohorts, although the pattern is the most pronounced in the case of WAGE. The only non-job-related variable that shows a pattern (and one of the few with a non-zero effect) is NEWBORN. Apparently, the presence of an infant raises the hazard rate by increasing amounts with each successive entry cohort. Because we must restrict our attention to the first three cohorts for each gender, there are only two (1968-69 and 1970-71) with which we can make a valid comparison across genders. Unfortunately, this information is too limited to allow us to draw inferences about the convergence of male and female turnover behavior.

Another limitation of these estimates is that the age and schooling distributions shift to the right with each successive cohort. Since all the members of the full sample were 14 to 24 years old in the first year, the workers who began their careers later in the survey were relatively younger and/or relatively better educated. In other words, the five entry cohorts differ significantly from each other in two important demographic dimensions.

Voluntary Transitions

Table 14 presents estimates based on samples of voluntary transitions. Summary statistics for these samples are reported in Tables A4 and A5 in the Appendix. As discussed in Section 3, NLS respondents were repeatedly asked why their last job ended. We are often able to link these responses to their last job, thereby learning why a subset of jobs *will* end. When the reported

Table 12: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLES: Five Entry Cohorts of Men)

	1966-67		1968-69		1970-71		1972-73		1974-75	
	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$
Nonwhite	.065	1.16	.031	.45	.094	.90	-.069	-.26	-.426	-.83
Married	-.188	-3.59	-.200	-2.71	-.509	-5.34	-.386	-2.05	.374	.93
Weds	-.395	-4.11	-.381	-3.36	-.787	-4.48	-.289	-.88	.429	.61
Divorces	.467	1.98	-.700	1.85	.858	2.25	-.271	-.50	1.463	1.52
Birth	-.423	-5.39	-.563	-5.37	-.454	-2.93	-.370	-1.17	-2.342	-2.65
School	-.033	-3.71	-.014	-.94	-.069	-3.23	.027	.51	-.172	-1.56
Priorexp	-.023	-1.07	-.482	-11.99	-1.330	-17.78	-.124	-.86	-.526	-1.95
Timeworking	-.815	-9.59	.723	8.37	-1.392	-11.79	-2.034	-3.83	-2.291	-2.68
Involuntary	.331	4.27	.351	3.88	.301	2.28	2.623	2.32	.056	.06
Wage	-.038	-.79	-.244	-3.92	-.192	-2.45	-.913	-3.56	-.279	-.81
Parttime	.428	6.71	.241	3.44	.665	6.30	-.069	-.26	4.218	6.32
Union	-.734	-8.16	-.576	-6.32	-1.083	-7.83	-.400	-.93	-1.003	-1.82
Construction	.285	4.28	.255	3.18	.485	3.40	.208	.71	-1.377	-1.75
Transportation	-.167	-1.64	-.172	-1.31	-.413	-2.52	.334	.76	-3.417	-3.48
Trade	.014	.24	.238	3.75	.033	.36	.018	.08	-2.078	-3.45
Pubadmin	-.351	-2.58	-.241	-1.51	-.519	-2.09	-.502	-1.19	-.607	-.93
SMSA	-.152	-2.90	-.227	-3.21	.043	.41	-.161	-.88	-.359	-.81
South	-.003	-.07	.014	.22	-.367	-4.43	-.303	-1.68	-.481	-1.18
Unemployment	-.057	-2.94	.027	1.52	-.172	-7.47	-.095	-2.59	-.046	-.55
Year dummy 1	-1.282	-10.19	-.029	-.29	-.059	-.48	-2.918	-6.08	-2.053	-3.42
Year dummy 2	-.507	-5.20	-.160	-1.61	2.142	9.67	-.842	-3.20	.568	1.18
γ	-.041	-18.23	-.038	-9.64	-.083	-14.23	-.026	-3.24	-.016	-1.08
$\log(\delta)$	-.969	-3.86	-1.655	-6.31	3.510	8.87	-11.839	.09	4.271	1.73
α	-.154	-.70	-.888	-6.22	-1.110	-7.39	.320	2.39	.026	.13
θ_2	1.019	8.84	1.270	17.67	-2.157	-13.45	13.391	.11	-3.866	-6.57
Log likelihood	-8904.015		-5814.019		-2281.705		-706.247		-243.233	
Year dummy 1	Y6667		Y6869		Y7273		Y7273		Y7475	
Year dummy 2	Y6869		Y7273		Y7475		Y7475		Y7879	
# of Workers	1183		741		395		170		63	
# of Obs.	18,175		10,507		5,759		2,372		833	

reason is health, family, pregnancy, job dissatisfaction, found a better job, school, or other quit, we view the job as ending in a voluntary transition. There are 3,403 such jobs for the men and 3,418 for the women.

