# WAGE AND JOB DYNAMICS AFTER WELFARE REFORM: THE IMPORTANCE OF JOB SKILLS☆

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## ABSTRACT

*I use data from employers and longitudinal data from former/current recipients covering the period 1997 to early 2004 to analyze the relationship between job skills, job changes, and the evolution of wages. I analyze the effects of job skill requirements on starting wages, on-the-job training opportunities, wage growth prospects, and job turnover. The results show that jobs of different skill requirements differ in their prospects for earnings growth, independent of the workers who fill these jobs. Furthermore, these differences in wage growth opportunities across jobs are important determinants of workers' quit propensities (explicitly controlling for unobserved worker heterogeneity). The determinants and consequences of job dynamics are investigated. The results using a multiplicity of methods, including the*

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*estimation of a multinomial endogenous switching model of wage growth, show that job changes, continuity of work involvement, and the use of cognitive skills are all critical components of the content of work experience that leads to upward mobility. The results underscore the sensitivity of recipients' job transition patterns to changes in labor market demand conditions.*

## 1. INTRODUCTION

Much of the current welfare reform debate centers around opposing views regarding the job and wage dynamics, and potential for wage growth, for former/current welfare recipients. There is consensus that initial wages are likely to be low for low-skilled workers. Some analysts think that low-wage jobs represent a port of entry into higher-paying jobs, whereas others are concerned that entry-level jobs simply represent the first in a succession of "dead-end" jobs (Connolly & Gottschalk, 2000; Edin & Lein, 1997).

Few studies analyze whether jobs differ in their prospects for earnings growth (independent of the worker who fills the job), and the existing evidence lacks a consensus. A further issue that remains elusive is whether serial correlation in wage increases is attached to jobs or to workers. It is difficult to sort out, for example, whether persistently low wages are a greater reflection of a lack of on-the-job training and other human capital investment opportunities, as opposed to the worker's learning and earnings ability. Two prominent studies (Topel, 1991; Topel & Ward, 1992), based on the time series properties of within-job wage changes of men, conclude that heterogeneity in permanent rates of wage growth among jobs is empirically unimportant. Their direct evidence seems to show that jobs do not in fact differ in their prospects for wage growth. However, it remains unclear whether these models and empirical estimates apply to less-skilled workers.

There is scant empirical evidence concerning the job and wage dynamics that accompany initial employment at low wages. Analyses that have focused on the wage growth of less-skilled workers have not distinguished between within-job wage growth and between-job wage growth. Understanding the mechanics of wage growth for less-skilled workers and assessing the relative contributions of different sources of wage growth (returns to general work experience, job tenure, and improvements in job matches) are as important as the estimates of the overall rate of wage growth. Labor market "success" is usually reduced to a single indicator measured at a point in time, such as whether employed, wage rate, or earnings. Employment activities within the firm, such as job skills used, on-the-job training, promotion activity, and the consequences of training and promotion, are typically unmeasured. This paper makes strides to bridge this gap by analyzing employment experiences of representative samples of former/current welfare recipients using both individual-level and employer survey data.

This paper addresses the following set of research questions. Do jobs of differing skill requirements exhibit differential wage growth opportunities independent of the workers who fill these jobs? What is the skill content of work experience that leads to upward mobility? How do those characteristics contrast with those prevalent in dead-end jobs? Are differences in wage growth opportunities across jobs (independent of wage levels) an important determinant of workers' quit propensities? Do jobs (as opposed to workers in them) have different turnover behavior? How much of wage growth depends on job transitions, and how much is accounted for by the accumulation of tenure and experience?

The study of these questions is relevant to our understanding of less-skilled labor markets and may help inform the development of policy initiatives designed to facilitate the transition of disadvantaged workers into steady-living wage jobs. The importance of analyzing the returns from holding a steady job versus the return from switching jobs, as well as how these returns may depend on the skill requirements of the job, is evidenced by two contrasting views of the effects that turnover has for workers. One view is based on the belief that the labor market experiences of low-skilled workers are often characterized by cycling through a series of low wage, unstable, dead-end jobs. Proponents of this view argue that this results in a waste of human capital because the job instability prevents workers from developing skills or behaviors that might lead to higher-paying jobs. An alternative view posits that through the job search process workers gain knowledge about their aptitudes, skills, and interests that lead to better job matches as they move from job to job and up the job ladder. This view is supported by several studies that show that, on average, job mobility accounts for the dominant share of wage growth among young men (Topel & Ward, 1992). The findings of this paper reveal that the skill content of work experience is a critical determinant of which one of these viewpoints becomes a reality for former welfare recipients.

I analyze unique longitudinal individual-level and firm-level survey data over a seven-year period (1997 to early 2004) to provide a complimentary evidence from both the supply and demand side. Both data sets were dministered after the implementation of welfare reform in Michigan, and the same set of detailed questions about job tasks/work skills were asked in each survey.

A primary goal of this paper is to investigate the effects of skill requirements of jobs on starting wages, on-the-job training opportunities, wage growth prospects (likelihood of within-job pay increases and promotion within the firm, and voluntary inter-firm job mobility), and job turnover. There are two key features of my empirical analysis that differentiate it from earlier studies and allow for the possibility of new insight. First, because jobs differ in the learning opportunities they provide, I explore how differences in these opportunities generate heterogeneity of wage-growth rates among jobs that have different job skill requirements. I provide evidence of heterogeneity across workers and jobs in the experience-earnings profile – its steepness (in return to experience) and its discontinuities (due to wage changes associated with job change) – and document systematic differences in expected wage changes with job mobility that depend on reason for and type of job change. Second, the interrelationship between wage growth prospects and job turnover behavior will be examined using both the employer survey and longitudinal individual-level survey data. I will investigate how wage growth and the types of jobs held (job skill requirements) are associated with job turnover. The analysis contributes to our understanding of the nature of the job mobility and wage growth process for less-skilled workers, and highlights the importance of jointly considering both processes. The analysis also underscores the sensitivity of former/current welfare recipients' job transition patterns to changes in local labor market demand conditions.

This paper consists of four parts. In the next section, I briefly review related research on wage growth and job turnover. Section 3 describes the data sets and the definitions of the key variables. Section 4 discusses the estimation strategy, model specification, and central results. In the final section, I summarize the findings and discuss their policy significance.

## 2. RELATED STUDIES

The rapid development and diffusion of new technologies in the workplace over the past several decades, coupled with globalization, has led to growing concerns that these innovations have displaced less-skilled jobs that were once a good source of career earnings paths and replaced them with dead-end, high-turnover service and retail jobs.[1] Recent research has documented the growing importance of cognitive skills in wage determination, for all workers, including less-educated workers (Murnane, Levy, & Willett, 1995; Jencks & Phillips, 1998; Tyler, Murnane, & Willett, 1999). However, the explanation of increasing returns to dimensions of skill not proxied by educational attainment has not resolved the puzzle as to which particular job skills have become relatively more valued in the labor market (Krueger, 1993; DiNardo & Pischke, 1997). Most analyses of earnings have relied on survey data that have limited information on the characteristics of the jobs individuals hold. Because little attention has been given to the skills required, we currently have little systematic knowledge of the evolution of job assignments and resulting effects on wages, particularly in less-skilled labor markets.

Studies of women who have left AFDC find low-paying jobs to be the norm, and there is little wage growth in the first several years after leaving welfare (Harris, 1996; Riccio, Fredlander, & Freedman, 1994; Pavetti, Holcomb, & Duke, 1995; Cancian, Haveman, Meyer, & Wolfe, 2000). Burtless (1995), using NLSY data, showed that women with low levels of schooling and low AFQT scores had lower rates of wage growth with age than did other women and conjectured that these low rates of wage growth reflect recipients' low skill levels.

Loeb and Corcoran (2001), on the other hand, claim that AFDC recipients have low rates of wage growth with age because they work fewer years and are more likely to work part-time than are nonrecipients. They report that wage growth per years actually worked is similar for AFDC recipients and nonrecipients (roughly 6% for every year of full time work), and that wage growth is slow when individuals work part-time. Gladden and Taber (2000) find no significant differences in wage growth with experience by educational attainment.

