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A Continuous-Time Stochastic Model of Job Mobility: A Comparison of Male-Femals Hazard Rates of Young Workers

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ABSTRACT

A CONTINUOUS-TIME STOCHASTIC MODEL OF JOB MOBILITY: A COMPARISON OF MALE-FEMALE HAZARD RATES OF YOUNG WORKERS

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This study examines male and female hazard rates in the periods 1968-1971 and 1979-1982 using data for young workers from the various samples of the National Longitudinal Surveys. Contrary to a number of previous micro-data studies, I demonstrate that for the period 1968-1971 female workers quit their initial full-time jobs at substantially higher rates than male workers. Moreover, while male hazard rates show a monotonic decline, female rates show a nonmonotonic u-shaped pattern, which I attribute to a "birth effect" -- young women leaving the labor force to have children.

For the period 1979-1982, however, young women had become almost indistinguishable from young men in terms of job tenure, attachment to the labor force, and percentage of workers who are professional, managerial, and technical. The finding of the equality in hazard rates between male and female workers in the later period was invariant to different parametric assumptions about the nature of duration dependence and the existence of unobserved heterogeneity.

Two factors contributed to the elimination of the first-job "tenure gap" between young men and women: (1) women's increased commitment to

the paid workforce, and (2) their increasing age at the time of first marriage and/or first pregnancy. Evidence from examining the last job held during the sample period suggests that these factors delay, but do not entirely eradicate, the point at which women begin to leave their jobs at a higher rate than men.

In the period 1968-1971 the female-male ratio of expected tenure on initial full-time jobs was 59% and the corresponding ratio of earnings was roughly 73%. By 1979-1982, the tenure gap had closed and the earnings gap had narrowed to almost 90%. Since the narrowing of the wage gap seems to lag the narrowing of the tenure gap, the direction of causation may be from lower tenure to lower wages.

A CONTINUOUS-TIME STOCHASTIC MODEL OF JOB MOBILITY: A COMPARISON OF MALE-FEMALE HAZARD RATES OF YOUNG WORKERS

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John Joseph Donohue III

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Preface

At seemingly critical points in my life -- right before I came to Yale to do graduate work in economics and just at the time that Rick Levin and Al Klevorick were pressing me to choose a dissertation topic -- important legal decisions were rendered touching upon the issue of comparable worth. Both the initial Supreme Court decision in County of Washington v. Gunther, 452 U.S. 161 (1981), and the district court opinion in AFSCME v. State of Washington, 578 F. Supp 846 (1983), rev'd, 770 F. 2d 1401 (9th Cir. 1985), intrigued and puzzled me, and so began my interest in labor economics.

Rick and Al instructed me to unleash my inchoate thoughts on Paul Schultz, and it is probably fair to say my life has never been the same since. As my advisor on this dissertation, Paul has played an immensely important role in focussing my research, assisting my progress, and demonstrating the wisdom of Learned Hand's remark that "the spur of constant stress is necessary to counteract an inevitable disposition to let well enough alone." U.S. v. Alcoa, 148 F. 2d 416 (2d Cir. 1945). I am deeply grateful to him for all the time and advice that he has so generously given to me over the past two years.

Another central figure in my life over the past five years, both as friend and colleague, has been George Priest. His insightful suggestions have invariably improved my own work, and my year as a Fellow in the Yale Law School Program in Civil Liability has been a wonderfully enriching experience.

Jim Heckman deserves the credit (or blame) for introducing me to the intellectually stimulating world of duration analysis during his stunning series of lectures at Yale in the fall of 1984. I also profitted greatly from my discussions with Burt Singer about the limits of what can be known through statistical analysis. I hope that I have not tried to surpass these limits in this work. While I am discussing these luminaries of econometrics and statistics, it is fitting to give thanks to the other member of my committee, Vassilis Hajivassiliou. Vassilis has been an exceptionally thoughtful and considerate reader and, in general, a joy to work with. A number of other members of the Yale economics department have offered valuable advice along the way including John Strauss, Steve Stern, Joe Tracy, John Bigelow, Don Andrews, and the participants in the Labor and Population Workshop.

I would like to thank Paul Allison, Charles Hammerslough, Michael Hannan, Mark Meitzen, and James Trussell for help concerning the mysteries of hazard rate modelling. Linda Waite and Lawrence Kahn also generously discussed the details of their work with me. Laura Branden, the data archivist at the Center for Human Resources, deserves special thanks for answering a seemingly endless stream of questions about the minutiae of the National Longitudinal Survey, as does JoAnn Dionne of Yale's Social Science Library, who has always succeeded in obtaining mounds of data for me.

I have also been blessed to receive outstanding research and computer assistance as well as sound advice from a number of exceptionally valuable and valued workers: Dan Klerman, Hui Ouliaris, Jim Wan, Julie Wang, Peter Siegelman, Jonathan Silverman, Marijke Rijsberman, Sam Ouliaris, Karen Ginty, and Jeanne Miner. The collective talent embodied within this group is breathtaking, and they all have my deepest gratitude.

This research was supported by a grant from the National Institutes of Health, which I gratefully acknowledge. Moreover, I will forever be indebted to the Yale Law School Program in Civil Liability for financial and logistical support, without which a work of this scope would simply not have been possible.

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Chapter 1

PREVIOUS STUDIES OF MALE-FEMALE QUIT RATES

1.1 Introduction

The perception that women have higher turnover rates than men is widespread. A recent study has argued, with a touch of sarcasm, that "[p]opular stereotypes, which economists refer to as 'stylized facts,' portray women as relatively poor bets as workers because they have ... higher quit rates than males." Waite and Berryman [1985: 61]. Indeed, in a recent article on occupational segregation, Goldin takes this "fact" as the premise for her model, although in support of this position she cites only a 1920 study. Goldin [1985]. While this may well be adequate for Goldin's historical analysis, a study conducted at a time when the labor market experience of women was completely different than it is today does not illuminate the question of the current relative turnover rates of men and women.

The issue of differences -- or perceived differences -- in expected job tenure between male and female workers may have an important bearing on the size of the male-female wage differential. If there are large personnel investment costs associated with job turnover, an employer attempting to earn a normal rate of return on a fixed personnel investment would not be willing to pay women the same wage as equally productive men who are expected to remain on their jobs longer.

1.2 Do Women Have Higher Turnover Rates Than Men?

It seems appropriate then to ask whether the assumption of shorter expected tenure by female workers is correct. In his classic 1962 paper, Oi acknowledged the frequency of the assertion that women have higher turnover rates than men, but then concluded: "The evidence that there are differences in employment tenure by sex is not at all convincing." Oi [1962: 552]. Not much has changed since 1962. Until the last few years, all of the work examining this issue has been based on aggregate industry data, and the results have often been in conflict.

Barnes and Jones [1974], using BLS industry data for the years 1950-1968, found that in 16 out of 19 industries the quit rate for women exceeded that of men. Parsons [1972], in examining quit rates across 47 Census Bureau 3-digit industries in 1959 and 1963, came to a different conclusion. After controlling for the effects of wage, education, managers, professionals, youth, race, sex, region, etc., Parsons found that women had either lower or roughly the same quit rates as men. Armknecht and Early [1972] have presented evidence that a dramatic change in female quit rates occurred in 1964. The authors estimated quit rates from cross-section data for 94 industry groups and found that the variable indicating the percentage of women in the industry had a positive coefficient prior to 1963 and a negative coefficient after 1964. In other words the higher the percentage of women in an industry after 1964 the smaller the industry quit rate. These findings may be undermined by the fact that the authors were unable to adjust for differences among the industries in the age and tenure composition of their workers.

1.3 Longitudinal Studies of Quit Rates

Three more recent articles have focussed on individual micro-data rather than aggregate industry data to address the issue of sex differences in worker quitting: a probit study by Blau and Kahn [1981] using the original panel of the National Longitudinal Surveys and logit studies by Viscusi [1980] using the Michigan Panel Study of Income Dynamics and by Waite and Berryman [1985] using the 1979 Youth sample of the National Longitudinal Surveys. The three studies, which are quite similar in design, seem to argue that, once one has held constant certain personal and job characteristics, the quit rates of young women and men are about the same.[1] One significant difference in the studies is that Blau and Kahn and Waite and Berryman use data that is restricted to relatively young workers -- the various samples of the National Longitudinal Surveys[2] -- while Viscusi examines all workers, whose mean age is roughly 35. Thus, Blau and Kahn and Waite and Berryman are undoubtedly seeing fewer females who have returned to the labor force after raising families than Viscusi. A tabular comparison of these three studies is presented in Appendix I.[3]

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[1]For example, Viscusi concludes that "women display greater stability than they would if characterized by the coefficients in the male quit equation." Viscusi [1980: 397]. Similarly, Blau and Kahn state that, "other things equal, women ... are no more likely to quit their jobs than men." Blau and Kahn [1981: 573].

[2]At the time of the initial sampling for the original NLS panel used by Blau and Kahn, the male respondents were aged 14-24 in 1966 and the female respondents were aged 14-24 in 1968. At the time of the initial sampling for the later NLS panel used by Waite and Berryman, all the respondents were aged 16-21 in 1979.

[3]Appendix I also includes a fourth study by Osterman [1982], which has a similar format as the other three studies but a different objective. Osterman estimates male and female quit equations using the

1.4 Problems With the Previous Micro-Data Studies

All three of these studies proceed in the following manner: (1) in the first survey year they note everyone who is currently employed; (2) in the second year they examine whether the worker is still employed in his previous year's job -- in which case the worker is assigned a dependent variable of 0 -- or whether the worker has quit -- in which case the dependent variable is set at 1; (3) they then use limited dependent variable techniques to estimate the effect of personal and job characteristics on the probability of quitting. Blau and Kahn compare the quit behavior of men in the period from 1969 - 1971 to that of women in the period from 1970 - 1972.[4] Viscusi examines the quit behavior in 1976 of those employed in 1975, and Waite and Berryman examine the quit behavior in 1980 of those employed in 1979.

Note, then, that these three studies provide information about individuals at only two points in time: the first survey selects a sample of those who are in the midst of a spell of employment and the

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Michigan Panel Study of Income Dynamics for 1978-1979 to show that enforcement activities of the Federal Contract Compliance Program reduce quits among female workers. Osterman opines that these programs "create better opportunities for women and hence increase their incentive to be stable employees." Osterman [1982: 611]. While Osterman is not directly interested in evaluating relative quit rates, his male and female quit equations are precisely analogous to those estimated in the three other studies presented in Appendix I.

[4]Blau and Kahn did not follow workers over a two-year period; they merely identified which of the workers who were earning wage and salary income in the survey week had quit in the following year. The authors state that they had to use different survey years for their male and female samples in order to obtain information on collective bargaining coverage for all workers.

second interview identifies whether the members of this sample are still employed in the same job a year later. There is no attempt to exploit the longitudinal character of the data more fully by following a worker until he or she exits from either the job or the survey.

While they fail to address the issue, all three studies implicitly assume that job quits can be considered a semi-Markov process -- that is, the probability of leaving a job is independent of the individual's history prior to entering the job.[5] But previous history does matter in at least two respects. First, one would expect that the accumulation of labor market experience prior to the current job might affect current quit probabilities both because it enhances the worker's knowledge of suitable job opportunities and increases his or her productivity. The Appendix I studies do not measure such accumulated experience and must resort to age as an obviously imperfect proxy.[6] Second, previous history will affect who shows up in a job during the initial survey week. Heckman and Singer [1984: 97-113] refer to this second problem as the initial conditions problem.

The initial conditions problem is troublesome in this context because the studies are looking at the dynamic process of an unfolding labor market career without examining how the previous history of the

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[5]Semi-Markov models do allow hazard rates from a state j to depend on the duration in state j. This assumption is implemented in the three studies by including job tenure as one of the explanatory variables in the logit (or probit) quit equation.

[6]Instead of using "age" as an explanatory variable, Blau and Kahn use "age - year last attended school." While this is a fairly good proxy for experience for men, it is much less satisfactory for women. In any event, the fundamental point is that the hazard rates estimated in these studies are considered to be independent of any previous labor market state of the individual before the start of the current job.

individual has affected his or her current economic status. This problem may be particularly serious when comparing the job tenures of male and female workers under a sample selection criterion that includes only those respondents who are caught midstream in a spell of employment. For example, assume that men tend to quit more often to change jobs while women tend to quit more often to leave the labor force. By analyzing only those individuals who are working during a certain sample week, Blau and Kahn, Waite and Berryman, and Viscusi have tended to weed out more high quit women than high quit men. This is true because high quit men will be included in the sample -- one would expect these men to have low levels of tenure, but they will probably be working -- while high-quit women who are often out of the labor force will tend to be under-represented in the sample.[7] As I discuss further below, I have tried to reduce the chance that "high-quit" females will be sorted out of the sample by focussing on the initiation of the individual's labor market experience. This is accomplished by limiting my analysis to those who have recently finished school or who have recently turned from a primary commitment to education to a primary commitment to the labor market.

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[7]Even in the face of this selection effect, there can a dramatic difference between the proportions of men and women who are captured at the date of interview during their first year on their current job. For example, in Viscusi's study, only 27.6% of the male workers but fully 48.8% of the female workers had less than a year's tenure when first interviewed. Viscusi [1980: 390]. Since Viscusi examines workers of all ages, this finding is undoubtedly influenced by the large number of women in the seventies who returned to the labor force after raising chilren.

1.5 A Recent Hazard Model Approach

A recent study by Meitzen [1986] has attempted to avoid the shortcomings of discrete-time duration analysis by estimating male and female quit rates using a continuous-time stochastic model. Meitzen analyzes data from the Employment Opportunties Pilot Programs (EOPP) Employers' Survey, which collected information between March and May 1980 from around the country on lower-skilled workers in their initial stages of employment with a firm. Meitzen finds that the overall yearly probabilities of quitting are quite close for the sexes: .242 for males and .248 for females. Meitzen [1986: 155]. He also finds that quit rates decline over time for men but rise over time for women.

Meitzen concludes from this different pattern of duration dependence that the nature of job matching for men and women are quite different. Men, he posits, discover the quality of a job match quickly, and then quit if the quality seems low. On the other hand, since women appear to quit with an increasing frequency as tenure increases, Meitzen concludes that

> Women may have more on-the-job learning to do regarding their labor market preferences or in discovering whether they will be discriminated against. In either case, this on-the-job learning causes females to make their match-quality (and quit-stay) decisions later in the match as opposed to the more immediate match-quality decisions of males.

Meitzen [1986: 164].[8]

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[8]The EOPP survey that Meitzen relied on limited its sample to those with at most 2.5 year of tenure. As a result, the average tenure of females in his sample was .79 years. Meitzen [1986: 158]. Therefore, it is conceivable that the female hazard rate might turn down beyond the observation period of that study. If so, Meitzen's finding would be consistent with a model advanced by Jovanovic, in which the hazard first increases and then decreases. Such a result is possible if (1) information about the quality of a particular job match can be obtained

While Meitzen's findings are interesting, I am troubled by the potentially serious sample selection problems in his study. To be included in his sample, someone would have to be a low-skilled worker hired within the last 2.5 years. It is quite possible that the stringent time limitation on tenure could adversely affect the hazard rate estimations. Moreover, the restriction of the analysis to low-skilled workers may introduce biases. In the economy as a whole, a large proportion of women are in low-skilled jobs and thus are candidates for inclusion in the EOPP, while a much smaller proportion of men are found in low-skilled jobs.[9] Therefore, one would expect that the average quality of the women respondents would be higher than of the men respondents.[10] This fact suggests that the sample population of men will be skewed toward relatively high quit men, since worker quality seems to be negatively associated with the rate of job quitting. This effect is reinforced by the restriction of the sample to recently hired workers. One would imagine that the 40-year old men who are recently hired low-skilled workers tend to be the high-probability quitters, while the 40-year old women who are included may well be recent reentrants after raising children. Again, one might expect that this

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only after the start of the job, and (2) learning is Bayesian. Jovanovic [1979b].

[9]In 1980 -- the year in question in Meitzen's study -- the median usual weekly earnings of full-time wage and salary workers was $306 for men but only $199 for women. Norwood [1984: 6]. Clearly, then, the percentage of women in low paid -- and thus presumably low-skilled -- jobs will be greater than the percentage of men.

[10]If 100 men and 100 women have the same distribution of abilities, and the 10 least-talented men and the 50 least-talented women work in low-skilled jobs, then the average quality of the low-skilled women will be greater than the average quality of low-skilled men.

factor would tend to narrow any differential in quit probabilities between men and women as relatively more high-quit men are included in the comparison.

Chapter 2

ESTIMATING MALE AND FEMALE HAZARD RATES

2.1 A Continuous-Time Stochastic Model

In order to tackle the question of whether women have shorter expected job tenure than men it is essential to begin with a suitable theoretical framework. I basically adhere to that strand of the literature that envisions job selection and mobility as probabilistic processes in which both the employer and the worker are seeking to maximize their particular interests in deciding whether to establish and then maintain an employment relationship. Both actors can be thought of as selecting their best option at time 0 and constantly reevaluating whether to remain in that state or not. In this sense, while the cost accounting may be somewhat different, the tasks of evaluating which job to select for someone who is not working or whether to remain at a certain job for someone already working are conceptually similar.

2.1.1 The Worker's Decision

I begin by examining the worker's decision. If V_1 represents the total expected value (expressed in dollar terms) of the current job and V_2 represents the total expected value of the best alternative job, then one would expect a worker not to switch to another job as long as

$V_1 > V_2$.[1] At the same time the worker would also be evaluating whether to remain in the workforce by comparing V_1 to the total value V_o of being out of the labor force. Considering both possible transitions, then, the worker will remain with the current employer as long as $V_1 > V_2$ and $V_1 > V_o$.

Note that a number of factors can influence the values of V_1, V_2, and V_o. If the characteristics of the current job suddenly became more attractive -- e.g., the worker just received a promotion -- then ceteris paribus one would expect the probability of leaving to fall. The reverse would be true if the current job suddenly became less attractive. Similarly, one might expect that other opportunities might come to the attention of the worker, and a particularly favorable opportunity might prompt a job shift if not matched by the current employer. In all of these cases, the employer can increase the probability that a worker will leave or stay either directly, by firing the worker, or indirectly, by enhancing or decreasing the attractiveness of the current position.

Finally, opportunities or responsibilities outside the labor market might suddenly increase V_o, causing a departure from the labor market. A fairly dramatic example of recent vintage that underscores the probabilistic nature of the arrival of these new nonmarket opportunities

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[1]Note the discussion in the text is general enough to embrace a number of complexities. V_1 represents the total present discounted value of all compensation -- wages, perquisites, nonpecuniary advantages, etc. -- associated with the current job. V_2 can be thought of as encompassing all of these elements of the best alternative job, minus any costs of leaving the present job to take this alternative. These transition costs might include the loss of any nonvested pension or other benefits as well as any job search and job change costs that are not reimbursed. Any expected severance pay for job changers would be treated as a negative transition cost.

is winning a million dollar lottery.[2] A more prosaic example might be leaving the labor force to raise a child or to take care of an ailing relative.

Moreover, the values of any given option will be based on estimates that depend on the individual's information set I. One would expect that increased information tends to improve job selection, thereby diminishing the probability of a quit caused from an erroneous job decision. This "information effect" suggests that increases in education would tend to reduce job mobility.[3] Less educated individuals might be less effective in evaluating job prospects before they begin work, leading to a greater amount of trial-and-error information acquisition and a concomitantly higher quit rate.[4] On the other hand, increased education might have the effect of increasing mobility by expanding one's options.[5] Which of these conflicting effects will dominate is an empirical question that will be answered below.

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[2]Of course, this is virtually a zero-probability event.

[3]Increased information concerning any particular option will tend to reduce quit rates. If the increased information acquaints one with additional options, however, it may increase quit rates.

[4]At the same time, more education may be associated with a longer expected tenure if employers spend more time and effort searching for workers to fill positions requiring greater education. Barron, Bishop, and Dunkelberg [1985: 47] present evidence that this is the case. More intense search by employers would presumably yield better workers, thereby increasing expected tenure because (1) fewer workers would be fired, and (2) quit rates might decline as a greater proportion of workers performed well and received promotions and wage hikes.

[5]Tuma [1976: 357] argues that more education -- indeed more human capital in general -- tends to increase one's attractiveness to employers, thereby expanding employment options and increasing quit probabilities. Cf. Barron, Bishop, and Dunkelberg [1985: 45 fn. 9].

Note that the process of searching for a job can be thought of as the augmentation of one's information set -- an augmentation that is purchased at the expense of increasing search costs. If these search costs are high then an individual has a greater incentive both to find a satisfactory job in the first instance and to remain in any job since the value of alternative jobs must be discounted by these high search costs.

Once one is on the job, increases in specific human capital associated with the particular employer would tend to increase one's attachment to the job. At the same time, the longer one stayed with a job, the greater the probability that the match was particularly felicitous, and thus the more likely that one would remain. Both of these factors suggest that hazard rates should decline monotonically. On the other hand, young women on their first job after school may be planning to leave the workforce to raise children at some point, and this probability of departure may increase with time.

2.1.2 The Employer's Decision

The employer may also decide to terminate the employment relationship if (1) the worker's wage rises above marginal productivity (and the employer is constrained from simply lowering the wage) or (2) another equally productive worker is available for work at a lower wage. If the employee happens to have a very high wage relative to his or her productivity, one would expect the employee's quit probability to fall. At the same time, however, one would expect the probability of firing to increase. Which effect will dominate when looking at reduced form data representing the outcomes of this two-party maximization process is an empirical question. It is not always the case, however, that a factor that reduces the probability of quitting will increase the probability of firing, and vice versa. Theory does provide an unambiguous prediction concerning the "tenure effect" on hazard rates, because the same factors that lead to a lower quit rate with duration tend to lower the probability of firing as well. Tuma [1976: 348].

An employer seeking to fill a job will ordinarily be interested in hiring a worker who will remain in his employ for a period long enough to repay the fixed costs of hiring and the training costs associated with the position. In making this determination the employer may be able to assess the prospective employee's steadiness by examining his employment history. On the other hand, if the individual has recently finished his education and is about to enter full-time employment for the first time, he or she will have no employment history to be examined. In this case, the question arises: will knowledge of the sex of the applicant be useful in predicting expected job tenure on this first job? It is to this question that I now turn.

2.2 Details of the Estimation

I have estimated the male and female hazard rates for the first spell of full-time employment in the civilian labor force after termination of school. While the other analysts who have examined the relative quit rates of men and women have not limited their analyses to the first job, they have all implicitly assumed that hazard rates from first jobs are completely representative of hazard rates from any random

n^{th} job.[6] Indeed this is one of the most important, and questionable, aspects of their implicit assumption that job terminations can be treated as semi-Markov processes.

2.2.1 Defining the Sample

My basic goal is to analyze the hazard rates for a set of workers who have in some sense terminated their primary tie to education and have shifted toward a primary commitment to the labor force. This is important because the analysis of hazard rates based on a person's first full-time job is severely impaired if one includes students taking their first full-time summer job before returning to school in the fall.[7]

Accordingly, a person was classified as a recent school leaver in year x if (1) the respondent was not enrolled in school full time in year x, (2) the respondent was enrolled full-time in year x-1. The first condition ensures that those who are still full-time students are excluded from the analysis.[8] The second condition is necessary to

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[6]As discussed below, my results are quite different from those obtained by the Appendix I studies. If they are correct that first job hazard rates are entirely representative of hazard rates from any random job, then there is a direct conflict in results that I would attribute to their improper methodology. On the other hand, if the assumption of uniformity of hazard rates across jobs is not valid, then these other studies have erred in aggregating all jobs in their hazard rate estimations.

[7]Tuma and Hannan [1984: 55] note that a plot of the survival function for white men on their first full-time job reveals a precipitous drop at three months, making it difficult to fit standard parametric models to such data. Moreover, since "the first full-time job is more likely for white men than for black men to be a summer job ending with a return to school," a distorted picture emerges of the hazard rates for black and white male workers if one does not remove the effect of those who are still basically committed to school rather than to the labor market.

ensure that the analysis is limited to the first job obtained after the respondent finished his or her tenure in school.

Having identified those who have ended their primary attachment to education, I then ascertained when these individuals entered the full-time labor market, defined as taking a job for which the "usual hours worked" per week was greater than 20.[9] Obviously, a selection effect enters here as well, since those who tend to move from full-time education to work more quickly will tend to be represented in relatively higher numbers than those who make this transition more slowly.[10] Once a person is identified as working in a job for at least 20 hours per week, I then search through the successive surveys to discover when the job terminated.[11]

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[8]Full-time employment is initially defined as 20 or more hours of work per week. Although it is conceivable that a person is working 20 hours per week while attending school full time, my selection criteria did not consider this job to be the first full-time job. The reason has already been addressed: I am interested in examining the job mobility of those who have turned from full-time education to a more complete commitment to the labor force. Many jobs undertaken while engaged in full-time education -- some of which might exceed 20 hours of work per week -- are expressly intended to end with the student's education, if not before. Moreover, these jobs are often qualitatively different from the type of job that the individual will pursue when his or her education is complete.

[9]I subsequently restrict the definition of full-time works to 30 or more hours of work per week.

[10]For example, if an individual finishes school in 1971 but has not yet found a job by the time of the 1971 interview, then he or she will not enter the estimation of the duration of first job. Examination of the results in the individual years beginning in 1968 suggested that this selection effect is not correlated with gender.

[11]Having identified a job as "full-time," I consider its full duration, even if subsequently the hours worked drop below 20 hours. That is, if "usual hours worked" is reported as 35 in November of 1970, it is assumed that this figure remained constant at 35, or at least 20, from the time the job was taken until the job was terminated. On the other hand, if the job is initially a part-time job and then becomes

Note that the selection stategy ensures that no jobs will be "left censored" -- *i.e.*, each job will have a definitely specified starting date.[12] On the other hand, for a number of reasons, the ending date is not always known -- *i.e.*, the data may be "right censored." First, some of the jobs will extend past the time of the 1971 survey. These jobs will be treated as lasting up to the 1971 interview date, at which point they are censored.[13] Second, there are a number of cases in which the data seem to be incorrectly recorded so that it becomes impossible to identify the end of a job. These observations were either deleted from the sample or treated as censored at the last point at which I was certain the subject was still employed at his or her first full-time job.

2.2.2 The Nature of the Termination

In estimating hazard rates from jobs, one must choose which job exits will be counted as terminating the job spell. Clearly, voluntary quits will end the duration of the job spell, but what about layoffs and

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full-time, I deem the start of the job to be the beginning of full-time employment.

[12]If the first job of an individual identified as a recent school leaver at time x started a year or more earlier, then this job must have commenced when the worker was still in school. (This follows from my definition of recent school leavers.) In that case, I defined the starting date of the job to be a year prior to x. For details on the practical and theoretical reasons for this choice, see Appendix II's discussion of "starting dates."

[13]It is important that these jobs not be viewed as ending at the date of the final interview as Tuma did in an early study of job mobility. Tuma [1976]. Using the early Tuma approach clearly biases downward one's estimates of job durations by necessarily truncating all jobs that are longer than the sample period.

discharges? Analysts have differed in their approach to this issue. Blau and Kahn simply exclude "individuals who were laid off or discharged from their initial jobs ... since it is not possible to ascertain whether they would have quit in the absence of a layoff or a discharge." Blau and Kahn [1981: 567]. Waite and Berryman, on the other hand, do not distinguish between voluntary and involuntary job exits. Waite and Berryman [1985: 45]. In their study, all terminations -- whether voluntary quits, layoffs, or discharges -- are treated as defining complete job spells.

Both of these studies used discrete time models, which require them to choose between these two polar positions. By using survival analysis, it is possible to distinguish between discharges, quits, and layoffs. For example, if one wants to focus on exits caused by voluntary quits and discharges, then survival analysis can efficiently use the relevant information by simply noting that the event in question -- a voluntary quit or firing -- had not occurred by, say, the time of the layoff. This is accomplished by treating layoffs as censored job spells.[14] Mindful of the controversy over whether voluntary and involuntary exits can or should be distinguished, I have estimated my hazard rates both ways -- that is, layoffs are first treated as censored spells and then treated as completed spells.

A related question is the relative transition rates of men and women from the first job to a second job and from the first job to out

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[14]Of course, these categories are not entirely reliable. A worker who is told that a layoff is imminent may well quit to take another job. If the worker had been laid off, this event would be treated as a censored spell at the time of the layoff; by quitting, the worker is considered to be a voluntary job leaver, whose job tenure is complete at termination.

of the labor force. I argue that the voluntary quit rate -- rather than the destination upon leaving -- is the important variable to an employer who is interested in minimizing the investment costs in employees. Therefore, I will aggregate these two transition rates into a single hazard rate estimation.

Chapter 3

RESULTS FOR THE PERIOD 1968-1971

3.1 The Sample

My compilation of the durations of first full-time (20 or more hours per week) jobs yielded a sample of 1431 men and 1527 women.[1] Tables 1 and 2 provide summary statistics on the male and female samples. Female workers on average had about a half-year less education than male workers -- 12.47 years compared to 12.89 years.[2] This half-year difference explains most of the age difference between the sexes at the time of the start of the first job. The percentage of workers with less than a high school education is quite similar for men and women -- 18.1% vs. 18.6%. The percentage of workers with eighteen or more years of education, however, was almost six times as high for men as for women -- 2.73% vs. 0.46%.

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[1]This sample was limited to those workers who were at least age 16 at the start of the first job, who were working for pay and were not self-employed, and for whom there were no missing values for the explanatory variables included in Tables 4 and 5. These restrictions led to the exclusion of 85 cases from the men's sample and 56 cases from the women's sample.

[2]The cited education figures refer to the first information collected on "years of education completed" following the start of the first job. If the job continued past the date of the interview at which this educational information was collected, then this information refers to years of education completed by the early stage of the first job. If the individual remained in school part-time while working on this job, subsequent measures of education could be higher.

TABLE 1

Descriptive Statistics for Male First-job Holders,
Hours ≥ 20, 1968-1971 (1431 Cases)

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	20.28	2.587	16.07	30.07
EDUCATION				
Years of Schooling	12.89	2.249	5.00	18.00
Distribution (percent of sample)				
Less than 12 years	18.10			
12 years	40.67			
13-15 years	21.10			
16-17 years	17.40			
18 years or more	2.73			
TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	73.24			
Black	25.72			
Other	1.04			
TOTAL	100.00%			
FATHER'S EDUCATION[1] (In Years)	10.50	3.689	0.00	18.00
SIZE OF LABOR FORCE				
INDEX 1-8	3.729	2.484	1.00	8.00
1: <50,000	.2509			
2: 50,000-199,999	.1922			
3-5: 200,000-799,999	.2593			
6-8: >800,000	.2977			
HOURS WORKED PER WEEK	41.05	10.11	20.00	99.00

NOTES: [1] Omits 271 cases for which father's education is missing.

TABLE 2

Descriptive Statistics for Female First-job Holders, Hours $\geq$ 20, 1968-1971 (1527 Cases)

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	19.47	1.906	16.03	27.08
EDUCATION				
Years of Schooling	12.47	1.980	0.00	18.00
Distribution (percent of sample)				
Less than 12 years	18.60			
12 years	51.60			
13-15 years	17.29			
16-17 years	12.05			
18 years or more	0.46			
TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	70.66			
Black	28.29			
Other	1.05			
TOTAL	100.00%			
FATHER'S EDUCATION[1] (In Years)	10.40	3.552	0.00	18.00
SIZE OF LABOR FORCE				
INDEX 1-8	3.546	2.417	1.00	8.00
1: <50,000	.2711			
2: 50,000-199,999	.1978			
3-5: 200,000-799,999	.2705			
6-8: >800,000	.2606			
HOURS WORKED PER WEEK	38.45	8.057	20.00	90.00

NOTES: [1] Omits 350 cases for which father's education is missing.

Young workers in the period 1968-1971 had received over two more years of education than their fathers. Moreover, a comparison of the respective standard deviations, indicates that the level of education was more uniform for this younger generation of workers. The racial composition of the sample reflects the higher labor force participation rates of black women over white women. For the male sample, 73.2% of the workers were white and 25.7% were black. For the female sample, 70.7% were white and 28.3% were black.

3.2 A Hazard Rate Constant Over Time for Each Sex

The simplest comparison of male and female hazard rates from first full-time ($\geq$ 20 hours) jobs for the period 1968-1971 is presented in Table 3.A. The constant rate model (the top panel) implicitly assumes that job duration t has an exponential distribution and is characterized by the following functions:

$F(t) = 1 - e^{-rt}$	Distribution Function
$f(t) = re^{-rt}$	Density Function
$S(t) = 1 - F(t) = e^{-rt}$	Survival Function
$h(t) = f(t)/S(t) = r$	Hazard Rate.

This model is restrictive because it assumes that: (1) the probability of leaving a job is identical for all members of the same sex, thus ignoring both observed and unobserved heterogeneity, and (2) the hazard rate is constant over time.

The table shows that the quit rates (multiplied by 1000) are substantially greater for women than for men -- 2.325 vs. 1.392. In such a model, where the constant hazard rate is given by r, the expected tenure will simply be the reciprocal of r. Thus, the expected tenure for this sample of men and women is 67.4% greater for men than for women -- 23.6 months vs. 14.1 months.

TABLE 3

Maximum Likelihood Estimates of Hazard Rates From First Jobs (x1000), Hours $\geq$ 20, 1968-1971

	Men		Women	
Number of Cases	1431		1527	
A. Constant Rate Model--No Covariates, No Time Dependence				
All Durations	1.392		2.325	
Completed Spells	685		773	
Censored Spells	746		754	
-ln likelihood	5190.3		5460.6	
Expected Tenure (Months)	23.6		14.1	
B. Duration Only Model				
Duration (Months)				
0-3	2.054	(.06551)	3.082	(.0530)
3-6	1.990	(.08006)	2.295	(.07647)
6-12	1.551	(.07809)	1.837	(.08165)
12-18	0.9760	(.1231)	1.347	(.1348)
18-24	0.7209	(.1741)	1.568	(.2132)
24-	0.4065	(.1741)	3.182	(.2294)
-ln likelihood	5111.9		5430.4	
likelihood ratio test statistic	156.90*		60.24*	

Notes: *Significant at .05 level.

The standard errors in parentheses correspond to the estimated parameters r, where exp(r) * 1000 is the rate presented.

3.3 A Time-Varying Hazard Function

The assumption of time homogeneity in the constant rate model implies that the probability that a worker would leave a job within, say, the next six months is the same whether he or she is just starting the job or has been working there for some time. For the reasons discussed earlier -- such as, the accumulation of job-specific human capital and improved information about the value of the job -- one would expect that hazard rates would fall with rising job tenure.[3] I now test whether the hazard rate $h(t)$ is a constant r over time, as assumed in Table 3.A, or whether it varies over time.

In Table 3.B the hazard rate was estimated according to the function

$$h(t) = r_p$$

where p identifies 6 time periods measured from the start of the spell. In this case, $h(t)$ is a step function, which has a constant hazard within each subperiod. While many other time-varying hazard specifications could have been chosen, this form was selected because it is a simple estimator that does not constrain the hazard to rise or fall monotonically. Table 3.B demonstrates for both men and women that hazard rates are not constant over time.

A number of points should be made about the Table 3.B results. First, for every period, women quit at a higher rate than men. Second, both men and women quit at a far higher rate in the first few months of

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[3] At least this is the expectation for male workers.

their first job. For both sexes, hazard rates in the initial period are more than twice as high as the rates for the period from 12-18 months. Third, the pattern of duration dependence is quite different for the two sexes. The male rates decline monotonically throughout the entire sample period, while the female rates decline for the first 18 months, at which point they begin to rise sharply. For the final period -- duration greater than 24 months -- the female hazard rate is almost 8 times as great as the male rate. I suspect that the rate of child-bearing for the female workers who appear in my sample increases with time after they start work, tending to cause quit rates to rise -- a possible "birth effect".[4] At the same time, there is a "tenure effect," which tends to lower quit rates as job duration increases, that operates on both men and women. After two years, the birth effect overwhelms the tenure effect for these young female workers.

3.4 Introducing Population Heterogeneity

The results of the chi-squared tests in Table 3 indicate that the observed hazard rates vary significantly with time. Before one can state with confidence that the hazard rates should be modeled as time-varying, one must consider the effect of heterogeneity within the sample population. To consider the simplest case, imagine that those with less than high school degrees all had a constant hazard rate r_1 and those with at least a high school diploma had a lower constant hazard rate

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[4]Evidence in favor of this birth effect is provided in Felmlee [1984a: 178], which shows that transition rates to nonemployment because of pregnancy show positive duration dependence -- i.e., such transitions increase with time.

r_2. In this case, time would have no effect on anyone's hazard rates, which are assumed to be constant at r_1 and r_2. But estimating a hazard model as in Table 3.B that varied across different time periods would generate a monotonically decreasing hazard rate simply because the high-quit rate workers would tend to quit faster and the remaining population would be comprised of a larger percentage of low quit rate workers. Ultimately, one would expect the hazard rate to fall to r_2, when only the low-quit individuals remained.

The lesson of this example is that one cannot automatically assume that significant differences in hazard rates over time represent true time dependence -- one may be observing spurious duration dependence caused by uncorrected sample heterogeneity. In order to illuminate this issue, I now estimate hazard rates for each individual according to the following functional form:

$$h(t) = r(X) = e^{BX}$$

where X is a vector of explanatory variables and B is the vector of asssociated parameter estimates. Tables 4 and 5 reveal that indeed there are significant differences in hazard rates within the sexes -- that is, heterogeneity with respect to hazard rates exists among both men and women. Note that the models presented in these tables once again assume that the hazard rate for each individual is constant over time -- i.e., job durations have an exponential distribution conditional on the X's -- but now different groups within the two sex categories are permitted to have different hazard rates.