Since Table 14 is based on all workers in the "full sample" who report a voluntary transition, it should be compared to Table 9. For the men, the coefficients on PRIOREXP, TIMEWORKING, and WAGE are roughly the same regardless of whether we look at all transitions or voluntary transitions; the primary difference is that PRIOREXP is not as important a factor in deterring voluntary transitions as it is in deterring other types of transitions. Looking at the demographic variables, we see that MARRIED remains negative, but has a smaller magnitude than in the all-transitions sample. Also, SCHOOL is not an important determinant of voluntary transitions, although it previously had a negative (and significant) coefficient.

Among the women, PRIOREXP and WAGE continue to have the same negative effect on the hazard. TIMEWORKING, however, is no longer a significant factor. Apparently, a woman's labor market history influences her chance of being laid off or fired, but not her propensity to quit. Surprisingly, we see that the coefficients on WEDS and NEWBORN are no longer significant. Women who have pre-school aged children, on the other hand, are more likely to quit their jobs.

Although this latter finding is unsurprising, the fact that WEDS and NEWBORN do not increase the hazard prompts us to ask whether our measure of voluntary transitions is reliable. Not only might workers provide insincere responses to questions about the reasons behind their job separations, but the difference between a quit and a layoff is conceptually indistinct. Furthermore, because so few jobs can be associated with a reason for their eventual dissolution, we may be left with a nonrepresentative sample. Although we do not entirely distrust the results in Table 14, the data quality is not high enough to warrant further analysis.

Job-to-Job Transitions

We can view our sample of job-to-job transitions with considerably more confidence. As noted in Section 3, this sample consists of all job separations that are followed less than three months later by a new job. That is, we eliminate virtually all job-to-unemployment and job-to-non-employment

Table 13: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLES: Five Entry Cohorts of Women)

	1968-69		1970-71		1972-73		1974-75		1976-77	
	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$	$\hat{\beta}$	$\frac{\hat{\beta}}{S_{\hat{\beta}}}$
Nonwhite	.077	1.16	.086	1.16	.162	1.47	-.174	-.79	.184	.59
Married	.280	4.50	.014	.20	.164	1.73	-.228	-1.11	.024	.07
Weds	.003	.03	-.399	-3.79	-.176	-1.14	.325	1.09	1.630	2.97
Divorces	-.556	-2.98	-.391	-1.64	.436	1.57	.419	.78	-19.419	-7.75
Birth	.263	3.43	-.385	-4.01	-.203	-1.71	.071	.28	.239	.73
Newborn	.433	3.91	.680	5.11	.902	4.79	.688	1.72	-1.139	-1.48
Preschool	-.055	-.79	-.285	-3.14	-.364	-2.75	.135	.42	.278	.53
School	-.017	-1.18	.000	.03	.027	1.02	-.042	-.72	.025	.27
Priorexp	-.259	-8.96	-.439	-9.61	-.359	-6.04	-.275	-1.81	-.545	-2.85
Timeworking	-.560	-5.32	-.674	-5.71	-.622	-3.65	-.335	-.66	-2.159	-2.75
Involuntary	.581	7.96	.643	6.19	.304	1.86	.753	1.75	-.902	-1.31
Wage	-.651	-10.48	-.780	-10.80	-.805	-6.89	.248	1.06	-.337	-1.20
Parttime	.382	5.86	.365	5.01	.482	4.67	.776	3.72	1.427	4.65
Union	.835	12.85	.823	12.66	.786	7.11	-.142	-.44	.093	.25
Construction	.449	2.48	.281	1.29	.597	2.08	.393	.39	1.589	1.42
Transportation	-.468	-3.42	-.922	-5.60	-1.150	-3.35	.185	.36	-19.251	-8.17
Trade	.280	4.44	.297	4.27	.539	4.89	.190	.71	1.107	1.77
Pubadmin	-.343	-2.44	-.515	-2.76	.080	3.44	-.114	-.30	-.232	-.39
SMSA	.142	2.25	.019	.25	.054	.55	.192	.97	-.543	-1.57
South	.102	1.69	.050	.72	.017	.18	.205	1.06	-.405	-1.06
Unemployment	-.037	-2.22	.038	2.82	.076	4.09	-.150	-2.49	-.282	-4.09
Year dummy 1	-.431	-4.60	.142	1.71	-.389	-1.76	.221	.80	-.295	-.81
Year dummy 2	.094	1.22	-.044	-.26	-1.097	-7.78	-.483	-1.53	2.271	4.39
γ	-.030	-14.55	-.030	-7.20	-.016	-2.97	-.030	-3.10	-.001	-.15
$\log(\delta)$	-1.565	-5.75	-2.693	-10.52	-3.789	-6.90	-1.374	-1.09	1.631	1.16
α	-.137	-1.21	.103	1.35	.034	.24	1.782	.13	-.086	-.55
θ_2	1.470	16.42	2.107	17.42	2.058	9.64	.200	.50	-3.845	-8.46
Log likelihood	-6613.047		-4795.413		-2640.479		-707.034		-409.085	
Year dummy 1	Y6667		Y6869		Y7273		Y7273		Y7475	
Year dummy 2	Y6869		Y7273		Y7475		Y7475		Y7879	
# of Workers	964		725		419		161		109	
# of Obs.	13,869		10,811		7,433		2,647		1,693	