Neither Loeb and Corcoran (2001) nor Gladden and Taber (2000), however, consider dimensions of skill not proxied by educational attainment and experience. Their estimates include both individuals in jobs that require only soft skills who may gain little from work experience, and those in jobs requiring hard skills (e.g., reading, writing, math, or computer skills) who may experience significant gains from work experience.

The wage premium associated with particular job skills reflects a combination of the cost of acquisition, quasi-rent due to rising demand, and the extent to which the skill can be signaled to the external labor market (Green, 1998). The premium arises because workers can credibly threaten to quit for higher wages elsewhere. Krueger (1993) documented that computer users earn higher pay than nonusers. It remains unclear, however, to what extent their higher wages are due to computing skills, or whether people with higher abilities are selected to use computers and would have received higher pay even in the absence of computer usage (DiNardo & Pischke, 1997). Computer skills have received the bulk of the attention in the literature on U.S. wage inequality. Apart from computer skills, there has been little analysis of the link between other job skills (such as reading/writing and math) and the wage growth process and job dynamics for less-skilled workers. In this paper, I will analyze these relationships.

The extant evidence on whether jobs differ in their prospects for earnings growth (independent of the worker who fills the job) is limited. Topel (1991) and Topel and Ward (1992) analyze the time-series properties of within-job wage changes of men and conclude that heterogeneity in permanent rates of growth among jobs is empirically unimportant. Their results, however, are based on weak tests that fail to reject the hypothesis that within-job wages evolve as a random walk. An important implication of the result for job turnover, if indeed true, is that the current wages, along with experience and seniority, are sufficient statistics for future wages and the value of the job. Thus, this would predict that job separations should decline as a function of the wage level and not as a function of wage growth. However, Topel and Ward's (1992) own job turnover analysis contradicts this prediction and reveals that jobs offering higher wage growth are significantly less likely to end in worker-firm separations than jobs offering lower wage growth. This finding not only implies that the source of wage growth must have a firm-specific component, but it also implies heterogeneity of wage growth among jobs.

Other work analyzing serial correlation in wage increases (Abowd & Card, 1989; Baker, 1997) have yielded mixed results, but the most recent of these studies conducted by Baker (1997) provides a strong evidence in support of the wage profile heterogeneity model. To tackle the related issue of whether serial correlation in wage increases is attached to jobs or to workers, the approach taken in this paper (using longitudinal data of a sample of former/current welfare recipients) estimates the effects of job skills and explicitly controls for unobserved worker heterogeneity by contrasting recipients' wage growth and turnover rates in jobs held of differing skill requirements.

In human capital and job matching models, wage growth over a career reflects accumulation of experience, growth in seniority within a given firm, and movement toward better job matches (Altonji & Shakotko, 1987). The returns to job tenure (relative to job mobility) is an increasing function of the accumulation of job/firm-specific skills (i.e., skills acquired that are valued within the firm, but less easily transferable to other jobs/employers) and the quality of the job match. The proportion of on-the-job training opportunities that are job/firm-specific rises with the skill-level/education requirements of the job (Simpson, 1992). As a result, the human capital model predicts job changes to be a more important source of wage growth for less-skilled workers.[2]

Compared to the voluminous empirical literature on wage growth via human capital accumulation, much less work has been done on wage growth via job changes.[3] Altonji and Williams (1997) after surveying alternative estimates of wage growth reach a consensus estimate of on-the-job wage growth of 1.1% per year. Moreover, this is likely an upper bound since the Altonji–Williams estimate is based on the worker being continuously employed for 10 years. The on-the-job wage growth component appears to account for a small fraction of overall wage growth, which suggests that job mobility may be the most important component in earnings growth.

Topel and Ward (1992) and Loprest (1992) highlight the importance of job mobility (that is, job-to-job transitions) to early career wage growth, estimating that job changes account for roughly one-third of total wage growth during the first 10 years in the market. These studies, however, are based on samples of better-educated workers. Studies that have focused on the wage growth of less-skilled workers have not distinguished between within-job wage growth and between-job wage growth.[4] One exception is Connolly and Gottschalk (2000) who find that high school dropouts experience both lower wage growth within-jobs and lower wage growth in starting wages across jobs than do females with more education. Royalty (1998) and Holzer and LaLonde (2000) show that the kinds of job-to-job changes that have potentially positive effects on the earnings of young workers are relatively infrequent among young, less-educated women, while job-to-nonemployment changes occur more frequently among this group.

Few previous studies adequately take into consideration unobservable differences between job changers and stayers and the endogenous determination of mobility (i.e., the self-selection problem).[5] Moreover, with the exception of Antel (1986) and Garcia-Perez and Sanz (2004), these studies do not distinguish between voluntary and involuntary separations when computing average mobility returns and job turnover. In this paper, I estimate a multinomial endogenous switching model of wage growth to attempt to address the endogeneity between job transitions and wage growth. The analysis explores the relationship between turnover and expected wage growth opportunities, and examines differences in job skill requirements that link these two dynamic processes.

## 3. DATA DESCRIPTION AND DEFINITIONS OF KEY VARIABLES

### *3.1. The Women's Employment Survey (WES)*

The Women's Employment Study drew a random sample of single mothers who received cash assistance in February 1997 in an urban Michigan county. To be eligible for the sample, the women had to reside in this county, be U.S. citizens between the ages of 18 and 54, and be either Caucasian or African-American. Interviews were conducted in Fall 1997, Fall 1998, Fall 1999/Winter 2000, Fall 2001/Winter 2002, and Fall 2003/Winter 2004. The response rate was 86% for the first wave ($N = 753$), 92% for the second wave ($N = 693$), 93% for the third wave ($N = 632$), 91% for the fourth wave ($N = 577$), and 92% ($N = 532$) for the fifth wave of this panel study. Roughly 80 months of data are available for respondents.

The sample was drawn as the transition from the old welfare system to the new one was being implemented. Whereas all respondents received cash assistance in February 1997, about one-quarter had left welfare by Fall 1997, one-half by Fall 1998, 70% by Fall 1999, and 75% by Fall 2001.

I utilize many measures not available in other studies, including information about respondents' work histories, welfare histories, basic job skills, hourly wage of their main job, number of hours worked in this job, and whether they received employer-provided health benefits. Human capital variables include years of schooling, years of full-time and part-time work experience, occupation in which recipient has previous work experience, and number and type of job tasks ever performed on a daily basis in any previous job held. Type of job tasks include reading/writing paragraph-length material, arithmetic, use of computer, supervising co-workers, keeping a close watch on gauges/dials/instruments, filling out forms on a daily basis, and use of client/customer communication skills on a daily basis.[6] The health-related measures I use include physical limitations, mental health problems, child health problems, and experiences of severe domestic abuse.

### 3.2. *The Michigan Employer Survey (MES)*

In Fall 1997 (during the same period the initial wave of WES was underway), Harry Holzer administered a telephone survey to 900 establishments in three large metropolitan areas in Michigan. The employers surveyed were drawn from a sample that was stratified ex-ante by establishment size, so that the sample roughly represents the distribution of the workforce across establishment size categories. The survey was administered to the individual responsible for entry-level hiring, and to all establishments that had hired someone within the past two years. Conditional on meeting these criteria, response rates averaged over 70% (Holzer, 1999). In Fall 1999, a follow-up survey of these firms was conducted, yielding a response rate of 70%.

Each employer was asked a series of questions about the characteristics of the most recently filled job that did not require a college degree. Because the firms are represented in proportion to the number of workers they employ, this sample of recently filled noncollege jobs constitutes a representative sample of the jobs that are available in the local labor markets over a period of several months (Holzer, 1996). Employers were also asked a similar series of questions about the characteristics of jobs previously (within the past two years of the survey) filled by welfare recipients. Questions focused on: (1) the hourly wage, hours, and health benefits offered in the job; (2) the occupation/position in which this worker was hired; (3) the credentials and skills employers sought and the hiring criteria used; (4) the daily task requirements of the job (where the job task measures are identical to those used in WES); (5) the wage growth prospects of the job (including provision of on-the-job training, chance of within-job pay increases, and chance of promotion within the firm assuming good performance); and (6) job performance and job tenure of the recently hired worker.