Education tends to be a highly significant covariate for both women and men. Whether measured by a single variable -- "highest grade completed" -- or by a series of dummies indicating varying levels of

TABLE 4

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Invariant Hazard Rates,
First Jobs, Hours ≥ 20, 1968-1971, Men

	1	2	3	4	5
Constant	-3.797* (.3171)	-3.793* (.3165)	-4.599* (.4346)	-3.799* (.3180)	-4.579* (.4348)
Age at start	-.07348* (.02255)	-.07168* (.02260)	-.06307* (.02352)	-.07371* (.02261)	-.06608* (.02351)
Black	.2576* (.09164)	.2792* (.09237)	.3149* (.09126)	.2782* (.09226)	.3127* (.09120)
Education in years	-.05847* (.02643)	-.05303* (.02653)		-.05284* (.02656)	
Education =12 years			.09456 (.1032)		.0878 (.1032)
Education =13-15 y.			-.1296 (.1461)		-.1344 (.1455)
Education ≥ 16 y.			-.3284** (.1885)		-.3193** (.1880)
Unempl.[1] Rate	-.1319* (.0275)	-.1318* (.0272)	-.1319* (.0273)	-.1349* (.0272)	-.1347* (.0274)
SLF[2]		-.03027** (.01597)	-.03105** (.01601)		
50≤ <200 (1000's)				.1419 (.1136)	.1284 (.1138)
200≤ <800 (1000's)				-.1505 (.1087)	-.1549 (.1087)
≥800,000				-.1472 (.1061)	-.1542 (.1063)
n	1431	1431	1431	1431	1431
-ln likeli.	5130.5	5128.7	5127.0	5126.1	5124.6
Chi-square	119.57*	123.20*	126.65*	128.49*	131.47*

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]Mean unemployment rate for local labor market across job spell.
[2]Size of labor force of local labor market (index 1-8).

TABLE 5

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Invariant Hazard Rates,
First Jobs, Hours ≥ 20, 1968-1971, Women

	1	2	3	4	5
Constant	-4.232* (.4029)	-4.147* (.4051)	-4.928* (.5445)	-4.195* (.4058)	-4.987* (.5447)
Age at start	-.02705 (.02749)	-.02771 (.02762)	-.02211 (.02967)	-.02641 (.02763)	-.02091 (.02971)
Black	.2042* (.08180)	.2391* (.08359)	.1815* (.08354)	.2305* (.08322)	.1740* (.08327)
Education in years	-.1064* (.02575)	-.1030* (.02596)		-.1043* (.02593)	
Education =12 years			-.7008* (.09192)		-.7011* (.09193)
Education =13-15 y.			-.7281* (.1486)		-.7300* (.1487)
Education ≥ 16 y.			-1.017* (.1937)		-1.026* (.1938)
Unempl.[1] Rate	-.0072 (.0210)	-.0095 (.0209)	-.0051 (.0207)	-.0095 (.0209)	-.0046 (.0208)
SLF[2]		-.03181* (.01530)	-.03198* (.01526)		
50< <200 (1000's)				-.00925 (.1050)	-.02945 (.1052)
200< <800 (1000's)				-.09559 (.09915)	-.09393 (.09927)
≥800,000				-.1690** (.1005)	-.1746** (.1003)
n	1527	1527	1527	1527	1527
-ln likeli.	5429.9	5427.7	5406.7	5428.1	5407.2
Chi-square	61.23*	65.61*	107.60*	64.85*	106.64*

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]Mean unemployment rate for local labor market across job spell.

[2]Size of labor force of local labor market (index 1-8).

education, education is negatively related to the hazard rate. For women, the coefficients on the years of education variable indicates that each additional year lowers the hazard rate by roughly 10%. When the education dummies are included, it appears that female high school graduates will quit their first job at a roughly 50% lower rate than those who have not completed high school. Moreover, female college graduates quit at almost a 65% lower rate than those without a high school diploma. The effect of education in lowering quit rates is less pronounced for men. Each additional year of education reduces the male quit rate by only 5-6%. Moreover, the coefficients on the education dummies suggest that there is no significant difference in the quit rates of men with less than a college education. Those with a college degree are shown to have roughly a 28% lower rate than those with less than a high school education, but even this finding is significant only at the .10 level.

It is interesting to speculate on the reasons for the different impacts of education for male and female workers. I suspect that education causes a greater reduction in quit rates for women because, in addition to the "informational" effects of increased education, which apply to all workers, education can influence female hazard rates through the mechanism of the proposed "birth effect." Thus, since increased education for women tends to be negatively associated with childbearing, this may explain the greater impact of education in reducing quit rates of women. In section 2.1, I discussed the possibly conflicting effects of education on quit rates. Apparently, at the outset of one's labor market career, increased education tends to improve one's information about the job market and enables one to conduct a more efficient search for employment, thereby decreasing one's quit probabilities.[5] For men, however, this informational benefit does not become significant until one has completed a college education -- male high school graduates do not appear to quit at a lower rate than their less educated fellow workers.

These results stand in sharp contrast to those found elsewhere. In the four studies compared in Appendix I, the effect of "years of education" on quitting was either insignificant or positive in all but one case.[6] Education was also found to have a positive effect on mobility in a number of continuous-time studies of job shifting by men -- Tuma [1976: 349-350] -- and by women -- Felmlee [1984a: 176]; Felmlee [1984b: 271]; Felmlee [1982: 147].[7] These differences may result because my study examined only those in their first job while the other studies considered any current job. It is quite likely that the factors that lead to a negative relationship between education and quit rates -- such as that more education enables one to make a better job selection

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[5]Another possible explanation for higher quit rates among young individuals with lower education is that they tend to quit to return to school to seek further education. While I do not report the estimations, I did run regressions in which father's educations was an explanatory variable. While the positive coefficient on this variable was not significant, the inclusion of "father's education" did tend to raise the significance of the own-education variable for men and women. This may suggest that if a child's education is low vis-a-vis the father's education then the likelihood of quitting work to seek more education is greater.

[6]Waite and Berryman found that education did significantly lower quit rates for men but not for women.

[7]Felmlee always found that education positively affected mobility. When she disagregated the hazard rate to focus only on transitions from one employer to another based on the number of hours worked, she found that the effect of education was significant only when shifting from full-time to part-time work and from part-time to full-time work. Felmlee [1984b: 276].

and that less education raises the chance that one will quit work to return to school -- are both stronger influences at the start of one's labor market career and less important subsequently.[8]

Another finding that contradicts the results of the other studies presented in Appendix I is that I find no evidence that blacks have lower quit rates than whites. In fact, the coefficient on BLACK was uniformly positive and significant, reflecting a 32-37% higher rate for black men and a 19-27% higher rate for black women. Using NLS data over roughly the same time period as my study, Blau and Kahn reached a contrary conclusion: "With regard to race, it was found that blacks actually quit less frequently than whites with similar personal and job characteristics." Blau and Kahn [1981: 577]. Viscusi and Osterman obtain similar results in their studies using the PSID.

Another interesting difference between the male and female workers is that the mean unemployment rate across the duration of the job spell has a significant negative effect on quitting for men but is totally insignificant for women. Each percentage point increase in this unemployment rate lowers the male hazard rate by roughly 12%.[9] Again,

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[8]I also considered the possibility that the insignificant and positive coefficients on education in these other studies might be caused by their inclusion of the worker's wage in the estimated quit function, thereby diminishing the significance of the education variable and other covariates that are highly correlated with earnings. Moreover, if two individuals are making the same wage and one is much more educated than the other, one might expect the more educated worker would tend to be in a position to increase his earnings by a job move, thereby elevating his probability of quitting. When I included a wage variable in my quit equations, however, the coefficients on the years of education variable remained negative and significant, although at a slightly lower level for the male sample. See Tables 21 and 22.

[9]The average value of this measure of unemployment for all male workers in the 1968-1971 period is 4.6% and for all female workers is 4.8%.

this difference between male and female workers shows the greater sensitivity of men to labor market conditions in their decisions to terminate employment. As one would expect if female workers are making decisions to quit in response to pregnancies, the connection between quitting and the unemployment rate becomes more attenuated.

For both women and men, the coefficient on the index (1-8) of the size of the local labor market is negative and significant -- although only at the .10 level for the men. When I substituted three dummy variables in place of the single index covariate, however, the effect of size of labor market was considerably weakened. Moreover, the influence of this explanatory variable proved not to be monotonic: for both men and women, the hazard rate for those living in a local labor market of from 50,000 to 200,000 workers was higher than for labor markets smaller than 50,000, while for labor force sizes above 200,000 the effect on quit rates was negative. The basic dichotomy to which I continue to allude -- that greater options can either raise quit rates by making quitting more attractive or lower them if the richer options permit a more satisfying initial job choice -- is again confronted. While the pattern is not entirely clear, the latter effect seems to be dominant, since increasing labor force size tends to reduce quits at the start of one's labor market career.

The "age at start" variable is significant only for the male sample -- reducing quit rates by roughly 6-7% per year. Undoubtedly, much of the effect of age is captured by the education variable, and one would imagine that there would be relatively little variation in the age that, say, a male high school graduate begins his first full-time job.

The results from Tables 4 and 5 can now be used to assess the relative tenure levels of men and women workers holding constant a number of explanatory variables. For example, model (2) predicts that the expected tenure for white, high school graduates will be 20.1 months for men and 13.3 months for women.[10] This compares with the estimates obtained in Table 3.A of 23.6 months vs. 14.1 months, based on the assumption that each sex had a constant hazard rate. Clearly, controlling for the measured covariates in estimating a constant hazard rate has reduced, but not eliminated, the tenure gap between male and female workers.[11]

3.5 Combining Time and Population Heterogeneity

The models presented in Tables 6 and 7 combine the results of Tables 3-5 by estimating time-varying hazard rates while correcting for a number of covariates. In all of these models, the hazard rates are estimated using a proportional hazards model across the same six time periods that were presented in Table 3.B. The particular estimation

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[10]This estimation assumed that the workers were aged 20, the unemployment rate was 4%, and the size of the local labor market was under 50,000. This yielded hazard rates (multiplied by 1000) of 1.628 for the men and 2.461 for the women, which translate into the expected tenure figures presented in the text.

[11]Model (2) controls for education using a single measure of highest grade completed. Using one of the models in which high school education is measured through a dummy variable would have narrowed this tenure differential between men and women workers. For example, model (3) predicts that the expected tenure for white, high school graduates is 18.3 months for men and 15.0 months for women, based on the respective hazards of 1.792 and 2.191. This narrowing of the tenure differential occurs because models (3) and (5) of Table 4 estimate that male high school graduates have almost a 10% higher quit rate than those with less education. At the same time, models (3) and (5) of Table 5 predict that female, high school graduates tend to quit at only the half the rate of those with less education.

technique restricts the effect of each explanatory variable to be the same in each time period. For example, if one estimated the model with a single covariate identifying black workers (BLACK) and the same six time periods, one would obtain a coefficient estimate c and six parameters p_i (for i = 1 - 6) associated with each time period. The rate r_{bi} for black workers (b) in any period i would then be given by

$$r_{bi} = e^{c} * e^{p_i}$$
$$= ke^{p_i} \qquad \text{where } k=e^{c} \text{ is a constant for all i.}$$

Thus, if c=0, then k=1, and the rate is the same in each period for white and black workers. If c>0 then the rate for black workers will be greater than for white workers because k will be greater than 1. If c<0 then blacks will have lower rates because k will be some positive fraction. Note that one of the features of the proportional hazard model is that the ratio of the hazards of any two individuals at any particular duration will be a constant.[12] In general then the rate for worker h in period i would be

$$r_{hi} = e^{BX} * e^{p_i}$$

where X is a vector of explanatory variables and B is the associated vector of estimated coefficients.

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[12]In this simplified example, the ratio for two workers of the same race would simply be 1, and for a black and a white it would be k.

TABLE 6

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours ≥ 20, 1968-1971, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.06019*	-.05948*	-.05642*	-.06115*	-.05918*
	(.02306)	(.02309)	(.02422)	(.02311)	(.02422)
Black	.1915*	.2061*	.2325*	.2075*	.2333*
	(.09110)	(.09183)	(.09076)	(.09175)	(.09074)
Education in years	-.05113**	-.04721**		-.04689**	
	(.02672)	(.02684)		(.02690)	
Education =12 years			.05135		.04612
			(.1027)		(.1028)
Education =13-15 y.			-.1129		-.1142
			(.1457)		(.1453)
Education ≥ 16 y.			-.2675		-.2566
			(.1900)		(.1897)
Unempl.[1] Rate	-.1185*	-.1188*	-.1175*	-.1204*	-.1191*
	(.02715)	(.02692)	(.02696)	(.02694)	(.02699)
SLF[2]		-.02043	-.02143		
		(.01587)	(.01590)		
50< <200 (1000's)				.1471	.1342
				(.1134)	(.1135)
200< <800 (1000's)				-.0882	-.0967
				(.1088)	(.1087)
≥800,000				-.0934	-.1017
				(.1060)	(.1061)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1] Mean unemployment rate for local labor market across job spell.
[2] Size of labor force of local labor market (index 1-8).

Table 6 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.866 (.3239)	-3.858 (.3237)	-4.483 (.4509)	-3.878 (.3256)	-4.473 (.4512)
3-6 Months	-3.879 (.3277)	-3.870 (.3275)	-4.492 (.4527)	-3.888 (.3294)	-4.480 (.4530)
6-12 Months	-4.103 (.3292)	-4.092 (.3290)	-4.712 (.4531)	-4.110 (.3309)	-4.700 (.4534)
12-18 Months	-4.537 (.3455)	-4.524 (.3454)	-5.140 (.4648)	-4.540 (.3471)	-5.127 (.4651)
18-24 Months	-4.816 (.3689)	-4.801 (.3688)	-5.417 (.4819)	-4.817 (.3705)	-5.403 (.4822)
24- Months	-5.295 (.3757)	-5.279 (.3755)	-5.893 (.4845)	-5.292 (.3778)	-5.877 (.4851)
n	1431	1431	1431	1431	1527
-ln likeli.	5070.9	5070.0	5069.6	5068.0	5067.8
Chi-square	238.90*	240.57*	241.42*	244.57*	245.12*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 7

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours $\geq$ 20, 1968-1971, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03077	-.03155	-.02480	-.03048	-.02385
	(.02778)	(.02789)	(.03008)	(.02789)	(.03011)
Black	.1857*	.2153*	.1654*	.2078*	.1588**
	(.08203)	(.08377)	(.08362)	(.08340)	(.08335)
Education in years	-.09647*	-.09351*		-.09465*	
	(.02605)	(.02625)		(.02622)	
Education =12 years			-.6421*		-.6421*
			(.09251)		(.09253)
Education =13-15 y.			-.6674*		-.6694*
			(.1501)		(.1503)
Education $\geq$ 16 y.			-.9308*		-.9372*
			(.1960)		(.1962)
Unempl.[1] Rate	-.01258	-.01463	-.01021	-.01458	-.009877
	(.02094)	(.02083)	(.02072)	(.02087)	(.02076)
SLF[2]		-.02734**	-.02750**		
		(.01529)	(.01526)		
50< <200 (1000's)				.00647	.01038
				(.1050)	(.1053)
200< <800 (1000's)				-.08009	-.07837
				(.09920)	(.09931)
$\geq$800,000				-.1392	-.1433
				(.1005)	(.1004)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1] Mean unemployment rate for local labor market across job spell.

[2] Size of labor force of local labor market (index 1-8).

Table 7 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.993 (.4052)	-3.918 (.4075)	-4.673 (.5520)	-3.963 (.4083)	-4.727 (.5522)
3-6 Months	-4.263 (.4098)	-4.185 (.4122)	-4.919 (.5550)	-4.231 (.4129)	-4.974 (.5551)
6-12 Months	-4.475 (.4114)	-4.395 (.4139)	-5.128 (.5558)	-4.441 (.4146)	-5.183 (.5558)
12-18 Months	-4.770 (.4251)	-4.687 (.4276)	-5.394 (.5667)	-4.733 (.4281)	-5.450 (.5666)
18-24 Months	-4.629 (.4525)	-4.549 (.4546)	-5.236 (.5874)	-4.594 (.4555)	-5.290 (.5874)
24- Months	-3.899 (.4680)	-3.825 (.4703)	-4.592 (.6070)	-3.868 (.4702)	-4.645 (.6064)
n	1527	1527	1527	1527	1527
-ln likeli.	5403.5	5401.8	5384.2	5402.1	5384.6
Chi-square	114.18*	117.41*	152.65*	116.89*	151.91*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

The models estimated in Tables 6 and 7 provide further support for the view that the rates do indeed vary with time: the general patterns that were observed in the "duration-only" model of Table 3.B persist after controlling for a number of explanatory variables. The male rates decline across the six periods, while the female hazard rates decline for the first 18 months and then rise thereafter. In every case, the female hazard for the final period is greater than the hazard in the first period. These results are invariant to the different specifications presented in the two tables.[13]

A comparison of the coefficient estimates for the time-invariant models (Tables 4 and 5) with those of the time-varying models (Tables 6 and 7) reveals remarkably stable results. In virtually every case, the conclusions about the sign and size of coefficients that were drawn with respect to the time-invariant models apply to the time-varying models as well. Once again, the unemployment rate tended to be the most significant covariate for the male hazard rate but was totally insignificant for the female hazard rate.[14] This tends to support the

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[13]The nonmonotonic nature of the female hazard rates indicates another potential problem with the approach employed in the Appendix I studies, all of which implicitly assumed a monotonic effect of tenure on the probability of quitting.

[14]I experimented with a number of different definitions of the unemployment rate variable in addition to the mean unemployment rate measure reported in the text. When I used the measure of unemployment closest to the end of the job, the negative size and significance of this variable grew for both men and women, although the estimated impact was far greater for men. I chose not to report this measure, though, because of the large number of missing values in the 1968-1971 period, which would have reduced both samples by more than 10%.

I also employed a third measure of unemployment -- the first unemployment rate measured after the job started. The estimated coefficients for this variable were positive for both men and women. Since this same pattern holds for both sexes, it appears not to be gender specific. Perhaps it represents a business cycle phenomenon in notion that female decisions to quit during this period were less governed by external economic forces and more affected by household considerations.

3.6 Treating Layoffs As Completed Spells

All of the estimations presented until this point have treated layoffs as censored spells. This treatment in effect assumes that the event of interest -- voluntary departures from employment -- has not occurred in a spell of employment that ends when the worker is laid off. As noted earlier, however, there are a number of arguments that suggest that the distinction between voluntary and involuntary departures is unsound and that layoffs should be treated as completed spells, or, in other words, that layoffs should be treated as quits. Accordingly, treating layoffs as quits, I have re-estimated the hazard rates presented in Tables 6 and 7. The results from this re-estimation are presented in Tables 8 and 9.

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which a high unemployment rate at the start of one's job may be a rough proxy for the trough of a business cycle. In the subsequent boom, quits will rise, thus leading to a positive relationship between the unemployment rate at the start of the job and the subsequent quit rate.

TABLE 8

Time-Varying Hazard Rates,
Layoffs Treated as Completed Spells:
First Jobs, Hours ≥ 20, 1968-1971, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03992* (.01990)	-.03907* (.01993)	-.03793** (.02094)	-.03957* (.01995)	-.03901** (.02098)
Black	.1926* (.08081)	.2088* (.08136)	.2477* (.08034)	.2092* (.08132)	.2479* (.08034)
Education in years	-.06262* (.02318)	-.05774* (.02329)		-.05883* (.02334)	
Education =12 years			.1008 (.09271)		.09657 (.09284)
Education =13-15 y.			-.1015 (.1293)		-.1065 (.1292)
Education ≥ 16 y.			-.2813** (.1669)		-.2823** (.1670)
Unempl.[1] Rate	-.06784* (.02337)	-.06934* (.02316)	-.06750* (.02320)	-.06985* (.02320)	-.06796* (.02323)
SLF[2]		-.02489** (.01412)	-.02656** (.01415)		
50≤ <200 (1000's)				.06285 (.1020)	.04216 (.1021)
200≤ <800 (1000's)				-.04746 (.09523)	-.06260 (.09503)
≥800,000				-.1310 (.09429)	-.1455 (.09429)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]Mean unemployment rate for local labor market across job spell.
[2]Size of labor force of local labor market (index 1-8).

Table 8 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.048 (.2853)	-4.034 (.2851)	-4.780 (.3923)	-4.062 (.2866)	-4.801 (.3932)
3-6 Months	-4.109 (.2890)	-4.094 (.2888)	-4.836 (.3942)	-4.121 (.2902)	-4.856 (.3951)
6-12 Months	-4.415 (.2911)	-4.397 (.2909)	-5.135 (.3952)	-4.424 (.2923)	-5.156 (.3960)
12-18 Months	-4.823 (.3058)	-4.802 (.3056)	-5.536 (.4060)	-4.830 (.3069)	-5.557 (.4068)
18-24 Months	-5.220 (.3320)	-5.198 (.3319)	-5.931 (.4258)	-5.226 (.3332)	-5.952 (.4266)
24- Months	-5.532 (.3310)	-5.507 (.3309)	-6.240 (.4228)	-5.535 (.3325)	-6.261 (.4239)
n	1431	1431	1431	1431	1431
-ln likeli.	6224.26	6222.70	6221.76	6222.21	6221.46
Chi-square	294.27*	297.41*	299.28*	298.38*	299.87*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 9

Time-Varying Hazard Rates,
Layoffs Treated as Completed Spells:
First Jobs, Hours ≥ 20, 1968-1971, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.01012 (.02485)	-.01108 (.02495)	-.01442 (.02732)	-.009845 (.02496)	-.01345 (.02735)
Black	.2240* (.07412)	.2564* (.07566)	.2200* (.07555)	.2497* (.07532)	.2139* (.07530)
Education in years	-.1078* (.02318)	-.1045* (.02338)		-.1057* (.02338)	
Education =12 years			-.6321* (.08457)		-.6321* (.08460)
Education =13-15 y.			-.6663* (.1375)		-.6682* (.1377)
Education ≥ 16 y.			-.8959* (.1775)		-.9014* (.1777)
Unempl.[1] Rate	.01995 (.01810)	.01694 (.01803)	.02132 (.01785)	.01694 (.01807)	.02159 (.01788)
SLF[2]		-.03079* (.01401)	-.03089* (.01398)		
50< <200 (1000's)				.01491 (.09530)	-.00002 (.09549)
200< <800 (1000's)				-.08762 (.09072)	-.08517 (.09082)
≥800,000				-.1648** (.09209)	-.1671** (.09197)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]Mean unemployment rate for local labor market across job spell.
[2]Size of labor force of local labor market (index 1-8).

Table 9 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.188 (.3669)	-4.098 (.3692)	-4.805 (.5016)	-4.151 (.3700)	-4.865 (.5019)
3-6 Months	-4.511 (.3714)	-4.419 (.3738)	-5.106 (.5044)	-4.472 (.3746)	-5.167 (.5047)
6-12 Months	-4.777 (3.733)	-4.682 (.3758)	-5.370 (.5056)	-4.736 (.3766)	-5.432 (.5058)
12-18 Months	-5.168 (.3889)	-5.069 (.3914)	-5.731 (.5178)	-5.123 (.3920)	-5.793 (.5178)
18-24 Months	-4.995 (.4174)	-4.900 (.4195)	-5.543 (.5393)	-4.953 (.4204)	-5.604 (.5396)
24- Months	-4.087 (.4225)	-3.999 (.4249)	-4.718 (.5502)	-4.049 (.4249)	-4.776 (.5498)
n	1527	1527	1527	1527	1527
-ln likeli.	6279.40	6276.95	6258.95	6277.07	6259.25
Chi-square	177.67*	182.57*	218.57*	182.33*	217.97*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the éxponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

The new treatment of layoffs has no effect on the patterns of duration dependence for men and women, and has little effect on the coefficient estimates with one exception: the negative coefficient on the unemployment variable for the male sample is reduced in absolute value and significance, although it still remains significant at the .05 level. This is predictable, since the act of treating layoffs -- which tend to occur when the unemployment rate is high -- in the same manner as voluntary quits -- which tend to occur when the unemployment rate is low -- will necessarily diminish the previously observed inverse relationship between the unemployment rate and the male hazard rate. With this single exception, virtually all of the other variables rise in significance for the male and female samples under this new treatment of layoffs. Interestingly, though, the coefficient estimates themselves do not change much, even though they become more precise.[15] The reason for this change is that more precise hazard rate estimates can be obtained as the proportion of completed spells of employment rises. Treating layoffs as censored spells raises the proportion of completed spells from 47.9% to 60.7% for the male sample and from 50.6% to 60.6% for the female sample.

3.7 Introducing Unobserved Population Heterogeneity

All of the models discussed thus far have assumed that variations in hazard rates within a population depend on only two factors: (1) variation in the measured variables used as covariates, and (2) duration

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[15]The coefficient on the BLACK dummy for the female sample does increase in size under the new treatment of layoffs, suggesting that black women are more layoff-prone than white women.

on the job. But what if the observed categories are too broad and that not all white, high school graduates, aged 20, for example, have the same (time-varying) hazard rate? It is virtually certain that there will be some variation around the mean rate for every category of measured covariates that can be devised, and the failure to account for this unobserved heterogeneity can at times lead to seriously biased results.

Unfortunately, attempting to model unobserved heterogeneity requires some rather strong assumptions.[16] I assume, in effect, that each job entrant samples from a gamma distribution to obtain a number that will represent a constant multiple of the mean hazard rate for that worker's job duration and observed covariates. Accordingly, if R_{ip} is the true hazard rate for the i^{th} worker -- i.e., the rate at which the i^{th} worker actually leaves his or her first job -- then

$$R_{ip}(x_i) = r_{ip}(x_i)*g_i$$

where R depends on the subgroup rate $r_{ip}(x_i)$ based on worker i's measured covariates x_i and time period p, as well as a multiplicative constant g_i drawn from a gamma distribution for each i.[17]

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[16]Heckman and Singer [1984] showed that, given a parametric specification of the underlying hazard, estimates could vary significantly under different parametric assumptions concerning the nature of unobserved heterogeneity. Trussell and Richards [1985] showed that, given the Heckman-Singer nonparametric correction for unobserved heterogeneity, estimates could vary significantly under different parametric assumptions concerning the underlying hazard. There is simply no way to avoid the requirement of making <u>some</u> parametric assumption.

[17]The choice of this particular parametric specification to model the distribution of unobserved variables was motivated primarily for

Constraining the mean of the g_i's to equal one ensures that the expected value of R is given by the deterministic function of time and the observed covariates:

$$E[R_{ip}(x_i)] = r_{ip}(x_i).$$

Table 10 presents parameter estimates for time-varying hazard rates assuming that unobserved heterogeneity is present within the observed sample categories. A comparison of men's models (1) and (2) in Table 10 with their counterpart models (2) and (3) in Table 6 reveals that the correction for unobserved heterogeneity has not had a dramatic effect on the hazard rate estimations. This result is consistent with the finding in Table 10 that the variance of the gamma-distributed factors was insignificant for men in both cases. The parameter estimates for these two men's models are, however, slightly greater (in absolute value) in Table 10. This result is plausible because in the hazard rates estimated in Table 6 some of the unobserved population heterogeneity would be attributed incorrectly to time dependence. Therefore, correcting for heterogeneity should tend to increase the impact of the measured covariates and to diminish the estimated time dependence. Indeed, the correction for unobserved heterogeneity does alter the previous monotonic duration dependence in the men's sample: in both models shown in Table 10, the male hazard rate peaks in the second period -- three to six months -- and then declines monotonically from that point on. Moreover, the ratio of the underlying first period to

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computational ease. Analysts have found that the gamma distribution performs well because of its great flexibility -- it can range from a highly skewed J-shape to a nearly symmetric unimodal shape. Tuma and Hannan [1985].

TABLE 10

Time-Varying Hazard Rates Given Unobserved Heterogeneity, First Jobs, Hours ≥ 20, 1968-1971

A. Time-Independent Coefficient Estimates

	1		2	
	Men	Women	Men	Women
Age at start	-.0600 (.000)	-.0200 (.000)	-.07597* (.03257)	-.01814 (.03363)
Black	.2517* (.1148)	.2176* (.09095)	.2809* (.1139)	.1725** (.09034)
Education in years	-.07438* (.02740)	-.1185* (.02695)		
Education =12 years			.07082 (.1272)	-.7150* (.1161)
Education =13-15 y.			-.1210 (.1749)	-.7654* (.1824)
Education ≥ 16 y.			-.2784 (.2268)	-1.070* (.2415)
Unempl.[1] Rate	-.1356* (.03253)	-.01656 (.02223)	-.1291* (.03222)	-.01149 (.02195)
SLF[2]	-.02466 (.01940)	-.03011** (.01677)	-.02486 (.01924)	-.03025** (.01652)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]Mean unemployment rate for local labor market across job spell.

[2]Size of labor force of local labor market (index 1-8).

The estimates in columns (1) and (2) of this table correspond to those of models (2) and (3) in Tables 6 and 7. To obtain convergence in column (1), the "age at start" coefficient was constrained to the listed values.

Table 10 (cont'd)

B. Time Parameters[1]

	1		2	
	Male	Female	Male	Female
0-3 Months	-3.389 (.4074)	-3.793 (.3789)	-4.013 (.6345)	-4.704 (.6078)
3-6 Months	-3.257 (.4723)	-3.997 (.4290)	-3.886 (.6879)	-4.893 (.6123)
6-12 Months	-3.332 (.5424)	-4.152 (.4720)	-3.967 (.7486)	-5.055 (.6177)
12-18 Months	-3.632 (.6179)	-4.375 (.5376)	-4.269 (.8165)	-5.263 (.6364)
18-24 Months	-3.807 (.6825)	-4.182 (.6039)	-4.449 (.8750)	-5.058 (.6644)
24- Months	-4.195 (.7323)	-3.309 (.7288)	-4.840 (.9210)	-4.253 (.7215)
n	1431	1527	1431	1527
Variance	.5921	.2076	.5599	.1725*
-ln likeli.	5068.5	5401.4	5068.4	5383.5
Chi-square	243.68*	118.30*	243.83*	154.07*
Monotonic[2]	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

final period rates is 4.1 in both models (2) and (3) in Table 6 and 2.2 and 2.3 for models (1) and (2) in Table 10. Correcting for unobserved heterogeneity has flattened the declining male hazard rate. This suggests that men's quit rates may not be dropping very sharply, but only appear to do so because of the rapid departure of the high probability quitters.[18]

Similar results are obtained by comparing the estimated female hazard rates with and without correcting for unobserved heterogeneity. Comparing women's models (1) and (2) in Table 10 with models (2) and (3) in Table 7, one sees again that the parameters are consistently somewhat larger with the correction for unobserved heterogeneity. The variance of the gamma distributed unobserved heterogeneity is statistically significant in model (2) of Table 10. The effect of the correction on this model is to cause the upturn in the female quit rate to be more pronounced -- in Table 10, the final rate is about three times the size of the minimum rate, while in Table 7 it is only twice as large. This suggests that the postulated "birth effect" may be even stronger than the earlier results had indicated.

3.8 Focussing on White, High School Graduates

The three previous sections have discussed three sets of estimations involving time-varying parameters and measured covariates with (1) layoffs being censored, (2) layoffs treated as completed spells, and (3) corrections for unobserved heterogeneity. In order to

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[18]This pattern is presented in Table 11.B, which is based on the time-varying hazard rate estimates generated from model (3) of Table 10.

compare directly the quit rates of male and female workers for these three sets of estimations, Table 11 presents estimated hazard rates for men and women workers who have the same basic characteristics: they are white, high school graduates, aged 20.[19] The upper panel provides estimates from model (3) in Tables 6 and 7 (layoffs are censored) and Tables 8 and 9 (layoffs are completed spells).[20] The lower panel presents rates derived using the correction for unobserved heterogeneity on the same model (column (2) of Table 10).

All three sets of estimates presented in Table 11 reveal the same basic patterns of monotonic decline in the male hazard rate and a u-shaped female hazard. Interestingly, the inclusion of the explanatory variables has altered somewhat the results of the time-periods model without covariates, for which in every period the female hazard rate had been greater than the male hazard rate.[21] In all three cases in Table 11, the female hazard rates start higher and end much higher than the male hazard rates but for the interval in between, the female rates are actually somewhat lower. This interval in which the female rates are lower extends from 3 months to a year in Table 11.A when layoffs are censored, and from 3 months to 18 months when layoffs are treated as completed spells or when correcting for unobserved heterogeneity.

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[19]The hazard rates are based on the further assumptions that the size of the local labor market is less than 50,000 and the unemployment rate is 4%.

[20]As noted above, model (3) tends to yield the highest male rates and lowest female rates because of the positive coefficient on the male educational dummy and the large negative coefficient on the female educational dummy. Had I used one of the models in which education was measured in years, the male rate would have fallen and the female rate would have risen considerably.

[21]See Table 3.B.

Largely because of the dramatic upturn in female rates after 18 months, which I have attributed to the "birth effect," the expected tenure of white, high school graduates remains significantly lower for female workers than for male workers. In all three pairs of estimates, the final period female rates are 4 or 5 times higher than the final period male rates.

TABLE 11

Maximum Likelihood Estimates of Time-Varying Hazard Rates From First Jobs (x 1000):
White, High School Graduate, Age 20, Hours $\geq$ 20, 1968-1971

A. Homogeneous Subgroups

Duration (Months)	With Layoffs Treated As Censored Spells: Men	With Layoffs Treated As Censored Spells: Women	With Layoffs Treated As Completed Spells: Men	With Layoffs Treated As Completed Spells: Women
0-3	2.35437	2.79635	3.23295	3.44404
3-6	2.33328	2.18653	3.05688	2.54886
6-12	1.87250	1.77414	2.26686	1.95746
12-18	1.22052	1.35977	1.51800	1.36431
18-24	0.92522	1.59252	1.02265	1.64649
24-	0.57480	3.03228	0.75081	3.75709

B. Heterogeneous Subgroups

Duration (Months)	Men	Women
0-3	2.47172	2.85692
3-6	2.80644	2.36492
6-12	2.58808	2.01123
12-18	1.91346	1.63353
18-24	1.59826	2.00520
24-	1.08103	4.48503

Notes: The rates in (A) are derived from model (3) in Tables 6 - 9. The rates in (B) are derived from model (2) in Table 10. They assume that the size of the labor force is less than 50,000 and the unemployment rate is 4%. The number of cases used in deriving the estimates was 1431 for men and 1527 for women.

3.9 Adopting A More Stringent Definition of Full-time Employment

Thus far I have been analyzing initial post-schooling jobs that involved 20 or more hours of work per week. In order to test whether my results are sensitive to this selection criteria, I adopted a more stringent definition of full-time employment -- 30 or more hours per week. This more stingent criterion led to a decline in sample size from 1431 to 1407 for the men and from 1527 to 1457 for the women. Tables 12 and 13 set forth some summary statistics for the male and female data sets for this "30 hour" data set. The measured characteristics for this 30 hour data set change little from those presented for the 20 hour data set in Tables 1 and 2. Virtually the only noteworthy difference between the charactistics of the two samples is that, under the new definition, the average work week for men rises from roughly 41 to 43 hours and for women from 38.5 to 40.3 hours.

Table 14 presents the parallel models for the 30 hour data set that were presented in Table 3 for the 20 hour data set. Once again, whether one looks at the single constant rate or the 6 time-period model with no covariates, the rates are always higher for female workers. While for the 20 hour data set, the expected durations of male and female first jobs had been 23.6 and 14.1 months, respectively, these figures rise to 24.9 and 14.6 months for the 30 hour sample. Moreover, the patterns of duration dependence depicted in Table 14.B -- monotonic decline for the men and the u-shaped pattern for the women -- are identical to those observed in the 20 hour sample. Note that this pattern leads to diverging hazard rates for the sexes, so that by the final period, the

TABLE 12

Descriptive Statistics for Male First-job Holders, Hours $\geq$ 30, 1968-1971 (1407 Cases)

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	20.31	2.563	16.08	30.07
EDUCATION				
Years of Schooling	12.87	2.227	5.00	18.00
Distribution (percent of sample)				
Less than 12 years	17.48			
12 years	41.79			
13-15 years	20.90			
16-17 years	17.20			
18 years or more	2.63			
TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	72.92			
Black	26.01			
Other	1.07			
TOTAL	100.00%			
FATHER'S EDUCATION[1] (In Years)	10.48	3.685	0.00	18.00
SIZE OF LABOR FORCE INDEX 1-8	3.698	2.482	1.00	8.00
1: <50,000	.2544			
2: 50,000-199,999	.1976			
3-5: 200,000-799,999	.2537			
6-8: >800,000	.2942			
HOURS WORKED PER WEEK	42.99	8.603	30.00	99.00

NOTES: [1] Omits 265 cases for which father's education is missing.