Table 14: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: Jobs Ending in a Voluntary Transition)

	MEN		WOMEN	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	.163	1.99	-.009	-.14
MARRIED	-.125	-1.90	.017	.29
WEDS	-.263	-2.22	-.131	-1.33
DIVORCES	.212	.99	-.101	-.75
BIRTH	-.336	-3.99	-.047	-.58
NEWBORN	—	—	.161	1.28
PRESCHOOL	—	—	.150	2.18
SCHOOL	-.006	-.48	-.022	-1.52
PRIOREXP	-.059	-4.27	-.078	-5.68
TIMEWORKING	.444	4.53	.072	.77
INVOLUNTARY	.310	3.65	.435	5.12
WAGE	-.182	-2.85	-.495	-7.34
PARTTIME	.584	6.89	.296	4.74
UNION	-.135	-1.42	.721	10.43
CONSTRUCTION	.331	3.77	.472	2.57
TRANSPORTATION	-.165	-1.14	-.566	-3.48
TRADE	.243	3.71	.270	4.37
PUBADMIN	-.362	-2.16	-.216	-1.37
SMSA	.173	2.65	.088	1.36
SOUTH	.016	.25	-.004	-.08
UNEMPLOYMENT	.053	3.48	-.023	-1.73
Y6869	.617	3.83	.054	.17
Y7071	.853	4.75	.053	.16
Y7273	-.083	-.42	-.547	-1.68
Y7475	-1.438	-6.17	-.639	-1.86
Y7677	.046	.21	-.967	-2.75
Y7879	.862	4.02	-.864	-2.48
Y8081	1.272	4.82	.153	.41
Y8283	—	—	.634	1.51
γ	-.009	-5.71	.002	1.12
$\log(\delta)$	-1.390	-5.82	-.705	-1.91
α	.263	3.20	-1.208	-7.89
θ_2	-1.930	-18.24	-1.533	-12.91
Log likelihood	-6212.378		-6323.322	

transitions.

The estimates for these samples, which appear in Table 15, reveal several contrasts. First, the coefficients on a number of key variables go to zero. The coefficient on MARRIED, which was -0.205 for the men in the full (all transitions) sample (Table 9), is now zero. Relative to what we saw in Table 9, the coefficient on WEDS is now smaller for men and larger for women, but neither coefficient remains significant. The effect of SCHOOL and TIMEWORKING goes to zero for both genders, although each had a negative effect on the hazard rates of the full samples. PRIOREXP no longer lowers the hazard for men, while UNION no longer raises the hazard for women. Apparently, all of these factors make workers more or less likely to leave the labor force or become unemployed, but they have no effect on a worker's propensity to accept a new job.

Other variables prove to be more important in explaining job-to-job transitions than they were in explaining all transitions. In Table 9, we saw that BIRTH lowers the hazard for men, but not for women. Now we see a coefficient of roughly -0.7 for both genders; that is, both men and women are far less likely to change jobs around the time of a new birth. We also see that DIVORCE now has a negative and significant coefficient for women, while the effect of PRESCHOOL increases dramatically relatively to what we saw in Table 9. Both results are somewhat surprising, since we expect recently divorced women to be more likely to accept a new job, while women with young children might be constrained in their ability to undertake a job hunt. Overall, however, we see that job-to-job movements are generated by a smaller set of covariates than are other types of transitions.