Given the high response rates and extensive survey instruments, these data sets provide complimentary evidence from the supply and demand side on the relationships between job skill requirements, and the wage and job dynamics of former/current recipients in the post-welfare reform era.[7]

### *3.3. Job Skill Variables*

The MES and the WES contain the same sets of questions about job tasks/work skills. WES collected information from each respondent about whether she performed each of these job tasks on a daily basis in a job(s) held between waves, as well as whether she had ever performed these tasks on any job previously held. I use this information to construct a job task work history for each respondent. I compute a measure of experience using each of these job skills for every individual and build a dynamic measure of job skill use. Suppose that a worker reports having no prior work experience using computer skills as of the Wave 1 interview, then reports using computer skills on a job(s) held between Waves 1 and 2, and also reports using computer skills on a job(s) held between Waves 2 and 3. Hence, between 1997 (Wave 1) and 1998 (Wave 2), the computer-use indicator in the wage regression changes from zero to one. Furthermore, between 1998 (Wave 2) and 1999 (Wave 3), experience using computer skills also changes from zero to one.

I measure workers' ability to perform tasks based on their having done so on a previous job, even though previous job skill experience may not accurately reflect current abilities. Because previously acquired skills may depreciate during periods of nonwork (Mincer & Ofek, 1982; Corcoran, Duncan, & Ponza, 1983; Stratton, 1995), I focus on respondents' job skills used within the year prior to the employment outcome. In the analyses that follow, I measure years of job skill experience like a tenure-skill measure – i.e., the number of consecutive years using the relevant job skill. I also tried, alternatively, measuring years of job skill experience as a pure experience-skill measure – i.e., the cumulative number of years in which a worker ever used the relevant job skill. This alternative way of measuring job skill experience did not qualitatively change any of the underlying findings reported in this paper.[8]

Now, consider an individual who reports having prior work experience using computer skills at Wave 1, but reports not using computer skills on a job(s) held between Waves 1 and 2, and then reports using computer skills on a job(s) held between Waves 2 and 3. I count an accumulated year of experience using a particular job skill only if the job skill has been used in consecutive periods. Thus, this individual is not counted as having accumulated an additional year of experience using the particular job skill over the period because of her intermittent job skill use.

### *3.4. Job-Transition Pattern Variables*

Using the WES, I characterize employment patterns and the extent of job stability and job mobility between waves, using retrospective questions from each wave on job tenure, monthly job/employment history, and reported reason for job separation (if any occurred). The wages, hours, and health benefits of the most recent job are recorded at each interview (given the individual has worked at some point between interviews).[9] Therefore, I count job separations over the period between two interviews.[10] If a person is between jobs at the time of an interview, the separation is assigned to the interview year when she starts her next job. I distinguish job separations both by whether they were voluntary or involuntary (i.e., due to being laid-off or fired), and by whether they were followed by a nonemployment spell of four or more weeks.

I define three patterns of job transitions: job stability, job mobility, and job instability. Individuals whose the current/most recent job at wave $t$ was the same as that held at the previous wave are denoted as experiencing job stability. Job mobility occurs when respondents made a voluntary job change without experiencing any involuntary separations or transitions into nonemployment. I distinguish between job instability that is due to being laid-off or fired from instability that results from an employee-initiated job-to-nonemployment transition.[11,12] I define a "transition" as a job-to-job transition if the job change was voluntary and the interval between jobs was less than four weeks. Conversely, I define a transition as being into nonemployment only if the spell of nonwork lasts four or more weeks, or if the job change results from being laid-off or fired. Nonemployment spells of more than a month are less likely to be the result of nonemployment chosen in order to search for a new job more intensively, and are more likely to be the result of nonmarket/nonsearch reasons.[13] Royalty (1998) and Gladden and Taber (2000) use similar definitions of job transitions.

## 4. ESTIMATION STRATEGY, MODEL SPECIFICATION, AND RESULTS

I begin by using the MES to estimate the determinants of the starting wage earned on jobs recently filled by former/current welfare recipients, with particular emphasis on the effects of job skill requirements. To examine the determinants of wage growth prospects, I next estimate a series of probit equations of whether the job provides on-the-job training opportunities, a chance of merit-based pay increases, the likelihood of promotion (ordered probit: poor, fair, good, excellent), and whether a promotion was received within the past year (since date of hire), respectively, using MES.

The longitudinal aspect of the WES is then exploited to take into account unobserved heterogeneity on (i) the effects of various job skills on the wage profile, (ii) the effects of different job transition patterns (job stability, job mobility, job instability) on wage growth, and (iii) the propensity to change jobs. I also identify the returns to various job skills. Are workers who use a given set of job skills better paid than workers who do not use these skills? If the answer is positive, I examine whether workers using these skills received higher pay before using these skills on the job, or received higher pay as soon as they started using these skills on the job, or finally, received higher pay once they had sufficient experience using these skills on the job.

In the models estimated below, I conceptualize a job in terms of its production aspects (inputs) as a collection of tasks. Job tasks are not independent of the workers who perform the tasks. Thus, disentangling person-specific and job-specific effects has implications for whether low-wage jobs are inherently dead-end – and if so, which kinds of jobs? A job can be defined by the technological investment opportunity it provides a worker

(Lazear, 1995; Rosen, 1972). On-the-job training typically provided in non-college jobs are not firm-specific (i.e., training received, which is valued within the firm but less easily transferable to other jobs), but rather consist of general and occupation-specific training. These opportunities may be of especial importance for low-skilled workers, affecting both their probability of experiencing wage growth within jobs and the probability of experiencing wage growth via job changes.[14] If at all training costs are paid by the employers, and the skill enhancement programs are, at least to some degree, portable, then we would expect the workers to bear some portion of the costs by receiving lower starting wages (Parent, 1999).

### 4.1. Wage Analysis Using MES

#### 4.1.1. Specification

Consider the following log starting wage equation augmented with a set of job task/skill variables:

$$\begin{aligned}\ln(\text{STARTWAGE})_{ijt} = {} & \beta_0\text{HSGRAD}_{it} + \beta_1\text{PRIOREXP}_{it} \\ & + \beta_2\text{SKILLCERT}_{it} + \beta_3\text{JOBSKILL}_{ijt} \\ & + \beta_4\text{JOBHOURS}_{ijt} + \beta_5\text{OJT}_{ijt} + \Gamma\mathbf{Z}_{ijt} + \varepsilon_{ijt} \qquad (1)\end{aligned}$$

where STARTWAGE represents the real starting hourly wage of person $i$ in job $j$ at time $t$; HSGRAD, PRIOREXP, and SKILLCERT are variables indicating whether the individual possesses a high school diploma/GED, prior occupation-specific work experience, and training/skill certification, respectively; JOBSKILL is a vector of job skill/task variables; JOBHOURS indicates whether the job is part-time; on-the-job training (OJT) indicates whether on-the-job training opportunities are provided; and $\mathbf{Z}$ represents a vector of firm characteristics. I include OJT to test whether workers pay for formal OJT by accepting lower starting wages.

I am particularly interested in estimating the effects of the set of job skills. The inclusion of employee characteristics used in conventional human capital specifications – specifically, possessing high school diploma, previous occupation-specific work experience, and skill or training certification – may lead to an underestimate of the impact of job skills because the output of schooling presumably includes many of the observed job skills. In addition, it is not clear whether occupation dummies are appropriate variables to include in the regressions that follow, because possessing particular job skills may enable workers to qualify for jobs in higher paying occupations. Thus, I present several alternative specifications of the model using MES in

Columns (1–3) of Table 1. The specifications differ in whether they control for conventional human capital characteristics and/or differences across occupation. This helps to determine whether particular job skills are associated with higher pay because they are associated with higher paying occupations or because, within occupation those with more job skills receive higher pay. This also helps identify whether education is associated with higher pay because it is associated with the possession of essential job skills that are associated with higher pay. Column (1) includes only the set of job skill variables as measures of skill; the specification in Column (2) includes controls for conventional human capital variables (but not occupation); both conventional human capital variables and occupation controls are included in Column (3). Because the inclusion of occupation variables in such a regression is likely to lead to an underestimate of the impact of job skills, I emphasize the regression results from specification (2).