TABLE 13

Descriptive Statistics for Female First-job Holders, Hours $\geq$ 30, 1968-1971 (1457 Cases)

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	19.53	1.888	16.09	27.09
EDUCATION				
Years of Schooling	12.52	1.980	0.00	18.00
Distribution (percent of sample)				
Less than 12 years	17.16			
12 years	52.23			
13-15 years	17.64			
16-17 years	12.49			
18 years or more	0.48			
TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	70.90			
Black	28.00			
Other	1.10			
TOTAL	100.00%			
FATHER'S EDUCATION[1] (In Years)	10.46	3.552	0.00	18.00
SIZE OF LABOR FORCE INDEX 1-8	3.570	2.432	1.00	8.00
1: <50,000	.2704			
2: 50,000-199,999	.1977			
3-5: 200,000-799,999	.2670			
6-8: >800,000	.2649			
HOURS WORKED PER WEEK	40.26	6.304	30.00	90.00

NOTES: [1] Omits 337 cases for which father's education is missing.

male rate is almost 8.5 times as great as the female rate.

Tables 15 and 16, which replicate Tables 6 and 7 using this more stringent definition of full-time employment, estimate male and female time-varying hazard rates with covariates. The signs, significance, and size of the estimated coefficients for both men and women are quite similar under both hourly definitions. For the men -- comparing the results in Tables 6 and 15 -- the negative size and significance of "years of education" and the unemployment rate are increased in the 30 hour sample. This seems logical for, if a 30 hour job is a greater prize than a 20 hour job, then more-educated individuals will have a greater incentive to use their presumably superior search skills in selecting these jobs, and all workers will try to hold onto these jobs more tightly when the economy turns down. The shift to the 30 hour definition of full-time employment has some interesting consequences for the education dummies on the male sample: while in the 20 hour sample, those with a high school diploma showed a 5% higher hazard rate above those with less education, in the 30 hour sample the high school graduates had a 5% lower rate. I suspect this change in coefficients results from a greater inclusion in the 20 hour sample of part-time jobs held by students in their final year of high school. If these jobs tend to be of fairly short duration, then they would tend to raise the coefficient on the "12 years of education" dummy in the 20 hour data set; with fewer of these jobs included in the 30 hour data set, this dummy becomes negative, although it remains insignificant, and the pattern of monotonic decline in hazard rates with increasing education is established. Finally, the estimated amount by which the hazard rates of blacks are greater than those of nonblacks also increased, rising from roughly 21-26% in the 20 hour sample to 27-34% in the 30 hour sample.

For the women -- comparing the results in Tables 7 and 16 -- the significance of the estimated coefficients changes in only two cases for all five models: (1) in column 4, the previously insignificant coefficient on the largest size of labor force dummy becomes significant at the .10 level, and (2) in column 5, the coefficient on BLACK rises in significance from the .10 level to the .05 level. The shift from the 20 hour to 30 hour sample also changes the pattern of the education dummies somewhat -- in the 20 hour sample, the female hazard rate declines with each educational increment; in the 30 hour sample, the high school graduates have a lower hazard rate than those with some college education. In every other respect, the estimates are quite close, and the identical u-shaped pattern of time dependence is again present.

TABLE 14

Maximum Likelihood Estimates of Hazard Rates From First Jobs (x1000), Hours $\geq$ 30, 1968-1971

	Men		Women	
Number of Cases	1407		1457	
A. Constant Rate Model--No Covariates, No Time Dependence				
All Durations	1.319		2.249	
Completed Spells	647		723	
Censored Spells	760		734	
-ln likelihood	4937.4		5131.3	
Expected Tenure (Months)	24.9		14.6	
B. Duration Only Model				
Duration (Months)				
0-3	2.038	(.06637)	2.998	(.05488)
3-6	1.855	(.08392)	2.122	(.08085)
6-12	1.413	(.08165)	1.858	(.08248)
12-18	0.9691	(.1222)	1.269	(.1400)
18-24	0.6576	(.1796)	1.617	(.2132)
24-	0.3736	(.1826)	3.162	(.2357)
-ln likelihood	4859.7		5103.2	
likelihood ratio test statistic	155.30*		56.15*	

Notes: *Significant at .05 level.

The standard errors in parentheses correspond to the estimated parameters r, where exp(r) * 1000 is the rate presented.

TABLE 15

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours ≥ 30, 1968-1971, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04599* (.02343)	-.04559** (.02345)	-.05556* (.02490)	-.04669* (.02344)	-.05835* (.02492)
Black	.2412* (.09246)	.2518* (.09351)	.2884* (.09286)	.2586* (.09344)	.2891* (.09288)
Education in years	-.06867* (.02725)	-.06460* (.02741)		-.06569* (.02753)	
Education =12 years			-.05436 (.1061)		-.06007 (.1063)
Education =13-15 y.			-.1190 (.1481)		-.1192 (.1480)
Education ≥ 16 y.			-.3237** (.1939)		-.3157 (.1938)
Unempl.[1] Rate	-.1295* (.02805)	-.1304* (.02784)	-.1276* (.02785)	-.1317* (.02789)	-.1287* (.02789)
SLF[2]		-.01982 (.01639)	-.02206 (.01644)		
50< <200 (1000's)				.1275 (.1167)	.1097 (.1166)
200< <800 (1000's)				-.09215 (.1123)	-.1062 (.1122)
≥800,000				-.08615 (.1090)	-.1027 (.1092)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]Mean unemployment rate for local labor market across job spell.
[2]Size of labor force of local labor market (index 1-8).

Table 15 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.897 (.3388)	-3.885 (.3387)	-4.415 (.4685)	-3.896 (.3399)	-4.401 (.4692)
3-6 Months	-3.968 (.3437)	-3.955 (.3435)	-4.485 (.4712)	-3.964 (.3446)	-4.469 (.4718)
6-12 Months	-4.211 (.3454)	-4.197 (.3452)	-4.729 (.4717)	-4.205 (.3465)	-4.713 (.4723)
12-18 Months	-4.561 (.3593)	-4.544 (.3592)	-5.075 (.4817)	-4.551 (.3604)	-5.058 (.4824)
18-24 Months	-4.922 (.3848)	-4.905 (.3848)	-5.435 (.5006)	-4.910 (.3861)	-5.417 (.5013)
24- Months	-5.397 (.3929)	-5.377 (.3928)	-5.906 (.5042)	-5.380 (.3946)	-5.886 (.5054)
n	1407	1407	1407	1407	1407
-ln likeli.	4818.18	4817.44	4818.64	4815.94	4817.30
Chi-square	238.40*	239.87*	237.48*	242.88*	240.16*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 16

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours ≥ 30, 1968-1971, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.02074 (.02903)	-.02261 (.02910)	-.04520 (.03213)	-.02069 (.02911)	-.04324 (.03221)
Black	.2019* (.08463)	.2466* (.08676)	.2007* (.08735)	.2349* (.08627)	.1888* (.08691)
Education in years	-.1098* (.02701)	-.1062* (.02721)		-.1082* (.02719)	
Education =12 years			-.7516* (.09700)		-.7533* (.9704)
Education =13-15 y.			-.6973* (.1555)		-.7074* (.1562)
Education ≥ 16 y.			-.8775* (.2012)		-.8870* (.2018)
Unempl.[1] Rate	-.01028 (.02203)	-.01312 (.02183)	-.00830 (.02194)	-.01293 (.02196)	-.00755 (.02209)
SLF[2]		-.03792* (.01585)	-.03772* (.01583)		
50< <200 (1000's)				.05383 (.1080)	.05248 (.1084)
200< <800 (1000's)				-.1011 (.1031)	-.09520 (.1034)
≥800,000				-.1732** (.1043)	-.1676 (.1043)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]Mean unemployment rate for local labor market across job spell.

[2]Size of labor force of local labor market (index 1-8).

Table 16 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.058 (.4252)	-3.934 (.4283)	-4.223 (.5931)	-4.017 (.4292)	-4.332 (.5934)
3-6 Months	-4.373 (.4308)	-4.245 (.4341)	-4.504 (.5975)	-4.329 (.4349)	-4.615 (.5978)
6-12 Months	-4.493 (.4312)	-4.362 (.4347)	-4.619 (.5973)	-4.447 (.4354)	-4.731 (.5974)
12-18 Months	-4.862 (.4441)	-4.725 (.4475)	-4.956 (.6070)	-4.809 (.4479)	-5.067 (.6068)
18-24 Months	-4.632 (.4680)	-4.500 (.4709)	-4.716 (.6246)	-4.583 (.4716)	-4.826 (.6245)
24- Months	-3.952 (.4851)	-3.829 (.4884)	-4.146 (.6437)	-3.902 (.4877)	-4.245 (.6429)
n	1457	1457	1457	1457	1457
-ln likeli.	5075.9	5073.0	5052.3	5073.3	5052.7
Chi-square	110.72*	116.54*	158.03*	115.95*	157.14*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

3.10 Treating Layoffs as Completed Spells in the 30 Hour Sample

Tables 17 and 18 present the results of estimations conducted while treating layoffs as completed spells. First, the patterns of male and female time dependence are unchanged from those observed in estimations where layoffs are censored (see Tables 15 and 16). Second, treating layoffs as completed spells once again reduces the negative effect of unemployment on male hazard rates. Third, this treatment of layoffs decreases the size of the coefficient on the male BLACK dummy and increases it on the female BLACK dummy. Apparently, then, white men tend to be more layoff-prone than black men, but white women tend to be less layoff prone than black women. Clearly, this finding indicates which groups (white men and black women) hold the jobs that are more susceptible to layoffs. Fourth, this treatment tends to strengthen the negative relationship between education and the hazard rate for both men and women. While this suggests that education tends to help one avoid jobs that are layoff prone, the effect is actually somewhat more complicated. If one examines the effect of this treatment of layoffs on the education dummies, one finds that for both men and women, the coefficients on the dummy representing high school graduates actually becomes less negative or even positive. It seems, then, that the layoffs are less common for the most educated and the least educated individuals -- a pattern that once again seems plausible if one considers the types of jobs that are more susceptible to layoffs.

TABLE 17

Time-Varying Hazard Rates,
Layoffs Treated as Completed Spells:
First Jobs, Hours ≥ 30, 1968-1971, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03092 (.02040)	-.03045 (.02042)	-.03587** (.02160)	-.03067 (.02044)	-.03681** (.02166)
Black	.2102* (.08279)	.2283* (.08357)	.2677* (.08284)	.2284* (.08354)	.2680* (.08286)
Education in years	-.07539* (.02385)	-.07056* (.02399)		-.07227* (.02409)	
Education =12 years			.02072 (.09619)		.01725 (.09637)
Education =13-15 y.			-.1278 (.1330)		-.1324 (.1331)
Education ≥ 16 y.			-.3431* (.1712)		-.3453* (.1715)
Unempl.[1] Rate	-.07423* (.02412)	-.07630* (.02395)	-.07345* (.02395)	-.07668* (.02399)	-.07368* (.02398)
SLF[2]		-.02305 (.01463)	-.02559** (.01466)		
50< <200 (1000's)				.05813 (.1052)	.03144 (.1050)
200< <800 (1000's)				-.03940 (.09850)	-.05699 (.09833)
≥800,000				-.1203 (.09756)	-.1415 (.09756)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1] Mean unemployment rate for local labor market across job spell.

[2] Size of labor force of local labor market (index 1-8).

Table 17 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.062 (.2993)	-4.045 (.2992)	-4.772 (.4089)	-4.068 (.3001)	-4.794 (.4100)
3-6 Months	-4.159 (.3037)	-4.141 (.3035)	-4.865 (.4114)	-4.163 (.3045)	-4.886 (.4124)
6-12 Months	-4.513 (.3062)	-4.493 (.3061)	-5.219 (.4126)	-4.516 (.3070)	-5.240 (.4173)
12-18 Months	-4.796 (.3182)	-4.773 (.3182)	-5.496 (.4215)	-4.796 (.3191)	-5.518 (.4225)
18-24 Months	-5.322 (.3479)	-5.298 (.3479)	-6.022 (.4440)	-5.321 (.3489)	-6.044 (.4450)
24- Months	-5.636 (.3478)	-5.609 (.3478)	-6.331 (.4419)	-5.634 (.3492)	-6.354 (.4434)
n	1407	1407	1407	1407	1407
-ln likeli.	5884.3	5883.1	5884.3	5882.7	5884.1
Chi-square	293.89*	296.39*	293.97*	297.14*	294.32*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 18

Time-Varying Hazard Rates,
Layoffs Treated as Completed Spells:
First Jobs, Hours ≥ 30, 1968-1971, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.003733 (.02610)	-.005916 (.02615)	-.03060 (.02918)	-.003948 (.02616)	-.02866 (.02926)
Black	.2308* (.07662)	.2748* (.07848)	.2368* (.07904)	.2645* (.07803)	.2263* (.07865)
Education in years	-.1176* (.02418)	-.1137* (.02436)		-.1156* (.02435)	
Education =12 years			-.7205* (.08879)		-.7227* (.08884)
Education =13-15 y.			-.7217* (.1434)		-.7321* (.1440)
Education ≥ 16 y.			-.8566* (.1825)		-.8658* (.1831)
Unempl.[1] Rate	.02830 (.01906)	.02431 (.01894)	.02959 (.01902)	.02469 (.01907)	.03053 (.01917)
SLF[2]		-.03854* (.01449)	-.03783* (.01447)		
50< <200 (1000's)				.05557 (.09851)	.05848 (.09884)
200< <800 (1000's)				-.1081 (.09448)	-.09902 (.09475)
≥800,000				-.1819** (.09534)	-.1719** (.09537)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]Mean unemployment rate for local labor market across job spell.
[2]Size of labor force of local labor market (index 1-8).

Table 18 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.254 (.3853)	-4.119 (.3885)	-4.478 (.5395)	-4.204 (.3895)	-4.587 (.5401)
3-6 Months	-4.620 (.3907)	-4.482 (.3940)	-4.814 (.5436)	-4.568 (.3949)	-4.925 (.5442)
6-12 Months	-4.806 (.3916)	-4.665 (.3952)	-4.995 (.5438)	-4.751 (.3960)	-5.107 (.5442)
12-18 Months	-5.256 (.4064)	-5.109 (.4099)	-5.415 (.5548)	-5.193 (.4104)	-5.526 (.5549)
18-24 Months	-4.996 (.4314)	-4.853 (.4344)	-5.148 (.5733)	-4.938 (.4351)	-5.258 (.5736)
24- Months	-4.123 (.4374)	-3.991 (.4407)	-4.380 (.5834)	-4.065 (.4402)	-4.479 (.5828)
n	1457	1457	1457	1457	1457
-ln likeli.	5891.8	5888.2	5867.5	5888.3	5867.8
Chi-square	172.58*	179.77*	221.09*	179.46*	220.48*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

Table 11.A compared the quit rates of male and female workers with similar characteristics for the 20 hour data set. Table 19 provides the same information for the 30 hour data set.[22] When layoffs are treated as censored spells, the hazard rates for white, high school graduate women are generally higher in every period, and owing to the "birth effect" diverge sharply from the male rates after 18 months. The one exception is the second period -- from 3 - 6 months -- when the male and female rates are virtually the same.[23] When layoffs are treated as completed spells, the differential hazard rates of men and women narrow somewhat. In fact, while the female rates begin higher than the male rates, they are somewhat lower than the male rates for the period from 3 - 18 months, after which the sharp divergence occurs that I have attributed to the "birth effect."

A comparison of Table 19 with Table 11.A reveals that the hazard rates for white, high school graduates, aged 20, are similar but somewhat lower in the 30 hour sample as opposed to the 20 hour sample. This result holds regardless of the treatment of layoffs.

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[22]Once again, in selecting model (3)'s hazard rate estimates, I have chosen the model that minimizes the female rate for high school graduates and maximizes the corresponding male rate.

[23]It is possible that the male and female quit rates are effectively equal for the first six months until the impact of the "birth effect" begins to take hold. This may be the case if women more frequently hold jobs that are designed to be of short duration. In this event, the employer may be getting exactly what he or she wants -- a worker for a short duration -- but my hazard rate estimate would thereby be elevated for women in the first few months.

TABLE 19

Maximum Likelihood Estimates of Time-Varying Hazard Rates From First Jobs (x 1000):
White, High School Graduate, Age 20, Hours $\geq$ 30, 1968-1971

	A. With Layoffs Treated As Censored Spells		B. With Layoffs Treated As Completed Spells	
	Men	Women	Men	Women
Number of Cases	1407	1457	1407	1457
Duration (Months)				
0-3	2.21385	2.60706	3.06389	3.24717
3-6	2.06418	1.96840	2.79180	2.32051
6-12	1.61726	1.75457	1.95949	1.93631
12-18	1.14423	1.25260	1.48540	1.27225
18-24	0.79830	1.59237	0.87782	1.66161
24-	0.49844	2.81573	0.64448	3.58151

Notes: The rates in (A) are derived from model (3) in Tables 15 and 16. The rates in (B) are derived from model (3) in Tables 17 and 18. They assume that the size of the labor force is less than 50,000, and the unemployment rate is 4%.

3.11 Estimating the Impact of Differences in Tenure on Wages

This study has proposed that differences in tenure between men and women can lead to differences in wages as employers try to recover their fixed personnel investment costs over different time periods. If male and female workers have equal marginal products (MP) but differ in expected tenure, then the larger the fixed personnel investment costs (FC), the greater the male-female wage differential. Conversely, by considering an example drawn from the the 30 hour sample, which provides estimates of wages and expected tenures for male and female workers, one can estimate the value of FC that would explain the observed male-female wage differential.

Consider white, high school graduates, aged 20, living in an area with a labor force of less than 50,000 and an unemployment rate of 4%. For this group, the mean duration for first jobs is 21.1 months for men and 13.2 months for women.[24] To ascertain the expected wage for men and women workers, I estimated separate male and female wage equations, using the log of the initial real hourly wage as the dependent variable. The resulting coefficient estimates, with t-statistics in parentheses, are as follows:

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[24]These figures are obtained by estimating a time-invariant hazard model, in which education is measured as years of schooling. The respective male and female hazards (multiplied by 1000) for the specified characteristics were 1.555 and 2.483, which yield the expected tenure figures cited in the text.

TABLE 20

Estimated Starting Wages By Sex: First Jobs, Hours $\geq$ 30, 1968-1971

	Constant	Age	Educ.	Black	SLF	Unem. Rate	R^2
Male:	.5483	.0323	.0421	-.0728	.0351	-.0006	.25
	(5.78)	(4.83)	(5.22)	(2.72)	(7.56)	(1.09)	
Female:	-.0294	.0201	.0887	-.0747	.0382	-.0009	.33
	(0.27)	(2.52)	(11.41)	(3.30)	(9.46)	(1.87)	

These equations yielded estimated wages for white, high school graduates of \$5.65 for men and \$4.36 for women in 1983 dollars.[25]

Assume that all workers with the above-described characteristics are equally productive and work 176 hours per month (roughly 40 hours per week) and that the employer (by giving lower wages) makes the employee pay for the personnel investment cost associated with hiring and training the worker. What must the size of this investment cost be if this factor alone were to explain this observed female-male wage ratio of 77.2%? An investment cost of \$8020 per worker would do it: this would imply a pre-investment-cost marginal product of \$7.81 per hour with \$2.16 subtracted from the male hourly wage over the duration of 21.1 months and \$3.45 subtracted from the female hourly wage over the duration of 13.2 months.

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[25]The explanatory variables used in these wage estimations are the same as those used to estimate hazard rates in model (2) of Tables 15 and 16, with one exception. In estimating the beginning wage, I used the initial measure of the unemployment rate in the local labor market, rather than the mean measure for the entire job spell. Moreover, to exclude outliers, I discarded hourly wage figures that were less than \$1 or greater than \$100. There were 1083 male workers and 1229 female workers included in these wage estimations.

Is $8020 a reasonable estimate of turnover costs? The evidence on this point is limited. Data presented by Barron, Bishop, and Dunkelberg [1985] from the 1980 Employer Opportunity Pilot Project on the hours spent interviewing, hiring, and training new employees suggests that average turnover cost are substantially lower -- perhaps in the neighborhood of $1500 per worker.[26] A turnover cost of this size would explain almost 20% of the male-female wage gap.

3.12 Is Wage A Proper Explanatory Variable?

Thus far, I have not included wage as an explanatory variable in any of my hazard rate estimations. The reason for this omission is that wage does not appear to be a truly exogenous variable. Indeed, the previous section suggests that high expected tenure may lead to higher wages as employers attempt to amortize a fixed cost over a longer period of time. Thus, the causation may run from low tenure to low wage rather than vice versa. More generally, to the extent that wage can be thought of as a choice variable, it is improper to include it in an estimation that is attempting to explain another choice variable (tenure), unless there is some basis for econometric identification of the wage.

One can find supporting precedents for either view in the debate over whether to include wage as an explanatory variable in estimating a quit rate. While no one appears to have addressed the question explicitly, all four Appendix I studies and Tuma and Hannan [1984: 181]

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[26]Interestingly, though, the Boston Globe recently offered to pay a $5000 scholarship to paper deliverers who would agree to work for at least three years. The company announced that it hoped the plan would reduce its high turnover costs among delivery personnel.

include wages, while Heckman and Singer [1984: 82] and Abraham and Farber [1985] do not. What is the argument then for including wage as an independent variable? One might argue that, if the worker has succeeded in securing a job with a particularly high wage relative to the worker's other options, then it is less likely that the worker will quit -- either to join another firm or to leave the labor force. But this argument overlooks the opposing incentive of the employer who will want to fire (or lower the wage of) any individual who is earning an unusually attractive wage relative to his or her worth. If both these forces operated with the same intensity, one would expect that the net effect of an unusually high wage on tenure would be zero. Perhaps, though, these opposing interests are not in balance -- i.e., the employer is much less likely or able to effectuate his or her interest in terminating an unreasonably high paid worker than an unreasonably low paid worker is in quitting such a job.[27] In such a case the effect of a high wage in lowering the quit rate would exceed its effect in raising the firing rate, and one might expect to see a high wage correlated with longer tenure.

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[27]In support of this argument Tuma cites the fact that "restraints on firing are greater than the restraints on quitting." Tuma [1976: 349]. She then cites some indirect support for this position, noting that in retrospective life histories for men aged 30-39 in 1968, between 70 and 80% of all job terminations are reported to be voluntary. One must be careful, however, in accepting the validity of self-reported data of this kind.

TABLE 21

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours ≥ 30, Wage Included, 1968-1971, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04390 (.02739)	.04376 (.02744)	.01982 (.02908)	.04322 (.02741)	.01816 (.02905)
Black	.2268* (.1131)	.2284* (.1144)	.2554* (.1149)	.2257* (.1143)	.2519* (.1149)
Education in years	-.05912** (.03288)	-.05870** (.03319)		-.05943** (.03329)	
Education =12 years			-.1248 (.1339)		-.1315 (.1342)
Education =13-15 y.			-.1067 (.1844)		-.1106 (.1843)
Education ≥ 16 y.			-.1782 (.2323)		-.1728 (.2320)
Unempl.[1] Rate	-.09808* (.03325)	-.09817* (.03324)	-.09204* (.0330)	-.09959* (.03329)	-.09328* (.03303)
SLF[2]		-.001852 (.02032)	-.004819 (.02027)		
50≤ <200 (1000's)				.08734 (.1437)	.07414 (.1436)
200≤ <800 (1000's)				-.06086 (.1373)	-.07740 (.1371)
≥800,000				.01143 (.1347)	-.006815 (.1344)
Wage[3]	-.1405* (.02057)	-.1401* (.02099)	-.1427* (.02096)	-.1397* (.02107)	-.1425* (.02103)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]Mean unemployment rate for local labor market across job spell.

[2]Size of labor force of local labor market (index 1-8).

[3]Real hourly wage in 1983 dollars.

Table 21 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-5.252 (.4103)	-5.251 (.4108)	-5.414 (.5493)	-5.238 (.4127)	-5.383 (.5504)
3-6 Months	-5.503 (.4163)	-5.501 (.4168)	-5.665 (.5536)	-5.488 (.4187)	-5.633 (.5546)
6-12 Months	-5.691 (.4150)	-5.689 (.4155)	-5.857 (.5525)	-5.676 (.4175)	-5.825 (.5536)
12-18 Months	-5.719 (.4235)	-5.717 (.4242)	-5.886 (.5586)	-5.704 (.4261)	-5.855 (.5597)
18-24 Months	-6.092 (.4475)	-6.090 (.4482)	-6.260 (.5759)	-6.075 (.4503)	-6.228 (.5772)
24- Months	-6.565 (.4568)	-6.562 (.4574)	-6.732 (.5813)	-6.543 (.4604)	-6.694 (.5836)
n	1139	1139	1139	1139	1139
-ln likeli.	3356.2	3356.2	3357.2	3355.6	3356.7
Chi-square	187.02*	187.03*	185.01*	188.06*	186.02*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 22

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
First Jobs, Hours ≥ 30, Wage Included, 1968-1971, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	.01115 (.03085)	.01038 (.03099)	-.02001 (.03362)	.01287 (.03097)	-.01674 (.03364)
Black	.1557** (.09079)	.1611** (.09316)	.1165 (.09361)	.1540** (.09245)	.1086 (.09301)
Education in years	-.06287* (.03058)	-.06304* (.03059)		-.06368* (.03059)	
Education =12 years			-.6960* (.1039)		-.6948* (.1039)
Education =13-15 y.			-.5319* (.1649)		-.5413* (.1657)
Education ≥ 16 y.			-.5845* (.2151)		-.5823* (.2162)
Unempl.[1] Rate	-.01054 (.02256)	-.01083 (.02257)	-.00433 (.02262)	-.01147 (.02278)	-.004807 (.02284)
SLF[2]		-.00459 (.01747)	-.009521 (.01745)		
50< <200 (1000's)				.1547 (.1140)	.1425 (.1144)
200< <800 (1000's)				-.0342 (.1102)	-.05132 (.1105)
≥800,000				.04649 (.1133)	.02223 (.1131)
Wage[3]	-.1881* (.02727)	-.1860* (.02844)	-.1723* (.02782)	-.1893* (.02820)	-.1762* (.02760)

Notes: *Significant at the .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]Mean unemployment rate for local labor market across job spell.

[2]Size of labor force of local labor market (index 1-8).

[3]Real hourly wage in 1983 dollars.

Table 22 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-4.364 (.4529)	-4.342 (.4612)	-4.091 (.6152)	-4.412 (.4605)	-4.185 (.6146)
3-6 Months	-4.740 (.4595)	-4.718 (.4676)	-4.435 (.6211)	-4.789 (.4670)	-4.530 (.6204)
6-12 Months	-4.738 (.4581)	-4.716 (.4663)	-4.434 (.6193)	-4.786 (.4655)	-4.530 (.6185)
12-18 Months	-5.025 (.4685)	-5.002 (.4765)	-4.694 (.6276)	-5.068 (.4753)	-4.784 (.6265)
18-24 Months	-4.841 (.4915)	-4.818 (.4992)	-4.494 (.6437)	-4.884 (.4985)	-4.584 (.6429)
24- Months	-4.265 (.5133)	-4.242 (.5207)	-4.009 (.6662)	-4.299 (.5182)	-4.090 (.6642)
n	1322	1322	1322	1322	1322
-ln likeli.	4562.6	4562.5	4543.4	4561.1	4542.1
Chi-square	156.62*	156.69*	195.00*	159.59*	197.63*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

Tables 21 and 22 report the results of simply adding the real wage as an explanatory variable to the models of Tables 15 and 16, respectively.[28] The inclusion of the wage variable reduces the sample size -- primarily because of nonreporting -- from 1407 to 1139 for men and from 1457 to 1322 for women in the 30 hour sample.[29] The simple mean hourly wages for these male and female samples were $6.97 and $5.09, yielding an unadjusted male-female wage differential of 73.03%.

The augmented models reveal that the coefficient on wage is negative and highly significant. Moreover, the size of the wage coefficient is somewhat greater for women than for men: an extra $1 in hourly wage reduces the female hazard rate by roughly 16-17% and the male hazard rate by about 13%. In general, the inclusion of the real wage variable tended to reduce the size (whether positive or negative) and significance of all the other explanatory variables. For men, blacks continued to show significantly higher quit rates than whites (roughly 25-29% more), and unemployment continued to have a significant negative impact on hazard rates. The coefficients on age and education were greatly reduced in significance. For women, the coefficient on BLACK became only marginally significant, and the previously insignificant unemployment rate was unaffected by the addition of real wage. As with the men, the coefficient on age became

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[28] I use the first measure of the hourly wage that appears in the data. This is done to reduce the obvious endogeneity of final wage with tenure; clearly, wages tend to rise with job duration since specific and general human capital will be accumulating. The wage estimate is expressed in constant 1983 dollars.

[29] Other analysts have noted the reporting problems with the NLS data on rates of pay. Freeman [1981: 289 fn. 8]. Again, I excluded cases in which the hourly wage was less than $1 or greater than $100.

positive and insignificant, although, unlike the men, the addition of real wage did not undermine the significantly negative effects of education.

Table 23 shows the impact of holding wages constant when examining the relative quit rates of men and women workers. I chose to hold the hourly wage constant at both $6, which is roughly the mean for the combined male-female sample, and at $7, which is roughly the male mean. For both of these wages, the male and female rates are relatively close for the first 18 months, after which they diverge sharply. Consequently, in both cases, by the final period the female hazard rate is more than four times the male hazard rate.

One might expect that the inclusion of wage in the hazard rate estimation would cause the gap in expected tenure between the sexes to narrow. Why? Because one would expect that higher wages would be associated with lower quit rates, so the higher hazard rates of women would be attributed in part to their lower pay rates. A comparison of the rates presented in Tables 19.A and 23 confirms this hypothesis. For example, in Table 19.A, the female first-period and final-period hazard rates are 17.8% and 464.9% higher than the corresponding male rates. When the wage is held constant at $6.00 in Table 23, however, the female hazard rates are only 13.2% and 358.9% higher than the corresponding male rates in the first and final periods.

TABLE 23

Maximum Likelihood Estimates of Time-Varying Hazard Rates From First Jobs (x 1000):
White, High School Graduate, Wage Included, Hours $\geq$ 30, 1968-1971

	Wage = 6 (1983)		Wage = 7 (1983)	
	Men	Women	Men	Women
Number of Cases	1139	1322	1139	1322
Duration (Months)				
0-3	1.70946	1.93463	1.48212	1.62843
3-6	1.33000	1.37151	1.15313	1.15444
6-12	1.09766	1.37288	0.95168	1.15559
12-18	1.06628	1.05857	0.92448	0.89102
18-24	0.73358	1.29293	0.63602	1.08830
24-	0.45757	2.09995	0.39672	1.76759

Notes: The rates are derived from model (3) in Tables 21 and 22, which include the real hourly wage as an explanatory variable. They assume that the size of the labor force is less than 50,000, the unemployment rate is 4%, and the worker is 20 years old.

Chapter 4

RESULTS FROM THE PERIOD 1979-1982

4.1 The Sample

My analysis of the period from 1968-1971 indicated that young female workers quit their initial jobs at substantially higher rates than young male workers. This chapter will explore whether this tenure differential has persisted after a decade in which the commitment of women to the paid workforce increased substantially. To answer this question, I began by examining the first full-time job for "recent school leavers" from the National Longitudinal Studies youth cohort over the four year period from 1979-1982.[1] Tables 24 and 25 present summary statistics for the resulting male and female samples, in which full-time jobs are defined as having a usual workweek of 20 or more hours. The number of male and female workers included in the sample are quite close: 2305 men and 2342 women. The mean father's education proved to be higher for women than for men -- 11.11 vs. 11.00 years -- as was the mean years of education for the young workers themselves -- 12.21 vs. 11.67. As I discuss in greater detail in Section 4.4, at least some of this sex-based difference in the workers' mean education at the time of

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[1]The details of the program used to generate this sample and the specific definitions of terms such as "recent school leavers" are provided in Appendix II.

the first full-time job reflects the tendency of men to enter the labor force relatively more frequently while still in high school. Thus, 46.6% of the men and 32.6% of the women that are included in the first job 20 hour sample have not yet completed high school. Moreover, the average age at the beginning of the total sample of first jobs is 18.9 for men and 19.1 for women.

As I had done in the 1968-1971 period, I also created a sample in which I selected the first job that was at least 30 hours per week. The summary statistics for the male and female "30 hour" samples are presented in Tables 26 and 27. Relatively more women than men never held a 30 hour job during the sample period, as evidenced by the greater decline in the size of the female sample from that obtained with the 20 hour definition of full-time employment: for men, the sample size declined from 2305 to 2217, and for women, from 2342 to 2154.

As one would expect, this 30 hour sample is somewhat older -- mean age rises to 19.0 for the men and 19.2 for the women -- and more educated -- the mean years of education are 11.75 for men and 12.32 for women. Moreover, the proportion of first-job holders with less than a high school education drops to 42.3% of the men and 27.2% of the women. Overall, since the overlap in the two samples is great, the mean figures in the 30 hour sample do not change dramatically.

TABLE 24

Descriptive Statistics for Male First-job Holders,
Hours ≥ 20, 1979-1982

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	18.87	1.762	15.10	24.58
EDUCATION				
Years of Schooling	11.67	1.931	2.00	18.00
By Race: White	11.75	1.999	3.00	18.00
Black	11.46	1.643	7.00	17.00
Other	11.49	2.155	2.00	16.00
Distribution (percent of sample)				
Less than 12 years	46.59			
12 years	31.37			
13-15 years	16.10			
16-17 years	5.86			
18 years or more	.09			
TOTAL	100.01%			
DISTRIBUTION BY RACE:				
White	70.85			
Black	24.25			
Other	4.90			
TOTAL	100.00%			
FATHER'S EDUCATION (In Years)	11.00	3.860	0.0	20.00
PROPORTION RESIDING WITHIN AN SMSA	73.53%			
HOURS WORKED PER WEEK	37.18	10.824	20.00	96.00

NOTES: [1] The full sample contains 2305 males, although the value for father's education is missing for 307 individuals.

TABLE 25

Descriptive Statistics for Female First-job Holders, Hours ≥ 20, 1979-1982

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	19.06	1.766	15.00	24.76
EDUCATION				
Years of Schooling	12.21	1.880	0.00	18.00
By Race: White	12.26	1.968	6.00	18.00
Black	12.17	1.488	8.00	17.00
Other	11.64	2.091	0.00	16.00
Distribution (percent of sample)				
Less than 12 years	32.62			
12 years	36.59			
13-15 years	21.86			
16-17 years	8.84			
18 years or more	0.09			
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TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	72.20			
Black	22.76			
Other	5.04			
--------	------			
TOTAL	100.00%			
FATHER'S EDUCATION (In Years)	11.11	3.819	0.0	20.00
PROPORTION RESIDING WITHIN AN SMSA	76.26%			
HOURS WORKED PER WEEK	34.52	9.278	20.0	99.00

NOTES: [1] The full sample contains 2342 females, although the value for father's education is missing for 274 individuals.

TABLE 26

Descriptive Statistics for Male First-job Holders,
Hours $\geq$ 30, 1979-1982

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	18.98	1.772	15.10	24.58
EDUCATION				
Years of Schooling	11.75	1.950	3.00	18.00
By Race: White	11.84	2.030	3.00	18.00
Black	11.53	1.660	7.00	17.00
Other	11.61	1.976	7.00	16.00
Distribution (percent of sample)				
Less than 12 years	42.26			
12 years	35.18			
13-15 years	15.34			
16-17 years	7.13			
18 years or more	0.09			
TOTAL	100.00%			
DISTRIBUTION BY RACE:				
White	71.27			
Black	23.86			
Other	4.87			
TOTAL	100.00%			
FATHER'S EDUCATION (In Years)	10.99	3.883	0.0	20.00
PROPORTION RESIDING WITHIN AN SMSA	73.21%			
HOURS WORKED PER WEEK	41.09	8.351	30.00	96.00

NOTES: [1] The full sample contains 2217 males, although the value for father's education is missing for 292 individuals.

TABLE 27

Descriptive Statistics for Female First-job Holders, Hours $\geq$ 30, 1979-1982

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
AGE	19.21	1.767	15.00	24.76
EDUCATION				
Years of Schooling	12.32	1.894	0.00	18.00
By Race: White	12.39	1.971	6.00	18.00
Black	12.27	1.479	8.00	16.00
Other	11.63	2.203	0.00	18.00
Distribution (percent of sample)				
Less than 12 years	27.21			
12 years	40.95			
13-15 years	21.45			
16-17 years	10.26			
18 years or more	0.14			
TOTAL	100.01%			
DISTRIBUTION BY RACE:				
White	72.89			
Black	21.96			
Other	5.15			
TOTAL	100.00%			
FATHER'S EDUCATION (In Years)	11.11	3.831	0.0	20.00
PROPORTION RESIDING WITHIN AN SMSA	76.04%			
HOURS WORKED PER WEEK	39.01	6.360	30.0	99.00

NOTES: [1] The full sample contains 2154 females, although the value for father's education is missing for 249 individuals.

4.2 The Time-Varying Hazard Model

I began my analysis of the 1979-1982 sample of first jobs by estimating separate time-varying hazard rates for the male and female populations. Surprisingly, the coefficients and the estimated duration patterns were almost indistinguishable for men and women. This contrasted with the estimations based on the 1968-1971 period in a number of respects. First, in the earlier period men showed a constantly declining hazard rate over time -- i.e., monotonic negative duration dependence -- while the hazard rate for women was nonmonotonic -- at first declining and then rising. In the later period, both men and women showed monotonic negative duration dependence on their first jobs. Second, the unemployment rate variable was now negative and significant for both men and women, while in the earlier period it had been significant only for men.

The similar hazard rate estimates for men and women prompted me to examine whether one could aggregate the male and female data. Table 28 presents the test statistics and critical values for a series of ten different likelihood ratio tests on the 20 and 30 hour samples.[2] Remarkably, these tests revealed that the male and female data could always be pooled while retaining a sex dummy coefficient.[3] These results, which held for a number of different specifications and with

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[2]The models tested in Table 28 are the same models presented in Tables 29 and 30.