Continuously Employed Workers

In focusing on job-to-job transitions, we effectively looked at all types of workers, regardless of their overall commitment to the labor force; in some sense, we were looking at workers who were job shopping "at the moment." We now look at a sample of workers who are likely to be "earnest" job shoppers by virtue of their demonstrated commitment to the labor force. Though, of course, workers with a demonstrated commitment to the labor force need not be constantly shopping for a new job. To identify these workers, we measured the percent of their *observed* time that is

Table 15: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: Job-to-Job Transitions)

	MEN		WOMEN	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	-.101	-1.24	.125	1.03
MARRIED	.091	1.27	.028	.26
WEDS	-.271	-1.61	-.326	-1.59
DIVORCES	-.121	-.38	-1.662	-3.85
BIRTH	-.733	-6.13	-.710	-3.60
NEWBORN	—	—	-.144	-.64
PRESCHOOL	—	—	.441	3.24
SCHOOL	-.002	-.13	.032	1.29
PRIOREXP	-.003	-.18	-.125	-4.12
TIMEWORKING	.022	.23	.027	.15
INVOLUNTARY	.160	1.82	1.225	9.26
WAGE	-.244	-3.41	-.539	-6.34
PARTTIME	.224	2.31	.365	3.06
UNION	-.571	-3.96	1.213	11.55
CONSTRUCTION	.214	2.43	.708	2.48
TRANSPORTATION	-.018	-.10	-.337	-1.09
TRADE	.072	.92	.174	1.55
PUBADMIN	-.654	-3.52	-.368	-1.59
SMSA	.013	.17	-.188	-1.81
SOUTH	-.017	-.24	.183	1.58
UNEMPLOYMENT	-.035	-1.85	.251	10.30
Y6869	1.253	7.62	—	—
Y7071	2.193	11.51	-.317	-1.61
Y7273	.495	2.12	.003	.01
Y7475	.437	1.71	-2.410	-7.25
Y7677	1.041	3.91	-1.489	-4.90
Y7879	1.366	4.96	-2.014	-5.06
Y8081	2.353	7.42	-2.512	-5.68
Y8283	—	—	.225	.49
γ	-.024	-9.66	-.007	-2.34
$\log(\delta)$	-2.378	-9.49	-4.213	-10.59
α	-1.120	-9.67	-.167	-1.34
θ_2	2.317	13.26	1.988	18.41
Log likelihood	-3709.703		-1848.164	

known to be spent working; anyone with a number above the median of the male distribution (88 percent) is considered "continuously" employed. More accurately, these are workers who are more committed to the work force than is the median man in our sample.

Looking at Table 16, we again see the disappearance of several effects that are evident in the full sample. MARRIED lowers the hazard for men in the full sample, but it has an insignificant effect on continuously employed men. To some degree it is likely that marital status has no effect because most of these men are married: 69 percent of the continuously employed men and 59 percent of the full sample of men are married. We saw a positive coefficient on PRESCHOOL in Table 9, but now we see that it has no effect on the turnover of continuously employed women. Among the full sample, becoming married deters turnover; among continuously employed workers, it has no effect on women and a smaller effect on men.

Given the criterion for selecting the samples of continuously employed workers, the variable TIMEWORKING is likely to have a value close to one for most workers' second and subsequent jobs. Therefore, we expect that there is little variance in TIMEWORKING across second and higher numbered jobs. Since the variable is set equal to zero for the first job, most of the variance in TIMEWORKING arises from the difference in its value between first jobs and the rest. We find that, for the samples of continuously employed workers, TIMEWORKING is no longer a significant determinant of turnover. This is an interesting finding since it implies that first jobs are no shorter than higher numbered jobs for these workers.

Chief among the variables that now show a more pronounced effect is BIRTH. The coefficient for men does not change relative to Table 9, but the coefficient for women increases from zero to 0.199. Presumably, this effect would disappear if we could look at workers who were truly continuously employed, since it is likely to be picking up the job-to-OLF movements that remain in our sample rather than job changes. An alternative explanation for this effect is that women choose to change jobs upon giving birth to a child. Women may favor jobs that demand fewer hours, or jobs on a fixed schedule, or even part-time jobs.

The coefficient on SCHOOL also increases for women, from -0.026 to 0.039. This may reflect that well educated "career women" are successful job shoppers. We also find that the coefficients

Table 16: Estimates for Gompertz Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: Continuously Employed Workers)