*4.1.2. MES Results*

Columns (1–3) of Table 1 show the results obtained by estimating the starting wage equation using MES. The mean and median starting wage in jobs previously filled by former/current welfare recipients was $6.75 and $6.50, respectively. As can be seen from specification (2), possessing a training or skill certification increases the starting wage by 8%; neither the possession of a high school diploma nor previous experience in the particular line of work significantly affected the starting wage after the set of job skill variables were included. Use of reading/writing skills is associated with a 12.7% higher starting wage; while use of math and customer communication skills are both linked with lower pay. The likely reason for the negative coefficients on the use of math and customer communication skills is that these activities are negatively correlated with other unobserved activities using valued skills. Thus, where math and/or customer communication skills are very important, workers are not using other more highly valued skills. Another explanation is that math (including making change) and customer communication skills have a relatively low supply price, as they are more easily learnable, with an effectively zero/low cost of acquisition. It is also likely that computers have increased the value of some skills (e.g., reading/writing), while decreased the value of others (e.g., arithmetic, see, Levy and Murnane's, 1996, work examining with what skills are computers a complement). Somewhat surprisingly, jobs that required the use of computer skills did not pay significantly higher starting wages than those that did not require these skills. The set of job skill/task variables are not simply capturing attachment to specific occupations (e.g., fast-food jobs (math/customer communication),

***Table 1.*** Determinants of Starting Wages using MES. Dependent Variable: Log of Real Starting Hourly Wages ($1999). (Robust Standard Errors in Parentheses).

| Explanatory Variables | Mean | (1) | (2) | (3) |
|---|---|---|---|---|
| *Human capital variables* | | | | |
| High school Diploma/GED | 0.8239 | – | 0.0197 | 0.0229 |
| | | | (0.0249) | (0.0244) |
| Prior occupation-specific work experience | 0.5074 | – | −0.0257 | −0.0131 |
| | | | (0.0285) | (0.0271) |
| Training/skill certification | 0.3743 | – | 0.0801*** | 0.0953*** |
| | | | (0.0309) | (0.0291) |
| *Job skill variables* | | | | |
| Reading/writing | 0.4771 | 0.1357*** | 0.1273*** | 0.1011*** |
| | | (0.0271) | (0.0284) | (0.0276) |
| Computer | 0.4060 | 0.0399* | 0.0334 | −0.0353 |
| | | (0.0290) | (0.0291) | (0.0298) |
| Math | 0.6327 | −0.1005*** | −0.0952*** | −0.1090*** |
| | | (0.0271) | (0.0266) | (0.0279) |
| Customer communication | 0.7399 | −0.1006*** | −0.1049 | −0.0469* |
| | | (0.0282) | (0.0274) | (0.0339) |
| *Occupation* | | | | |
| (Reference category: service) | | | | |
| Sales | 0.1996 | – | – | 0.1357*** |
| | | | | (0.0358) |
| Clerical | 0.2067 | – | – | 0.2492*** |
| | | | | (0.0385) |
| Blue-collar | 0.1767 | – | – | 0.1920*** |
| | | | | (0.0441) |
| *Other job characteristics* | | | | |
| Part-time | 0.2500 | −0.1084*** | −0.1156*** | −0.0859*** |
| | | (0.0306) | (0.0311) | (0.0316) |
| On-the-job training | 0.6371 | – | −0.0369* | −0.0355* |
| | | | (0.0243) | (0.0230) |
| *Firm characteristics* | | | | |
| % Employees unionized | 16.1507 | 0.0025*** | 0.0025*** | 0.0021*** |
| | | (0.0004) | (0.0004) | (0.0004) |
| Firm Size (Reference category: $\geq$100 employees) | | | | |
| 1–9 employees | 0.2071 | −0.0760* | −0.0772* | −0.0891** |
| | | (0.0400) | (0.0399) | (0.0369) |
| 20–99 employees | 0.3636 | −0.0588* | −0.0518* | −0.0678** |
| | | (0.0325) | (0.0321) | (0.0307) |
| $R^2$ | | 0.2266 | 0.2400 | 0.3223 |
| Sample size | | 505 | 505 | 505 |

*Note:* Regressions also include metropolitan area dummies and a constant term. The mean and median wage for this sample of jobs filled by former/current welfare recipients is $6.75 and $6.50, respectively. See Section 3 for description of MES.
*Statistically significant at the 0.10 level (one-tailed test).
**Statistically significant at the 0.05 level.
***Statistically significant at the 0.01 level.

clerical jobs (reading/writing)), since the pattern of results is similar when occupation variables are included. Among the occupations, the results indicate that service jobs – the occupation in which recipients are disproportionately concentrated – offered the lowest starting pay, while clerical jobs offered the highest starting pay.

Part-time jobs are associated with 11.6% lower starting wages; while both larger firms and firms with greater fractions of unionized employees pay higher starting wages. I also find evidence that workers pay for part of their training programs by accepting lower starting wages. The starting wage estimates reveal that provision of OJT opportunities lowers starting wages by 3.7%. Furthermore, the potential effect of job-match or individual heterogeneity biases will be to underestimate the effect of OJT on the starting wage since higher ability (and better matched) individuals are likely to be paid more and receive more training. Thus, this estimate of the impact of OJT may be considered a lower bound.

The emphasis of the remainder of my empirical analysis is on modeling the process of wage changes resulting in the current hourly earnings (as opposed to modeling wage levels), because a fundamental question that needs closer investigation concerns earnings dynamics that accompany initial employment at low wages. Employers report that jobs filled by previously hired recipients that require both reading/writing and computer skills were more likely to offer potential wage increases for merit, greater chances for promotion (with good performance), and were more likely to offer formal job training opportunities. Recipients who received formal job training and worked in jobs requiring reading/writing and computer skills experienced almost twice the number of formal job training hours relative to those holding jobs that require only soft skills.[15] This suggests that a lack of cognitive skills may not only affect the kinds of jobs some recipients can get, but, because of fewer OJT opportunities, may also affect their potential for wage growth.

In columns 1–4 of Table 2, I present estimates from a series of probit equations of whether the employer reports that the job provides OJT opportunities, a chance of merit-based pay increases, the likelihood of promotion (ordered probit: poor, fair, good, excellent), and whether a promotion was received within the past year (since date of hire), respectively.[16,17] As shown in the first column, 63.7% of the sample of jobs recently filled by former/current welfare recipients provided some type of OJT (not including training that was remedial).[18] The results indicate that the probability that a given job offers OJT increases by eight percentage points if the job requires reading/writing skills, and increases by 4.4 percentage points if the job