[3]As long as the test statistic for a particular model in Table 28 is less than the given chi-squared value, then the null hypothesis that the slope coefficients for men and women are identical cannot be rejected. This condition holds in every case at both the .10 and .05 significance levels.

both definitions of full-time employment, underscore the considerable changes that have occurred in the labor market experience of young women in the decade of the 70's. This is the first time I have ever seen a study in labor economics on a large sample of men and women workers in which their economic behavior was sufficiently similar to permit aggregation.[4]

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[4]Moreover, as discussed below, the coefficient on the SEX dummy was uniformly insignificant.

TABLE 28

Likelihood Ratio Tests for Pooling Male and Female Workers

A. The Basic Models, $\geq$ 20 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	12.26	9	14.68	16.92
2	14.83	10	15.99	18.31
3	16.60	11	17.28	19.68
4	16.91	12	18.55	21.03
5	18.72	13	19.81	22.36

B. The Basic Models, $\geq$ 30 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	7.63	9	14.68	16.92
2	8.89	10	15.987	18.31
3	10.72	11	17.275	19.68
4	13.56	12	18.549	21.03
5	15.30	13	19.812	22.36

NOTES: These models are set forth in Tables 29 and 30.

[1] The test statistic is constructed as 2 times the absolute value of the difference between the log likelihood statistic for the partitioned sample and the log likelihood statistic for the aggregated sample.

[2] The number of degrees of freedom is the number of restrictions imposed by partitioning the sample into separate male and female subsamples. In estimating the aggregated sample, I have included a sex dummy, which therefore allows the implicit constant term to vary for men and women. The remaining slope coefficients are constrained to be the same in the aggregated model, and it is the number of these slope coefficients that determines the degrees of freedom for each model.

4.3 Examining the Aggregated Sample of First Jobs

Having confirmed the propriety of aggregating the samples of male and female workers, I proceeded to test whether the finding from the earlier period -- that women had a dramatically higher rate of quitting from first jobs -- would apply in the later period from 1979-1982. This merely required an examination of the coefficient and t-statistic for the SEX dummy in each estimation.[5] The basic conclusion that emerges from the data is that the female hazard rate is never significantly greater than the male hazard. This finding was robust to a number of different model specifications and sample restrictions.

Tables 29 and 30 summarize the results from five basic models that were estimated on the 20 and 30 hour samples and that control for the effects of race, sex, age, education, unemployment rate, and location within a standard metropolitan statistical area (SMSA).[6] The hazard rates presented therein were estimated using the following proportional hazards model that was discussed in greater detail in section 3.5:

$$r_{hi} = e^{BX} * e^{p_i}$$

where r represents the hazard rate for worker h in time period i, X is a

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[5]Since males are indicated by SEX=1 and females by SEX=0, if the coefficient on this dummy is negative, the men have a lower rate.

[6]These models were designed to correspond with those employed previously in the analysis of the 1968-1971 period. The 1979 NLS Youth sample did not publish information on the size of the local labor market, which I had used in my analysis of the earlier period. Accordingly, in the analysis of the later period, I used information on SMSA's as a proxy.

vector of explanatory variables, and B is the associated vector of estimated coefficients. Consequently, one can think of the term e^{p_i} as defining the basic underlying time-varying hazard, which then shifts up or down by a constant percentage across all periods depending upon the observed characteristics of the particular worker. Once again, the time-independent coefficient estimates based on these observed characteristics are presented in part A of the table, and the estimates for the six time intervals are presented on the following page in part B. The second page also presents the sample size n and the chi-squared value, which tests whether the particular model improves over the case in which all the estimated coefficients, except a single constant, are constrained to be zero.

TABLE 29

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates For First Jobs,
Hours $\geq$ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04846* (.01862)	-.04341* (.01884)	-.04278* (.01887)	-.06824* (.01796)	-.06803* (.01797)
Education in years	-.04814* (.01697)	-.05183* (.01712)	-.05264* (.01717)		
Education =12 years				-.1176* (.04592)	-.1184* (.04594)
Education =13-15 y.				-.09884 (.07340)	-.1004 (.07349)
Education $\geq$16 y.				-.1846 (.1144)	-.1866 (.1145)
Black	.09747* (.04279)	.08104** (.04372)	.08682** (.04476)	.09162* (.04387)	.09626* (.04496)
Unempl.[1] rate	-.1374* (.00657)	-.1430* (.006816)	-.1430* (.006815)	-.1430* (.006825)	-.1430* (.006825)
NSMSA[2]		.08640** (.04431)	.05505 (.06836)	.09310* (.04436)	.06860 (.06826)
SMSA[3]			-.01634 (.02720)		-.01280 (.02715)
Sex	-.00661 (.03694)	-.02645 (.03748)	-.02620 (.03749)	-.01919 (.03735)	-.01889 (.03736)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 29 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.106 (.2246)	-3.134 (.2282)	-3.106 (.2329)	-3.218 (.3184)	-3.198 (.3213)
3-6 Months	-3.178 (.2271)	-3.230 (.2308)	-3.202 (.2354)	-3.315 (.3206)	-3.295 (.3235)
6-12 Months	-3.643 (.2290)	-3.670 (.2325)	-3.642 (.2370)	-3.756 (.3215)	-3.736 (.3243)
12-18 Months	-3.784 (.2353)	-3.807 (.2388)	-3.779 (.2433)	-3.894 (.3254)	-3.874 (.3283)
18-24 Months	-4.020 (.2460)	-4.037 (.2494)	-4.009 (.2538)	-4.127 (.3335)	-4.107 (.3363)
24- Months	-4.367 (.2540)	-4.379 (.2574)	-4.351 (.2616)	-4.459 (.3381)	-4.439 (.3408)
n	4748	4647	4647	4647	4647
-ln likeli.	20643.61	20106.16	20105.98	20107.14	20107.02
Chi-square	1175.62*	1158.34*	1158.7*	1156.39*	1156.61*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 30

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates For First Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.06083* (.01969)	-.05217* (.01993)	-.05198* (.01995)	-.08656* (.01929)	-.08656* (.01929)
Education in years	-.05669* (.01781)	-.06068* (.01796)	-.06097* (.01801)		
Education =12 years				-.08582** (.04912)	-.08584** (.04917)
Education =13-15 y.				-.07234 (.07879)	-.07238 (.07887)
Education $\geq$16 y.				-.1866 (.1211)	-.1866 (.1211)
Black	.09976* (.04587)	.07789** (.04689)	.07995** (.04799)	.08797** (.04706)	.08809** (.04822)
Unempl.[1] rate	-.1514* (.007118)	-.1600* (.007373)	-.1600* (.007372)	-.1598* (.00738)	-.1598* (.00738)
NSMSA[2]		.1749* (.04653)	.1636* (.07262)	.1799* (.04654)	.1793* (.07249)
SMSA[3]			-.005857 (.02908)		-.000347 (.02904)
Sex	.02963 (.03938)	.008204 (.03989)	.008241 (.03989)	.02061 (.03988)	.02062 (.03988)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 30 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-2.814 (.2419)	-2.911 (.2459)	-2.901 (.2514)	-2.935 (.3428)	-2.934 (.3465)
3-6 Months	-2.858 (.2445)	-2.959 (.2485)	-2.948 (.2540)	-2.983 (.3451)	-2.983 (.3488)
6-12 Months	-3.296 (.2466)	-3.386 (.2505)	-3.376 (.2560)	-3.413 (.3464)	-3.413 (.3500)
12-18 Months	-3.457 (.2530)	-3.544 (.2569)	-3.534 (.2623)	-3.573 (.3505)	-3.572 (.3542)
18-24 Months	-3.699 (.2624)	-3.770 (.2660)	-3.759 (.2712)	-3.802 (.3571)	-3.801 (.3607)
24- Months	-4.007 (.2680)	-4.084 (.2717)	-4.074 (.2766)	-4.113 (.3600)	-4.113 (.3634)
n	4456	4371	4371	4371	4371
-ln likeli.	18493.23	18046.54	18046.52	18050.09	18050.09
Chi-square	1152.45*	1143.46*	1143.5*	1136.35*	1136.35*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

Two findings that emerge from these tables are in sharp contrast to the results from the period 1968-1971. First, in every case the hazard rates decline monotonically, which indicates that there is no evidence of the previously observed u-shaped female hazard rates that I had attributed to a "birth effect."[7] Second, while the signs on the SEX coefficient alternate in the 20 and 30 hour samples, in no case is there a significant difference in the rate of quitting for male and female workers.[8]

An examination of the other estimated coefficients reveals that the most significant variable, assessed by the size of the t-statistic, is the unemployment rate. In my analysis of the earlier period, I had experimented with two different estimates of the unemployment rate -- the mean rate over the observed job duration and the first measured unemployment rate after the start of the job. Here I use a different measure, which invariably led to more precise estimates: i.e., the measure of unemployment that is closest in time to the final date observed in the job. This increase in precision led me to prefer this measure of unemployment to the other two.[9] The sizeable negative

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[7]Although I am only estimating a single hazard rate for men and women in Tables 29 and 30, the fact that aggregation is permissible indicates that the monotonically declining hazard rates characterize the duration dependence of both genders. Moreover, this conclusion was confirmed directly by separate estimations on the male and female data sets, which I do not report since aggregation is permissible.

[8]Women have the insignificantly higher quit rate in the 20 hour sample, and men have the higher quit rate in the 30 hour sample. Since the shift to the 30 hour sample excluded relatively more women than men, it appears to have disproportionately eliminated a number of high quit women.

[9]Ideally, one would like to be able to estimate the hazard rate for a particular individual at time t based on the unemployment rate at t. If the unemployment rate changes over time, the hazard should change as

coefficients on the unemployment variable in Tables 29 and 30 indicate that each percentage point increase in the unemployment rate decreases the quit rate by about 14%.[10]

In general, the five models in Tables 29 and 30 suggest that education and age at the start of the job inversely affect the probability of quitting and that being black raises this probability. Each year of age reduces the hazard rate by roughly 5%, and models (1)-(3) suggest a similar effect from each additional year of education. Interestingly, the linear impact of education on the hazard rate breaks down when dummy variables are substituted for the single measure of years of education completed. Models (4) and (5) reveal that a large dichotomy seems to exist between those with less than 12 years of education (the omitted category in the regression), and those those with exactly 12 years of education, who have a roughly 11% lower hazard probability on the 20 hour data set and a roughly 8% lower rate on the 30 hour data set. The other two education dummies identifying those with some college education as well as those with at least four years of

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well. By using a single measure of the unemployment rate for each job spell, I am necessarily assuming that the effect of my unemployment rate measure is the same for the entire job spell of that individual. This assumption applies under all three measures of the unemployment rate: first, last, or mean.

[10]This figure is obtained in the following manner. Consider the hazard for a particular worker at a particular time to be given by $r = e^{ax}*k$, where x is the unemployment rate, a is the estimated coefficient for the unemployment rate, and k is a constant. If the unemployment rate increases by 1 percentage point and everything else is unchanged, the rate will become $r_1 = e^{a(x+1)}*k = e^{ax}*e^{a}*k = r*e^{a}$. In other words, the exponential of the unemployment rate parameters presented in Table 29 and 30 is the scale factor indicating how much the hazard rate has changed in response to the one point change in the unemployment rate. Since this figure is roughly .86, it corresponds to a rate reduction of 14%.

college tend to be negative but insignificant at the .10 level. Moreover, the three education dummies do not become increasingly larger in absolute value, as did the education dummies for the women's data set in the previous period from 1968-1971.[11] I explore the reasons for the observed effect of education in greater detail in section 4.4, below.

The attempt to correct for location of the worker's residence did not yield consistent results. In models (2) and (4), being outside an SMSA (identified by NSMSA = 1) significantly raised one's quit probability by 9-10% on the 20 hour data set and by almost twice that amount on the 30 hour data set. When the four-point SMSA index used by the NLS was added to create models (3) and (5), respectively, NSMSA became insignificant.[12] Including NSMSA can have important effects on the estimated coefficients for other variables: specifically the coefficient on the BLACK dummy, which was highly significant in model (1) and reflected a roughly 10% higher hazard rate for blacks, was reduced in significance when NSMSA was introduced in model 2. Apparently, then, being black and living outside SMSA's are positively correlated and both raise hazard rates.[13] Perhaps one's first-job

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[11]The men's data set in 1968-1971 showed a somewhat different nonmonotonic pattern: the dummy for high school graduates was positive while the two dummies representing additional education were negative and rose in absolute value.

[12]This index is composed as follows: 0 implies the worker's current residence is not in an SMSA, while 1-3 represent different responses for those living in an SMSA. 1 implies not in the central city, 3 implies in the central city, and 2 implies the NLS does not know if the person lived in the central city. Obviously, then, this is not an ideal geographic proxy.

[13]Note, however, that two effects operate in moving from model (1) to (2): first, an additional explanatory variable is introduced, and second, over 100 cases are excluded because of missing values of this variable. The second factor may induce significant selection effects.

hazard rate is higher for those living outside SMSA's because people tend to leave these areas to seek better jobs in cities.

As in the analysis of the 1968-1971 period, the results are relatively insensitive to the changes in the definition of full-time employment. Since there is a large overlap in the two samples, it is perhaps not surprising that the results are quite similar. Increasing the cutoff to 30 hours reduced the number of first jobs from 4748 to 4456 for Model 1.[14] In other words, the higher cutoff eliminated 292 individuals who had 20 hour jobs but never worked at 30 hour jobs during the course of the survey. Any individual whose first job was between 20 and 30 hours but who subsequently obtained a 30 hour job would be retained in both samples, although with different jobs in each.[15] The 30 hour sample probably eliminated a number of jobs that were really part-time jobs held in the last year of the individual's education. It seems less likely that a very large number of individuals hold jobs involving 30 or more hours per week during their last year of school.

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[14]The figure of 4456 represents the number remaining in the 30 hour sample after excluding 149 individuals with missing values for any of the explanatory variables and 77 individuals who were self-employed or in jobs providing no compensation. The NLS sample was designed to be limited to the civilian labor force. Consequently, although I also imposed a filter to screen out those listing "armed forces" as their occupation (580 to 590 in the three-digit occupation code), only one such worker was eliminated.

[15]Note, then, that exclusion of a job is not the same as exclusion of an individual.

4.4 Exploring the Effects of Education on Hazard Rates

4.4.1 Full-Time Workers Who Are Still In School

As noted above, in determining which individuals to include in my study, I identified individuals who were attending school full-time at the time of the year x interview and were not attending school full-time at the time of the subsequent interview in year x+1. These individuals were termed "recent school leavers in year x+1."[16] The first job held after the year x interview was then included in my sample. Because I am unable to identify the precise date of a respondent's final attendance in full-time education, it is inevitable that this selection criterion will capture some jobs that might more properly be considered part-time school jobs. For example, an individual who was attending school full-time when interviewed in February of 1979 but not when interviewed a year later would be identified as a recent school leaver in 1980. If in March, 1979, this respondent took a full-time job while still attending school full-time, this job was added to the sample. The inclusion of such jobs could adversely affect my results if two conditions hold: (1) these jobs tend to be of shorter duration than the first jobs taken after schooling is complete and (2) men are relatively more likely than women to have such jobs before they finish school. In this event, the average duration of male jobs might be diminished vis-a-vis that of female jobs, making male and female job durations appear closer than they really are.

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[16]For further details, see the discussion of this point in Appendix II.

In order to screen out jobs that were simply held during the worker's final year in school, I determined which jobs were terminated before May 15 and June 15 of the worker's final year in school. Thus, in the example above, I ascertained if the job he or she first held after the February, 1979 interview was terminated before May 15 or June 15, 1979. The number of such jobs was consistently higher for men than for women. Thus, for the 30 hour sample, the percentages of first jobs that had ended by May 15 and June 15 of the last year in school when interviewed were 4.3% and 9.1% for men but only 3.0% and 5.4% for women.[17] Thus, the second condition appears to be true: my selection criteria seem to catch more men than women who are still in school when they begin working "full-time."

Tables 31 and 32 present the results from estimating the five models on the 20 and 30 hour samples respectively while excluding those first jobs that had ended by this June 15 cutoff.[18] As one might

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[17]For the 20 hour sample, the corresponding percentages of first jobs that had ended by May 15 and June 15 were 7.8% and 15.5% for men and 7.1% and 12.0% for women.

[18]An important distinction between the manner in which I limited this sample using the "June 15" requirement as opposed to the way in which I use different definitions of full-time jobs must be made. In the latter case, the program that reads the NLS data is set up to pick off the data tape the first job that satisfies the definition of full-time job -- whether 20 or 30 hours per week. If a job lasts only 25 hours when my criterion is 30 hours, I do not simply exclude this individual but rather search ahead to find the first job, if any, that does satisfy this criterion. Once I have this 30 hour data set, I can then exclude those jobs that end before the appropriate June 15 cutoff if I wish. In doing so, however, I am eliminating a certain worker from the sample, and thus introducing the possibility of sample selection bias -- for example, the people who work long hours while still attending school full-time may differ in their labor patterns from individuals who do not work while in school. Note, though, that this is not true for the 20 and 30 hour samples: I did not obtain the 30 hour sample of first jobs by simply eliminating from the 20 hour sample all jobs with weekly hours of from 20-29.

expect, this selection limitation is more important on the 20 hour sample than the 30 hour sample, since it is certainly more common for students to work 20 hours a week during their last year in school than 30 hours a week. For the 20 hour sample, the negative coefficient on the SEX dummy doubles in size from that obtained on the unrestricted 20 hour sample. Nonetheless, the estimated higher female hazard never becomes significant at even the .10 level. The sample restriction does raise the size and significance of the BLACK dummy coefficient, which suggests that fewer blacks than nonblacks obtain jobs during their final year in school. For the 30 hour data set, however, the effect appears to be minimal, since the estimated coefficients on both the race and sex dummies are quite similar to those of the complete sample shown in Table 30.

Perhaps the most interesting finding to emerge from this exercise is that the pattern of duration dependence becomes nonmonotonic for the first time -- the underlying hazards in both the 20 and 30 hour samples rise after the first period before declining from the second period on. I suspect this occurred because, in screening out the first jobs that ended before June 15, I not only eliminated part-time school jobs, I also excluded a number of properly included jobs that were quite short in duration. For example, if an individual completed school in May, immediately began working full-time, and then quit before June 15, this job would properly be considered the first full-time job but would be excluded by the June 15 selection criterion. Eliminating a significant number of jobs that last less than 3 months necessarily decreases the estimated hazard rate for this first time period. This is exactly what occurred in these two restricted samples of the 20 and 30 hour data sets.[19]

[19]While I do not present the results, the same nonmonotonic pattern emerged when I excluded first jobs that had ended by May 15 of the individual's last year in school. The other results from these "May 15" samples run on the 20 and 30 hour data sets were quite similar to those obtained with the "June 15" samples presented in Tables 31 amd 32.

TABLE 31

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates for First Jobs,
Excluding "June 15" Jobs,
Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04151* (.02045)	-.03730** (.02062)	-.03698** (.02065)	-.08427* (.01992)	-.08424* (.01992)
Education in years	-.05827* (.01854)	-.06186* (.01865)	-.06227* (.01870)		
Education =12 years				-.007545 (.05038)	-.007655 (.05042)
Education =13-15 y.				-.06374 (.08148)	-.06395 (.08156)
Education ≥16 y.				-.01980 (.1243)	-.0200 (.1244)
Black	.1429* (.04694)	.1316* (.04764)	.1346* (.04884)	.1476* (.04783)	.1483* (.04909)
Unempl.[1] rate	-.1385* (.007183)	-.1438* (.007426)	-.1438* (.007426)	-.1432* (.007430)	-.1432* (.007430)
NSMSA[2]		.09221** (.04868)	.07593 (.07560)	.09486** (.04870)	.09145 (.07549)
SMSA[3]			-.008446 (.03004)		-.001773 (.03001)
Sex	-.04914 (.04088)	-.06616 (.04133)	-.06604 (.04133)	-.04558 (.04119)	-.04554 (.04120)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 31 (cont'd.)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.419 (.2495)	-3.431 (.2529)	-3.416 (.2580)	-3.282 (.3534)	-3.279 (.3566)
3-6 Months	-3.280 (.2512)	-3.316 (.2545)	-3.301 (.2597)	-3.168 (.3551)	-3.166 (.3583)
6-12 Months	-3.635 (.2526)	-3.653 (.2558)	-3.639 (.2609)	-3.508 (.3557)	-3.505 (.3588)
12-18 Months	-3.776 (.2586)	-3.790 (.2619)	-4.776 (.2669)	-3.646 (.3594)	-3.643 (.3626)
18-24 Months	-4.011 (.2685)	-4.020 (.2717)	-4.005 (.2766)	-3.876 (.3669)	-3.874 (.3701)
24- Months	-4.358 (.2759)	-4.361 (.2792)	-4.347 (.2828)	-4.216 (.3710)	-4.213 (.3741)
n	4094	4035	4035	4035	4035
-ln likeli.	17787.31	17053.93	17053.89	17058.88	17058.88
Chi-square	799.48*	797.07*	797.15*	787.17*	787.17*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 32

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates for First Jobs,
Excluding "June 15" Jobs,
Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.05100* (.02071)	-.04279* (.002090)	-.04226* (.02092)	-.08737* (.02038)	-.08730* (.2039)
Education in years	-.05805* (.018740)	-.06223* (.01885)	-.06302* (.01891)		
Education =12 years				-.01344 (.05202)	-.01409 (.05207)
Education =13-15 y.				-.03823 (.8326)	-.03929 (.08336)
Education $\geq$16 y.				-.09250 (.1260)	-.09339 (.1260)
Black	.1085* (.04851)	.09018** (.04933)	.09588** (.05052)	.1027* (.04706)	.1059* (.05077)
Unempl.[1] rate	-.1499* (.007465)	-.1581* (.007714)	-.1581* (.007713)	-.1578* (.007718)	-.1578* (.007718)
NSMSA[2]		.1713* (.04915)	.1406** (.07648)	.1748* (.04915)	.1583* (.07634)
SMSA[3]			-.01602 (.03066)		-.008653 (.03062)
Sex	-.009549 (.04162)	-.02673 (.04204)	-.02665 (.04205)	-.006534 (.04204)	-.006410 (.04204)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 32 (cont'd.)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.154 (.2555)	-3.237 (.2592)	-3.209 (.2649)	-3.131 (.3629)	-3.116 (.3668)
3-6 Months	-3.081 (.2575)	-3.173 (.2612)	-3.145 (.2669)	-3.069 (.3648)	-3.054 (.3687)
6-12 Months	-3.460 (.2594)	-3.544 (.2630)	-3.515 (.2687)	-3.441 (.3659)	-3.426 (.3698)
12-18 Months	-3.623 (.2655)	-3.704 (.2691)	-3.675 (.2748)	-3.604 (.3699)	-3.589 (.3738)
18-24 Months	-3.865 (.2745)	-3.930 (.2778)	-3.901 (.2833)	-3.832 (.3761)	-3.817 (.3800)
24- Months	-4.174 (.2798)	-4.246 (.2832)	-4.217 (.2884)	-4.150 (.3787)	-4.135 (.3824)
n	4131	4072	4072	4072	4072
-ln likeli.	17298.17	16529.45	16529.32	16534.49	16534.45
Chi-square	899.45*	904.94*	905.21*	894.87*	894.95*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.4.2 Workers Who Subsequently Return to School

Another potential problem with my sample is that I may be catching individuals who have taken a semester or year off but who subsequently return to school. This problem is potentially more severe for the period from 1979-1982 than in the period 1968-1971 because the age of the NLS sample was older (14-24) in the earlier period than in the later period (14-21).[20] Some evidence of this problem is provided by the relatively high proportion of individuals -- almost half the men and one-third of the women -- who have not yet completed high school. Many of these individuals may subsequently complete high school, and with an older sample, I would have captured more of these individuals at the time they left school for the final time.

To explore whether this phenomenon was affecting my results I examined a number of restricted samples. I first identified all individuals who in the course of the four year sample period from 1979-1982 increased their education above the level specified at the start of their "first job." Thus, if an individual who was originally listed as having a first job that began in 1979 when the individual had completed 11 years of school, I searched ahead for each subsequent year in the sample to see if he or she subsequently completed grade 12 (or more).[21] For the 30 hour data set, 25.4% of the women and 28.9% of the

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[20]To be more precise, the initial NLS young men's sample was created by surveying men aged 14-24 in 1966. Therefore, by 1968, the ages of these young men ranged from 16-26. The initial young women's sample began in 1968 and included those aged 14-24 at that time. The Youth sample of the NLS, which began in 1979, selected both young men and women who were aged 14-21 in that year.

[21]The later in the sample period that an individual began working, the less likely it is that he or she would be identified as having

men completed more education than they had at the time they began their first job.[22]

Tables 33 and 34 show the results from estimating hazard rates on the respective 20 and 30 hour samples that exclude all those who continued their education at some point in the observed sample period.[23] The results are quite similar to those obtained on the full sample. The monotonic pattern of duration dependence is preserved, and once again, the coefficient on the SEX dummy is always insignificant. Consequently, any fear that the male hazard rate is disproportionately elevated because men return to school more frequently than women would appear to be unjustified. Somewhat surprisingly, the coefficient on the BLACK dummy became uniformly insignificant in this sample. This raises

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subsequently obtained additional education because the opportunity to do so within the survey period would be diminished. The individual alluded to in the text who begins a first job in 1979 would be questioned about his or her education in subsequent interviews in 1980, 1981, and 1982. An individual whose first job begins just before the 1982 interview would obviously have no chance of being identified as someone who subsequently returns to school.

[22]These percentages exclude those individuals who were only interviewed once after obtaining their first job, and who therefore could not have been identified as having completed additional schooling. The numbers of such individuals were 447 women (20.1% of the entire female sample) and 446 men (18.8% of the entire male sample).

[23]This method of sample selection will exclude some individuals who I would otherwise want to keep in the sample. Specifically, an individual who has begun full-time employment and then increases his education by attending school part time will be excluded.

In addition, not all those excluded by this restriction will actually have "returned to school" after beginning full-time work. For example, a worker who is working full time when interviewed during his or her senior year in high school will be captured in my unrestricted sample even though this job ends at the time of graduation from, say, high school. This individual's "education at the start of the job" would be listed as 11 years. A few months later, when the student graduated, the education measure would rise to 12 years (although this would not be recorded until the following interview). Such individual's would be excluded by the "additional education" cutoff.

the question as to why the elimination of those whose first full-time job is taken before they complete their schooling would diminish the previously higher rates found for the black workers. Perhaps blacks tend to begin working while still in school and these jobs tend to be of relatively short duration. But this possibility was ruled out by the previous analysis, restricting the sample with the "June 15" cutoff. That cutoff tended to raise the size of the coefficient on the BLACK dummy. A more probable explanation, then, is that this sample restriction eliminates a relatively large number of very stable white employees. This could occur if the whites who continued their education and are thereby eliminated from the sample included a large number of stable employees who attended school part time while working.

Finally, for the first time for the 1979-1982 sample, the coefficients on the education dummies adhere to a monotonic pattern in which increased education uniformly led to lower hazard rates. For the 30 hour data set, those with at least a high school education quit at a 25% lower rate and those with at least 4 years of college quit at a 35% lower rate than those with less than a high school diploma. This suggests that screening out school returnees may provide more reliable estimates of the effect of education on the rate of exit from initial full-time jobs.

TABLE 33

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates Omitting Subsequent School Returnees. First Jobs, Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.06932* (.02122)	-.06333* (.02142)	-.06268* (.02143)	-.06536* (.02098)	-.06491* (.02099)
Education in years	-.05186* (.01850)	-.05620* (.01861)	-.05730* (.01867)		
Education =12 years				-.2780* (.05635)	-.2819* (.05652)
Education =13-15 y.				-.3137* (.09107)	-.3188* (.09128)
Education ≥16 y.				-.3666* (.1327)	-.3735* (.1330)
Black	.07297 (.05143)	.06643 (.05220)	.07415 (.05324)	.07073 (.05268)	.07998 (.05369)
Unempl.[1] rate	-.1257* (.00765)	-.1315* (.008049)	-.1315* (.008050)	-.1326* (.008077)	-.1326* (.008078)
NSMSA[2]		.1020** (.05239)	.05499 (.008239)	.1166* (.05245)	.06011 (.08220)
SMSA[3]			-.02430 (.03296)		-.02925 (.03293)
Sex	.02270 (.04490)	.003563 (.04535)	.004074 (.04535)	-.01349 (.04558)	-.01303 (.04559)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 33 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3	-2.690 (.2674)	-2.738 (.2709)	-2.692 (.2780)	-3.158 (.3680)	-3.109 (.3721)
3-6 Months	-2.873 (.2713)	-2.928 (.2748)	-2.881 (.2818)	-3.343 (.3709)	-3.293 (.3750)
6-12 Months	-3.267 (.2734)	-3.307 (.2768)	-3.261 (.2837)	-3.720 (.3718)	-3.671 (.3759)
12-18 Months	-3.401 (.2815)	-3.439 (.2849)	-3.393 (.2917)	-3.850 (.3771)	-3.801 (.3812)
18-24 Months	-3.904 (.3020)	-3.935 (.3051)	-3.889 (.3116)	-4.343 (.3927)	-4.293 (.3967)
24- Months	-4.068 (.2997)	-4.122 (.3030)	-4.076 (.3091)	-4.520 (.3908)	-4.472 (.3945)
n	3353	3304	3304	3304	3304
-ln likeli.	14020.83	13770.30	1377.002	13762.45	13762.06
Chi-square	875.62*	866.94*	867.48*	882.63*	883.42*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 34

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates Omitting Subsequent School Returnees.
First Jobs, Hours ≥ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.07344* (.02165)	-.06315* (.02188)	-.06264* (.02189)	-.07182* (.02152)	-.07153* (.02153)
Education in years	-.05916* (.01901)	-.06470* (.01912)	-.06566* (.01918)		
Education =12 years				-.2805* (.05790)	-.2846* (.05814)
Education =13-15 y.				-.2821* (.09324)	-.2868* (.09347)
Education ≥16 y.				-.4154* (.1352)	-.4213* (.1354)
Black	.06241 (.05304)	.04656 (.05398)	.05319 (.05504)	.04807 (.05442)	.05641 (.05547)
Unempl.[1] rate	-.1413* (.008051)	-.1502* (.008355)	-.1502* (.008355)	-.1508* (.008381)	-.1508* (.008381)
NSMSA[2]		.1762* (.05300)	.1366** (.008328)	.1904* (.05305)	.1406** (.08315)
SMSA[4]			-.02058 (.03348)		-.02596 (.03350)
Sex	.05310 (.04550)	.02996 (.04597)	.03025 (.04598)	.01765 (.04623)	.01787 (.04624)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 34 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3	-2.541 (.2738)	-2.651 (.2777)	-2.661 (.2851)	-3.049 (.3801)	-3.004 (.3846)
3-6 Months	-2.618 (.2774)	-2.723 (.2812)	-2.683 (.2886)	-3.117 (.3826)	-3.072 (.3872)
6-12 Months	-3.098 (.2802)	-3.197 (.2841)	-3.157 (.2914)	-3.590 (.3842)	-3.544 (.3888)
12-18 Months	-3.255 (.2883)	-3.349 (.2921)	-3.309 (.2994)	-3.740 (.3894)	-3.694 (.3941)
18-24 Months	-3.690 (.3051)	-3.775 (.3086)	-3.735 (.3154)	-4.163 (.3927)	-4.117 (.4063)
24- Months	-3.881 (.3032)	-3.973 (.3069)	-3.934 (.3133)	-4.356 (.3999)	-4.312 (.4040)
n	3469	3416	3416	3416	3416
-ln likeli.	13838.03	13571.73	13571.54	13565.52	13565.22
Chi-square	952.50*	948.17*	948.55*	960.60*	961.20*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.4.3 High School Graduates and Above

I previously noted that my standard selection criteria that identified first full-time jobs captured a large proportion of individuals who had not completed high school when the job began. Moreover, this proportion is greater for men than for women: for the 20 hour sample, 46.6% of the men and 32.6% of the women had less than 12 years of education; for the 30 hour sample, the respective figures were 42.3% of the men and 27.2% of the women. In order to assess the sensitivity of my results to this potential problem of sample selection, I estimated hazard rates while limiting my sample to those who had completed at least the twelfth grade.[24] These results are presented in Tables 35 and 36.

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[24]It is possible that some of those included in this estimation did not actually complete high school before beginning their first full-time job. For example, an individual who is enrolled full-time in February, 1979 and not enrolled in February, 1980 (because he or she graduated from high school in June, 1979) will be considered a recent school leaver. If this individual is also working full time when interviewed in February, 1979, then the worker's educational level would be recorded as "11 years," and this job would be excluded by this sample restriction. On the other hand, if the job begins after the February, 1979 interview but before graduation in June, it would be included in the sample because the educational level would be recorded as "12 years."

TABLE 35

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates For First Jobs.
Hours $\geq$ 20, 1979-1982, Workers With at Least 12 Years of Education

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.06708* (.02521)	-.05975* (.02552)	-.05964* (.02555)	-.05437* (.02348)	-.05432* (.02348)
Education in years	-.004597 (.02915)	-.007916 (.02941)	-.008065 (.02947)		
Education =13-15 y.				-.00281 (.0711)	-.002979 (.07113)
Education $\geq$16 y.				-.1051 (.1174)	-.1054 (.1174)
Black	.09714** (.05661)	.09584** (.05736)	.09690** (.05879)	.09098 (.05696)	.09208 (.05848)
Unempl.[1] rate	-.1430* (.008757)	-.1489* (.008997)	-.1489* (.008997)	-.1489* (.008979)	-.1489* (.008979)
NSMSA[2]		.1540* (.05881)	.1483** (.08997)	.1555* (.05889)	.1499** (.08995)
SMSA[3]			-.0030 (.03609)		-.002998 (.03605)
Sex	.03697 (.04865)	.02080 (.04919)	.02089 (.04920)	.01975 (.04919)	.01986 (.04921)

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.
[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).
[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 35 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.303 (.2981)	-3.403 (.3048)	-3.398 (.3111)	-3.597 (.4392)	-3.593 (.4424)
3-6 Months	-3.397 (.3011)	-3.503 (.3075)	-3.498 (.3139)	-3.698 (.4414)	-3.693 (.4447)
6-12 Months	-3.837 (.3033)	-3.928 (.3097)	-3.923 (.3159)	-4.123 (.4422)	-4.118 (.4453)
12-18 Months	-3.976 (.3109)	-4.069 (.3172)	-4.064 (.3233)	-4.264 (.4465)	-4.260 (.4497)
18-24 Months	-4.130 (.3222)	-4.212 (.3280)	-4.207 (.3340)	-4.410 (.4544)	-4.405 (.4575)
24- Months	-4.387 (.3231)	-4.480 (.3294)	-4.475 (.3351)	-4.678 (.4552)	-4.674 (.4582)
n	2846	2809	2809	2809	2809
-ln likeli.	12021.60	11814.00	11813.99	11813.44	11813.44
Chi-square	638.46*	634.11*	634.11*	635.22*	635.22*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 36

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates For First Jobs.
Hours $\geq$ 30, 1979-1982, Workers With at Least 12 Years Of Education

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.08218* (.02625)	-.0698* (.02654)	-.07057* (.02657)	-.0788* (.02479)	-.07913* (.02479)
Education in years	-.02508 (.02993)	-.03177 (.03018)	-.03079 (.03021)		
Education =13-15 y.				.001447 (.07311)	.00270 (.07310)
Education $\geq$16 y.				-.1217 (.1216)	-.1206 (.1216)
Black	.1017** (.05848)	.08801 (.05944)	.07951 (.06101)	.08907 (.05913)	.07951 (.06080)
Unempl.[1] rate	-.1597* (.009159)	-.1676* (.009398)	-.1677* (.00940)	-.1674* (.009392)	-.1674* (.009394)
NSMSA[2]		.2054* (.06013)	.2485* (.09203)	.2075* (.06018)	.2543* (.09201)
SMSA[3]			.02286 (.03687)		.02491 (.03683)
Sex	.09845* (.04982)	.07543 (.05040)	.07476 (.05041)	.07865 (.05044)	.07781 (.05046)

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.
[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).
[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 36 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-2.797 (.3145)	-2.949 (.3208)	-2.987 (.3266)	-3.174 (.4659)	-3.212 (.4692)
3-6 Months	-2.802 (.3178)	-2.944 (.3239)	-2.982 (.3297)	-3.169 (.4684)	-3.207 (.4717)
6-12 Months	-3.270 (.3208)	-3.409 (.3268)	-3.447 (.3326)	-3.635 (.4699)	-3.673 (.4731)
12-18 Months	-3.436 (.3278)	-3.575 (.3338)	-3.614 (.3395)	-3.802 (.4738)	-3.840 (.4771)
18-24 Months	-3.588 (.3372)	-3.713 (.3427)	-3.752 (.3483)	-3.943 (.4799)	-3.981 (.4831)
24- Months	-3.819 (.3368)	-3.955 (.3426)	-3.992 (.3479)	-4.186 (.4791)	-4.223 (.4822)
n	2887	2848	2848	2848	2848
-ln likeli.	11545.41	11331.04	11330.85	11330.82	11330.59
Chi-square	689.62*	687.04*	687.42*	687.48*	687.94*
Monotonic[2]	yes	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

A number of interesting results emerge from this inquiry. First, for both the 20 and 30 hour data sets, the coefficient on the SEX dummy became more positive than it had been for the complete sample (presented in Tables 29 and 30). In both cases, the antilog of the coefficient became roughly 5 percentage points greater on the restricted sample than it had been with the full sample. For the 20 hour data set, this change reversed the sign, but not the insignificance, of the SEX coefficient. For the 30 hour data set, the increase in the size of the SEX coefficient, indicating a hazard rate for men that was roughly 8-10% higher than for women, was sufficiently large to reach statistical significance in one of the five estimations.[25]

Second, limiting the analysis to only those with at least twelve years of education undermines the previously observed effects of education on first-job hazard rates. Thus, none of the education coefficients in Tables 35 or 36 is statistically significant at any conventional level. This is not entirely surprising in that one expects the coefficient estimate to be less precise if one has eliminated a considerable portion of the variation in the explanatory variable of interest. In the extreme case, if one looked only at those with precisely twelve years of schooling, no information about the effect of education on a dependent variable could be obtained. Moreover, the sample size has been substantially reduced, which further reduces the precision of the coefficient estimates on the education dummies. Thus, while the coefficient on the dummy indicating education of at least 16 years is a rather large negative number in both tables -- implying these

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[25]The hazard rate for men was significantly greater at the .05 level in model (1) of Table 36.

individuals have substantially lower quit rates than high school graduates -- the lack of precision in its estimation renders it insignificant.