	MEN		WOMEN	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	-.083	-1.57	-.142	-1.66
MARRIED	-.061	-1.33	-.088	-1.20
WEDS	-.292	-3.67	-.109	-.93
DIVORCES	.211	1.49	-.099	-.46
BIRTH	-.376	-6.66	.199	1.77
NEWBORN	—	—	.286	1.46
PRESCHOOL	—	—	-.149	1.50
SCHOOL	-.025	-3.15	.039	1.88
PRIOREXP	-.102	-10.38	-.060	-3.44
TIMEWORKING	.016	.27	-.245	-1.88
INVOLUNTARY	.420	6.82	.334	3.05
WAGE	-.207	-4.60	-.649	-6.95
PARTTIME	.680	11.41	.580	6.36
UNION	-.408	-6.40	.263	3.17
CONSTRUCTION	.326	5.71	.407	1.75
TRANSPORTATION	-.436	-4.70	-.581	-3.77
TRADE	.173	3.81	.296	3.36
PUBADMIN	-.577	-5.29	-.410	-2.82
SMSA	-.100	-2.45	.181	2.19
SOUTH	-.002	-.04	.015	.21
UNEMPLOYMENT	-.028	-2.58	.055	3.53
Y6869	.507	6.23	-1.178	-3.06
Y7071	.877	8.99	-1.222	-3.21
Y7273	.175	1.70	-1.116	-2.93
Y7475	.315	2.57	-1.849	-4.64
Y7677	.602	4.58	-1.805	-4.50
Y7879	.802	6.26	-1.855	-4.60
Y8081	.694	4.17	-1.891	-4.45
Y8283	—	—	-2.178	-4.77
γ	-.022	-21.41	-.015	-9.20
$\log(\delta)$	-2.335	-16.54	-2.440	-5.54
α	-1.718	-5.65	-1.115	-3.93
θ_2	.942	13.57	1.237	12.75
Log likelihood	-13647.154		-5585.833	

on PRIOREXP are less negative for both genders. This may point to the fact that continuously employed workers maintain a relatively high (and beneficial) rate of turnover for a longer period of time than does the full sample.

The final result that emerges from Table 16 concerns unobserved heterogeneity. When we examined the full sample, we learned that unobserved heterogeneity raises the hazard by a factor of 2.8 for the men and 3.4 for the women. This result is virtually unchanged when we focus on continuously employed workers: the corresponding statistics are 2.6 and 3.5. However, our conclusions about movers and stayers are now significantly different. Among all workers, we found that 46 percent of the men and 58 percent of the women are movers for unobserved reasons. Among continuously employed workers, these percentages are 16 and 28. Although an employer is still more likely to "draw" a mover from among a pool of women than from among a pool of men, each pool contains very few movers. In other words, employers can readily use observables to predict which continuously employed workers will quit.

Section 6: Conclusions

In this study, we estimated hazard models for various samples of young men and women in order to learn how they differ in their turnover behavior. We can now provide answers to the three questions posed in the introductory section.

Do young women separate from their jobs more often than men? When we estimate a hazard model for a combined sample of men and women, controlling only for characteristics that the employer can observe at the time of hire, the coefficient on FEMALE is zero for the early cohort and negative for the late cohort. This indicates that men and women in the early cohort have roughly the same overall quit rate, but that women in the later cohort actually have *lower* quit rates than their male counterparts. These overall quit rates reflect the activities of both movers and stayers. We have also found that, in a sample of combined birth cohorts, women are more likely than men to be movers (for unobserved reasons). We conclude, therefore, that women as a group have a lower quit rate than men, but that an individual woman is more likely than an individual man to be a quitter. For the late cohort, however, we conclude unequivocally that women have lower quit rates than men.

Do young women quit primarily to have babies, or do they also engage in job shopping? Although we do not put the job shopping hypothesis to a rigorous test, we control for match quality and previous (potential) job matching by including such measures as prior experience and wages in our hazard models. We find that increases in experience and wages lower the hazard rates of both men and women in our full samples. Even though the estimates reveal that the hazard for men has a more pronounced degree of negative duration dependence, our estimates are consistent with the hypothesis that the labor force consists of significant numbers of "career-oriented" women who use the early part of their careers to shop for a durable employment relationship. Furthermore, when we looked at successive labor market entry cohorts, we found that the effects of prior experience have become even more important over time; among women, the same is true for the current wage.

When we focused on voluntary and job-to-job transitions, we found that the presence of a newborn has no effect on the hazard rate. Women with a preschooler are more likely to make either type of transition, however. In addition, we learned that women who are continuously employed are more likely to leave their job when they give birth, but the turnover of these women is not influenced by either newborn or preschool-age children. Only among continuously employed women and the late cohort of women is there the suggestion that the birth of a baby induces turnover.

Given that employers can only observe a handful of characteristics at the time of hire, is it more difficult for them to identify non-quitters among the women than among the men? We have learned (as did Heckman and Willis (1977) and others) that not all women are alike. In particular, our full sample reveals considerable unobserved heterogeneity among the women—in fact, much more than among the men. If an employer were to hire a man and a woman with similar observable characteristics, the woman would be more likely to emerge as a quitter. This finding, coupled with the fact that women quit for reasons that cannot be observed *ex ante*, leads us to conclude that it is harder to identify female non-quitters.

When we focus on the late cohort of workers, however, our conclusion is dramatically altered. Unobserved heterogeneity becomes an insignificant factor among women, and the only important determinants of women's turnover that may not be known at the time of hire are the presence of a newborn child and the act of becoming married. Both factors raise the hazard rate of women, but neither represents a long-term deterrent to job stability. Among this cohort, we conclude that non-quitters can be identified equally well among the men and the women.