**Table 2.** Determinants of Wage Growth Prospects.

| Explanatory Variables | Dependent Variables (Robust Standard Errors in Parentheses) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | (4) | |
| | Provision of on-the-job training (probit estimates) | | Offers chance of within-job pay increase (probit estimates) | | Employer-reported promotion prospect (1 = poor, 2 = fair, 3 = good, 4 = excellent) (ordered probit estimates) | Received promotion since date of hire (probit estimates) | |
| | Mean | d$F$/d$x$ | Mean | d$F$/d$x$ | Coefficient | Mean | d$F$/d$x$ |
| *Work performance-related variables* | | | | | | | |
| Absenteeism problem | | | | | | 0.4203 | −0.0385 |
| | | | | | | | (0.0386) |
| Work attitude problem | | | | | | 0.1884 | 0.0510 |
| | | | | | | | (0.0692) |
| Job skill-related problem | | | | | | 0.1304 | −0.0866 |
| | | | | | | | (0.0287) |
| On-the-job training | | | 0.6371 | 0.1221*** | 0.3166*** | 0.6860 | 0.0588* |
| | | | | | (0.1234) | | (0.0392) |
| Remedial training | | | | | | 0.2657 | −0.0788** |
| | | | | | | | (0.0338) |
| *Job skill variables* | | | | | | | |
| Reading/writing | 0.4771 | 0.0803* | 0.4771 | 0.0202 | 0.0665 | 0.5217 | 0.0255 |
| | | (0.0460) | | (0.0441) | (0.1103) | | (0.0456) |
| Computer | 0.4060 | 0.0438 | 0.4060 | 0.0711* | 0.3894*** | 0.3140 | 0.1761*** |
| | | (0.0466) | | (0.0438) | (0.1295) | | (0.0722) |
| Math | 0.6327 | −0.0017 | 0.6327 | 0.0356 | 0.1160 | 0.5652 | −0.1149** |
| | | (0.0442) | | (0.0451) | (0.1139) | | (0.0526) |
| Customer communication | 0.7399 | −0.0419 | 0.7399 | −0.0455 | −0.0820 | 0.7053 | 0.0366 |
| | | (0.0484) | | (0.0474) | (0.1497) | | (0.0446) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Human capital variables* | | | | | | | |
| Job tenure (months) | | | | | | 7.4 | 0.0062** |
| | | | | | | | (0.0032) |
| High school Diploma/ GED | | | | | | 7101 | 0.0027 |
| | | | | | | | (0.0446) |
| Prior occupation-specific work experience | | | | | | 0.4976 | −0.0057 |
| | | | | | | | (0.0452) |
| Training/skill certification | | | | | | 0.4300 | −0.0086 |
| | | | | | | | (0.0428) |
| Sales | | | | | 0.3610** | 0.1836 | −0.0152 |
| | | | | | (0.1521) | | (0.0519) |
| Clerical | | | | | −0.1047 | 0.1884 | −0.0135 |
| | | | | | (0.1709) | | (0.0470) |
| Blue-collar | | | | | 0.2644* | 0.1691 | 0.0285 |
| | | | | | (0.1744) | | (0.0683) |
| *Other job characteristics* | | | | | | | |
| Part-time | 0.2500 | −0.0955** | 0.2500 | −0.1123** | 0.0140 | 0.3768 | −0.0542* |
| | | (0.0472) | | (0.0498) | (0.1215) | | (0.0388) |
| *Firm characteristics* | | | | | | | |
| % Employees unionized | 16.1507 | 0.0001 | 16.1507 | −0.0032*** | −0.0034** | 19.2121 | −0.0004 |
| | | (0.0006) | | (0.0006) | (0.0017) | | (0.0007) |
| Firm size (Reference category: ≥100 employees) | | | | | | | |
| 1–9 employees | 0.2071 | −0.0531 | 0.2071 | 0.1209** | −0.1600 | 0.1594 | 0.1732** |
| | | (0.0609) | | (0.0512) | (0.1642) | | (0.1082) |
| 20–99 employees | 0.3636 | 0.0168 | 0.3636 | 0.0676* | 0.0012 | 0.3285 | 0.1208** |
| | | (0.0490) | | (0.0430) | (0.1248) | | (0.0653) |
| Log-likelihood | | −377.7363 | | −297.3637 | −580.7765 | | −63.2523 |
| Observed Fraction providing OJT | | 0.6371 | | | | | |
| Predicted problem of OJT (eval at sample means) | | 0.6395 | | | | | |

**Table 2.** (*Continued*)

| Explanatory Variables | Dependent Variables (Robust Standard Errors in Parentheses) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | (4) | |
| | Provision of on-the-job training (probit estimates) | | Offers chance of within-job pay increase (probit estimates) | | Employer-reported promotion prospect (1 = poor, 2 = fair, 3 = good, 4 = excellent) (ordered probit estimates) | Received promotion since date of hire (probit estimates) | |
| | Mean | d$F$/d$x$ | Mean | d$F$/d$x$ | Coefficient | Mean | d$F$/d$x$ |
| Obsvd fraction offer chance of W/in-job pay increase | | | | 0.7036 | | | |
| Predicted problem of within-job pay increase | | | | 0.7238 | | | |
| Sample Size | 587 | | 550 | | 502 | 207 | |

*Note:* Regressions also include controls for metropolitan area, starting hourly wages, and employee human capital characteristics. 43.8% of employers reported excellent promotion prospects; 33.7% reported good promotion prospects; 13.9% reported fair promotion prospects, and 8.6% reported poor promotion prospects. The mean length of time represent the derivative of the probability of the outcome with respect to a unit-change in the explanatory variable (discrete change of dummy variable from 0 to 1), evaluated at the sample means.

*Statistically significant at the 0.10 level (one-tailed test).

**Statistically significant at the 0.05 level.

***Statistically significant at the 0.01 level.

requires computer skills (though the latter coefficient is not statistically significant). On the other hand, part-time jobs are 9.6 percentage points less likely to provide OJT.

As shown in the second column, according to employer reports, 70% of the jobs recently filled by welfare recipients offered chances for within-job pay increases (above cost of living increases) assuming good performance. The results show that jobs that provide OJT are 12.2 percentage points more likely to offer within-job wage growth opportunities. The impact of the use of reading/writing skills on the potential of within-job pay raises becomes insignificant after the inclusion of OJT, suggesting that one of the primary ways reading/writing skills affects wage growth prospects is through the provision of more OJT opportunities. Although computer skills did not significantly affect the starting wage (Table 1), jobs that require computer skills are 7.1 percentage points more likely to offer potential merit-based pay increases. On the other hand, part-time jobs are 11.2 percentage points less likely to offer chances of merit-based pay increases. While larger firms and firms with greater fractions of employees that are unionized offered higher starting wages (Table 1), these firms offer fewer chances for within-job merit-based pay increases.[19]

As shown in the third column, employers reported that, assuming good performance, 43.8% of the jobs recently filled by welfare recipients offered excellent promotion prospects, 33.7% offered good, 13.9% offered fair, and 8.6% offered poor promotion prospects. I estimate an ordered probit regression, where the dependent variable takes on the values: 1 = poor, 2 = fair, 3 = good, 4 = excellent. The same general pattern of results emerges: use of computer skills and OJT are associated with greater upward mobility prospects. I include a set of occupation dummy variables to control for differences in the structure of promotion opportunities across occupations. As expected, sales and blue-collar occupations have greater promotion prospects than service and clerical jobs.

Working in firms with smaller fractions of unionized employees is positively associated with promotion receipt, possibly because unionized firms are more likely to base promotion on seniority than are nonunionized firms (Abraham & Medoff, 1985). Unions are associated with flatter age-earnings profiles. Given that the sample is comprised of relatively young workers, seniority rules may hamper the promotion prospects of those who are unionized.

The results presented in columns 2 and 3 of Table 2 are based upon employer reports of the potential wage growth prospects, while the last column presents results from estimating a probit equation on actual receipt of a promotion since being hired with the firm. 44.7% of employers reported that former/current recipients' work performance was about the same as other workers that have previously filled the position; 16.5% reported recipients' work performance was much better, 25.7% reported recipients' work performance was a little better; while 9.2% and 3.9% reported recipients' work performance was a little worse and much worse, respectively, than other workers. 42% of employers reported previously hired recipients had absenteeism problems, 18.9% reported work attitude problems, and 13% reported previously hired recipients had job skill-related problems. I include these indicator measures of poor work performance, based upon employer reports, in the model of actual promotion receipt.