4.5 Treating Layoffs As Completed Spells

Up to this point in my analysis of the 1979-1982, I have proceeded on the assumption that layoffs should be treated as censored spells. For the complete 30 hour sample of 4371 male and female workers, 1084, or 24.8%, did not leave their job by the end of the survey period. Of those who had left their job, the breakdown of the reasons for leaving is as follows:[26]

TABLE 37

Reasons For Leaving First Jobs (1979-1982)

	FEMALE	MALE	TOTAL
Layoff, plant closed, or end of temporary job	17.78	23.16	20.57
Discharged or fired	5.42	6.93	6.20
Program ended	6.25	7.88	7.09
Quit for pregnancy or family reasons	6.88	1.01	3.84
Quit for other reasons	63.67	61.02	62.30
	100%	100%	100%

As in my analysis of the 1968-1971 period, I again estimated hazard rates by treating layoffs in the same manner as quits -- both

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[26]These figures omit 30 cases, for which the reason for leaving the job was not recorded in the NLS data, leaving a total of 3257 cases.

terminations were treated as completed spells.[27] Thus, 391 male jobs and 279 female jobs that had previously been treated as censored spells were now considered to be completed job spells.

Tables 38 and 39 present the results of treating layoffs as completed spells. As it did in the 1968-1971 period, this treatment of layoffs tended to elevate male rates proportionately more than female rates. The explanation for this result is that men are disproportionately in jobs that have high layoff rates, so treating layoffs as completed spells tends to raise male hazard rates vis-a-vis female hazard rates. For the 30 hour data set, although not for the 20 hour sample, the coefficient on the SEX dummy becomes significantly positive, indicating a 7-9% higher hazard rate for men. The effect works in the same direction for the 20 hour data set but it is not strong enough to raise the coefficient to statistical significance.

A number of other changes distinguish the results in these Tables from those of the standard models shown in Tables 29 and 30. First, treating layoffs as completed spells increases the significance of the coefficient on the BLACK dummy. Apparently, then, blacks are more likely than whites to suffer layoffs in this youth sample for the 1979-1982 period. Second, this treatment of layoffs reduces the size and significance of the unemployment measure, for the reasons discussed in the early period analysis. Third, there is an increase in the size of the negative coefficients on "years of education" in both the 20 and

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[27]The one difference is that, for the 1979-1982 period, a worker who is laid off but then returns to his job by the time of the following interview period is treated as having worked continuously, while an individual who happened to quit and then returned under the same circumstances would be treated as having started another job. For further details see Appendix II.

30 hour samples. Finally, as seen in the analysis of the earlier period, treating layoffs as completed spells generates some noteworthy nonmonotonic effects on the education dummies: in both periods, this treatment decreases the negative coefficient for high school graduates and increases the negative effect for college graduates. In other words, high school graduates are more likely to be laid off than less educated workers, while college graduates are less likely. The ultimate effect of this treatment of layoffs, however, is to restore a monotonically declining pattern for the education dummies, although the statistical significance of this pattern is particularly weak for the 30 hour data set.

TABLE 38

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates With Layoffs Treated as Completed Spells. First Jobs, Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03099** (.01658)	-.02497 (.01676)	-.02335 (.01678)	-.05687* (.01609)	-.05625* (.01611)
Education in years	-.05967* (.01513)	-.06267* (.01525)	-.06476* (.01529)		
Education =12 years				-.07870** (.04103)	-.08097* (.04105)
Education =13-15 y.				-.1187** (.06608)	-.1230** (.06618)
Education ≥16 y.				-.1738** (.1022)	-.1796** (.1023)
Black	.1293* (.03805)	.1168* (.03881)	.1317* (.03974)	.1287* (.03896)	.1421* (.03993)
Unempl.[1] rate	-.1159* (.005751)	-.1215* (.005959)	-.1215* (.005958)	-.1213* (.005963)	-.1214* (.005962)
NSMSA[2]		.1208* (.03920)	.03895 (.02457)	.1256* (.03923)	.05398 (.06093)
SMSA[3]			-.04271** (.02457)		-.03744 (.02453)
Sex	.05347 (.03317)	.03579 (.03361)	.03647 (.03361)	.04841 (.03350)	.04931 (.03350)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e. SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 38 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3	-3.234 (.2012)	-3.298 (.2043)	-3.225 (.2085)	-3.390 (.2856)	-3.332 (.2883)
3-6 Months	-3.365 (.2036)	-3.444 (.2067)	-3.371 (.2109)	-3.538 (.2876)	-3.479 (.2903)
6-12 Months	-3.868 (.2053)	-3.931 (.2083)	-3.858 (.2124)	-4.027 (.2885)	-3.968 (.2912)
12-18 Months	-4.003 (.2110)	-4.060 (.2140)	-3.987 (.2180)	-4.157 (.2921)	-4.097 (.2947)
18-24 Months	-4.262 (.2211)	-4.315 (.2240)	-4.241 (.2279)	-4.414 (.2996)	-4.354 (.3023)
24- Months	-4.517 (.2263)	-4.568 (.2292)	-4.495 (.2329)	-4.660 (.3024)	-4.600 (.3050)
n	4748	4647	4647	4647	4647
-ln likeli.	24828.29	24230.18	24228.67	24235.94	24234.77
Chi-square	1365.32*	1341.23*	1344.26*	1329.72*	1332.05*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 39

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates With Layoffs Treated as Completed Spells. First Jobs, Hours ≥ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04324* (.01746)	-.03423** (.01766)	-.03337** (.01768)	-.07291* (.01716)	-.07274* (.01717)
Education in years	-.06677* (.01581)	-.06925* (.01594)	-.07051* (.01599)		
Education =12 years				-.04917 (.04371)	-.05114 (.04376)
Education =13-15 y.				-.07927 (.07035)	-.08151 (.07043)
Education ≥16 y.				-.2054** (.1080)	-.2075** (.1080)
Black	.1239* (.04068)	.1098* (.04146)	.1189* (.04243)	.1196* (.04161)	.1265* (.04264)
Unempl.[1] rate	-.1241* (.006159)	-.1323* (.006374)	-.1324* (.006372)	-.1323* (.006378)	-.1323* (.006377)
NSMSA[2]		.1998* (.04099)	.1495* (.06452)	.2040* (.04099)	.1675* (.06440)
SMSA[3]			-.02627 (.02611)		-.01909 (.02607)
Sex	.08879* (.03521)	.06901** (.03560)	.06918** (.03560)	.08649* (.03559)	.08677* (.03560)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e. SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 39 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3	-2.982 (.2156)	-3.112 (.2190)	-3.065 (.2239)	-3.168 (.2856)	-3.135 (.3087)
3-6 Months	-3.101 (.2181)	-3.231 (.2214)	-3.185 (.2263)	-3.290 (.3075)	-3.257 (.3108)
6-12 Months	-3.572 (.2200)	-3.696 (.2233)	-3.649 (.2281)	-3.756 (.3087)	-3.723 (.3120)
12-18 Months	-3.740 (.2257)	-3.861 (.2289)	-3.814 (.2338)	-3.923 (.3123)	-3.890 (.3157)
18-24 Months	-3.984 (.2343)	-4.091 (.2373)	-4.044 (.2419)	-4.157 (.3184)	-4.124 (.3217)
24- Months	-4.221 (.2377)	-4.336 (.2409)	-4.289 (.2453)	-4.401 (.3199)	-4.369 (.3231)
n	4456	4371	4371	4371	4371
-ln likeli.	22486.49	21992.10	21991.59	21999.39	21999.12
Chi-square	1316.30*	1305.01*	1306.03*	1290.43*	1290.997*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.6 Parametric Assumptions About the Shape of the Hazard Function

Thus far, I have imposed relatively little structure on the estimation of the hazard function in terms of assumptions about the nature of time dependence. By estimating a step function with six intervals, I have allowed the data to define not only whether the hazard rate demonstrates positive or negative duration dependence (*i.e*, rises or falls as a function of time), but also whether the hazard rate adheres to a monotonic pattern. While I do allow the hazard to vary freely across each time interval, I have imposed a parametric assumption within each time period -- namely, that the hazard rate is constant within each interval. The parametric assumption that is implicitly made *within each time interval* is that job tenure conforms to an exponential distribution.

Contrary to the results of the 1968-1971 period in which women showed a strongly nonmonotonic pattern of duration dependence, the hazard rates for both men and women in the later period have persistently declined in a monotonic fashion.[28] It therefore seemed appropriate to estimate hazard rates on the later sample using a Gompertz model, which restricts the hazard rate to a monotonic form.

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[28] Of the estimates discussed thus far, the sole exception to this observation was the sample restricted to exclude those who had left jobs by June 15 of their last year in school, which I postulated caused a number of short jobs to be excluded from the sample. Even in that case, as shown in Tables 31 and 32, the hazard rate declined uniformly beginning with the second period.

4.6.1 The Gompertz Hazard Rates

Assume as before that the hazard rate r is a function of time t and a vector X of explanatory variables:

$$r = e^{[f(t) + BX]} = e^{f(t)} * e^{BX},$$

where f(t) is an unspecified function of time and B is the vector of parameters. Suppose that f is a linear function of time:

$$f(t) = c + dt.$$

In this case, completed tenures follow the Gompertz distribution.[29] Using this specification, the hazard rate r becomes:

$$r = e^{c + dt} * e^{BX}$$
$$= k * e^{dt} * e^{BX},$$

where the constant $k = e^{c}$. The nature of the duration dependence is then given by the parameter d. If this parameter is greater than 0, than e^{d} will be greater than one, indicating that the rate r will increase with time (positive duration dependence). With d less than 0, e^{d} will be less than one, indicating that r will decrease with time (negative duration dependence).

I used this specification to estimate hazard functions on both the 20 and 30 hour samples of first jobs. As Tables 40 and 41 reveal, the vector of explanatory variables is unchanged, but the number of parameters estimated in this model is reduced from the earlier estimates using six time intervals. Since the hazard rate is modelled as changing exponentially with time, the only remaining coefficients to be estimated are c (the constant) and d (the coefficient on the TENURE variable).

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[29]This model was first proposed by Gompertz in 1825 to describe adult human mortality. Kalbfleisch and Prentice [1980: 30].

In light of the previous results, one would expect that the coefficient on TENURE would be negative. Indeed, in every case, this coefficient is negative and highly significant. The other results conform quite closely to those previously observed in the time-interval estimations. Thus, the coefficient on the SEX dummy is always insignificant, while the coefficient on the unemployment rate is always highly significant. Variables such as the BLACK dummy, the education dummies, and NSMSA flirt with significance, while the years of education variable is always significant.

To demonstrate the different hazard rates that result from using either the time period approach, which generates a hazard function with six steps, or the Gompertz model, I have plotted the resulting graphs for the class of white, female high-school graduates in their first 30 hour job. The step function is derived from model (2) of Table 30 and the Gompertz function is derived from model (2) of Table 41. In both cases, the hazard is for a 20 year old, with 12 years of education, who is living within an SMSA.

The graph clearly depicts the pattern of negative duration dependence -- the hazard rate declines as tenure increases.[30] The close correspondence of the two curves suggests that the Gompertz function performs quite well on this particular data set. I did not present a companion curve representing a male hazard rate since the two hazards are virtually identical.

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[30]Tenure is expressed in days.

TABLE 40

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Gompertz Hazard Rates For First Jobs.
Hours $\geq$ 20, 1979-1982, All Workers

	1	2	3	4	5
Constant	-3.052*	-3.09*	-3.062*	-3.174*	-3.155*
	(.2243)	(.2279)	(.2325)	(.3184)	(.03213)
Age at start	-.04375*	-.04375*	-.04313*	-.06902*	-.06880*
	(.01883)	(.01883)	(.01885)	(.01796)	(.01797)
Education in years	-.05247*	-.05247*	-.05327*		
	(.01883)	(.01710)	(.01715)		
Education =12 years				-.1150*	-.1158*
				(.04589)	(.05652)
Education =13-15 y.				-.09821	-.09976
				(.07342)	(.07351)
Education $\geq$16 y.				-.1872	-.1891**
				(.1143)	(.1144)
Black	.09914*	.08301**	.08878*	.09346*	.09804
	(.04278)	(.04371)	(.04476)	(.04386)	(.04496)
Unempl.[1] rate	-.1380*	-.1437*	-.1438*	-.1438*	-.1438*
	(.00653)	(.00682)	(.00682)	(.00683)	(.00683)
NSMSA[2]		.08850*	.05730	.0951*	.07099
		(.04431)	(.06838)	(.04435)	(.06828)
SMSA[3]			-.01626		-.1259
			(.02712)		(.02716)
Sex	-.007602	-.02798	-.02773	-.02029	-.01999
	(.03694)	(.03748)	(.03749)	(.03735)	(.03736)
Tenure	-.00151*	-.00148*	-.00148*	-.00148*	-.00148*
	(.000096)	(.000096)	(.000096)	(.000096)	(.000096)
n	4748	4647	4647	4647	4647
-ln likeli.	20668.58	20129.77	20129.59	20130.97	20130.86
Chi-square	1125.68*	1111.13*	1111.49*	1108.73*	1108.95*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TABLE 41

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Gompertz Hazard Model For First Jobs.
Hours $\geq$ 30, 1979-1982, All Workers

	1	2	3	4	5
Constant	-2.743*	-2.846*	-2.834*	-2.864*	-2.862*
	(.2243)	(.2457)	(.2512)	(.3431)	(.3468)
Age at start	-.06203*	-.05329*	-.05308*	-.08089*	-.08808*
	(.01969)	(.01992)	(.01995)	(.01930)	(.01930)
Education in years	-.05665*	-.06067*	-.06100*		
	(.01779)	(.01795)	(.01800)		
Education =12 years				-.08130**	-.08137**
				(.04909)	(.04914)
Education =13-15 y.				-.06829	-.06814
				(.07881)	(.07889)
Education $\geq$16 y.				-.1855	-.1856
				(.1211)	(.1211)
Black	.1003*	.07870**	.08103**	.08852**	.08886**
	(.04586)	(.04688)	(.04798)	(.04705)	(.04822)
Unempl.[1] rate	-.1517*	-.1604*	-.1604*	-.1602*	-.1602*
	(.00712)	(.007376)	(.007375)	(.007383)	(.007383)
NSMSA[2]		.1759*	.1632*	.1809*	.1791*
		(.04652)	(.07264)	(.04653)	(.07251)
SMSA[3]			-.006642		-.00092
			(.02909)		(.02905)
Sex	.02907	.007378	.007424	.02030	.02031
	(.03939)	(.03989)	(.03989)	(.03988)	(.03988)
Tenure	-.001451*	-.001414*	-.001414*	-.001426*	-.001426
	(.000098)	(.000099)	(.000099)	(.000099)	(.000099)
n	4456	4371	4371	4371	4371
-ln likeli.	18509.01	18618.26	18061.73	18065.43	18065.43
Chi-square	1120.89*	1113.02*	1113.07*	1105.68*	1105.68*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

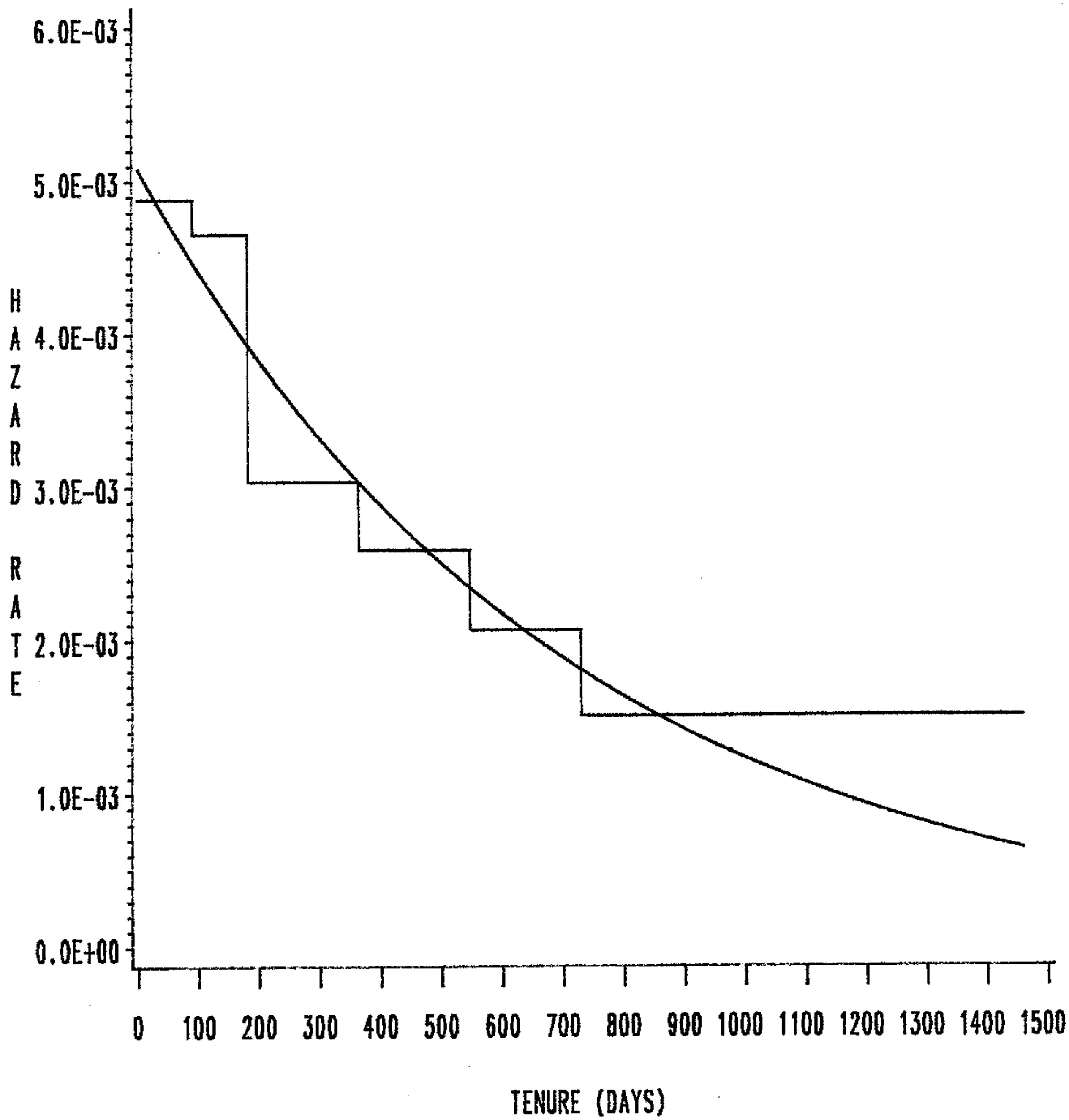
**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TWO HAZARD FUNCTIONS FOR WHITE FEMALE HIGH SCHOOL GRADUATES
FIRST JOBS, HOURS PER WEEK >= 30, 1979–1982



GOMPERTZ HAZARD RATE
STEP FUNCTION HAZARD RATE

4.7 Considering Job Characteristics

As Appendix I illustrates, in estimating hazard rates for jobs, analysts have frequently included a number of job specific characteristics as explanatory variables. All of the studies summarized therein include wage and union status as explanatory variables, and Blau and Kahn [1981] and Waite and Berryman [1985] include occupational measures, as well. As discussed in Section 3.12, above, the argument that is generally made for their inclusion follows these lines: women are disproportionately found in low-paid, low-status jobs, whose lack of attractiveness leads to the higher observed turnover. Therefore, in comparing the quit rates of men and women, one should control for the fact that it is the job itself rather than the sex of the worker that explains the shorter observed tenure.

The argument overlooks the possibility that the direction of causation runs the other way: from high turnover to low pay and low occupational status. It may well be the case that the factors that lead an individual to have short durations of job spells may cause the individual to choose certain types of jobs. Thus, one would not expect an individual who planned to leave the labor market in a short period of time -- perhaps because of pregnancy or other family responsibilities -- to take a job that involved a substantial period of training, during which time lower wages would be paid. If a large number of individuals with intentions of leaving the workforce avoided such jobs, then this occupation would be positively correlated with high job tenure. Since the direction of causation would be from short expected job tenure to occupational choice, it would be improper in these circumstances to include occupational variables as explanatory variables. As a general matter, then, it is inappropriate to insert one endogenous choice variable -- whether wage, occupation, or union status -- to explain another choice variable -- here, tenure -- unless the first choice variable is somehow identified. Nonetheless, for purposes of comparison with other studies, I thought it would be useful to consider some of these job characteristics in my analysis, even though their inclusion may cloud the meaning of the other estimated coefficients. Consequently, the next three subsections will consider seriatum the effects on tenure of controlling for wages, union status, and occupation.

4.7.1 Real Hourly Wages

Before introducing the worker's real hourly wage into my analysis of the 1979-1982 sample, I will address two preliminary questions. First, what happened to the wage differential between young male and female workers during the decade of the seventies? Second, is aggregation of male and female workers permissible when estimating hazard functions if wage is included as an explanatory variable?

4.7.1.1 The Male-Female Wage Differential

There are two approaches that are commonly used to examine trends in the male-female wage differential: (1) focussing on the respective male and female mean hourly wages, and (2) using OLS regression to estimate separate male and female earnings functions. I will now use both techniques. In 1979-1982, hourly wages (1983$) for those starting their first jobs in the 20 hour sample were $4.85 for men and $4.34 for women, which yielded a female-male earnings ratio of 89.5%. For the 30 hour sample, the mean wages were $4.97 for men and $4.43 for women, yielding a ratio of 89.1%.[31] This figure represented a substantial increase in the ratio of the female mean wage to male mean wage from the earlier period to the later period. For the 30 hour sample in 1968-1971, mean wages were $6.97 for men and $5.09 for women -- a female-male ratio of 73.0%. In other words, according to my examination of the two time periods, the female-male earnings ratio for starting wages narrowed from somewhat over 70% to almost 90% over the decade of the seventies.[32]

The comparison of wages across the two time periods suggests that wages have fallen by the second period. This comparison, however, is obscured by the fact that workers in the 1979-1982 sample are younger and less educated. To control for these effects more precisely, I estimated separate wage equations for each gender, using the log of the

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[31]In obtaining these estimates of mean wages, I excluded all wages that were given as less than $1 or greater than $100. Without these restrictions, the means for the 20 hour sample were $4.79 for men and $8.99 for women; for the 30 hour sample, the means were $4.92 for men and $9.39 for women. The driving force behind the high mean women's wage was one outlier of $9136.20 that appeared in both of the female samples -- undoubtedly the result of some coding error in the data. Perhaps this is the explanation behind the puzzling finding in the Waite and Berryman study that young women from the 1979 NLS sample had substantially higher mean wages than young men. Waite and Berryman report, but do not comment upon, this result in their summary statistics presenting the mean figures by sex for the log of the hourly wage. See Tables 6 and 8 in Waite and Berryman [1985].

[32]Of course, the simple means for male and female wages mask a great deal of important information. I report these figures to show that, while the so-called "59%" measure of the female-male earnings ratio has been quite stable for decades, two countervailing forces are operating below the surface: (1) there appears to have been convergence in the earnings of young male and female labor market entrants; and (2) at the same time, the swelling of the labor market participation of older women tends to widen the simple female-male mean wage ratio. See, Smith and Ward [1984].

initial real hourly wage as the dependent variable. The resulting coefficient estimates, with t-statistics in parentheses, are as follows:

TABLE 42

Estimated Starting Wages By Sex: First Jobs, Hours $\geq$ 30, 1979-1982

	Constant	Age	Educ.	Black	SMSA	Unem. Rate	R^2
Male:	.6251	.0196	.0410	-.0405	.0103	-.0075	.14
	(6.46)	(2.54)	(7.14)	(2.10)	(1.36)	(2.73)	
Female:	.4501	.0237	.0481	-.0635	.0257	-.0122	.16
	(4.96)	(3.13)	(6.79)	(3.41)	(3.53)	(4.73)	

These equations yielded estimated wages for white, high school graduates of \$4.94 for men and \$4.38 for women in 1983 dollars -- a ratio of 88.66%.[33] There estimates are noteworthy in a number of respects. First, for the group selected there happens to be relatively little difference between the female-male earnings ratio derived from comparing simple means or from the estimated wage equations. Second, a comparison with the previously presented wage estimates for white, high school graduates reveals that the female-male wage ratio has increased from 77.17% in 1968-1971 to 88.66% in 1979-1982. While these figures demonstrate that there has been considerable progress in the narrowing of the wage differential, the extent of this progress is somewhat

[33]The explanatory variables used in these wage estimations are the same as those used to estimate hazard rates in model (2) of Tables 29 and 30, with one exception. In estimating the beginning wage, I used the initial measure of the unemployment rate in the local labor market, rather than the measure closest to the end of the job. Moreover, to exclude outliers, I discarded hourly wage figures that were less than \$1 or greater than \$100. There were 1734 male workers and 1728 female workers included in these wage estimations.

overstated if one looks only at the mean wage figures.[34] In my study, a portion of the narrowing in the sex-based earnings differential based on a comparison of simple mean wages is caused by the greater mean age and education of female workers vis-a-vis male workers in 1979-1982; when one holds these factors constant through the regression comparison, the relative increase in women's earnings is necessarily less. Third, a comparison of the regression wage estimates for male and female white, high school graduates in the two time periods is instructive: in 1968-1971, $5.65 for men and $4.36 for women; in 1979-1982, $4.94 for men and $4.38 for women. Women's real wages are virtually unchanged in the two periods, but the real wages of male workers fell 12.6%. The female-male wage differential has been closing because male wages are dropping towards the levels previously experienced by women.

The elimination of a substantial portion of the sample for whom no wage is available counsels caution in interpreting these results. This sample reduction is caused by a feature in the NLS youth cohort interviewing procedure. Respondents were asked to give information on all the jobs they held in the past year, but only if the job lasted at least 9 weeks were they asked about their wage, occupation, industry, union status, etc. If, for example, the 9 week cutoff has excluded relatively more low-paid women, the ratio of female to male earnings could be artificially inflated. It turned out, however, that a relatively greater number of men were excluded by the 9 week rule: in both the 20 and 30 hour samples about 10% more men than women were

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[34]This suggests that one should interpret Smith and Ward's prediction of the strong trend towards equality in the sex-based wage differential, which is based on mean wage comparisons, with caution.

eliminated by this cut-off. Moreover, it is unlikely that a disproportionate number of high paid males were eliminated by this cutoff, assuming that the jobs that are left most quickly tend to be rather low paying.

4.7.1.2 Is Aggregation Still Permissible?

It was earlier established that aggregation of male and female workers was permissible in estimating hazard rates. I have just demonstrated, however, that male and female wages are not equal for the 1979-1982 period. Conceivably, the relationship between tenure and wage could differ enough for men and women that the inclusion of wage as an explanatory variable could reverse the previous finding concerning the propriety of pooling the male and female samples. As Table 43 indicates, however, this did not prove to be the case: likelihood ratio tests performed on both the 20 hour and 30 hour samples confirmed in every case that aggregation was permissible when wage was added to the standard models previously employed.

TABLE 43

Likelihood Ratio Tests for Pooling Male and Female Workers

A. Wage Included, $\geq$ 20 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	6.35	10	15.99	18.31
2	11.27	11	17.28	19.68
3	13.40	12	18.55	21.03
4	13.37	13	19.81	22.36
5	15.46	14	21.06	23.68

B. Wage Included, $\geq$ 30 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	5.79	10	15.99	18.31
2	11.09	11	17.28	19.68
3	11.95	12	18.55	21.03
4	16.66	13	19.81	22.36
5	17.30	14	21.06	23.68

NOTES: These models are set forth in Tables 44 and 45.

[1] The test statistic is constructed as 2 times the absolute value of the difference between the log likelihood statistic for the partitioned sample and the log likelihood statistic for the aggregated sample.

[2] The number of degrees of freedom is the number of restrictions imposed by partioning the sample into separate male and female subsamples. In estimating the aggregated sample, I have included a sex dummy, which therefore allows the implicit constant term to vary for men and women. The remaining slope coefficients are constrained to be the same in the aggregated model, and it is the number of these slope coefficients that determines the degrees of freedom for each model.

4.7.1.3 The Results of the Estimated Hazard Rates Including Wage

In the past, the greater representation of women in low-paid jobs meant that efforts to control for job characteristics such as wage or occupation would necessarily reduce the "tenure gap" between men and women. Consequently, for the period 1968-1971, including the wage variable in my estimation reduced the amount by which female hazard rates exceeded male hazard rates; the hazard rate for women remained statistically greater than that for men, but the difference was substantially reduced.[35]

Tables 44 and 45, which present the coefficient estimates for the pooled models with wage added to the vector of explanatory variables, show that this pattern no longer holds. Rather than narrowing the tenure gap between the sexes, the inclusion of wage in this later sample had the opposite effect: for the first time in the 1979-1982 sample, the SEX coefficient became significant for models in both the 20 and 30 hour data sets.[36] Moreover, <u>men have the significantly higher quit rates</u>, by roughly 10% for the 20 hour data set and 17% for the 30 hour data set. Given the previous findings that male and female hazard rates are similar, this result is at first surprising. But it is quite predictable since women have lower wages than men.[37]

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[35]Compare Tables 19 and 23 in Chapter 3.

[36]When layoffs were treated as completed spells, the coefficient on the SEX dummy became positive and significant for the 30 hour data set but not for the 20 hour data set. See Table 38 and 39.

[37]If (1) wages are inversely correlated with quit rates, and (2) men and women have the same mean quit rates but men have higher wages, then (3) including wage as a covariate will make it appear that men have higher quit rates.

TABLE 44

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates For First Jobs.
Hours $\geq$ 20, Wage Included, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03054 (.02202)	-.0293 (.02226)	-.03088 (.02229)	-.0532* (.02116)	-.05398* (.02116)
Education in years	-.01222 (.02036)	-.01451 (.02055)	-.0121 (.02063)		
Education =12 years				-.06034 (.05331)	-.05778 (.05334)
Education =13-15 y.				.02948 (.08595)	.0360 (.08601)
Education $\geq$16 y.				.09947 (.1336)	.1094 (.1337)
Black	.1276* (.04935)	.1176* (.05019)	.1032* (.05146)	.1304* (.05033)	.1146* (.05166)
Unempl.[1] rate	-.1500* (.007638)	-.1532* (.007891)	-.1533* (.007895)	-.1530* (.007905)	-.1532* (.007909)
NSMSA[2]		.0411 (.05177)	.1179 (.08012)	.04566 (.05184)	.1277 (.08001)
SMSA[3]			.03981 (.03153)		.0426 (.03145)
Sex	.1008* (.04351)	.08187** (.04414)	.08154** (.04413)	.08714* (.04399)	.08631* (.04398)
Wage[4]	-.1908* (.01553)	-.1898* (.01575)	-.1904* (.01574)	-.1928* (.01575)	-.1934* (.01574)

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at .10 level.
[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.
[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).
[3]SMSA (index 0-3) with 3 = SMSA, central city.
[4]Real wage in 1983 dollars.

Table 44 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.578 (.2656)	-3.556 (.2694)	-3.625 (.2750)	-3.264 (.3756)	-3.327 (.3783)
3-6 Months	-3.058 (.2664)	-3.065 (.2703)	-3.134 (.2758)	-2.772 (.3768)	-2.835 (.3795)
6-12 Months	-3.499 (.2682)	-3.485 (.2719)	-3.554 (.2774)	-3.193 (.3777)	-3.255 (.3804)
12-18 Months	-3.624 (.2742)	-3.601 (.2779)	-3.670 (.2833)	-3.309 (.3814)	-3.371 (.3841)
18-24 Months	-3.794 (.2833)	-3.769 (.2871)	-3.839 (.2924)	-3.478 (.3883)	-3.541 (.3910)
24- Months	-4.105 (.2912)	-4.075 (.2949)	-4.143 (.2999)	-3.777 (.3926)	-3.839 (.3952)
n	3698	3631	3631	3631	3631
-ln likeli.	15808.91	15446.60	15445.8	15445.22	15444.31
Chi-square	940.74*	914.56*	916.15*	917.32*	919.15*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 45

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates For First Jobs.
Hours ≥ 30, Wage Included, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03933** (.02313)	-.03493 (.02336)	-.03597 (.02338)	-.07097* (.02256)	-.07117* (.02254)
Education in years	-.01658 (.02132)	-.01929 (.02148)	-.01738 (.02157)		
Education =12 years				-.02941 (.05692)	-.02668 (.05697)
Education =13-15 y.				.1145 (.09103)	.1194 (.09107)
Education ≥16 y.				.08436 (.1420)	.09032 (.1421)
Black	.07888 (.05321)	.05975 (.05414)	.04747 (.05548)	.06952 (.05426)	.05553 (.05568)
Unempl.[1] rate	-.1599* (.008195)	-.1653* (.008465)	-.1655* (.008471)	-.1645* (.008478)	-.1647* (.008485)
NSMSA[2]		.1182* (.05436)	.1834* (.08425)	.1210* (.05441)	.1928* (.08414)
SMSA[3]			.03392 (.03332)		.03741 (.03325)
Sex	.1642* (.04616)	.1477* (.04670)	.1476* (.04669)	.1597* (.04669)	.1591* (.04668)
Wage[4]	-.2026* (.01662)	-.2004* (.01681)	-.2008* (.01680)	-.2044* (.01682)	-.2047* (.01681)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

[4]Real wage in 1983 dollars.

Table 45 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.380 (.2838)	-3.423 (.2878)	-3.486 (.2944)	-2.982 (.4012)	-3.047 (.4051)
3-6 Months	-2.825 (.2844)	-2.880 (.2884)	-2.943 (.2949)	-2.439 (.4024)	-2.503 (.4062)
6-12 Months	-3.240 (.2865)	-3.289 (.2904)	-3.351 (.2968)	-2.849 (.4037)	-2.913 (.4075)
12-18 Months	-3.395 (.2927)	-3.436 (.2966)	-3.499 (.3030)	-2.998 (.4078)	-3.063 (.4116)
18-24 Months	-3.573 (.3006)	-3.603 (.3043)	-3.667 (.3106)	-3.169 (.4131)	-3.234 (.4169)
24- Months	-3.843 (.3060)	-3.881 (.3099)	-3.943 (.3158)	-3.448 (.4157)	-3.511 (.4194)
n	3559	3503	3503	3503	3503
-ln likeli.	14361.6	14082.2	14081.68	14080.78	14080.15
Chi-square	939.39*	922.17*	923.21*	925.01*	926.27*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

The inclusion of the wage variable virtually eliminated the significance of age and education. This is to be expected in light of the well established correlation of these human capital proxies with earnings. It is also interesting to note that the size and significance of the BLACK dummy coefficients were substantially higher for the 20 hour sample -- where blacks showed a roughly 11-14% higher hazard rate -- than for the 30 hour sample, where the racial differential was only half as high. One cannot attribute this finding solely to the inclusion in the 20 hour sample of a substantial number of black workers with a tenuous attachment to the labor force, who are then excluded by the 30 hour definition of full employment. If this were the complete explanation, one would expect to see considerably higher coefficients on the BLACK dummy in the 20 hour sample than in the 30 hour sample when wage was not included as a covariate. But a comparison of the results of this estimation on the 20 and 30 hour samples in Tables 29 and 30 shows this not to be the case.[38] I suspect that the 20 hour sample includes a number of whites who are working at short duration minimum-wage jobs, while attending their final year of school. These whites and the "tenuous" black workers offset each other in the 20 hour data set leaving a value on the BLACK dummy of, say, x. Since the basic 30 hour model of Table 30 excludes both the "tenuous" black workers and the white minimum-wage student workers, this leaves the race coefficient x relatively unchanged. When one includes wage as an explanatory variable on the 20 hour sample, the higher quit rates for this group of white workers is attributed to their low wages rather than their race. As a

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[38]Those tables show that for both samples the coefficient estimates on the BLACK dummy are insignificant at even the .10 level.

result, the size of the BLACK dummy rises.