We reach a similar conclusion when we focus on continuously employed workers. In these samples, 16 percent of the men and 28 percent of the women can be termed movers for unobservable or unmeasured reasons. Clearly, an employer who randomly hires an employee of either gender would be unlikely to discover that the worker is a mover. Furthermore, continuously employed women who become married are not more likely to leave their jobs, although women who give birth are. We conclude that, among continuously employed workers, non-quitters can be readily identified regardless of gender.

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Appendix

Table A1: Estimates for Weibull Hazard Model
Correction for Unobserved Heterogeneity
(SAMPLE: Workers Whose Careers Have Not Started or Whose First Jobs Begin or Are in Progress in the First Year of the Survey)

	MEN		WOMEN	
Variable	Coefficient	Normal Statistic	Coefficient	Normal Statistic
NONWHITE	-.000	-.00	-.052	-1.57
MARRIED	-.258	-8.94	-.007	-.22
WEDS	-.353	-6.75	-.143	-2.71
DIVORCES	.106	1.07	-.097	-1.11
BIRTH	-.285	-7.19	.046	1.19
NEWBORN	—	—	.385	6.53
PRESCHOOL	—	—	.022	.67
SCHOOL	-.045	-8.54	-.017	-2.60
PRIOREXP	-.072	-11.83	-.069	-12.05
TIMEWORKING	-.533	-12.29	-.440	-9.25
INVOLUNTARY	.245	6.57	.409	10.11
WAGE	-.290	-10.27	-.579	-18.62
PARTTIME	.530	14.57	.398	12.48
UNION	-.571	-14.21	.444	13.56
CONSTRUCTION	.420	11.59	.359	4.12
TRANSPORTATION	-.279	-4.94	-.584	-7.86
TRADE	.120	3.92	.318	9.90
PUBADMIN	-.348	-5.30	-.401	-6.05
SMSA	-.080	-2.71	.049	1.59
SOUTH	-.087	-3.15	.045	1.55
UNEMPLOYMENT	.005	.65	-.015	-2.46
Y6869	.974	18.59	-.381	-3.56
Y7071	1.184	18.15	-.251	-2.29
Y7273	.382	5.61	-.573	-5.20
Y7475	.510	5.99	-1.371	-11.34
Y7677	.836	9.68	-.817	-6.72
Y7879	.830	9.96	-1.578	-12.62
Y8081	.763	7.13	-1.051	-7.89
Y8283	—	—	-.781	-5.42
$\log(k)$	-.371	-28.60	-.200	-15.21
$k \log(\rho)$	-2.023	-17.39	-1.569	-10.48
α	.130	1.77	.125	2.12
θ_2	1.233	19.68	1.461	24.62
Log likelihood	-30351.003		-27201.189	

Note: same samples as Table 9.

Table A2: Sample Means and Standard Deviations
(SAMPLE: "Early" and "Late" Cohorts of 24-31 Year Old Women)

		EARLY		LATE	
Variable	Definition	Mean	Std. Dev.	Mean	Std. Dev.
NONWHITE	1 if nonwhite	.298	.457	.314	.464
MARRIED	1 if married	.671	.470	.585	.493
WEDS	1 if marries during interval	.040	.196	.050	.219
DIVORCES	1 if divorces during interval	.027	.163	.028	.165
BIRTH	1 if child is born during interval	.114	.317	.140	.346
NEWBORN	1 if child age one or under	.024	.153	.031	.174
PRESCHOOL	1 if child age six or under	.244	.429	.244	.429
SCHOOL=12	high school graduate	.448	.497	.434	.496
SCHOOL=13-15	college dropout	.154	.361	.181	.385
SCHOOL=16+	college graduate	.209	.407	.219	.414
AGE		27.794	2.340	27.479	2.206
PRIOREXP	Years of potential prior experience	5.193	3.711	4.568	3.642
TIMEWORKING	Ratio of actual to potential experience	.281	.302	.422	.319
INVOLUNTARY	1 if left last job involuntarily	.025	.155	.056	.223
TENURE	Years of tenure	3.093	2.824	3.764	3.071
WAGE	Log of real hourly wage	1.743	.497	1.707	.452
UNION	1 if wages set by union	.151	.358	.193	.395
PARTTIME	1 if works less than 35 hours per week	.167	.373	.140	.346
	1 if industry is				
CONSTRUCTION	Construction, agriculture, mining	.013	.115	.016	.126
TRANSPORTATION	Transp., communication, utilities	.042	.201	.044	.206
TRADE	Trade	.149	.356	.154	.361
PUBADMIN	Public administration	.063	.243	.053	.223
UNEMPLOYMENT	Unemployment rate	6.773	1.476	7.703	1.072
SOUTH	1 if living in the South	.428	.495	.397	.489
SMSA	1 if living in an SMSA	.746	.435	.718	.450
	1 if year is				
Y6869	1968-69	.105	.307	—	—
Y7071	1970-71	.256	.437	—	—
Y7273	1972-73	.235	.424	—	—
Y7475	1974-75	.261	.439	—	—
Y7677	1976-77	.143	.350	.158	.365
Y7879	1978-79	—	—	.272	.445
Y8081	1980-81	—	—	.277	.447
Y8283	1982-83	—	—	.230	.421
Y8485	1984-85	—	—	.064	.244
Number of individuals		788		1,019	
Number of observations		14,865		20,673	