The mean length of time that had elapsed since the date of hire was 7.4 months. Fifteen percent of recipients had received a promotion as of the survey interview date. Despite the relatively short period of time that had elapsed since the date of hire, the results are instructive. Most of the significant predictors of the probability of promotion are the same for employer reports of promotion prospects as for actual promotion receipt. Job skill-related work performance problems significantly reduce the probability of promotion. The OJT (not including that which is remedial) significantly increases the probability of promotion receipt, while a remedial OJT is negatively associated with promotion receipt (this is likely picking up worker job-skill deficiencies). Use of computer skills is significantly associated with promotion receipt, while use of math skills is negatively associated with promotion receipt (likely explanation for negative association previously discussed). I do not find significant differences in promotion receipt across occupation groups, after the inclusion of the set of job skills. Job tenure is significantly related to promotion receipt. The effect of job tenure and company training on promotion likelihood suggests that the acquisition of job-specific skills resulted in promotion.

Working part-time is associated with a significant reduction of promotion rates, as is working in large firms. This latter result is counter-intuitive since we would expect larger workplaces to have greater availability of opportunities for upward mobility (Idson, 1989). Given the short length of time that had elapsed since the date of hire for this sample of relatively young workers, seniority rules may have hampered the promotion prospects of those who were working in large firms, due to the more structured organization of jobs that generally accompanies larger firms.

The results presented up to this point cannot be used to determine decisively between competing explanations – in particular, whether the estimated effects of different job skills (e.g., reading/writing, computer) reflect the true return to the job skill (i.e., job skill affecting wage profile), or whether the relationship between use of a set of job skills and wage growth is purely the result of job sorting (selection of abler workers/high-ability types). It remains unclear how the use of different sets of job skills affects the earnings profile, since unobservable worker characteristics are not directly controlled for here. Controlling for unobservable worker heterogeneity is important because workers using a particular job skill that is associated with higher wage growth may have experienced greater wage growth in the absence of the use of that skill (if unobserved fixed worker quality is driving results). Thus, in the next section, I use the longitudinal data on former/current welfare recipients to control for unobservable worker heterogeneity to isolate the return to job skills.

### *4.2. Wage Growth Analysis using WES*

#### *4.2.1. WES Sample Descriptive Statistics*

Overall work experience accumulated masks heterogeneity in job transition patterns, which may have significant effects on wage growth trajectories. In particular, while the most respondents worked in for the most of the months over the five years of the panel (the mean number of months worked is roughly 40 months),[20] and much of this accumulated experience working in full-time jobs, job instability was the most common employment pattern between successive waves. Roughly half of the respondents experienced job instability, while 27.4% experienced job stability and 20.2% experienced job mobility between successive waves.[21,22] The worsening economic conditions in 2001 increased the risk of job loss. Among individuals who experienced job separations between waves, separations resulting from being laid-off or fired increased from 21.3% to 27.9% between 1998–1999 and 1999–2001.

There was a significant amount of within-person changes in job skills used over the period. In estimating the wage growth models that follow, I include differences in job skills used, changes in job hours, and occupation transitions to account for the heterogeneity in wage growth. I am interested in the relationship between job transition patterns and wage growth. I examine the mean wage growth associated with different job transition patterns – job stability, voluntary job mobility, and job instability. I investigate the extent to which average wage growth masks heterogeneity in within- and between-job wage growth, and examine whether differences in job skill requirements can explain the observed heterogeneity in wage growth.

#### *4.2.2. WES Wage Specification and Estimation Strategy*

My estimation model assumes human capital characteristics (job task attributes) affect not only wage levels, but also the process of wage growth (e.g., via learning ability or differences in human capital investment opportunities across jobs). Low wages may be a greater reflection of a worker's learning ability (or lack of OJT opportunities) as well as their earning ability – e.g., individuals who have more ability and motivation may learn more from work experience.

Consider the following log wage equation augmented with job-skill variables:

$$\begin{aligned}\ln(\mathrm{WAGE})_{ijt} = \Gamma \mathbf{Z}_{ijt} + \beta_0 \mathrm{EXP}_{it} + \beta_1 \mathrm{JOBSKILL}_{ijt} \\ + \beta_2 (\mathrm{EXP\ \ using\ \ JOBSKILL})_{ijt} + \alpha_i + u_{ijt}\end{aligned} \tag{2}$$

where WAGE represents the real hourly wage of person $i$ in job $j$ at time $t$; **Z** is a vector of educational attainment, demographic variables, health-related variables, county unemployment rate, and other controls; EXP is years of full-time and part-time work experience (entered separately, with quadratic terms); JOBSKILL and EXP using JOBSKILL is a vector of job-skill variables and the corresponding years of experience using these job skills, respectively.

I include both the vector of job-skill variables and measures of the number of years of experience using the these job skills to allow the use of job skills to affect both the wage level and wage growth (i.e., the slope of the wage-experience profile). For example, the latter may capture the potentially enhancing productivity of computer usage or the greater provision of OJT opportunities in jobs requiring particular skills. I decompose returns to various job skills into a constant and a part related to experience.

Note that the error term in the above equation contains a time-invariant person-specific effect, $\alpha_i$. If less-able or less-motivated workers are less likely to work in jobs requiring valued job skills, estimates of returns to job skills that fail to control for $\alpha_i$ may be biased toward finding larger effects. I present the WES cross-sectional wages estimates of Eq (2) (which do not control for unobserved heterogeneity) in Appendix Table A1. I use the cross-sectional estimates as a benchmark to compare with the fixed effect estimates. The overall pattern of the WES cross-sectional results are similar to those yielded using employer reports. The fundamental problem with the cross-sectional results is that, despite the extensive set of controls, the measure of particular skills in the workplace may be positively correlated with unobserved characteristics that also generate wage premia, causing the job-skill coefficients to be upwardly biased.

I explore two different ways of assessing the likely size and significance of this bias by exploiting the longitudinal aspect of WES. First, to control for unobserved worker characteristics, I estimate a first-difference fixed effect wage equation of the following form (augmented with job transition-pattern variables):

$$\begin{aligned}\Delta \ln(\mathrm{WAGE})_{i(t-1,t)} = {} & \beta_0(\Delta \mathrm{EXP})_{i(t-1,t)} + \beta_1(\mathrm{JOBTRNSITN})_{i(t-1,t)} \\ & + \beta_2(\Delta \mathrm{EXP} * \mathrm{JOBTRNSITN})_{i(t-1,t)} \\ & + \beta_3(\Delta \mathrm{JOBSKILL})_{i(t-1,t)} \\ & + \beta_4(\Delta \mathrm{EXP\ using\ JOBSKILL})_{i(t-1,\ t)} \\ & + \Gamma(\Delta \mathbf{Z})_{i(t-1,t)} + \Delta u_{i(t-1,t)} \end{aligned} \tag{3}$$

Because the person-specific time-invariant effect ($\alpha_i$) has been differenced out, equation (3) can be estimated by OLS and is a consistent estimation method for identifying the effects of time-varying characteristics.[23] In estimating the first-difference fixed effect model, many of the terms in **Z**, such as education, sex, and race, have also been eliminated since they do not vary with time.

In the first-difference specification, I include job transition pattern variables and control for occupation transitions using a one-dimensional occupation index. The inclusion of these variables enables me to isolate the true return of job skills independent of the effects of job changes that may have led to the change in job skills used (for a given worker).

The JOBTRNSITN vector captures whether the individual experienced job stability, job mobility, a voluntary job separation with an intervening spell of nonemployment, or an involuntary job separation, between the most recent job of successive waves. The change in work experience and job transition variables are entered separately and interacted with each other in the first-difference specification. The sum of the relevant job transition and work experience terms along with their interactions, captures the sum of the returns to experience and returns to tenure for individuals who experienced job stability; and captures the sum of the returns to experience and the change in the job match component for individuals who experienced the relevant type of job change.

We expect wage growth to be higher for individuals who experience job mobility relative to those who experience job instability. Individuals are presumed to voluntarily change jobs because they expect a wage gain, while individuals who experience job instability (particularly, resulting from being laid-off/fired) may lose job-specific human capital and matching capital because employers use the stability of potential workers' employment histories as a signal for good matches (Gladden & Taber, 2000). We also expect that returns to job stability (i.e., individuals whose current/most recent job in wave *t* was the same as that held in the previous wave) will be higher than the returns to job instability.