Note that the pattern of duration dependence when wage is included is never one of monotonic decline. Instead, the hazard rate is higher in the second period and then declines monotonically from this point on. This finding was caused by the "9-week cutoff" discussed above. Accordingly, a large number of very short jobs were eliminated from the sample when I employed wage as an explanatory variable. As a result the number of quits observed in the first three-month time interval, and therefore the quit rate for this interval, were artificially reduced. This pattern is repeated in every case where the inclusion of the particular variable led to exclusion of all jobs with duration less than nine weeks.[39]

4.7.2 Occupational Variables

Analysts frequently have controlled for occupation in estimating hazard rates.[40] While many different approaches are possible, I chose to create two occupational dummies that identified (1) professional, technical, and managerial workers, and (2) blue collar workers.[41]

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[39]It is for this reason that I did not use the Gompertz model in any of these estimations. Had I done so, the low initial hazard rates caused by the exclusion of these short-duration jobs would have affected the entire estimated pattern of duration dependence. By using the step function estimation, I was able to confine the effects of this artificially lowered initial hazard to the first period.

[40]See Abraham and Farber [1986], Waite and Berryman [1985], and Blau and Kahn [1981].

[41]The first category included those listing three-digit census occupation codes from 1-195 (professional, technical, and kindred) or 201-245 (managers, officials, and proprietors). The second category included occupation codes 601-715 (operatives and kindred) plus 740-785 (nonfarm laborers). Both dummies were defined with reference to the

The proportion of workers who were professional, technical, or managerial was about the same for the male and female samples: in the 20 hour sample, 9.2% of the men and 9.6% of the women were included in this category. The respective percentages in the 30 hour sample were 10.1% for men and 10.9% for women. Men did dominate the blue collar category, however. In the 20 hour sample, 35.7% of the men and only 11.7% of the women were laborers. In the 30 hour sample, the figures were 38.2% of the men and only 12.9% of the women. Clearly, then, gender still has a strong effect on occupational selection in this category.

Tables 46 and 47 present the results of the hazard rate estimations with these two occupational dummies added to the basic models. For both the 20 and 30 hour samples, the coefficient on the SEX dummy is insignificant. Once again, it follows the fairly typical pattern that, in moving from the 20 to the 30 hour sample, quit rates fall relatively more for women than for men.

Being a member of either of these two occupational categories tended to lower quit rates, although for the laborers, who made up 23.6% of the combined male-female 20 hour sample and 25.68% of the combined 30 hour sample, this effect was not statistically significant. As expected, however, professional and managerial workers -- comprising 9.5% of the 20 hour sample and 10.7% of the 30 hour sample -- had a highly significant lower rate of job quitting. Their rates tend to be in the range of 35-40% below those of the omitted category of workers.

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first measure of occupation after the start of the job.

To give a clearer indication of the effect of a 40% reduction in a hazard rate consider model (5) of the 30 hour sample (Table 47). The mean rate for this sample of 3653 workers is .0017734, which translates into an expected tenure of 18.5 months.[42] If this rate were to be reduced by 39.74% -- which is the amount that the coefficient on the dummy for professional and managerial workers reduces the hazard in model (5) -- this would yield a rate of .0010686 and an expected tenure of 30.7 months. In other words, a 40% reduction in the mean hazard rate raised the expected tenure from a year and a half to over two and one-half years -- an increase of roughly 66%.

[42]To be more precise, the rate presented in the text is the estimated rate on the assumption that all individuals have an identical, time-invariant hazard. The reciprocal of this rate yields the expected duration in days, which I then converted to months by dividing by 30.5.

TABLE 46

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates Including Occupational Variables. First Jobs, Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04945* (.02137)	-.04733* (.02161)	-.04814* (.02165)	-.07239* (.02059)	-.07287* (.02059)
Education in years	-.03441** (.01973)	-.03607** (.01990)	-.03498** (.01997)		
Education =12 years				-.1105* (.05199)	-.1090* (.05203)
Education =13-15 y.				-.06984 (.08268)	-.0666 (.07349)
Education ≥16 y.				.02701 (.1330)	.0313 (.1132)
Black	.1329* (.04842)	.1256* (.04919)	.1186* (.05037)	.1398* (.04926)	.1316* (.0505)
Unempl.[1] rate	-.1440* (.00657)	-.1484* (.007638)	-.1484* (.007639)	-.1485* (.007652)	-.1485* (.007653)
NSMSA[2]		.08986** (.05043)	.1282** (.07816)	.09398** (.05049)	.13780** (.07805)
SMSA[3]			.01988 (.03088)		.02273 (.03080)
Sex	-.00367 (.04350)	-.02332 (.04408)	-.02403 (.04409)	-.01900 (.04397)	-.02001 (.04399)
Prof'n'l, Techn., Mgr.	-0.4202* (.08427)	-0.4178* (.08537)	-0.4181* (.08537)	-0.4763* (.08883)	-0.4764* (.08885)
Laborer	-0.06421 (.05180)	-0.06357 (.05271)	-0.06198 (.05277)	-0.06020 (.05279)	-0.05839 (.05285)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 46 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.728 (0.2666)	-3.729 (.2705)	-3.764 (.2758)	-3.639 (.3655)	-3.674 (.3684)
3-6 Months	-3.238 (0.2674)	-3.266 (.2713)	-3.300 (.2766)	-3.174 (.3666)	-3.208 (.3695)
6-12 Months	-3.690 (0.2689)	-3.698 (.2727)	-3.732 (.2779)	-3.606 (.3674)	-3.641 (.3702)
12-18 Months	-3.840 (0.2748)	-3.840 (.2786)	-3.874 (.2838)	-3.748 (.3711)	-3.783 (.3740)
18-24 Months	-4.059 (0.2843)	-4.057 (.2881)	-4.092 (.2932)	-3.965 (.3783)	-4.000 (.3812)
24- Months	-4.427 (0.2843)	-4.420 (.2956)	-4.455 (.3004)	-4.318 (.3823)	-4.353 (.3852)
n	3863	3796	3796	3796	3796
-ln likeli.	16999.72	16213.71	16213.52	16212.42	16212.15
Chi-square	842.84	821.72	822.13	824.29	824.84
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 47

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates Including Occupational Variables. First Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.05936* (.02244)	-.05416* (.02269)	-.05489* (.02272)	-.09237* (.02194)	-.09257* (.02193)
Education in years	-.05186** (.02073)	-.04166** (.02089)	-.04036** (.02098)		
Education =12 years				-.09183** (.05553)	-.08973 (.05558)
Education =13-15 y.				.002477 (.08764)	.00609 (.08770)
Education $\geq$16 y.				.02520 (.1327)	.02961 (.1421)
Black	.08593** (.05225)	.07229 (.05307)	.06420 (.05435)	.08552 (.05313)	.07563 (.05447)
Unempl.[1] rate	-.1565* (.007963)	-.1632* (.008203)	-.1632* (.008204)	-.1627* (.008215)	-.1628* (.008217)
NSMSA[2]		.1670* (.05273)	.2102* (.08213)	.1708** (.05276)	.2224* (.08200)
SMSA[3]			.02251 (.03269)		.02688 (.03261)
Sex	.05230 (.04611)	.03557 (.04659)	.03513 (.04658)	.04455 (.04558)	.04376 (.04660)
Prof'n'l, Techn., Mgr.	-0.4463* (.08717)	-0.4503* (.08838)	-0.4518* (.08842)	-0.5055* (.09276)	-0.5066* (.09283)
Laborer	-0.07104 (.05355)	-0.07721 (.05427)	-0.07590 (.05431)	-0.07184 (.05437)	-0.07032 (.05440)

Notes: * Significant at .05 level. (Standard errors in parentheses.)

** Significant at the .10 level.

[1] The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2] NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3] SMSA (index 0-3) with 3 = SMSA, central city.

Table 47 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.528 (.2862)	-3.594 (.2904)	-3.637 (.2971)	-3.343 (.3908)	-3.390 (.3948)
3-6 Months	-2.997 (.2867)	-3.075 (.2909)	-3.117 (.2975)	-2.823 (.3918)	-2.870 (.3958)
6-12 Months	-3.422 (.2886)	-3.493 (.2927)	-3.536 (.2993)	-3.242 (.3931)	-3.289 (.3971)
12-18 Months	-3.579 (.2945)	-3.661 (.2986)	-3.704 (.3052)	-3.421 (.3970)	-3.459 (.4010)
18-24 Months	-3.824 (.3027)	-3.877 (.3065)	-3.920 (.3130)	-3.631 (.4027)	-3.678 (.4066)
24- Months	-4.156 (.3080)	-4.217 (.3120)	-4.259 (.3181)	-3.967 (.4050)	-4.013 (.4088)
n	3708	3653	3653	3653	3653
-ln likeli.	15033.84	14756.44	14756.20	14756.29	14755.95
Chi-square	846.91	838.85	839.32	839.13	839.81
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

The inclusion of the occupational dummies tends to weaken the effect of education on the hazard rate, particularly at the higher levels. This is undoubtedly due to the high correlation between high education and being a professional or manager. The effect is so pronounced that the educational dummy representing individuals with at least a college education becomes positive, albeit insignificant. As when wage was included as a covariate, the coefficient on the BLACK dummy is almost twice as high on the 20 hour sample as on the 30 hour sample. Finally, as discussed with reference to the estimations that included wages, the pattern of time dependence becomes nonmonotonic because the sample excluded all those with jobs lasting less than nine weeks.

4.7.3 Unionization

Another common explanatory variable in quit rate studies is union status or membership in a collective bargaining unit. The NLS provides information on whether the respondent's wages were set by collective bargaining and once again, I decided to examine its influence subject to the same caveats about endogeneity that were expressed above with reference to wage and occupation. In the 20 hour sample, 17.1% of the men and 13.6% of the women were members of collective bargaining units. The numbers were quite similar in the 30 hour data set: 17.7% for men and 14.7% for women.

Tables 48 and 49 present the hazard rate estimations for the 20 and 30 hour data sets. As one might expect, unionization is associated with significantly lower quit rates in both samples -- 17-19% lower in the 20 hour data set and 15-17% lower in the 30 hour data set. In both cases, the coefficient on the SEX dummy is insignificant, although there is a reversal in sign between the two estimations -- men have slightly lower rates for the 20 hour data set, while women have the lower rates in the 30 hour data set. This same pattern was observed in the previous subsection, when controlling for the two occupational dummies. Blacks have significantly higher quit rates than nonblacks, especially in the 20 hour data set.

TABLE 48

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates Including Collective Bargaining Control. First Jobs, Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.05273* (.02228)	-.05071* (.02255)	-.05196* (.02259)	-.08098* (.02106)	-.08157* (.02106)
Education in years	-.04902* (.02067)	-.04937* (.02088)	-.04776* (.02095)		
Education =12 years				-.07136 (.05383)	-.06896 (.05387)
Education =13-15 y.				-.04972 (.08553)	-.04529 (.08557)
Education ≥16 y.				-.1379 (.1335)	-.1332 (.1335)
Black	.1594* (.05026)	.1495* (.05115)	.1393* (.05229)	.1595* (.05126)	.1474* (.05248)
Unempl.[1] rate	-.1435* (.007643)	-.1490* (.007909)	-.1490* (.007911)	-.1489* (.007917)	-.1489* (.007919)
NSMSA[2]		.1059* (.05160)	.1645** (.08067)	.1118* (.05169)	.1783* (.08059)
SMSA[3]			.03038 (.03201)		.03457 (.03197)
Sex	-.01114 (.04333)	-.03269 (.04390)	-.03323 (.04390)	-.02234 (.04381)	-.02321 (.04382)
Collective Bargain.	-.2091* (.06127)	-.1920* (.06215)	-.1950* (.06223)	-.1902* (.06219)	-.1936* (.06228)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 48 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.531 (.2644)	-3.544 (.2687)	-3.595 (.2741)	-3.527 (.3739)	-3.582 (.3772)
3-6 Months	-3.021 (.2655)	-3.064 (.2698)	-3.115 (.2752)	-3.048 (.3752)	-3.102 (.3785)
6-12 Months	-3.487 (.2674)	-3.509 (.2716)	-3.560 (.2769)	-3.494 (.3762)	-3.548 (.3794)
12-18 Months	-3.626 (.2734)	-3.641 (.2775)	-3.692 (.2829)	-3.627 (.3799)	-3.682 (.3831)
18-24 Months	-3.886 (.2838)	-3.899 (.2879)	-3.951 (.2932)	-3.889 (.3876)	-3.944 (.3909)
24- Months	-4.231 (.2913)	-4.237 (.2953)	-4.288 (.3003)	-4.221 (.3916)	-4.275 (.3948)
n	3626	3562	3562	3562	3562
-ln likeli.	15568.12	15211.06	15210.61	15212.69	15212.11
Chi-square	799.09*	778.09*	778.99*	774.83*	775.99*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 49

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates Including Collective Bargaining Control.
First Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.05918* (.02339)	-.05383* (.02365)	-.05479* (.02368)	-.09897* (.02245)	-.09917* (.02244)
Education in years	-.05979* (.02161)	-.06098* (.02181)	-.05951* (.02188)		
Education =12 years				-.04282 (.05718)	-.03994 (.05724)
Education =13-15 y.				.02444 (.09044)	.02878 (.09047)
Education $\geq$16 y.				-.1647 (.1410)	-.1615 (.1410)
Black	.1228* (.05386)	.1043** (.05483)	.09407** (.05611)	.1136* (.05490)	.1003** (.05628)
Unempl.[1] rate	-.1561* (.008182)	-.1631* (.008437)	-.1632* (.008439)	-.1627* (.008440)	-.1628* (.008443)
NSMSA[2]		.1741* (.05382)	.2301* (.08460)	.1803* (.05388)	.2499* (.08451)
SMSA[3]			.02913 (.03381)		.03634 (.03378)
Sex	.04154 (.04568)	.02167 (.04615)	.02137 (.04615)	.04121 (.04620)	.04054 (.04620)
Collective Bargain.	-.1839* (.06384)	-.1673* (.06448)	-.1688* (.06451)	-.1643* (.06455)	-.1660* (.06458)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 49 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.347 (.2823)	-3.422 (.2867)	-3.475 (.2931)	-3.287 (.4001)	-3.352 (.4043)
3-6 Months	-2.800 (.2832)	-2.885 (.2875)	-2.938 (.2939)	-2.752 (.4013)	-2.816 (.4055)
6-12 Months	-3.233 (.2854)	-3.312 (.2897)	-3.364 (.2960)	-3.181 (.4028)	-3.246 (.4069)
12-18 Months	-3.398 (.2915)	-3.471 (.2957)	-3.524 (.3021)	-3.343 (.4066)	-3.408 (.4108)
18-24 Months	-3.638 (.3002)	-3.699 (.3041)	-3.753 (.3103)	-3.577 (.4124)	-3.643 (.4166)
24- Months	-3.957 (.3056)	-4.023 (.3097)	-4.075 (.3155)	-3.904 (.4149)	-3.968 (.4190)
n	3500	3446	3446	3446	3446
-ln likeli.	14240.07	13958.72	13958.35	13960.74	13960.17
Chi-square	796.26*	785.96*	786.71*	781.92*	783.07*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.7.4 Including Wage, Occupation, and Collective Bargaining Status

To summarize the results of the three previous estimations, I decided to mimic the Appendix I studies by including wage, occupation, and collective bargaining status simultaneously. The results of this estimation are presented in Tables 50 and 51. This exercise demonstrates that the wage variable drives the results when adding these controls for job characteristics. Each increase of $1 in starting real hourly wage is associated with a roughly 16% decrease in the hazard rate. As in the case when only wage was added to the basic model, the coefficient on the SEX variable becomes significantly positive, reflecting higher male quit rates of from 9-11% on the 20 hour data set and 16-18% on the 30 hour data set.

The inclusion of the wage variable deprives the unionization variable of its significance, and eliminates the explanatory power of the education variables, which become either insignificant, or in the case of the highest level of education, positive. The coefficient on the BLACK dummy is positive in both cases, but statistically significant only for the 20 hour data set.

In conclusion, while it is not at all clear that the job characteristics controls represent suitable exogenous explanatory variables, their inclusion does not undermine the contention that female hazard rates have fallen vis-a-vis male hazard rates over the time periods analyzed in this study.

TABLE 50

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates Including Wage and Other Controls.
First Jobs, Hours $\geq$ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.02371 (.02266)	-.02238 (.02292)	-.02429 (.02296)	-.04485* (.02148)	-.04565* (.02148)
Education in years	-.0005862 (.02166)	-.00186 (.02188)	.001073 (.02199)		
Education =12 years				-.04172 (.05502)	-.03842 (.05506)
Education =13-15 y.				.05471 (.08761)	.06146 (.08765)
Education $\geq$16 y.				.2472** (.1385)	.2585** (.1387)
Black	.1075* (.05116)	.0965** (.05212)	.0811 (.05339)	.1090* (.05218)	.09233** (.05352)
Unempl.[1] rate	-.1494* (.007820)	-.1526* (.008060)	-.1527* (.008064)	-.1525* (.008071)	-.1526* (.008076)
NSMSA[2]		.03989 (.05297)	.1223 (.08172)	.04311 (.05306)	.1295 (.08156)
SMSA[3]			.04317 (.03240)		.04534 (.03229)
Sex	.1066* (.04598)	.08604** (.04663)	.08494** (.04664)	.09016** (.04657)	.08850** (.04659)
Collective Bargain.	-.08035 (.06310)	-.06288 (.06394)	-.06871 (.06408)	-.05681 (.06394)	-.06289 (.06408)
Prof'n'l, Techn, Mgr.	-.3463* (.08654)	-.3472* (.08774)	-.3492* (.08774)	-.3986* (.09049)	-.4003* (.09048)
Laborer	.01021 (.05483)	.01313 (.05584)	.01748 (.05594)	.01639 (.05586)	.02074 (.05595)
Wage[4]	-.1705* (.01503)	-.1699* (.01527)	-.1701* (.01524)	-.1725* (.01522)	-.1726* (.01520)

Table 50 (cont'd)

B. Time Parameters[5]

	1	2	3	4	5
0-3 Months	-3.917 (.2768)	-3.908 (.2807)	-3.986 (.2868)	-3.513 (.3822)	-3.583 (.3853)
3-6 Months	-3.382 (.2773)	-3.403 (.2813)	-3.480 (.2873)	-3.005 (.3833)	-3.075 (.3864)
6-12 Months	-3.817 (.2789)	-3.819 (.2827)	-3.895 (.2887)	-3.420 (.3842)	-3.489 (.3872)
12-18 Months	-3.929 (.2847)	-3.922 (.2886)	-3.999 (.2946)	-3.523 (.3880)	-3.593 (.3911)
18-24 Months	-4.160 (.2949)	-4.152 (.2989)	-4.230 (.3047)	-3.752 (.3957)	-3.823 (.3988)
24- Months	-4.503 (.3032)	-4.486 (.3071)	-4.563 (.3127)	-4.080 (.4005)	-4.150 (.4036)
n	3529	3466	3466	3466	3466
-ln likeli.	15056.53	14709.00	14708.11	14706.20	14705.21
Chi-square	924.78*	897.53*	899.30*	903.13*	905.10*
Monotonic[6]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

[4]Real wage in 1983 dollars.

[5]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[6]Identifies whether the hazard rate declines monotonically.

TABLE 51

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates Including Wage and Other Controls. First Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03054 (.02377)	-.02731 (.02401)	-.02862 (.02404)	-.06289* (.02285)	-.06311* (.02284)
Education in years	-.000224 (.02282)	-.001518 (.02302)	.001042 (.02312)		
Education =12 years				-.0009006 (.05847)	.002584 (.05853)
Education =13-15 y.				.1482 (.09275)	.1535** (.09275)
Education $\geq$16 y.				.2924* (.1474)	.3014* (.1476)
Black	.06235 (.05483)	.04660 (.05580)	.03117 (.05727)	.05700 (.05582)	.04019 (.05736)
Unempl.[1] rate	-.1597* (.008348)	-.1649* (.008601)	-.1650* (.008608)	-.1643* (.008612)	-.1644* (.008620)
NSMSA[2]		.1142* (.05540)	.1924* (.08582)	.1175* (.05546)	.2005* (.08568)
SMSA[3]			.04099 (.03414)		.04355 (.03403)
Sex	.1721* (.04858)	.1535* (.04913)	.1526* (.04913)	.1643* (.04919)	.1629* (.04919)
Collective Bargain.	-.03115 (.06574)	-.01559 (.06632)	-.01905 (.06638)	-.007235 (.06636)	-.01085 (.06641)
Prof'n'l, Techn, Mgr.	-.3722* (.08968)	-.3777* (.09100)	-.3807* (.09105)	-.4272* (.09447)	-.4299* (.09456)
Laborer	.01211 (.05665)	.009746 (.05745)	.01273 (.05750)	.01565 (.05746)	.01845 (.05749)
Wage[4]	-.1836* (.01592)	-.1812* (.01614)	-.1811* (.01611)	-.1855* (.01608)	-.1853* (.01605)

Table 51 (cont'd)

B. Time Parameters[5]

	1	2	3	4	5
0-3 Months	-3.821 (.2964)	-3.861 (.3005)	-3.941 (.3079)	-3.247 (.4076)	-3.325 (.4119)
3-6 Months	-3.246 (.2966)	-3.299 (.3007)	-3.379 (.3080)	-2.681 (.4087)	-2.759 (.4129)
6-12 Months	-3.647 (.2984)	-3.694 (.3024)	-3.773 (.3096)	-3.076 (.4100)	-3.154 (.4142)
12-18 Months	-3.787 (.3044)	-3.829 (.3085)	-3.909 (.3158)	-3.212 (.4142)	-3.290 (.4184)
18-24 Months	-4.002 (.3130)	-4.033 (.3169)	-4.114 (.3240)	-3.418 (.4199)	-3.497 (.4242)
24- Months	-4.317 (.3191)	-4.354 (.3232)	-4.433 (.3300)	-3.739 (.4233)	-3.816 (.4274)
n	3412	3360	3360	3360	3360
-ln likeli.	13773.78	13508.56	13507.84	13505.69	13504.87
Chi-square	927.10*	910.21*	911.65*	915.94*	917.58*
Monotonic[6]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

[4]Real wage in 1983 dollars.

[5]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[5]Identifies whether the hazard rate declines monotonically.

4.8 Correcting For Unobserved Heterogeneity

Thus far in discussing the results for the 1979-1982 period I have assumed that the included explanatory variables adequately captured the heterogeneity in quit probabilities among the workers in the sample. As discussed in Chapter 3, however, it is conceivable that certain variables that affect the hazard probabilities have been omitted. Some of these influences may in fact be unobservable, so there is little likelihood that an analyst can hope to control for these effects by simply searching through the NLS codebooks for additional variables. As I had previously done in my analysis of the 1968-1971 period, I estimated a time-varying hazard rate on the assumption that the unobserved variation within the subgroups defined by the explanatory variables could be approximated by a gamma distribution. The results of these estimations for the 20 and 30 hour data sets are presented in Tables 52 and 53.

To my surprise, however, the coefficient estimates and time parameters were virtually identical with and without the correction for unobserved heterogeneity. I report the variance of the gamma distributed terms modelling the unobserved heterogeneity in Tables 52 and 53. In all cases, this variance is miniscule and totally insignificant. Indeed this variance is orders of magnitude smaller than the variance measured in correcting for unobserved heterogeneity in the 1968-1971 data set. Two possibilities exist to explain these results: (1) the model is well specified without the correction for unobserved heterogeneity, and there is little variation in hazard rates within the subgroups; or (2) the unobserved heterogeneity that exists in this sample is not adequately captured by a gamma distributed set of multiplicative errors. Heckman and Singer's work suggests that the results derived from corrections for unobserved heterogeneity can be sensitive to the parametric representations adopted. Heckman and Singer [1984a]. Where the particular representation does not fit the data well, the correction may be unsuccessful. In light of the virtual identity of results with the basic model presented in Tables 29 and 30, there is little need to comment on the results of this correction, except to note that the SEX coefficient remains wholly insignificant.[43]

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[43]It is also possible that the convergence program improperly signalled convergence for these estimations.

TABLE 52

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rate Given Unobserved Heterogeneity. First Jobs, Hours ≥ 20, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04846* (.01862)	-.04341* (.01884)	-.04278* (.01887)	-.06824* (.01797)	-.06803* (.01797)
Education in years	-.04814* (.01697)	-.05183* (.01712)	-.05264* (.01717)		
Education =12 years				-.1176* (.04592)	-.1184* (.04595)
Education =13-15 y.				-.09884 (.07341)	-.1004 (.07350)
Education ≥16 y.				-.1846 (.1144)	-.1866 (.1145)
Black	.09747* (.04280)	.08104** (.04372)	.08682** (.04477)	.09162* (.04388)	.09626* (.04497)
Unempl.[1] rate	-.1374* (.006573)	-.1430* (.006818)	-.1430* (.006818)	-.1430* (.006827)	-.1430* (.006827)
NSMSA[2]		.0864** (.04432)	.05505 (.06838)	.0931* (.04437)	.06860 (.06828)
SMSA[3]			-.01634 (.02720)		-.0128 (.02716)
Sex	-.00661 (.03695)	-.02645 (.03749)	-.02620 (.03749)	-.01919 (.03736)	-.01889 (.03737)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 52 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.106 (.2247)	-3.134 (.2283)	-3.106 (.2329)	-3.218 (.3185)	-3.198 (.3213)
3-6 Months	-3.178 (.2272)	-3.230 (.2308)	-3.202 (.2355)	-3.315 (.3207)	-3.295 (.3235)
6-12 Months	-3.643 (.2290)	-3.670 (.2325)	-3.642 (.2371)	-3.756 (.3215)	-3.736 (.3244)
12-18 Months	-3.784 (.2354)	-3.807 (.2389)	-3.779 (.2434)	-3.894 (.3255)	-3.874 (.3284)
18-24 Months	-4.020 (.2461)	-4.037 (.2495)	-4.009 (.2539)	-4.127 (.3336)	-4.107 (.3364)
24- Months	-4.367 (.2542)	-4.379 (.2575)	-4.351 (.2617)	-4.459 (.3382)	-4.439 (.3410)
n	4748	4647	4647	4647	4647
Variance	.0002797	.0002584	.0002603	.0002495	.0002506
-ln likeli.	20643.63	20106.18	20106.00	20107.15	20107.04
Chi-square	1175.58*	1158.30*	1158.66*	1156.36*	1156.58*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 53

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rate Given Unobserved Heterogeneity. First Jobs, Hours ≥ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.06083* (.01970)	-.05217* (.01993)	-.05198* (.01996)	-.08656* (.01930)	-.08656* (.01930)
Education in years	-.05669* (.01781)	-.06068* (.01796)	-.06097* (.01802)		
Education =12 years				-.08582** (.04913)	-.08584** (.04918)
Education =13-15 y.				-.07234 (.07880)	-.07238 (.07888)
Education ≥16 y.				-.1866 (.1211)	-.1866 (.1211)
Black	.09976* (.04589)	.07789** (.04690)	.07995** (.04800)	.08797** (.04707)	.08809* (.04823)
Unempl.[1] rate	-.1514* (.007121)	-.1600* (.007376)	-.1600* (.007375)	-.1598* (.007383)	-.1598* (.007383)
NSMSA[2]		.1749* (.04654)	.1636* (.07263)	.1799* (.04655)	.1793* (.07251)
SMSA[3]			-.005857 (.02909)		-.00035 (.02905)
Sex	.029631 (.03939)	.008204 (.03990)	.008241 (.03990)	.02061 (.03989)	.02062 (.03989)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 53 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-2.814 (.2420)	-2.911 (.2460)	-2.901 (.2515)	-2.935 (.3429)	-2.934 (.3466)
3-6 Months	-2.858 (.2446)	-2.959 (.2486)	-2.948 (.2541)	-2.983 (.3452)	-2.983 (.3489)
6-12 Months	-3.296 (.2468)	-3.386 (.2506)	-3.376 (.2561)	-3.413 (.3465)	-3.413 (.3501)
12-18 Months	-3.457 (.2531)	-3.544 (.2570)	-3.534 (.2624)	-3.573 (.3506)	-3.572 (.3543)
18-24 Months	-3.699 (.2625)	-3.770 (.2661)	-3.759 (.2713)	-3.802 (.3572)	-3.801 (.3608)
24- Months	-4.007 (.2682)	-4.084 (.2718)	-4.074 (.2768)	-4.113 (.3601)	-4.113 (.3636)
n	4456	4371	4371	4371	4371
Variance	.0003285	.0002983	.0002984	.0002836	.0002837
-ln likeli.	18493.25	18046.55	18046.53	18050.11	18050.11
Chi-square	1152.41*	1143.43*	1143.47*	1136.32*	1136.32*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.9 Examining the Nature of the Quit

In Chapter 3, I proposed that the reason for the observed nonmonotonic pattern of duration dependence for women in the period 1968-1971 was their increasing likelihood over time to leave the workforce for family reasons, such as pregnancy, which ultimately caused the first-job hazard rate to begin rising. For the period 1979-1982, however, there is no upturn in the female hazard, which in general is identical to that of men. To ascertain what effect, if any, that "family quits" have on the patterns of job turnover, I decided to decompose the previously estimated first job hazard rates into those departures that were caused by "family reasons" and all other departures.

In order to effect this decomposition, I first had to provide consistency across the different years of the survey, by reclassifying some of the responses concerning the reason that the individual left his or her job. In 1979, the NLS asked respondents who had ended a job, "Why did you happen to leave this job?" If more than one reason was offered, the individual was asked to specify "the one main reason." Among 13 coded responses, such as "laid off" and "fired," were: (1) "pregnancy," and (2) "family reasons (to get married, to care for children, illnes of other family members)."[44] In subsequent years, however, these two categories were combined into one: "quit for pregnancy or family reasons."[45] Accordingly, I recoded the two

[44]1979 Youth Survey Questionnaire, National Longitudinal Survey of Labor Force Experience, p. 88.

[45]See, for example, 1980 Youth Survey Questionnaire, National Longitudinal Survey of Labor Force Experience, p. ES-4.

categories in the 1979 survey into one category of "pregnancy or family quits."[46]

To implement this estimation using the 6 time-periods model that I have been employing, it is essential that a sufficient number of transitions for family reasons occur in each of the time intervals. Because the number of quits for family reasons is relatively small, I decided to estimate this model using a parametric assumption about the nature of the time dependence. Since the Gompertz model had previously given good estimates, I resorted to this model once again. The results of the seperate estimations on the 20 and 30 hour data sets for the two types of job exits -- family related and non-family related -- are presented in Tables 54, 55, 56, and 57.

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[46]As always, these categories are not entirely precise. An individual who leaves a job to care for an ailing family member might choose to hire someone to perform this function if his or her job is sufficiently remunerative and/or satisfying. Therefore, a departure coded as a "family quit" may in some cases be deemed a quit because of insufficient wages or other job dissatisfaction.

TABLE 54

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Gompertz Hazard Rates For First Jobs, Non-Family-Related Exits.
Hours ≥ 20, 1979-1982, All Workers

	1	2	3	4	5
Constant	-3.120*	-3.160*	-3.112*	-3.156*	-3.117*
	(.2293)	(.2331)	(.2379)	(.3258)	(.3288)
Age at start	-.05303*	-.04827*	-.04721*	-.07448*	-.07408*
	(.01906)	(.01930)	(.01932)	(.01838)	(.01839)
Education in years	-.04197*	-.04494*	-.04632*		
	(.01736)	(.01753)	(.01758)		
Education =12 years				-.0960*	-.09748*
				(.04697)	(.04700)
Education =13-15 y.				-.05511	-.05804
				(.07510)	(.07520)
Education ≥16 y.				-.1427	-.1464
				(.1170)	(.1171)
Black	.08062**	.06428	.07426	.07398**	.08291**
	(.04391)	(.04489)	(.04596)	(.04504)	(.04615)
Unempl.[1] rate	-.1390*	-.1452*	-.1452*	-.1452*	-.1452*
	(.006727)	(.006984)	(.006983)	(.006994)	(.006993)
NSMSA[2]		.1013*	.04734	.1077*	.06063
		(.04518)	(.06976)	(.04523)	(.06966)
SMSA[3]			-.02818		-.02461
			(.02788)		(.02783)
Sex	.06360**	.04524	.04568	.05353	.05413
	(.03777)	(.03832)	(.03832)	(.03819)	(.03820)
Tenure	-.001526*	-.001499*	-.001498*	-.001504*	-.001503*
	(.00009814)	(.00009889)	(.00009887)	(.00009906)	(.00009905)
n	4748	4647	4647	4647	4647
-ln likeli.	19896.25	19367.15	19366.64	19367.99	19367.60
Chi-square	1089.60*	1074.84*	1075.87*	1073.16*	1073.94*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TABLE 55

Maximum Likelihood Estimates of Hazard Rate Coefficients: Gompertz Hazard Rates For First Jobs, Family-Related Exits. Hours $\geq$ 20, 1979-1982, All Workers

	1	2	3	4	5
Constant	-5.917*	-5.910*	-6.273*	-7.712*	-8.009*
	(1.048)	(1.055)	(1.081)	(1.480)	(1.489)
Age at start	.07432	.08372	.07593	.04009	.03320
	(.08131)	(.08109)	(.08179)	(.08322)	(.08318)
Education in years	-.2421*	-.2568*	-.2472*		
	(.07195)	(.07119)	(.07243)		
Education =12 years				-.5460*	-.5273*
				(.2111)	(.2115)
Education =13-15 y.				-1.058*	-1.016*
				(.3485)	(.3482)
Education $\geq$16 y.				-1.007**	-.9572**
				(.5242)	(.5238)
Black	.4220*	.4036*	.3276**	.4412*	.3636**
	(.1904)	(.1926)	(.1980)	(.1943)	(.1995)
Unempl.[1] rate	-.1202*	-.1175*	-.1171*	-.1183*	-.1173*
	(.03031)	(.03116)	(.03121)	(.03122)	(.03124)
NSMSA[2]		-.1169	.2980	-.1055	.3198
		(.2180)	(.3377)	(.2180)	(.3373)
SMSA[3]			.2074**		.2129**
			(.1251)		(.1249)
Sex	-1.975*	-2.082*	-2.0868*	-2.063*	-2.067*
	(.2555)	(.2688)	(.2688)	(.2679)	(.2679)
Tenure	-.001096*	-.001058*	-.00107*	-.001026*	-.001041*
	(.0004125)	(.0004127)	(.0004127)	(.0004167)	(.0004165)
n	4748	4647	4647	4647	4647
-ln likeli.	1312.80	1290.824	1289.443	1290.876	1289.416
Chi-square	133.02*	137.77*	140.53*	137.66*	140.58*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TABLE 56

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Gompertz Hazard Rates For First Jobs, Non-Family-Related Exits.
Hours $\geq$ 30, 1979-1982, All Workers

	1	2	3	4	5
Constant	-2.752*	-2.863*	-2.834*	-2.782*	-2.764*
	(.2477)	(.2519)	(.2576)	(.3519)	(.3558)
Age at start	-.06999*	-.06101*	-.06051*	-.09708*	-.09701*
	(.02022)	(.02048)	(.02050)	(.01980)	(.01981)
Education in years	-.04932*	-.05306*	-.05383*		
	(.01827)	(.01844)	(.01849)		
Education =12 years				-.06917	-.06995
				(.05031)	(.05036)
Education =13-15 y.				-.02956	-.03081
				(.08082)	(.08091)
Education $\geq$16 y.				-.1304	-.1315
				(.1241)	(.1242)
Black	.07734	.05531	.06085	.06533	.06914
	(.04718)	(.04826)	(.04939)	(.04843)	(.04962)
Unempl.[1] rate	-.1520*	-.1612*	-.1612*	-.1609*	-.1609*
	(.007287)	(.007555)	(.007554)	(.007563)	(.007563)
NSMSA[2]		.1869*	.1568*	.1918*	.1717*
		(.04748)	(.07420)	(.04749)	(.07408)
SMSA[3]			-.01575		-.01049
			(.02985)		(.02980)
Sex	.1039*	.08352*	.08363*	.09658*	.09675*
	(.04036)	(.04087)	(.04088)	(.04086)	(.04087)
Tenure	-.001479*	-.001442*	-.001442*	-.001454*	-.001454*
	(.0001012)	(.0001017)	(.0001017)	(.0001018)	(.0001018)
n	4456	4371	4371	4371	4371
-ln likeli.	17780.68	17337.74	17337.60	17340.42	17340.36
Chi-square	1093.34*	1084.73*	1085.01*	1079.37*	1079.49*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TABLE 57

Maximum Likelihood Estimates of Hazard Rate Coefficients: Gompertz Hazard Rates For First Jobs, Family-Related Exits. Hours $\geq$ 30, 1979-1982, All Workers

	1	2	3	4	5
Constant	-6.728*	-6.674*	-6.946*	-8.459*	-8.706*
	(1.078)	(1.089)	(1.117)	(1.506)	(1.519)
Age at start	.1220	.1238	.1187	.08092	.07701
	(.08120)	(.08144)	(.08199)	(.08376)	(.08372)
Education in years	-.2432*	-.2495*	-.2415*		
	(.07249)	(.07221)	(.07328)		
Education =12 years				-.3662**	-.3499
				(.2204)	(.2209)
Education =13-15 y.				-.8739*	-.8392*
				(.3496)	(.3499)
Education ≥16 y.				-1.165*	-1.131*
				(.5322)	(.5324)
Black	.4659*	.4419*	.3922**	.4672*	.4111*
	(.1972)	(.1994)	(.2043)	(.2007)	(.2058)
Unempl.[1] rate	-.1485*	-.1498*	-.1498*	-.1514*	-.1512*
	(.03290)	(.03367)	(.03372)	(.03362)	(.03369)
NSMSA[2]		.02836	.3180	.02985	.3524
		(.2237)	(.3461)	(.2235)	(.3457)
SMSA[3]			.1455		.1625
			(.1299)		(.1297)
Sex	-1.886*	-1.935*	-1.935*	-1.910*	-1.911*
	(.2571)	(.2634)	(.2634)	(.2632)	(.2632)
Tenure	-.0008695*	-.0008541*	-.0008627*	-.0008544*	-.0008633*
	(.0004007)	(.0004006)	(.0004009)	(.0004033)	(.0004034)
n	4456	4371	4371	4371	4371
-ln likeli.	1221.001	1209.864	1209.235	1211.498	1210.712
Chi-square	120.38*	122.15*	123.41*	118.89*	120.46*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 54 estimates the exit rates from first jobs for the 20 hour data set when all family-related quits -- whether male or female -- are treated as censored spells. Accordingly, it measures the rate of quitting for all reasons other than "family related." The significant negative sign on the tenure coefficient indicates negative duration dependence, which is to be expected. The coefficient on the SEX dummy is insignificant in all cases except model (1), where it is positive and significant at the .10 level, indicating a higher quit rate for men. The other coefficient estimates are much the same as before, such as the education dummies, which again are insignificant at the high levels and depart from the predicted monotonically declining values.