Note: same samples as Table 11.

Table A3: Sample Means and Standard Deviations
(SAMPLE: "Early" and "Late" Cohorts of 24-31 Year Old Men)

		EARLY		LATE	
Variable	Definition	Mean	Std. Dev.	Mean	Std. Dev.
NONWHITE	1 if nonwhite	.195	.396	.274	.446
MARRIED	1 if married	.773	.419	.651	.477
WEDS	1 if marries during interval	.037	.190	.058	.235
DIVORCES	1 if divorces during interval	.021	.142	.030	.172
BIRTH	1 if child is born during interval	.177	.381	.172	.377
SCHOOL=12	high school graduate	.379	.485	.394	.489
SCHOOL=13-15	college dropout	.156	.363	.235	.424
SCHOOL=16+	college graduate	.238	.426	.219	.414
AGE		27.248	2.201	26.644	2.074
PRIOREXP	Years of potential prior experience	4.196	3.279	4.995	3.384
TIMEWORKING	Ratio of actual to potential experience	.306	.336	.467	.302
INVOLUNTARY	1 if left last job involuntarily	.033	.178	.053	.223
TENURE	Years of tenure	3.295	2.822	3.555	2.844
WAGE	Log of real hourly wage	2.125	.457	2.046	.429
PARTTIME	1 if works less than 35 hours per week	.028	.165	.028	.165
UNION	1 if wages set by union	.153	.360	.273	.445
	1 if industry is				
CONSTRUCTION	Construction	.085	.279	.101	.301
TRANSPORTATION	Transp., communication, utilities	.081	.274	.106	.308
TRADE	Trade	.136	.343	.154	.361
PUBADMIN	Public administration	.062	.242	.075	.263
UNEMPLOYMENT	Unemployment rate	3.333	1.309	5.694	1.260
SOUTH	1 if living in the South	.350	.477	.438	.496
SMSA	1 if living in an SMSA	.709	.454	.717	.450
	1 if year is				
Y6667	1966-67	.077	.266	—	—
Y6869	1968-69	.269	.444	—	—
Y7071	1970-71	.287	.452	—	—
Y7273	1972-73	.242	.428	—	—
Y7475	1974-75	.126	.332	.147	.354
Y7677	1976-77	—	—	.299	.458
Y7879	1978-79	—	—	.288	.453
Y8081	1980-81	—	—	.265	.442
Number of individuals		853		1,438	
Number of observations		20,019		28,220	

Note: same samples as Table 11.

Table A4: Sample Means and Standard Deviations for Women
(SAMPLE: Voluntary Transitions, Job-to-Job Transitions, and Continuously Employed Workers)