The job mobility decisions are likely endogenous with respect to wage changes. One reason individuals stay in the same job is because they work in jobs with more potential wage growth opportunities. This produces a downward bias on the estimated effects of job mobility (relative to job stability), since the counterfactual – the wage growth of the individual would have experienced had she stayed in the same job – is not observed. In this way, the estimates of the gains to job mobility (relative to job stability) may be considered lower bound estimates. For this precise reason, in the final empirical section of this paper, I estimate a multinomial endogenous switching model of wage growth to better address the endogeneity of job mobility, which is described at the end of Section 4 and Appendix A.

In light of the prevalence of occupation changes among our sample, I include a control for occupation-transition characteristics. I create a one-dimensional occupation index that is designed to capture the amount of human capital needed to work in different occupations. I detail in Appendix B the derivation of the occupation index. My construction of the index is adapted from that previously developed by Sicherman and Galor (1990).[24]

#### *4.2.3. Mean Wage Growth*

Table 3 shows the distribution of annual within-job real wage growth and the distribution of annual real wage growth with voluntary job mobility and with job instability. On average, real wages grew 4.1% per year for individuals who remained in the same job, but by 7.3% per year for individuals working full-time on the same job, and not at all for individuals working part-time on the same job. The mean wage gain for workers who experienced voluntary job mobility was 6.2%. The selected sample of individuals who experienced voluntary job mobility is not representative of all workers, and thus their mean wage growth does not represent that which a random worker would experience if she changed jobs, but rather represents the expected wage growth conditional on voluntarily changing jobs.[25] In terms of the underlying economic variables of standard wage models, these results suggest that the improvement in job match, for those who find successful job matches, is comparable to the gains from returns to work experience and tenure; and, thus job changes are an important source of wage growth.

**Table 3.** Distribution of Average Annual Real Wage Growth (in natural logs), by Type of Job Transition.

| | Within-Job Wage Growth, Full-Time Job | Within-Job Wage Growth, Part-Time Job | Wage Growth w/Vol Job Mobility | Wage Growth w/Invol Job Change | Wage Growth w/EE-initiated Job Instab |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Annual wage growth* | | | | | |
| Mean | 0.073* | −0.014 | 0.062*** | 0.007 | 0.024** |
| Median | 0.042 | 0.012 | 0.051 | −0.006 | 0.032 |
| Cumulative distribution: | | | | | |
| −0.10 | 0.108 | 0.259 | 0.197 | 0.277 | 0.220 |
| 0 (percent non-positive) | 0.280 | 0.452 | 0.384 | 0.518 | 0.401 |
| +0.10 | 0.693 | 0.716 | 0.605 | 0.712 | 0.633 |

All wages have been converted to real wages (1999 dollars) using the Consumer Price Index for All Urban Consumers (CPI-U).
*Source:* Women's Employment Survey, 1997 – early 2004.
*Statistically significant at 10% level.
**Statistically significant at 5% level.
***Statistically significant at 1% level (two-tailed tests).

The results in Table 3 reveal the importance of differentiating between job changes resulting from voluntary job mobility and those resulting from job instability. Annual wage growth was nonexistent among individuals who experienced involuntary job separations, and 2.4% among those who experienced employee-initiated job-to-nonemployment transitions. Table 3 also reveals that average wage growth masks substantial heterogeneity in wage growth within each of the job transition patterns. Large fractions of individuals experienced real wage declines, particularly those who experienced job instability. Part of the declines in real wages, however, is likely due to measurement error (Gottschalk, 2002).

*4.2.4. First-Difference Fixed Effect Results*

The first-difference estimates are presented in Table 4. The first column reports estimates of a model that includes only the job transition and standard work experience variables, while the second column shows the full model. Results from the parsimonious specification indicate that an additional year of full-time work experience with job stability is associated with 4.8% increase in pay, and an additional year of full-time work experience accompanied by a voluntary job change is associated with 10.3% increase. This evidence suggests that job mobility is a critical component of the wage growth process for these less-skilled women. On the other hand, the return to an additional year of full-time work experience that includes an involuntary job separation is small and statistically insignificant. Accumulated part-time work experience had a negligible effect on wage growth (this was true with any of the job transition patterns).

The average annual amount of full-time work experience accumulated for individuals who experienced job instability was roughly five months – or only 44% of the amount accumulated by individuals working full-time continuously over the year. The indirect effect of job instability on wage growth through its effect on the loss of potential full-time work experience accumulation is, therefore, estimated to be a wage loss of 2.7% relative to the rate of annual within-job wage growth (0.56*0.048), and a loss of 5.8% relative to the rate of annual wage growth occurring with voluntary job mobility (0.56*0.103).

The model in column (2) estimates the effects of job skills. I find that when workers change from not using reading/writing skills to using these skills on a daily basis, their wage increases immediately by 4.7%. Furthermore, workers earn an additional 4.6% wage premium with each additional year of experience using reading/writing skills (over and above the return to general work experience). In contrast, in the longitudinal dimension, the

***Table 4.*** First-Difference Fixed Effect Wage Estimates.

| Explanatory Variables | (1) | (2) |
|---|---|---|
| Dependent Variable: First-Difference of Log of Real Hourly Wages ($1999) | | |
| *Human capital variables* | | |
| ΔFull-time work experience | 0.0484*** | 0.0150 |
| | (0.0103) | (0.0159) |
| ΔPart-time work experience | 0.0286 | 0.0115 |
| | (0.0242) | (0.0272) |
| Job mobility | 0.0996* | 0.0533 |
| | (0.0617) | (0.0612) |
| Involuntary job instability | 0.0662 | 0.0069 |
| | (0.0523) | (0.0508) |
| Employee-initiated job instability | 0.0180 | −0.0341 |
| | (0.0348) | (0.0367) |
| (ΔFull-time work experience)*(Job mobility) | −0.0453 | −0.0175 |
| | (0.0413) | (0.0406) |
| (ΔFull-time work experience)*(Employee-initiated job instability) | −0.0187 | 0.0067 |
| | (0.0341) | (0.0355) |
| (ΔFull-time work experience)*(Involuntary job instability) | −0.0920** | −0.0445 |
| | (0.0418) | (0.0414) |
| (ΔPart-time work experience)*(Job mobility) | −0.0972* | −0.0852 |
| | (0.0551) | (0.0553) |
| (ΔPart-time work experience)*(Employee-initiated job instability) | 0.0026 | 0.0453 |
| | (0.0455) | (0.0451) |
| (ΔPart-time work experience)*(Involuntary job instability) | −0.1159* | −0.0524 |
| | (0.0648) | (0.0635) |
| *Return to (FTExp+Tenure) w/job stability* | 0.0484*** | 0.0150 |
| *Return to (FTExp+ΔJobMatch component) w/Job mobility* | 0.1027*** | 0.0509* |
| *Return to (FTExp+ΔJobMatch component) w/InvolJobInstability* | 0.0226 | −0.0226 |
| *Return to (FTExp+ΔJobMatch component) w/EE-InitiatedJobInstability* | 0.0477*** | −0.0124 |
| *Job skill variables* | | |
| ΔReading/writing | | 0.0472** |
| | | (0.0198) |
| ΔExperience using reading/writing | | 0.0461*** |
| | | (0.0154) |
| ΔComputer | | −0.0071 |
| | | (0.0212) |
| ΔExperience using computer | | −0.0119 |
| | | (0.0189) |
| ΔMath | | 0.0213 |
| | | (0.0183) |
| ΔExperience using math | | 0.0086 |
| | | (0.0173) |

***Table 4.*** (*Continued*)

| Explanatory Variables | (1) | (2) |
|---|---|---|
| Dependent Variable: First-Difference of Log of Real Hourly Wages ($1999) | | |
| ΔGauges/dials/instruments | | 0.0496*** |
| | | (0.0189) |
| ΔExperience using gauges/dials/instruments | | 0.0095 |
| | | (0.0161) |
| ΔCustomer communication | | −0.0815*** |
| | | (0.0251) |
| ΔExperience using customer communication | | 0.0184 |
| | | (0.0194) |
| ΔOccupation index | | 0.1164*** |
| | | (0.0231) |
| ΔUnion | | 0.0948*** |
| | | (0.0288) |
| ΔFull-time | | 0.0361* |
| | | (0.0188) |
| ΔUnemployment rate | | −0.0009 |
| | | (0.0061) |
| Observations | 1,844 | 1,822 |
| $R^2$ | 0.0261 | 0.0825 |

*Note:* Robust standard errors in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.

wage premium associated with computer skills disappears (both the immediate returns as well as the returns to computer usage experience). This finding suggests that the large and significant effects of computer skills observed in the cross-sectional results do not reflect the true return of computer skills (i.e., the productivity enhancing effect of computers in the workplace), but rather is a result of the job sorting process through which abler workers (i.e., workers with greater ability) are systematically selected into the jobs requiring computer skills. Unobserved but compensated characteristics of the workers matter.