Table 55 estimates the family-related exit rates from first jobs for the 20 hour data set. As one would expect, female workers quit at a much higher rate than male workers for "family-related" reasons -- the estimates indicate a male rate that is roughly 87 or 88% lower than the corresponding rate for females. This is not surprising in that an important "family-related" reason for quitting is pregnancy, which obviously increases the hazard rate only of women.

Being black and increased age tended to increase the probability of family-related exits for this sample, while increased education and high unemployment rates tended to decrease the quits for this reason. As one might expect, though, the influence of the unemployment rate was neither as significant nor as large for family-related quits as for other exits. This probably reflects the fact that at least some family-related exits are caused by emergencies that lead to quits without regard to the unemployment rate. Note that, while the probability of family-related exits declines with tenure, the decline is much less steep than that of the non-family related exits.[47]

Table 56 presents the estimated hazard rates for non-family related reasons for the 30 hour data set. While the results for this data set are broadly similar to those obtained in the 20 hour set, there are noteworthy changes in the coefficients on the race and sex dummies. In both data sets, men and blacks show higher quit rates for non-family related reasons. These higher rates are significant for the men only in the 30 hour data set, and for blacks only in the 20 hour data set. Thus, family responsibilities aside, male workers appear to be more mobile than women.

Table 57 presents the estimates for the family-related quit rates on the 30 hour data set. The estimates are quite similar to those for the 20 hour data set. Note, however, that the unemployment rate coefficient on the 30 hour data set is more significant and a larger negative number. This indicates that, when unemployment is high, the probability of quitting a job for family reasons is smaller for 30 hour jobs than for 20 hour jobs. Apparently, those with 30 hour jobs tend to be more sensitive to economic factors when deciding to give up 30 hour jobs than they would be if they only held the relatively less valuable 20 hour job.[48]

To obtain some sense of the magnitude of family-related quits, one

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[47]The absolute value of the tenure coefficient in Table 54 (non-family related exits) is roughly 50% greater than that of the tenure coefficient in 55 (family-related exits).

[48]An additional consideration may be that those who are most likely to have to quit for family reasons may be trying to balance their family demands by taking jobs with shorter working hours in the first instance. In this case, it is the pre-determined nature of family demands that makes the rate of family-related quits higher and less sensitive to the unemployment rate.

should note the following two results. First, the earlier analysis showed that aggregate first-job quit rates are virtually identical for men and women in both the 20 and 30 hour data sets. Second, the decomposition of the hazard rates according to the nature of the quits shows that women quit for family related reasons at a much higher rate than men in both the 20 and 30 hour data sets. If family quits constituted a sizeable portion of total quits, then these two facts would imply that non-family related quits would be significantly higher for men than for women. Nonetheless, this conclusion is true only for the 30 hour data set, which demonstrates the relatively small contribution to the overall hazard that occurs from family-related quits.[49] Since terminations prompted by pregnancy constitute only a subset of the total number of family-related quits for women, the effect of pregnancy on the job exit rates for the young women in this sample is quite small.[50]

4.10 An Examination of All Jobs

The finding of the equality in first-job hazard rates among women and men in the 1979-1982 period constituted a dramatic shift from the

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[49]As noted in Table 37, for the 30 hour sample in 1979-1982, 3.8% of the jobs that have ended were terminated for family-related reasons. The percentages by sex were 6.88% for women (108 cases) and 1.01% for men (17 cases).

[50]It is possible that some women who take pregnancy leave are back on the job before they are next interviewed. For example, a woman interviewed in January, 1979 might have taken a pregnancy leave in March and then returned to work before being interviewed in January, 1980. In this case, the analyst would never know of the job interruption and the employment would be deemed constant for purposes of estimating durations.

earlier period. Would this result persist, however, if one looked at all jobs held over the four-year sample period? With women postponing marriage and pregnancy in the 1979-1982 period, perhaps the phenomena that led to the higher female quit rates in the 1968-1971 period did not emerge until after workers had completed their initial jobs. Accordingly, I extended my analysis from the first full-time job held after the individual completed school to all such jobs that were observed prior to the last interview date for each individual. Of course, in so doing, one departs from the relative purity of the analysis of first jobs, which avoids the initial conditions problem by focussing on the start of each worker's labor market career. One must keep this potential shortcoming in mind when evaluating the results that follow.

After obtaining information on the duration of all jobs, one can compute the percentage of time that each individual worked after the start of his or her first job. For the 20 hour data set, this percentage was 70.7% for men and 70.9% for women. For the 30 hour data set, the percentage was 70.2% for men and 70.1% for women. Thus, no tendency on the part of women to drop out of the labor force more frequently than men emerges from these figures. While women and men work virtually the same percentage of time after beginning their first job, though, women hold fewer jobs over this period. For the 20 hour data set, men averaged 2.8 jobs and women averaged 2.4. For the 30 hour data set, men averaged 2.5 jobs and women averaged 2.1. Note that this does not necessarily imply that the average duration per job was greater for women, since men are more likely to hold multiple jobs.[51]

4.10.1 Theoretical Problems in Examining All Jobs

Every study concerning quit rates has implicitly assumed that all jobs are the same -- that is, the relationships defined by the explanatory variables is the same whether one is examining the exit from the first job or from any subsequent job.[52] Mathematically, the assumption implies that the hazard rate h for the ith job for the jth individual can be expressed as follows:

$$h_{ij}(t) = h_j(t) = g(X) \text{ given } X_{ij},$$

where the hazard rate is a function g of the vector of explanatory variables X. X can include variables that will change over time, such as age at the start of the job and years of previous job experience, as well as time-invariant variables, such as the worker's race and sex. The inclusion of the time-varying variables implies that the hazard rate will not be the same for, say, a worker's third job as it was for his first, but the functional relationship that governs the two jobs is deemed to be the same. Thus, in a proportional hazards model that included only the four covariates -- age at start, education, race, and sex -- the coefficient on the age variable is implicitly assumed to be identical whether one estimates the hazard on a sample of first jobs or

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[51]For example, two individuals who both worked for two years while having two jobs over this period could have quite different hazard rates if one worked at the two jobs consecutively and the other held the two jobs simultaneously.

[52]This assumption is implicit in all the Appendix I studies as well as in many others, such as Abraham and Farber [1986].

on a sample of all jobs.[53]

But this implicit assumption will not always be appropriate. If unobserved heterogeneity is a serious problem then the estimation of a hazard rate using all job spells may be perilous. Consider a case in which the finest subgrouping permitted by the observed covariates still leads to heterogeneous subgroups. Assume that this heterogeneity exists because two classes are indistinguishable to the analyst: one class of workers who all work for three years on each job and another equal-sized class of those who work only 1 year on each job. Under the first-job estimation approach, the average duration for this sample will be 2 years, which defines a constant yearly hazard rate of 1/2. If all jobs are considered rather than just first jobs, a different result obtains. For every three-year job that is included in the estimation, three one-year jobs will be included.[54] Hence, the average duration will fall to 1.5 years, and the constant yearly hazard will rise to 2/3.

Note that this problem will not exist if one can correct for the heterogeneity. Using the same example as above but now assuming that women tend to work three years and men only one year, it is clear that a sex dummy will properly identify the hazard rates for these two classes of workers whether one estimates the hazard from the sample of all jobs or only from first jobs. With unobserved heterogeneity, the "all jobs" estimation implicitly gives greater weight to those who take many jobs.

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[53]If education, race, and sex were fixed over the entire sample, the hazard rate would still be different for each job as long as the coefficient on the age variable differed from zero.

[54]This example assumes that workers are constantly employed. Therefore, over the time that one individual has one three-year job, a member of the other class of workers will have three one-year jobs.

Before I began to examine the class of all jobs, I first explored the issue of heterogeneity. Having found that unobserved heterogeneity was not a serious problem, as noted in the discussion of Tables 52 and 53, I was less fearful of proceeding to an analysis of all jobs.[55]

4.10.2 Is Aggregation of First and Subsequent Jobs Permissible?

Even if the problem of excessive weighting of short jobs is not serious because of the small degree of unobserved heterogeneity, one must still examine whether it is appropriate to aggregate first and subsequent jobs. Since the underlying theoretical model is one of repeated job turnover until a worker and employer find a suitable match, one must consider whether a worker gains the same amout of information about job opportunities and personal work preferences by working, say, in one job for two years or in two jobs that each last only one year. If not, there may be problems in simply aggregating all jobs into one estimation.

To explore this issue, I performed a likelihood ratio test by partitioning the aggregate sample of all 30 hour jobs into a first-jobs subsample and a subsequent-jobs subsample. As Table 58 shows, the

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[55]An employer who is trying to decide which of two students to hire upon graduation would clearly prefer an estimate of expected duration that was weighted by the probability the person was a three-year or a one-year worker, such as would be provided by an analysis of first jobs. For other purposes, however, the employer might prefer the "all jobs" estimation that weighted by the total number of spells of each type. For example, if there were fixed costs associated with hiring each worker, an employer who wanted to estimate how many times he or she would have to pay these costs over say a three year period would want to know how many individuals will be hired in total if the employer cannot distinguish in advance between the two workers. In this case, the employer will want to consider that more of the individuals who show up for work will be one-year employees.

resulting chi-squared values for the five estimations using the 6 time intervals are far in excess of the critical values at the .10 and .05 levels of significance. In other words, first jobs should not be considered identical to subsequent jobs and aggregated into an "all jobs" sample for purposes of hazard rate estimation.

I must hasten to add that I am not stressing the point about the dangers in estimating hazard rates based on the "all jobs" sample because the results from the aggregated sample diverge from my other findings. On the issue of the relative quit rates of men and women, all three estimations -- whether limited to first jobs, to subsequent jobs, or inclusive of all jobs -- support the same conclusion: there is no statistical difference in the hazard rates of men and women in the 1979-1982 sample.

Table 59 presents the estimated hazard rates for the subsequent-jobs sample, which consists of all jobs except first jobs. Table 60 provides estimates obtained using all jobs. While the results for the "subsequent jobs" and "all jobs" samples are quite similar, a few differences, both between these estimations and those derived from the first jobs sample, are worth noting. First, the effect of education on quit rates is stronger and more uniform with the multiple-jobs samples than with the first jobs sample. Thus, each educational subgroup demonstrates lower quit rates than its predecessor.[56] Second, while the estimated coefficients on the BLACK dummy are virtually zero on the all jobs sample, they are actually negative and significant at the .10 level

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[56]This finding provides further support for the view that the nonmonotonic pattern frequently observed in the first job hazard rate estimations resulted from distortions caused by the inclusion of a number of workers who had not really completed their education.

TABLE 58

Likelihood Ratio Tests for Pooling First and Subsequent Jobs

The Basic Model, ≥ 30 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	76.76	11	17.28	19.68
2	77.14	12	18.55	21.03
3	77.96	13	19.81	22.36
4	109.32	14	21.06	23.69
5	109.80	15	22.31	25.00

NOTES: These models are set forth in Table 59.

[1] The test statistic is constructed as 2 times the absolute value of the difference between the log likelihood statistic for the partitioned sample and the log likelihood statistic for the aggregated sample.

[2] The number of degrees of freedom is the number of restrictions imposed when estimating hazard rates on the aggregated sample of the first-job and subsequent-jobs subsamples, which in this case is the number of coefficients estimated in the aggregated sample. Note that in estimating the first job hazard, I did not include the years of previous job experience variable, as I did in the other two estimations. The reason is that previous experience is always zero for the first job.

for the subsequent jobs sample. Since the only difference between these two samples is the inclusion/exclusion of the set of first jobs, this may indicate that blacks start out quitting at higher rates, but then become somewhat more stable than nonblacks.[57] Third, the size of the (negative) coefficient measuring years of prior job experience is far greater in the subsequent jobs sample than in the all jobs sample. This may indicate that the effect of experience is not linear, when ranging from zero (on first jobs) to positive values on subsequent jobs.[58]

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[57]If this were true it might reconcile the previous conflict between my analysis of first jobs, which showed higher rates for blacks, and that of Viscusi [1980] and Osterman [1982], which showed significantly lower rates for blacks using a sample of all workers under 65. On the other hand, the results in Tables 64 and 68 may undermine this view.

[58]I also estimated the all jobs hazard rates without including "years of prior job experience," which led to only slight changes in the results reported in Table 60. At least for this young sample, age appears to be a fairly good proxy for experience.

TABLE 59

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates Excluding First Jobs.
Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.01481 (.01607)	-.01110 (.01620)	-.01125 (.01621)	-.004694 (.01701)	-.005003 (.01701)
Education in years	-.09214* (.01262)	-.09209* (.01273)	-.09192* (.01276)		
Education =12 years				-.3863* (.04507)	-.3857* (.04508)
Education =13-15 y.				-.4269* (.06912)	-.4261* (.06910)
Education $\geq$16 y.				-.8228* (.1131)	-.8186* (.1132)
Black	-.07996** (.04657)	-.07947** (.04698)	-.08635** (.04747)	-.08962** (.04752)	-.09528* (.04794)
Unempl.[1] rate	-.1340* (.006550)	-.1400* (.006818)	-.1399* (.006821)	-.1398* (.006844)	-.1397* (.006847)
NSMSA[2]		.1711* (.04341)	.2205* (.06548)	.1700* (.04342)	.2137* (.06559)
SMSA[3]			.02620 (.02589)		.02313 (.02593)
Sex	.002993 (.03700)	-.01471 (.03723)	-.01634 (.03727)	-.03885 (.03758)	-.04015 (.03761)
Experience	-.2032* (.03238)	-.1994* (.03254)	-.1997* (.03254)	-.1920* (.03285)	-.1920* (.03284)

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.
[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.
[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).
[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 59 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.017 (.2334)	-3.084 (.2356)	-3.132 (.2402)	-3.999 (.3078)	-4.037 (.3106)
3-6 Months	-3.218 (.2356)	-3.297 (.2377)	-3.344 (.2423)	-4.204 (.3087)	-4.241 (.3115)
6-12 Months	-3.563 (.2371)	-3.623 (.2391)	-3.670 (.2435)	-4.521 (.3094)	-4.558 (.3121)
12-18 Months	-3.866 (.2441)	-3.930 (.2462)	-3.976 (.2504)	-4.816 (.3140)	-4.853 (.3166)
18-24 Months	-3.943 (.2566)	-4.006 (.2586)	-4.052 (.2626)	-4.891 (.3239)	-4.928 (.3264)
24- Months	-4.450 (.2813)	-4.512 (.2830)	-4.558 (.2867)	-5.404 (.3444)	-5.441 (.3468)
n	5841	5795	5795	5795	5795
-ln likeli.	20855.21	20635.47	20634.96	20615.26	20614.86
Chi-square	1180.30*	1179.82*	1180.84*	1220.25*	1221.04*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)
**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

4.10.3 Potential Sampling Problems When Analyzing All Jobs

In Chapter 2, I discussed a potentially severe sampling problem that occurs in many of the previous quit rate studies. This problem is essentially a length-biased sampling problem, which arises when an individual must be currently working if he or she is to be included in the sample. An example may help to clarify this issue. Assume that there are two types of workers: those who work all the time while changing jobs exactly once every year, and those who work intermittently with six continuous months working and six continuous months not working in every year. If ten "continuous" workers and 10 "intermittent" workers are interviewed, all ten of the first group will be found to be currently working, but on average only 5 of the second group will be working when interviewed. Since all of the Appendix I studies include only those who are currently working when interviewed, they will necessarily cull from their sample the high-quit intermittent workers. In this example, a first-job analysis, such as I performed in this study, which ensures that the first job of each individual is included, would yield an average duration of 3/4 of a year since half the workers worked for a year and the other half worked for six months. Using the length-biased sampling approach of the Appendix I studies, the average duration would be 5/6 of a year.[59]

This form of sampling bias is particularly serious when one is attempting to estimate the relative quit rates of men and women and

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[59]This figure is obtained as follows. All ten year-long workers are included in the sample, but only 5 of the half-year workers are. The total duration for the 15 workers is 12.5 years, so the mean equals 12.5/15 = 25/30 = 5/6.

there is reason to expect that women are more likely to be among the group of intermittent workers. In this case, by culling out relatively more high quit women, one reduces the hazard rates for women, which I have argued contributes to the major differences in my results for the 1968-1971 period from those obtained by the authors of the Appendix I studies.

The results presented thus far for the 1979-1982 period suggest, though, that there is no longer any reason to expect that the intermittent workers are more likely to be women rather than men. All of the preceding evidence from this study has suggested that women work just as great a percentage of the time as men and that their quit rates from jobs are virtually identical to men. Consequently, it seems unlikely that the application of the sampling scheme of the Appendix I studies to this sample of young workers for the 1979-1982 period would yield significantly different results about the relative hazard rates from those obtained. To test this hypothesis, I compared the results of estimations based on the sample of all 30 hour jobs, with an artificially restricted subset of this complete sample that was designed to mimic the selection criteria employed in the Appendix I studies. To be included in this restricted subset, the job had to have been held at any of the dates that the respondent was interviewed. In other words, this restricted sample comprised only those jobs that would have been included if the interviewer had asked about all currently held jobs.

Two sets of comparisons were performed to examine the effect of this sample restriction: (1) a time periods model was estimated on the full sample (Table 60) and the restricted sample (Table 61); and (2) a Gompertz model was estimated on the full sample (Table 62) and the restricted sample (Table 63). The effect of this sample restriction on the coefficient on the SEX dummy was slight in that in no case -- whether in the complete or restricted sample -- did it ever reach significance. Nonetheless, there was a tendency for the sample restriction to shift the sign of the SEX coefficient from positive in the complete sample -- indicating a higher quit rate for men -- to negative in the restricted sample -- indicating a lower quit rate for men.[60] I suspect this occurs because men appear to hold more dual jobs than women, and the sample restriction tends to cull out relatively more of these jobs, which are often of shorter than average duration.

The most striking finding to emerge from this exercise concerns the nature of the time dependence of the estimated hazard. In both the time periods and Gompertz estimations, limiting the analysis to "current jobs" virtually eliminated the effect of tenure on the probability of quitting. The estimated time parameters in Table 60 based on the sample of all jobs are all negative and rise in absolute value, thereby indicating a declining hazard rate or negative duration dependence. A very different pattern is found in Table 61 where, in every case, the hazard for the final period is slightly higher than that for the first period. This same pattern is confirmed in the Gompertz estimations of these same data sets: on the complete sample the coefficient on the tenure variable is negative and significant, reflecting the expected negative duration dependence (see Table 62); on the sample restricted to current jobs, the tenure variable is actually positive (although with a very small slope).

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[60]This pattern was observed with both the time periods and Gompertz estimations.

I have noted two potentially serious problems that are common in the hazard rate literature. The first, which characterizes all of the studies summarized in Appendix I, involves the length-biased sampling problem of limiting the sample to those jobs that are held at the time of interview. This selection criterion necessarily excludes more short duration jobs, and, as I have just shown, distorts estimates on important parameters. The second problem is the inclusion of multiple spells by high-quit individuals, which in effect oversamples individuals who hold numerous jobs over the course of the survey.[61] In order to avoid both these pitfalls while looking past the initial job to see if the observed pattern of identical male and female hazard rate begins to break down as women age, I decided to examine the last job held by each individual in the sample.

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[61]This problem is found in the study of Abraham and Farber [1986].

TABLE 60

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates.
All Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.02534* (.01228)	-.01922 (.01240)	-.01935 (.01240)	-.03504* (.01273)	-.03514* (.01273)
Education in years	-.08515* (.01037)	-.08658* (.01045)	-.08637* (.01046)		
Education =12 years				-.2390* (.03326)	-.2384* (.03327)
Education =13-15 y.				-.2732* (.05210)	-.2724* (.05211)
Education $\geq$16 y.				-.5371* (.08241)	-.5356* (.08245)
Black	.006357 (.03258)	-.004495 (.03310)	-.007431 (.03364)	-.002740 (.03336)	-.006085 (.03388)
Unempl.[1] rate	-.1427* (.004826)	-.1501* (.005009)	-.1501* (.005010)	-.1504* (.005020)	-.1504* (.005021)
NSMSA[2]		.1791* (.03173)	.1971* (.04860)	.1848* (.03174)	.2056* (.04861)
SMSA[3]			.00950 (.01932)		.01091 (.01933)
Sex	.02160 (.02694)	.00259 (.02718)	.002247 (.02719)	.001857 (.02729)	.001481 (.02730)
Experience	-.05693* (.02536)	-.05299* (.02551)	-.05289* (.02551)	-.02235 (.02538)	-.02234 (.02538)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 60 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.060 (.1661)	-3.149 (.1682)	-3.166 (.1719)	-3.699 (.2280)	-3.717 (.2304)
3-6 Months	-3.196 (.1677)	-3.293 (.1698)	-3.310 (.1735)	-3.843 (.2290)	-3.862 (.2314)
6-12 Months	-3.588 (.1690)	-3.670 (.1710)	-3.688 (.1746)	-4.221 (.2297)	-4.240 (.2320)
12-18 Months	-3.815 (.1737)	-3.899 (.1757)	-3.916 (.1793)	-4.447 (.2327)	-4.466 (.2351)
18-24 Months	-3.989 (.1814)	-4.062 (.1832)	-4.080 (.1867)	-4.616 (.2385)	-4.634 (.2407)
24- Months	-4.377 (.1897)	-4.453 (.1915)	-4.471 (.1948)	-5.000 (.2445)	-5.019 (.2467)
n	10297	10166	10166	10166	10166
-ln likeli.	39386.82	38720.58	38720.46	38720.01	38719.85
Chi-square	2297.57*	2292.02*	2292.26*	2293.16*	2293.48*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 61

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates For All "Current Jobs." Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.04186* (.01998)	-.03658** (.02024)	-.03679** (.02026)	-.01162 (.02063)	-.01180 (.02063)
Education in years	-.08463* (.01653)	-.08298* (.01675)	-.08259* (.01679)		
Education =12 years				-.3666* (.05361)	-.3656* (.05364)
Education =13-15 y.				-.4158* (.08301)	-.4136* (.08305)
Education $\geq$16 y.				-.9051* (.1328)	-.9029* (.1328)
Black	.02995 (.05151)	.01088 (.05251)	.004037 (.05346)	-.002477 (.05284)	-.008706 (.05376)
Unempl.[1] rate	-.2059* (.008010)	-.2150* (.008335)	-.2151* (.008338)	-.2163* (.008362)	-.2163* (.008364)
NSMSA[2]		.1876* (.05162)	.2273* (.07789)	.1899* (.05162)	.2265* (.07791)
SMSA[3]			.02088 (.03065)		.01931 (.03065)
Sex	.004502 (.04266)	-.01882 (.04312)	-.01967 (.04315)	-.04218 (.04341)	-.04288 (.04343)
Experience	-.1258* (.04361)	-.1114* (.04380)	-.1112* (.04379)	-.1016* (.04353)	-.1016* (.04353)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 61 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.508 (.2744)	-3.630 (.2781)	-3.668 (.2837)	-4.805 (.3753)	-4.838 (.3787)
3-6 Months	-3.268 (.2745)	-3.379 (.2782)	-3.417 (.2838)	-4.548 (.3748)	-4.580 (.3782)
6-12 Months	-3.146 (.2736)	-3.239 (.2771)	-3.277 (.2827)	-4.404 (.3734)	-4.436 (.3768)
12-18 Months	-2.999 (.2758)	-3.092 (.2793)	-3.130 (.2849)	-4.248 (.3742)	-4.280 (.3776)
18-24 Months	-3.152 (.2804)	-3.234 (.2838)	-3.272 (.2892)	-4.396 (.3774)	-4.428 (.3808)
24- Months	-3.507 (.2856)	-3.592 (.2891)	-3.630 (.2943)	-4.742 (.3808)	-4.774 (.3841)
n	5592	5532	5532	5532	5532
-ln likeli.	17194.67	16877.02	16876.79	16855.78	16855.58
Chi-square	976.70*	980.71*	981.17*	1023.18*	1023.58*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 62

Maximum Likelihood Estimates of Hazard Rate Coefficients
Gompertz Hazard Model.
All Jobs, Hours $\geq$ 30, 1979-1982, All Workers

	1	2	3	4	5
Constant	-3.002*	-3.096*	-3.114*	-3.649*	-3.668*
	(.1659)	(.1680)	(.1718)	(.2281)	(.2305)
Age at start	-.02625*	-.02004	-.02017	-.03570*	-.03579*
	(.01227)	(.01239)	(.01239)	(.01274)	(.01274)
Education in years	-.08509*	-.08657*	-.08636*		
	(.01035)	(.01043)	(.01045)		
Education =12 years				-.2382*	-.2376*
				(.03326)	(.03328)
Education =13-15 y.				-.2717*	-.2708*
				(.05214)	(.05216)
Education $\geq$16 y.				-.5410*	-.5395*
				(.08244)	(.08247)
Black	.006329	-.004501	-.007439	-.003093	-.006440
	(.03258)	(.03310)	(.03363)	(.03335)	(.03388)
Unempl.[1] rate	-.1429*	-.1503*	-.1503*	-.1507*	-.1507*
	(.004827)	(.005011)	(.005012)	(.005022)	(.005023)
NSMSA[2]		.1813*	.1994*	.1871*	.2079*
		(.03173)	(.04861)	(.03174)	(.04861)
SMSA[3]			.009511		.01092
			(.01932)		(.01933)
Sex	.02173	.002572	.002220	.001792	.001407
	(.02694)	(.02718)	(.02719)	(.02729)	(.02730)
Experience	-.05687*	-.05285*	-.05276*	-.02249	-.02249
	(.02535)	(.02550)	(.02550)	(.02538)	(.02538)
Tenure	-.001659*	-.001633*	-.001633*	-.001633*	-.001633*
	(.00007476)	(.00007502)	(.00007502)	(.00007512)	(.00007512)
n	10297	10166	10166	10166	10166
-ln likeli.	39407.36	38740.36	38740.24	38739.77	38739.61
Chi-square	2256.49*	2252.46*	2252.70*	2253.64*	2253.96*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

TABLE 63

Maximum Likelihood Estimates of Hazard Rate Coefficients
Gompertz Hazard Model.
All "Current Jobs," Hours $\geq$ 30, 1979-1982, All Workers

	1	2	3	4	5
Constant	-3.337* (.2726)	-3.447* (.2763)	-3.487* (.2818)	-4.578* (.3730)	-4.612* (.3763)
Age at start	-.04058* (.02007)	-.03546** (.02033)	-.03574** (.02035)	-.01253 (.02060)	-.01276 (.02060)
Education in years	-.08379* (.01670)	-.08208* (.01693)	-.08162* (.01697)		
Education =12 years				-.3630* (.05362)	-.3618* (.05365)
Education =13-15 y.				-.4091* (.08282)	-.4067* (.08287)
Education $\geq$16 y.				-.8741* (.1326)	-.8716* (.1326)
Black	.02790 (.05153)	.009013 (.05252)	.001622 (.05348)	-.002861 (.05285)	-.009620 (.05377)
Unempl.[1] rate	-.2057* (.008018)	-.2146* (.008333)	-.2147* (.008337)	-.2156* (.008359)	-.2156* (.008362)
NSMSA[2]		.1826* (.05158)	.2254* (.07789)	.1851* (.05159)	.2250* (.07791)
SMSA[3]			.02256 (.03065)		.02099 (.03065)
Sex	.005426 (.04268)	-.01740 (.04314)	-.01825 (.04316)	-.03948 (.04340)	-.04019 (.04342)
Experience	-.1295* (.04360)	-.1157* (.04380)	-.1154* (.04379)	-.1047* (.04352)	-.1046* (.04352)
Tenure	.0001743* (.00008241)	.0002109* (.00008265)	.0002116* (.00008268)	.0002367* (.00008291)	.0002373* (.00008294)
n	5592	5532	5532	5532	5532
-ln likeli.	17229.23	16913.65	16913.38	16893.44	16893.21
Chi-square	907.57*	907.45*	908.00*	947.87*	948.34*

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

4.11 An Examination Of Last Jobs

Thus far, my analyses of (1) first jobs, (2) subsequent jobs (that is all jobs excluding first jobs), and (3) all jobs have uniformly shown that male and female hazard rates are not significantly different for the period from 1979-1982. The second two findings seem to undermine my hypothesis that the "birth effect" might emerge at some point after the initial job -- perhaps because in this later period women were delaying childbearing. Nonetheless, I speculated that the analysis of "subsequent jobs" might not detect any emerging male-female hazard rate differential if the inclusion of a large number of jobs by high quit men tended to elevate the male hazard rates. Since I have argued that there are important reasons for limiting one's analysis to one job per individual, I decided to examine one final restricted sample: the last job held by each worker in the four-year time period.[62] The result was noteworthy: estimating hazard rates on a pooled sample of male and female workers for the 30 hour data set revealed for the first and only time in my study of the 1979-1981 period that the coefficient on the SEX dummy was negative and significant. In each of the 5 standard models, the SEX coefficient was always signficant at the .05 level, and male hazard rates were roughly 20-27% less than female rates.[63] The results

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[62]The last job will be the current job if the person is working at the end of the sample period or the last job held if the individual is not working at the end of the sample period. While initial conditions problems exist with this sample of last jobs, the problem of severe sample selection caused by limiting one's analysis to those currently working is not present -- every individual who ever has a job during the sample period will be included.

[63]Tables 26 and 27 showed that the mean age at the start of the first job on the 30 hour data set was 19.0 for men and 19.2 for women. In comparison, the age at start of the last job on the 30 hour data set

of these estimations are presented in Table 64.

This finding is somewhat perplexing. If men and women have the same hazard rates both for first jobs and for all subsequent jobs how can women show such significantly higher quit rates on last jobs? Perhaps as the women in my sample get older, they do begin to quit at a higher rate than men. This trend sets in sometime after the first jobs have been completed -- a possible re-birth of the birth effect. But why is this trend not evident in either the all jobs or subsequent jobs analyses? The answer may lie in the nature of aggregation used in these two multiple-jobs samples. As noted above, men have more dual jobs than women. These jobs tend not to be as long as primary jobs. By restricting the sample to only one job per person, one screens out a disproportionately greater number of these male dual jobs, thereby possibly lowering male rates to a level significantly below that of women.

Since this finding is so important, I decided to examine whether aggregation of the male and female samples was permissible. As Table 65 shows, it was not -- in every case the computed test statistic is greater than the critical chi-squared value at the .05 level. Accordingly, I present the separate male and female hazard rate estimations for this last-job sample in tables 66 and 67.

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for 1979-1982 was 19.9 for men and 20.0 for women. Thus, slightly less than a year elapsed, on average, from the start of the first job to the start of the last job. Note too that the age at the start of the first job on the 1968-1971 period was 20.3 for men and 19.5 for women. (Tables 35 and 36.) Thus, for the reasons discussed earlier, the mean age for the first job in the early period is fairly close to the mean age for the last job in the later period.

TABLE 64

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates, Last Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	.005899 (.02549)	.02638 (.02585)	.02592 (.02593)	-.004745 (.02734)	-.006975 (.02730)
Education in years	-.2228* (.02015)	-.2332* (.02012)	-.2330* (.02040)		
Education =12 years				-.5994* (.07283)	-.5930* (.07291)
Education =13-15 y.				-.7931* (.1138)	-.7795* (.1137)
Education $\geq$16 y.				-1.504* (.1930)	-1.483* (.1930)
Black	.3176* (.06444)	.2836* (.06663)	.2481* (.06806)	.2903* (.06718)	.2562* (.06857)
Unempl. rate[1]	-.1113* (.009966)	-.1111* (.01059)	-.1111* (.01061)	-.1116* (.01054)	-.1115* (.01056)
NSMSA[2]		.09059 (.07393)	.3072* (.1135)	.09711 (.07386)	.3092* (.1137)
SMSA[3]			.1096* (.04284)		.1072* (.04301)
Experience	-.2891* (.05750)	-.2784* (.05811)	-.2744* (.05805)	-.1979* (.05715)	-.1942* (.05711)
Sex	-.2191* (.05939)	-.2966* (.06118)	-.3017* (.06123)	-.3130* (.06189)	-.3164* (.06190)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 64 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-2.875 (.3790)	-3.169 (.3881)	-3.370 (.3960)	-4.871 (.5046)	-5.038 (.5083)
3-6 Months	-3.108 (.3815)	-3.437 (.3907)	-3.637 (.3984)	-5.145 (.5056)	-5.311 (.5093)
6-12 Months	-3.711 (.3833)	-3.994 (.3921)	-4.193 (.3997)	-5.707 (.5060)	-5.873 (.5097)
12-18 Months	-4.185 (.3933)	-4.440 (.4016)	-4.640 (.4091)	-6.143 (.5123)	-6.309 (.5161)
18-24 Months	-4.245 (.4012)	-4.497 (.4092)	-4.696 (.4165)	-6.201 (.5183)	-6.367 (.5219)
24- Months	-4.533 (.4059)	-4.786 (.4139)	-4.987 (.4213)	-6.481 (.5216)	-6.648 (.5254)
n	4421	4343	4343	4343	4343
-ln likeli.	9105.743	8716.499	8713.229	8722.760	8719.652
Chi-square	800.34*	735.68*	742.22*	723.16*	729.37*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 65

Likelihood Ratio Tests for Pooling Men and Women, Last Jobs

The Basic Model, $\geq$ 30 Hours Per Week

MODEL	TEST STATISTIC[1]	DEGREES OF FREEDOM[2]	CHI-SQUARED .10	CHI-SQUARED .05
1	22.56	10	15.99	18.31
2	27.10	11	17.28	19.68
3	26.47	12	18.55	21.03
4	31.38	13	19.81	22.36
5	30.56	14	21.06	23.69

NOTES:

[1] The test statistic is constructed as 2 times the absolute value of the difference between the log likelihood statistic for the partitioned sample and the log likelihood statistic for the aggregated sample.

[2] In estimating the aggregated sample, I have included a sex dummy, which therefore allows the constant term to vary for men and women. The remaining slope coefficients are constrained to be the same in the aggregated model, and it is the number of these slope coefficients that determines the degrees of freedom for each model.