		Voluntary Transitions		Job-to-job Transitions		Continuously Employed	
Variable	Definition	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Nonwhite	1 if nonwhite	.251	.434	.248	.432	.261	.439
Married	1 if married	.540	.498	.489	.500	.488	.500
Weds	1 if marries during interval[a]	.079	.270	.068	.252	.061	.239
Divorces	1 if divorces during interval[a]	.040	.195	.031	.172	.028	.166
Birth	1 if child is born during interval[a]	.115	.319	.095	.294	.088	.283
Newborn	1 if child age one or under	.042	.200	.045	.207	.026	.160
Preschool	1 if child age six or under	.224	.417	.200	.400	.172	.378
School	Years of schooling	12.945	2.168	12.617	2.052	13.503	2.287
Age		24.526	3.901	24.247	4.064	27.140	4.737
Priorexp	Years of potential prior experience	3.078	3.439	2.858	3.262	2.544	3.402
Timeworking	Ratio of actual to potential exp.	.391	.337	.403	.347	.414	.391
Involuntary	1 if left last job involuntarily	.080	.271	.078	.268	.073	.261
Tenure	Years of tenure	1.647	1.890	1.913	2.166	3.918	3.685
Parttime	1 if works less than 35 hours/week	.178	.383	.126	.332	.076	.264
Wage	Log of real hourly wage[b]	1.628	.448	1.639	.453	1.865	.394
Union	1 if wages set by union	.138	.345	.143	.350	.216	.412
	1 if industry is						
Construction	Const., agriculture, mining	.015	.122	.028	.165	.016	.126
Transportation	Transp., communication, utilities	.044	.206	.024	.154	.083	.277
Trade	Trade	.188	.391	.196	.397	.098	.297
Pubadmin	Public administration	.049	.216	.065	.246	.081	.272
Unemployment	Unemployment rate[c]	10.090	3.083	10.380	3.184	11.118	3.327
South	1 if living in the South	.397	.489	.329	.470	.386	.487
SMSA	1 if living in an SMSA	.772	.420	.777	.417	.792	.406
	1 if year is						
Y6869	1968-69	.075	.263	.113	.316	.052	.222
Y7071	1970-71	.142	.349	.209	.407	.092	.289
Y7273	1972-73	.234	.424	.167	.373	.122	.327
Y7475	1974-75	.193	.394	.137	.343	.128	.334
Y7677	1976-77	.116	.320	.162	.368	.137	.343
Y7879	1978-79	.126	.332	.084	.278	.147	.354
Y8081	1980-81	.078	.269	.094	.292	.135	.341
Y8283	1982-83	.033	.178	.035	.183	.187	.390
Number of individuals		1105		653		789	
Number of observations		11,394		3,559		30,570	

[a] Since we only know that a change occurs between successive interviews, the variable equals one for every three-month interval falling between the two interview dates.
[b] In 1982 dollars.
[c] Unemployment rate during first month of the interval.

Table A5: Sample Means and Standard Deviations for Men
(SAMPLE: Voluntary Transitions, Job-to-Job Transitions, and Continuously Employed Workers)

Variable	Definition	Voluntary Transitions Mean	Voluntary Transitions Std. Dev.	Job-to-job Transitions Mean	Job-to-job Transitions Std. Dev.	Continuously Employed Mean	Continuously Employed Std. Dev.
Nonwhite	1 if nonwhite	.169	.375	.233	.423	.200	.400
Married	1 if married	.603	.489	.540	.498	.689	.463
Weds	1 if marries during interval[a]	.070	.255	.066	.249	.060	.237
Divorces	1 if divorces during interval[a]	.017	.129	.014	.117	.021	.142
Birth	1 if child is born during interval[a]	.158	.365	.144	.351	.174	.379
School	Years of schooling	13.116	3.034	12.534	2.930	13.089	2.938
Age		25.264	4.003	23.776	4.147	26.222	4.571
Priorexp	Years of potential prior experience	3.587	3.340	2.925	3.091	3.022	3.463
Timeworking	Ratio of actual to potential exp.	.483	.346	.478	.362	.497	.390
Involuntary	1 if left last job involuntarily	.093	.290	.111	.314	.060	.237
Tenure	Years of tenure	1.992	2.230	1.564	2.097	3.316	3.412
Parttime	1 if works less than 35 hours/week	.069	.254	.081	.273	.038	.192
Wage	Log of real hourly wage[b]	1.987	.511	1.922	.546	2.081	.477
Union	1 if wages set by union	.117	.322	.082	.275	.176	.381
	1 if industry is						
Construction	Const., agriculture, mining	.108	.311	.141	.348	.084	.278
Transportation	Transp., communication, utilities	.057	.233	.043	.204	.076	.265
Trade	Trade	.209	.407	.189	.392	.158	.364
Pubadmin	Public administration	.046	.210	.050	.218	.059	.236
Unemployment	Unemployment rate[c]	9.620	2.937	8.739	3.107	9.571	3.010
South	1 if living in the South	.402	.490	.434	.496	.431	.495
SMSA	1 if living in an SMSA	.704	.457	.706	.456	.711	.454
	1 if year is						
Y6869	1968-69	.109	.311	.209	.406	.109	.312
Y7071	1970-71	.189	.391	.276	.447	.148	.355
Y7273	1972-73	.108	.310	.087	.281	.134	.341
Y7475	1974-75	.172	.377	.127	.333	.152	.359
Y7677	1976-77	.220	.415	.133	.340	.150	.357
Y7879	1978-79	.140	.347	.068	.252	.140	.347
Y8081	1980-81	.031	.173	.037	.188	.127	.333
Number of individuals		1066		935		1353	
Number of observations		11,841		5,615		49,406	

[a] Since we only know that a change occurs between successive interviews, the variable equals one for every three-month interval falling between the two interview dates.
[b] In 1982 dollars.
[c] Unemployment rate during first month of the interval.