TABLE 66

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
Last Jobs, Hours $\geq$ 30, 1979-1982, Men

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	-.03293 (.03429)	-.02561 (.03459)	-.02452 (.03471)	-.003402 (.03721)	-.004974 (.03718)
Education in years	-.2028* (.02512)	-.2056* (.02537)	-.2059* (.02572)		
Education =12 years				-.6165* (.09718)	-.6128* (.09727)
Education =13-15 y.				-.9887* (.1515)	-.9742* (.1518)
Education $\geq$16 y.				-1.665* (.2513)	-1.647* (.2514)
Black	.1313 (.09347)	.1404 (.09387)	.1111 (.09581)	.1157 (.09522)	.09185 (.09684)
Unempl.[1] rate	-.1167* (.01375)	-.1253* (.01430)	-.1253* (.01433)	-.1227* (.01420)	-.1228* (.01423)
NSMSA[2]		.2719* (.09625)	.4448* (.1486)	.2420* (.09618)	.3959* (.1493)
SMSA[3]			.08988 (.05801)		.07951 (.05824)
Experience	-.1795* (.07962)	-.1801* (.07988)	-.1772* (.07980)	-.1345** (.07854)	-.1313** (.07854)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 66 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-2.291 (.5187)	-2.406 (.5234)	-2.591 (.5371)	-4.773 (.6867)	-4.897 (.6922)
3-6 Months	-2.645 (.5239)	-2.749 (.5284)	-2.933 (.5418)	-5.111 (.6889)	-5.235 (.6943)
6-12 Months	-3.095 (.5251)	-3.198 (.5295)	-3.380 (.5426)	-5.557 (.6886)	-5.679 (.6938)
12-18 Months	-3.501 (.5371)	-3.596 (.5412)	-3.780 (.5542)	-5.935 (.6962)	-6.059 (.7016)
18-24 Months	-3.614 (.5471)	-3.712 (.5510)	-3.896 (.5638)	-6.049 (.7034)	-6.174 (.7088)
24- Months	-3.809 (.5493)	-3.909 (.5535)	-4.094 (.5666)	-6.244 (.7060)	-6.368 (.7114)
n	2161	2147	2147	2147	2147
-ln likeli.	4895.339	4849.444	4848.246	4843.101	4842.171
Chi-square	393.85*	396.71*	399.10*	409.39*	411.25*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

TABLE 67

Maximum Likelihood Estimates of Hazard Rate Coefficients:
Time-Varying Hazard Rates,
Last Jobs, Hours $\geq$ 30, 1979-1982, Women

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	.05724 (.03913)	.1025* (.04026)	.09811* (.04029)	-.007931 (.04075)	-.01039 (.04069)
Education in years	-.2454* (.03464)	-.2769* (.03575)	-.2741* (.03579)		
Education =12 years				-.5830* (.1106)	-.5731* (.1107)
Education =13-15 y.				-.4692* (.1716)	-.4674* (.1711)
Education $\geq$16 y.				-1.235* (.3040)	-1.221* (.3037)
Black	.5125* (.09108)	.4664* (.09659)	.4279* (.09860)	.5160* (.09649)	.4744* (.09893)
Unempl.[1] rate	-.1028* (.01447)	-.09104* (.01572)	-.09118* (.01574)	-.09241* (.01568)	-.09251* (.01569)
NSMSA[2]		-.1554 (.1155)	.08935 (.1762)	-.1170 (.1153)	.1288 (.1762)
SMSA[3]			.1196** (.06388)		.1206** (.06425)
Experience		-.3924* (.08402)	-.3858* (.08398)	-.2537* (.08323)	-.2502* (.08312)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 67 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.938 (.5541)	-4.584 (.5789)	-4.765 (.5871)	-5.347 (.7571)	-5.537 (.7627)
3-6 Months	-4.041 (.5556)	-4.755 (.5802)	-4.934 (.5883)	-5.540 (.7573)	-5.728 (.7628)
6-12 Months	-4.807 (.5598)	-5.433 (.5833)	-5.616 (.5917)	-6.240 (.7594)	-6.430 (.7651)
12-18 Months	-5.383 (.5782)	-5.942 (.6000)	-6.126 (.6083)	-6.763 (.7705)	-6.954 (.7762)
18-24 Months	-5.351 (.5899)	-5.900 (.6108)	-6.081 (.6187)	-6.731 (.7792)	-6.919 (.7846)
24- Months	-5.799 (.6083)	-6.339 (.6285)	-6.520 (.6364)	-7.146 (.7913)	-7.335 (.7970)
n	2260	2196	2196	2196	2196
-ln likeli.	4199.127	3853.507	3851.746	3863.970	3862.201
Chi-square	425.20*	354.97*	358.49*	334.04*	337.58*
Monotonic[2]	no	no	no	no	no

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

In addition to the dangers of the initials conditions problem, there are other reasons for proceeding with caution before accepting the results of these "last job" hazard rate estimations. First, the proportion of censored spells in this sample is rather high. For most of the other samples reported in this study, about half of the cases were completed spells. For the last job sample, however, this proportion was only 26%. This is to be expected since any individual who is working at the time of the final interview will not only be in the middle of a job spell -- which implies that the job will be censored -- but also will be on his or her last job. It is possible that the reliability of the estimated hazard rates is impaired by this relatively small proportion of completed spells.[64]

A second problem is what I refer to as the "final conditions problem." Looking at "last jobs" in a sample period that ends in 1982 may also create biases. 1982 was the trough of the most severe recession experienced in the United States since the Great Depression. In the hazard rate estimates just discussed, all layoffs were treated as censored spells. If there are large differences in the numbers of men and women whose last job ended in layoff, then the previous estimates may be flawed. Indeed, an examination of the reasons given for leaving those "last jobs" that have terminated demonstrates that the proportion of male layoffs is over 50% higher than the proportion of female layoffs.[65] Accordingly, it seemed prudent to re-estimate the last job

[64]For an optimistic view on this issue, see Tuma and Hannan [1985: 143]: "In relatively large samples the effects of even extreme levels of censoring are modest."

[65]Of the 2196 male "last jobs," 1430 (or 65.1%) had not terminated. Of the 2148 female "last jobs," 1323 (or 61.6%) had not terminated. Of

hazard rates treating layoffs as completed spells. As shown in Table 68, this procedure reduced by half the size of the coefficients on the SEX dummy. While with layoffs censored, female hazard rates had exceeded male rates by 20-27%, the percentages fell to from 8-13.5% when these spells were treated as complete. Thus, hazard rate estimators should be sensitive to "final conditions problems" as well as initial conditions problems.[66]

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the remaining jobs that had terminated for a specified reason, 36.8% of the men and only 24.3% of the women had been laid off.

[66]The two problems are conceptually distinct. By looking only at first jobs, one can avoid initial conditions problems. But if the sample ends at a time of unusually large layoffs, the final conditions problem discussed in the text will be encountered. Ordinarily, though, the extent of this problem will be relatively small because it would be unusual to have an extremely large proportion of first jobs end in layoff at one time. What makes the final conditions problem so severe in the context of the last job sample in this case is the fact that the sample selection is based on the final job -- in effect the initial conditions problem and final conditions problem are acting in combination.

TABLE 68

Maximum Likelihood Estimates of Hazard Rate Coefficients: Time-Varying Hazard Rates With Layoff As Completed Spells, Last Jobs, Hours $\geq$ 30, 1979-1982, All Workers

A. Time-Independent Coefficient Estimates

	1	2	3	4	5
Age at start	.04452* (.02118)	.06413* (.02149)	.06393* (.02151)	.03228 (.02267)	.03160 (.02268)
Education in years	-.2379* (.01679)	-.2462* (.01686)	-.2462* (.01693)		
Education =12 years				-.5438* (.06060)	-.5418* (.06065)
Education =13-15 y.				-.8166* (.09540)	-.8129* (.09544)
Education ≥16 y.				-1.615* (.1639)	-1.609* (.1640)
Black	.3229* (.05424)	.3009* (.05568)	.2900* (.05687)	.3031* (.05612)	.2931* (.05727)
Unempl.[1] rate	-.07438* (.008102)	-.07830* (.008605)	-.07827* (.008610)	-.08026* (.008563)	-.08019* (.008567)
NSMSA[2]		.1926* (.05962)	.2602* (.09336)	.2006* (.05956)	.2637* (.09348)
SMSA[3]			.03456 (.03653)		.03227 (.03667)
Experience	-.2589* (.04650)	-.2560* (.04696)	-.2548* (.04696)	-.1846* (.04629)	-.1836* (.04629)
Sex	-.08048 (.04978)	-.1361* (.05085)	-.1377* (.05088)	-.1451* (.05144)	-.1461* (.05145)

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The unemployment rate in the local labor market at the time closest to the final date observed in the job.

[2]NSMSA implies not in SMSA (i.e., SMSA index = 0).

[3]SMSA (index 0-3) with 3 = SMSA, central city.

Table 68 (cont'd)

B. Time Parameters[1]

	1	2	3	4	5
0-3 Months	-3.444 (.3180)	-3.740 (.3248)	-3.801 (.3313)	-5.577 (.4205)	-4.897 (.6922)
3-6 Months	-3.766 (.3202)	-4.080 (.3270)	-4.142 (.3333)	-5.926 (.4213)	-5.235 (.6943)
6-12 Months	-4.403 (.3218)	-4.690 (.3283)	-4.751 (.3345)	-6.541 (.4218)	-5.679 (.6938)
12-18 Months	-4.827 (.3297)	-5.088 (.3358)	-5.150 (.3420)	-6.931 (.4269)	-6.059 (.7016)
18-24 Months	-4.909 (.3371)	-5.169 (.3430)	-5.230 (.3490)	-7014 (.4325)	-6.174 (.7088)
24- Months	-5.123 (.3393)	-5.387 (.3451)	-5.449 (.3513)	-7.229 (.4340)	-6.368 (.7114)
n	4421	4343	4343	4343	4343
-ln likeli.	12350.10	11915.55	11915.11	11932.90	11932.52
Chi-square	1044.68*	983.15*	984.05*	948.45*	949.23*
Monotonic[2]	yes	yes	yes	yes	yes

Notes: *Significant at .05 level. (Standard errors in parentheses.)

**Significant at the .10 level.

[1]The hazard rate is estimated as a step function of time. The actual value for each period is obtained by taking the exponential value of the parameter presented in the table. Thus, this underlying hazard rate will always be positive. All of the time-dependent hazard rate coefficients are statistically significant at the .05 level.

[2]Identifies whether the hazard rate declines monotonically.

Chapter 5

A COMPARISON OF THE RESULTS FROM THE TWO PERIODS

5.1 The Changing Labor Market Experience of Women

The two-part comparison between male and female hazard rates in the periods 1968-1971 and 1979-1982 is now complete. I have used hazard models to examine the expected job tenure of male and female entrants to the full-time labor force after they appear to have completed their full-time education. My results for the early period are quite different from those obtained by a number of recent micro-data studies, using different methodologies from mine, which found that there were no differences in quit rates by sex after controlling for the effects of a number of explanatory variables. I have found that for the period 1968-1971 female full-time workers quit their first job after completing school at substantially higher rates than male workers. This finding was robust to a number of different model specifications and selection criteria, as well as to estimations with and without duration dependence and with and without corrections for unobserved heterogeneity. Because of women's generally lower earnings, including wage as an independent variable tends to reduce, but not eliminate, the male-female tenure gap. While the changes were not dramatic, increasing the definition of full-time employment from 20 to 30 hours reduced overall quit rates and tended to widen the tenure gap between men and women workers. On the other hand, treating layoffs as completed spells of work raised overall quit rates and tended to narrow slightly the male-female tenure differential.

Also contrary to the other micro-data studies, whose results are summarized in Appendix I, I found that (1) increased education had a significant and negative effect on quitting for both men and women; (2) the unemployment rate had a significant, negative effect on quit rates for men; (3) the hazard rates for women did not decline monotonically with duration, but rather increased sharply after 18 months due to a proposed "birth effect;" and (4) nonwhites did not have lower rates than whites. In evaluating these four differences, one should remember that in this paper I have restricted my analysis to first full-time jobs, while the other studies analyzed the "current jobs" of those interviewed. If the nature of job selection and mobility clearly differs depending on the stage of one's labor market career, then it is improper to aggregate across all jobs as the Appendix I studies have done. In effect, to the extent that my results differ because of the restriction to first jobs, then I have demonstrated the invalidity of the semi-Markovian assumption in analyzing job mobility. Moreover, since the proposed "birth effect" plays such an important role in creating the tenure differential between women and men, one would expect this differential to be largest at those ages at which women are most frequently starting to bear children. An examination of female workers of all ages might not be able to uncover this effect.[1]

Two additional factors contribute to the different results. First,

[1]This is especially true since the Appendix I studies constrained the female hazards to be monotonic.

the other studies have included explanatory variables, such as wage, industry, occupation, and union status, that I have excluded on the grounds that they are not truly exogenous. Indeed, if the direction of causation tends to run in the direction from low tenure to low wage and occupational status, etc., it should not be surprising that the inclusion of these factors in estimating hazard rates would tend to reduce the tenure differential between men and women. Second, the sample design of the other studies created selection biases by increasing the chance that relatively high quit women -- who tend to move in and out of the labor market -- would be disproportionately excluded from the analysis, while relatively high quit men -- who tend to move from job to job -- would be included.

These findings provide important insights into the possible effects of differences in expected job tenure on the male-female wage differential. For example, considering white, high school graduates in 1968-1971, it is possible that the large gap in expected tenure between men and women workers -- 21.1 months vs. 13.2 months -- explains roughly 20% of the female-male earnings ratio of 77.2%. Put differently, equal tenure between men and women in the 1968-1971 period might have raised this earnings ratio to about 82%.

My findings for the period 1979-1982 are quite different from those obtained in the initial period from 1968-1971. The intervening decade had a dramatic effect on the labor market behavior of young women that made them appear almost indistinguishable from young men in terms of job tenure, attachment to the labor force, and percentage of workers who are professional, managerial, and technical. The finding of the equality in hazard rates between male and female workers in the later period was invariant to a wide range of different specifications and sample selection criteria, as well as to different parametric assumptions about the nature of duration dependence and the existence of unobserved heterogeneity.

It appears that the elimination of the first-job "tenure gap" between young men and women is the result of two phenomena: (1) the dramatic increase in the commitment of women to the paid workforce, and (2) the increase in age of women at the time of first marriage and/or first pregnancy.[2] It is possible that these factors delay, but do not entirely eradicate, the point at which women begin to leave their jobs at a higher rate than men. Evidence from examining the last job held during the sample period indicated that, by that juncture, female hazard rates had elevated significantly beyond those of men. One must qualify this finding because the "last job" analysis is subject to a number of potential infirmities, such as initial and final conditions problems and an excess of censored spells. Other findings in the later period were that (1) increased education had a significant and negative effect on quitting for both men and women; (2) the unemployment rate had a significant, negative effect on quit rates for both men and women; and (3) blacks did not have lower rates than whites.

At the same time that the tenure gap between young men and women was closed during the decade of the seventies, the wage gap narrowed considerably. The female-male earnings ratio for white, high school graduates for the 1968-1971 sample had been just over 77% and had risen

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[2]For the twenty year period ending in 1982, there has been a 30% decline in the first marriage rates of women and a two-year increase in the median age at first marriage. Bennett, Bloom, and Craig [1986: 4].

to almost 89% in the 1979-1982 sample. Over 40% of the improvement in the earnings ratio for women may have been due to the elimination of the tenure differential. This fact may shed light on whether the historically higher female quit rates observed in this study were a cause of or a response to the large male-female wage diffential. That the tenure gap appears to have been eliminated entirely while the narrowing of the wage gap seems to be proceeding with a lag suggests that the direction of causation is from lower tenure to lower wages as this study originally hypothesized.

The closing wage gap, coupled with the increased movement of young women into professional and managerial jobs, also has important ramifications for the debate over "comparable worth." Advocates of this policy argue that institutional labor market discrimination against women is rampant and must be addressed through government-induced wage enhancing measures for the jobs traditionally held by women. Even without this remedy, however, the evidence suggests that young women are facing an increasingly hospitable labor market. This makes the case for comparable worth more problematic in that the class of intended beneficiaries -- working women -- are clearly not a monolithic group: older women who have returned to the labor market after years of absence while raising children have undoubtedly been disadvantaged in the labor market, but young women are far less disadvantaged. The rather cumbersome device of comparable worth is not well-suited to reach the class of older women who have much stronger equitable claims for some form of relief. Changes in family law and the rules of property distribution in divorce, as well as improved enforcement of child-support and alimony awards, would appear to focus on the problem more directly.

Appendix I

A COMPARISON OF FOUR QUIT-RATE STUDIES

APPENDIX I — A Comparison of Four Quit Rate Studies

	VISCUSI (1980)		BLAU & KAHN[1] (1981)		OSTERMAN (1982)		WAITE & BERRYMAN (1985)	
Data Set	PSID 1976[2]		NLS: 1969-70, 70-71 for men Women 1970-71, 71-72		PSID 1978-1979		NLS: 1979-80	
Sample	Full-time (30 hrs. or more per week) workers younger than 65		Men & Women aged 14-24[3] (whites only)		Non-agricultural workers younger than 65		Workers aged 16-21 not enrolled full time in high school or college	
Type of Regression	logit		probit		logit		logit	
Dependent Variable	1 if worker had quit by the time of next interview; 0 otherwise							
	M	F	M	F	M	F	M	F
% Female Workers[4]	INSIGN.[5]						INSIGN.[5]	
Female Occ.[6]							-0.4757 (0.2298)	INSIGN.
Age	-0.040 (0.008)	-0.024 (0.006)			INSIGN.	-0.0379 (0.0072)	INSIGN.	-0.0514[7] (0.019)
Education in Years	INSIGN.	0.132 (0.031)	INSIGN.	0.0530 (0.0240)	INSIGN.		-0.0486 (0.0237)	INSIGN.
Hourly Wage	-0.214 (0.028)	-0.412 (0.039)	(Log of) -0.2746 (0.1048)	(Log of) -0.3824 (0.1177)	-0.0008 (0.0003)	-0.0018 (0.0004)	(Log of) INSIGN.	
Median Wage of Resp.'s Occup.			(Log of) -0.3662 (0.1107)	(Log of) -0.4745 (0.1179)			INSIGN.	
Union[8]	Included but not reported		-0.2526 (0.0794)	-0.3893 (0.0898)	-0.4936 (0.1841)	INSIGN.	INSIGN.	
Total Family Assets			INSIGN.				INSIGN.	
Family Income			INSIGN.		-0.00004 (0.00001)	INSIGN.	INSIGN.	
Unemployment Rate[9]	Included but not reported		INSIGN.		INSIGN.		INSIGN.	
Change in Unemployment Rate					INSIGN.			
Black	-0.730 (0.194)	-0.448 (0.166)			-0.3296 (0.1858)	-0.4468 (0.1575)	INSIGN.	
Residence in South			INSIGN.				INSIGN.	
Log of Firm Size							INSIGN.	

	VISCUSI		BLAU & KAHN		OSTERMAN		WAITE & BERRYMAN	
	M	F	M	F	M	F	M	F
Labor Force Size			INSIGN.					
Tenure Current Job	INSIGN.[10]		-0.0235 (0.0022)	-0.0080[11] (0.0020)	-0.0067[11] (0.0021)	INSIGN.	(Log of) -0.1379 (0.0217)	(Log of) -0.1320 (0.0235)
Tenure One[12]	0.545 (0.175)	1.316 (0.221)			0.3607 (0.1865)	0.7548 (0.2473)		
Experience in Labor Force			INSIGN.					
Dissatisfied with Job							0.1718 (0.0592)	INSIGN.
Job Hazards[13]	INSIGN.	0.052 (0.019)					INSIGN.	
Health[14]	0.574 (0.242)	0.445 (0.223)			INSIGN.			
Educational Aspirations							0.0324 (0.0115)	0.0302 (0.0125)
H.S. Diploma							INSIGN.	
Married	INSIGN.	-0.618 (0.169)	INSIGN.	0.1899 (0.0755)	INSIGN.		INSIGN.	0.1885[15] (0.0730)
Birth							INSIGN.[15]	
Number of Children	INSIGN.		INSIGN.		INSIGN.			
Children Under 7					INSIGN.			
Occupation[16]			.2808 (.0869)	INSIGN.				
Industry[17]			INSIGN.					
Shift							INSIGN.	
Travel Time[18]							INSIGN.	.0044 (.0017)
Benefits[19]							INSIGN.	-.0905 (.0211)
Full Time[20]							INSIGN.	
Multi-Site[21]							INSIGN.	
Male Occupation[22]							INSIGN.	
Hispanic[23]							INSIGN.	

Notes

1. Blau & Kahn do not include "involuntary quits"--defined as firings and layoffs--in measuring quit rates.

2. University of Michigan Panel Study of Income Dynamics.

3. When first surveyed.

4. Coefficient estimates (with standard errors in parentheses) are given only where coefficients are significant at the 0.5 level. Variables associated with insignificant coefficients are marked INSIGN. If a study has not included a given variable, the corresponding box is left blank.

5. Viscusi measures the percentage of female workers in respondent's industry; Waite & Berryman measure the percentage of female workers in respondent's occupation.

6. Respondent's census three digit occupation has 90 percent or more female workers.

7. Age at 1979 interview.

8. Viscusi's UNION dummy indicates whether a respondent is a union member. The other studies define this variable as indicating whether a respondent's wages are set by collective bargaining.

9. Blau & Kahn: SMSA unemployment rate (annual average).
Osterman: unemployment rate in respondent's county.
Waite & Berryman: 1979 unemployment rate (scale 1-6; low to high).

10. In months.

11. In years.

12. Variable definition: current job held for one year or less.

13. Viscusi defines the variable as the 1975 industry illness and injury rate, while Waite & Berryman measure the respondent's perceptions of job hazards.

14. Viscusi: 1 if health is impaired; 0 if otherwise;
Osterman: weeks of illness on 1978 job.

15. Waite & Berryman control only the event of marriage or birth during the survey year.

16. 1 if professional, technical, managerial, clerical or sales; 0 if otherwise.

17. 1 if in mining, construction or durable manufacturing industries; 0 if otherwise.

18. Minutes from home to work.

19. Benefits (scale 0-3, 3 = paid vacation + life insurance + health insurance).

20. Thirty-five hours or more per week.

21. Employer has establishments at more than one location.

22. Respondent's occupation (three-digit Census code) has no more than 25% female workers.

23. In addition, Waite & Berryman included the following statistically insignificant explanatory variables: KNOWLEDGE OF WORK; CONTROL (measuring resp.'s sense of control over job situation); SMSA (resp. lives in rural, urban or metropolitan area); JOB SIGNIFICANCE; EXTRINSIC REWARDS; WORK GROUP (all three variables measuring resp.'s assessment of aspects of his/her job); WORK 35 (respondent's expectations as to her employment situation at age 35); SEX ROLE ATTITUDES; and finally a number of variables measuring a respondent's background: NO MOM AT AGE 14; NO DAD AT AGE 14; LIVING IN URBAN ENVIRONMENT AT AGE 14; MOM WORKED WHEN RESP. WAS 14; FOREIGN LANGUAGE SPOKEN IN CHILDHOOD HOME; MOM'S EDUCATION; DAD'S EDUCATION; DAD WHITE COLLAR/CRAFT. Blau & Kahn also included in their men's sample the variables MILITARY EXPERIENCE and DRAFT STATUS 1A, both of which were insignificant.

Appendix II

A DETAILED DESCRIPTION OF THE 1979-1982 PROGRAM

I. Definitions Used In Creating The Sample

Recent School Leavers. The National Longitudinal Survey for the Youth sample does not provide sufficient information to determine the precise date at which an individual terminated full-time enrollment in school. I therefore devised a proxy called "recent school leavers," defined as those who were enrolled in school full-time at the date of previous interview (*i.e.*, enrolled in college full-time or listed as enrolled in grades 1-12, which presumably is full-time) and either not enrolled at all (*i.e.*, currently not enrolled or never enrolled since previous interview) or enrolled part-time in college at current interview. 1979 "Recent school leavers" had to be treated as a special case: since the NLS does not indicate a person's enrollment status (*i.e.*, full or part time) prior to the 1979 interview, I assumed that anyone who was enrolled before the 1979 interview was enrolled full-time. I then compared the date a year (exactly) before the 1979 interview with the date last enrolled; if the date last enrolled comes after the date a year prior to the 1979 interview, the person is considered a recent school leaver in 1979. Any recent school leavers in year x who was not aged 16 at the interview date in year x was not considered. Since the first full-time job may have started before this interview date, however, a small number of 15 year olds were included in the sample.

Full-Time Jobs. A full-time job is defined as a job at which a person indicated at the first interview after the job started that he or she usually worked at least x hours a week. The two values of x that I used in this study were 20 and 30. The task of determining the number of hours worked on a job varied in the four different sample years. In 1979 the questionnaire was integrated into one section providing information on all jobs held by the respondent in the past year. In the successive years, the sample was divided into two parts: questions asked in the Current Population Surveys (CPS) and those designed to uncover information on previous jobs in the past year, which appeared in the Employer Supplement. In 1980 and 1981, I had to ascertain if the job is the "current job," in which case the information on the number of hours worked in a week, as well as occupation, industry, class, and type of government job, is found in the CPS section of the questionnaire. In 1982, the Employer Supplement contained information on the hours worked per week on the current job; therefore, I did not have to look to the CPS section for that information, but I did have to look to this section to find information on the other variables, such as occupation etc.

Starting Date (STR). At each interview, a starting date was recorded for all jobs held since the last interview. Generally, if a job had started before the last interview, the starting date was recorded in the NLS survey as the last interview date. All such jobs would be recorded in the information sheet that lists the jobs that had not ended as of the previous interview date. In other words, if a person was currently employed at Sears at the time of the 1980 interview, the NLS asked about this job again at the 1981 interview. The 1981 questionnaire indicated that this job started at the interview date in 1980 (rather than the true starting date that presumably had already been obtained). In some cases, however, a respondent failed to mention a job held at the time of an interview, but brought it up at a subsequent interview instead. To deal with these issues, the job would not be found in the information sheet mentioned above, and the NLS interviewer would record the respondent's recollection of the starting date, which was necessarily more than one year earlier.

There are a number of situations in which I constructed an artificial starting date. Because I only began examining the labor market experience of those identified as recent school leavers, it is possible that the job of, say, a 1981 school leaver started before the 1980 interview. Some of these jobs went back a number of years, and thus were clearly jobs held during school, which I did not want to include in my survey. On the other hand, some of these jobs continued into the future, far beyond the termination date of the individual's education. In such cases, I used the date of the previous interview -- in this example, the 1980 interview -- as the starting date of the job. For 1979 school leavers, however, this option was not possible since there was no previous interview. In this case, I compared the ending date of the job with the date a year before the 1979 interview. If the former came before the latter, the job was omitted. Otherwise, the job was included, and the starting date was fixed at a year before the 1979 interview if it had started before that date.

Another complication arose in the event that a job held in one year was only 15 hours per week, and thus not deemed a full-time job, and then became "full-time" at a subsequent interview. In such a case, the job was included only when it became full-time. The starting date of such a job would be the date of the interview prior to the interview in which hours were sufficiently high to render the job "full-time". Once a job is classified as "full-time", however, it remained in the sample and its entire remaining tenure was counted, even if the respondent subsequently worked less than 20 hours a week at it.

II. Matching Jobs Across Interviews

Whenever a job was identified as a full-time job, I collected information on it. At each interview, it was determined if the job had ended. If it had not, I followed it through subsequent interviews. There exists an information sheet at each interview (excluding 1979) that lists the employer numbers of jobs that had not ended as of the last interview date. Questions in the Employer Supplement then try to match jobs of the current year to jobs listed in that information sheet. Through this method, I was able to obtain information on a full-time job from one interview date to the next and hence follow it from its starting date to either its ending date or the final interview, whichever came first.

If in the course of the year between interviews a worker left his job and then returned to it, the job spell was deemed to be continuous. To provide some uniformity across years -- for example, in the event of a one month interruption of work that bracketed an interview -- I decided to deem some such interruptions as continuous employment. Specifically, when the reason a job ended was given as "pregnancy" or "laid off", I looked to the next interview to see if the person subsequently returned to the job. At each interview (excluding 1979), there is an information sheet which lists the employer numbers of jobs that had ended as of the last interview date. Questions in the Employer Supplement then try to match jobs of the current year to jobs listed in that information sheet. Whenever there is such a match (i.e., a job had ended as of the date of last interview because of "pregnancy" or "laid off" but was picked up again according to information in the current interview) I did not treat the job as having ended prior to the last interview date. However, whenever I matched a job this way, I flagged it at the interview when the matching was done in two ways: (1) FLF80, FLF81, FLF82 are job related variables that were set to "1" when such matching occurred, and (2) FLEFT is also a job related variable which is set to "1" when one or more of the above flags (i.e., FLF80,FLF81,FLF82) is set to "1". I was therefore able to ascertain, whether this type of special matching in the case of brief interruptions owing to pregnancy or layoffs was common. For model (1) of the 20 hour sample (Table 29), such matches occurred in 1.43% of the male jobs and in 1.48% of the female jobs. For model (1) of the 30 hour sample (Table 30), such matches occurred in 1.44% of the male jobs and in 1.57% of the female jobs.

Implementing this special matching in the case of layoff and pregnancy was accomplished in the following manner. For each job considered (other than a 1979 job), I first checked to see if it matched a job that had ended as of the date of the last interview. If there was a match, I checked whether the previous job had ended because of "pregnancy" or "layoff". If so, that job would be matched with the current job (as described above). If the job had ended for some other reason, I considered the current job only if it was a full-time job. If the current job did not match a job that had ended as of the date of the previous interview, I checked whether it matched a job that had not ended as of the date of the last interview. If there was a match, I considered it as a new job only if the job at the previous interview had not already been taken into account. On the other hand, if there was no match and the job met the particular definition of full time, it was included.

III. Different Censoring Schemes

For each job a duration (DUR) was computed (where possible) using the starting and ending dates of the job. Whenever the duration of a job was known, ORGIST is set to "1" ("0" otherwise), which implies that the original state for that job was 1. If for some reason a job spell is censored, DESTIN is set to "1", which implies that, when last observed, this worker was still in the original state (employed). If the job spell is completed, then the destination state (DESTIN) was set to "2".

In the above case, DESTIN was set to 1 if the person had been laid off. I also created a destination variable (DEST) that enabled me to treat a job termination caused by a layoff as complete. The variable DEST is equal to DESTIN except when the person is laid off from a job, in which case DEST equals "2".

I wanted to be able to explore the rate of leaving a job for family or pregnancy reasons. This was done by defining a third destination state and setting DESTI3 = DEST3 = 3, reflecting that the reason the person left the job was given as family/pregnancy. Otherwise DESTI3 = DESTIN and DEST3 = DEST. Consequently, a job is censored if DESTIN, DEST, DESTI3, or DEST3 = 1 (depending on which of these measures is being used).

If I could not ascertain the termination date of the job, the job was censored and the ending date (STP) was fixed according to the following criteria:

1) If a person was not interviewed in any one year (identified by CSPL80, CSPL81, CSPL82), the full-time job(s) that had not ended the previous year (identified by CSPL3, CSPL4, CSPL5) were treated as censored as of the date of last interview.

2) Jobs were also censored (CSPL7,CWK80,CWK81,CWK82) if the answer to the question "Are you currently working for (employer) ?" is neither a "yes" nor a "no." In this case, the ending date of the job was set to the date of the last interview (provided the job had started before the last interview date).

3) If, for any reason, it is not possible to match a job that had not ended at one interview to a job in the following interview (identified by CSPL), then the job is censored and the ending date set to the date of previous interview. I suspect this occurrence is rare, if it happened at all.

4) If a job has not ended by the 1982 interview, it was censored (CSPL2), and the ending date was set to the date of the 1982 interview.

5) If a person was laid off from a job, it was censored (CSPL6) for the DESTIN and the DESTI3 cases but not for DEST and DEST3.

IV. Definitions of Explanatory Variables

Age. For each full-time job, I computed the age of the person at the start of the job.

Education. At each interview, information on the highest grade completed was collected. Some of the grades collected in 1979 were incorrect, but were corrected at the 1980 interview. (GRAD79,GRAD80,GRAD81,GRAD82). The previous available measure of "highest grade completed" is used if for some reason the current measure is missing. HGRADE is a job-related variable that takes the highest grade achieved to be that grade recorded in the interview immediately succeeding the start of the job. I set up my computer program to change any grade recorded as "95" (i.e., ungraded) to "11" and set the variable "WEIRD" to "1" to flag this. Although the NLS codebooks indicated there were a number of "95" entries no such case occurred in either my 20 or

30 hour samples.

Dummy variables for education for each job were defined as follows:

EDD0 = 1 when $HGRADE<12$

EDD1 = 1 when $HGRADE = 12$

EDD2 = 1 when $13 \leq HGRADE \leq 15$

EDD3 = 1 when $16 \leq HGRADE \leq 17$

EDD4 = 1 when $HGRADE \geq 18$

EDD5 = 1 when $HGRADE \geq 16$

EDD6 = 1 when $13 \leq HGRADE \leq 14$

EDD7 = 1 when $HGRADE=16$

Hourly Wage Rates. Hourly wage rates are measured once a year for each job lasting longer than 9 weeks (HRWG79,HRWG80,HRWG81,HRWG82). Where the rate of pay was not hourly, the hourly rate was computed as follows:

1) daily rate given -- wages divided by hours worked per day.
2) weekly rate given -- wages divided by the number of hours worked in a week.
3) bi-weekly rate given -- wages divided by the number of hours worked in two weeks.
4) monthly rate given -- I assumed there are 4.3 weeks in a month and computed the number of hours worked in a month by multiplying the number of hours worked in a week by 4.3. The hourly wage rate was then calculated.
5) annual rate given -- the number of hours worked in a year was obtained by multiplying the number of hours worked in a week by 52. The hourly wage rate was then computed.

Real Hourly Wage. This is computed by multiplying the hourly wage rate by the CPI index of the corresponding year in which the wages were earned to express all wage figures in $1983.
(RHRW79,RHRW80,RHRW81,RHRW82).

Reason Left Job (RL). I had to make some changes to the coding of this variable in 1979, 1980, and 1981 in order to establish some consistency over the different years. The following codes were used (which in effect translated all the different codings for this variable into those employed in the 1982 survey):

"1" -- layoff, plant closed, or end of temporary or seasonal job

"2" -- discharged or fired

"3" -- program ended

"4" -- quit for pregnancy or family reasons

"5" -- quit for other reasons.

To implement this scheme, I had to make the following changes in the individual year codings. For 1979, if the reason left was coded as less than or equal to 3, I made no change to it. If coded as 10 (pregnancy) or 13 (family reasons), it was changed to 4, (quit for pregnancy or family reasons); otherwise it is changed to 5 (quit for other reasons). For 1980 and 1981, RL is changed to 5 (quit for other reasons), if it had been recorded as 6 (other). No change was made for 1982.

Unemployment. I created 3 measures of unemployment that were all job related.

1) UNEM1 -- I averaged unemployment figures available at the interviews before the start of a job, during the lifespan of the job, and immediately after the

job ended. Since unemployment figures for years prior to the 1979 interview or after the 1982 interview were not available, I treated jobs that started before the 1979 interview as having started at the 1979 interview and jobs that had not ended by the 1982 interview as having ended at that interview for the purpose of creating this variable.

2) UNEM2 -- This measure takes the job related unemployment rate to be the rate provided at the interview that follows the start of the job.

3) UNEM3 -- This takes the measure of unemployment to be the closest measure available to the date the job was last observed -- that is, either the termination date or the censoring date.

SEX. The NLS Newsletter #46 (Feb 1986) listed some cases where the sex of the respondent had been coded incorrectly. After shuddering at the thought of such miscodings, I incorporated these changes.

Government Sponsored Jobs.

If a full-time job is government sponsored, it is flagged by one or more of the following variables -- GOVT79, GOVT80, GOVT81, GOVT82 -- depending on the year in which information on the job was collected. Then, depending on the type of sponsoring (codes 4 to 8), the relevant variable is flagged. For example, if a job is government sponsored in 1980 and is of category 5, then GOVT80 = 1 and GOVT580 = 5. Special case: In 1979, there was no code 8, while code 7 represented other types of government sponsoring. In order to be consistent with later years, I have changed code 7 to 8 and left GOVT779 = -9. Years after 1979 have "as part of tax credit program" as code 7. This category was not specifically recorded for 1979. If a job is government sponsored at any time in its life span, GJ is set to "1" to flag this.

V. Additional Job-Related Variables

For each job I extracted the following information available at the interview immediately following the start of the job:

HOURS -- number of hours worked a week

COLBAR -- whether the wages were set by collective bargaining

OCCUP -- the three-digit occupational category of the job

CLASS -- the class of the job. This variable allowed me to identify and exclude all workers who were "self-employed" or working "without pay."

GE -- identifies government employees. If the class of a job is "2" GE is set to "1". Otherwise, GE is set to "0" (provided the class of the job is known).

INDUST -- the industry of the job (3 digit SIC code).

STLOFE -- whether it was a job with the state, federal, or local government.

FED -- identifies a federal employee. If STLOFE is known, FED is set to "1" when STLOFE is 1 and to "0" otherwise.

RHRWG -- this was a created variable. See the discussion above of "real hourly wage."

LRHRWG -- log of RHRWG

SMSA -- the SMSA the respondent belonged to at the start of a job

NSMSA -- determines whether a person is not in an SMSA: NSMSA is set to "1" if SMSA is 0 and to "0" if SMSA is greater than 0

LDUR -- log of duration (DUR) of the job

PTM -- if the occupational category of the job was between 1 and 245 (that is, the job belonged to the "professional, technical, and managerial" category), PTM is set to "1"; otherwise PTM = 0.

BC -- if it is a blue collar job (that is, the occupational category is between 601 and 785), then BC=1; otherwise BC = 0.

WID -- this variable is set to "1" if the person was working at the job at any interview date

EXPER -- this reflects the amount of experience (in days) a person had at the start of a job. It takes into consideration the number of days the person had been employed at full-time jobs before the start of the current job. If there is an overlap between two or more jobs, I only counted the overlap period once. For the first full-time job, EXPER = 0. This variable is computed only for jobs where both the starting and ending dates are known and in computing this variable only such jobs were considered.

YEXPER -- gives the EXPER variable in terms of years

FJ -- this variable is equal to "1" for the first job the person had (i.e., the job with the earliest starting date) and "0" otherwise.

LJ -- is set to "1" for the job which ended the latest and "0" otherwise.

EXPOS -- This variable is not job related. It measures the exposure a person had to full-time jobs: it first computes the number of days a person could have been employed, starting from the day he/she started the first full-time job to the last interview date applicable to that person. I then computed "EXPOS" as the percentage of employable days that were utilized (for full-time employment). Here again, as in the EXPER variable, I considered overlap periods once only. In fact, the number of days a person was employed could be computed simply by adding the EXPER variable related to the last job to the duration of that job.

MARK -- is set to "1" to flag those respondents who stated in an interview in year n that they had completed their education in May or June of year n. I had created this variable in order to examine whether individuals interviewed in say July of 1980 who planned to return to school in September of 1980 would be treated as recent school leavers, and therefore be improperly included in my sample. I subsequently found out that the NLS had anticipated this problem and considered individuals who are on summer vacation to still be enrolled as long as they had the intention of returning to school full-time in the fall. See "Q-By-Q Spex: NLS - Year IV" at p. 3-15, which provides the interviewer instructions on this point.

CE, CE1 -- these variables are designed to reflect whether a person who started a full-time job was still going to school.

As mentioned before, at each interview, information is collected on the highest grade completed. CE then is the difference between the highest grade recorded at the interview immediately following the start of the first full-time job and the grade reported at the final interview. If there were no subsequent interviews, then CE is set to "-1". CE1 is set to "1" when CE is greater than 0 and to "0" when CE is equal to 0. Otherwise CE1 is set to "-1".

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