This evidence contrasts with the common interpretation given to the results found in Krueger (1993) (albeit for a different population), that the computer-use wage differential reflects the true return to computer use or skill. These results highlight the importance of using longitudinal data to isolate the true return to job skills, which was difficult to address by Krueger (1993) or DiNardo and Pischke (1997) using only cross-sectional information on workers. Entorf, Gollac, and Kramarz (1999) find similar results for the effects of computer usage on wages using panel data in France. An explanation for the estimated negligible effects of computer skills in the first-difference fixed effect model could be the small number of workers changing status from nonuser to user during the sample period. However, since the standard errors do not increase much when we move from the cross-sectional to the fixed effect model, it appears that there is a sufficient number of workers changing status from nonusers to users in order to identify the effects of computer use on wages.

I also find that the first-difference estimates of the effects of having job responsibilities that include keeping a close watch over gauges, dials, or instruments of any kind are larger in magnitude and significance than the cross-sectional estimates. We see that when workers change from not having these job responsibilities to carrying out these job tasks on a daily basis, their wage increases immediately by 5%. When workers job task responsibilities change from requiring customer communication skills (i.e., daily direct communication between worker and customers/clients) to not requiring the use of these skills on a daily basis, their wage increases immediately by 8.2% (likely reasons for negative coefficient on customer communication skills discussed above). The return to experience using customer communication skills and the return to math skills are small and statistically insignificant.

The estimated effects of job skills are robust to the inclusion/exclusion of the change in occupation index measure, designed to control for occupation transitions. There is a strong significant relationship between change in occupation index and wage growth, as expected.

The effect of unionism remains in the longitudinal dimension, as the first-difference estimates show that when workers change union status from nonunionized to unionized (vice versa), they receive 9.5% higher (lower) pay on average. The first-difference fixed effect estimates reveal that changing from part-time to full-time (and vice versa) work hours increased wages immediately by 3.6%. The hours' effect appears to also operate through the flatter wage profile associated with part-time work experience. Changes in the local unemployment rate, which capture changes in local labor market demand conditions, had small and insignificant effects on wage growth after the inclusion of the work experience and job transition variables. As we will see in the job turnover analysis that follows, however, changes in local labor market demand conditions impact job transition patterns, which we have shown affect wage growth.

#### *4.2.5. Double-Difference Model Results*

It is possible that workers using a particular job skill that is associated with higher wage growth may have experienced greater wage growth in the absence of the use of that skill if unobserved fixed worker quality is driving the first-difference results. The second approach I use to evaluate the magnitude and significance of potential bias from unobserved heterogeneity involves estimating a double-difference equation. This procedure is equivalent to estimating the determinants of changes in wage growth rates (between Wave 1–2 vs. Wave 2–3 vs. Wave 3–4 vs. Wave 4–5) for a given worker to isolate the return to job skill. The general pattern of results from the double-difference model was similar to the first-difference results reported in Table 4 (results available from author upon request). In fact, the double-difference estimates indicate even larger effects of the usage of reading/writing skills on wage trajectories.

### *4.3. Job Turnover Analysis*

The evidence presented in this paper has shown that jobs of different skill requirements differ in their prospects for wage growth. I now extend this analysis to study the effects of the skill requirements of jobs (via their effect on wage growth prospects) on job turnover. I am interested in the relationship between job transition patterns and wage growth. I have shown how average wage growth masks heterogeneity in within- and between-job wage growth. The first-difference estimates highlighted job mobility as a critical component of the wage growth process. This motivates the investigation of the determinants of job dynamics (job-to-job transitions – job mobility; job-to-nonemployment transitions – job instability) and the role of wage growth prospects in predicting job turnover. I also examine to what extent the worsening economic conditions in 2001–2002 affected job transition patterns.

#### *4.3.1. Model of Job Turnover*

Drawing on the key aspects of job search theory and human capital theory, I model job dynamics as on-the-job search with the wage offer distribution as the central factor that drives job transitions. Assume that while on the job, workers sample outside job offers in each period from a known wage offer distribution. Following Connolly and Gottschalk (2000), I extend the standard search model to include three key features of a job offer:

(1a) starting wage;
(2a) opportunity for wage growth on a job;
(2b) chance of upward mobility (promotion) within firm; and
(3) chance of job leading to job offers from superior wage offer distributions in future.

Assume workers have imperfect information about features (2a), (2b), and (3) of the job offer – workers learn about these characteristics of the job in the first several months of the job.

Other things being equal, we expect increases in job characteristics (1), (2a), and (2b) to reduce the hazard of leaving a job/employer, while we expect increases in job characteristic (3) to increase the hazard of leaving a job/employer.[26] Note, however, that job characteristic (3) is not observed by the econometrician. Assume individuals currently working in high wage-growth jobs, individuals working in jobs offering a high chance of upward mobility, and individuals working in jobs requiring more cognitive skills, are all more likely to receive job offers from the superior wage-offer distribution in the future.[27] This will result in a countervailing effect on the hazard of leaving a job/employer. For example, if skills acquired on a job become more valued in outside jobs/firms (than in the firm in which they are acquired), then high within-job wage growth could lead to higher quit rates.[28] Thus, high-learning jobs may or may not have lower quit rates than low-learning jobs –the expected effect is not clear as a matter of theory, it depends on which effect dominates in a particular type of job.[29]

The value of the present job depends on both the expected wage path and the uncertainty around that wage path. A central prediction of economic models of turnover is that, conditional on the present wage, quits will decline in the level of expected wage growth, and will increase in the value of outside opportunities. Factors that increased the present value of earnings on the job will be negatively associated with quits, while factors that increase the present value of earnings on alternative jobs and the arrival rate of alternative offers will be positively associated with quits holding the option value of jobs and the arrival rate of new information constant.

Within a search framework, local labor market conditions will affect the frequency and quality of job offers given a level of search intensity. Increases in the local availability of jobs will increase work by women through increases in the frequency of job offers and stability of employment. Labor market conditions affect wage levels and the probability of finding and keeping employment.

I use three different approaches to analyze job turnover. First, using the WES, I estimate a dependent competing-risks hazard model of job turnover, distinguishing between involuntary job separations (due to being laid-off/fired), voluntary job-to-job transitions, and employee-initiated job-to-nonemployment transitions. Drawing from the wage growth results above, I use the set of job skills/tasks to proxy for the effects of earnings growth prospects on job turnover. Given the results from the wage growth analysis of the large-and-significant returns to reading/writing skills, we would expect individuals working in jobs requiring reading/writing to have lower rates of job-to-nonemployment transitions, but potentially greater rates of job-to-job transitions (job mobility), if potential wage growth is an important factor affecting job turnover behavior. Similarly, we expect individuals working in jobs that require more cognitive skills to have lower layoff rates, and turnover rates overall, because these workers accumulate greater levels of firm-specific human capital as a result of greater OJT provision (Devereux, 2000).

It is difficult to sort out "person" from "job" effects using the first approach that analyzes job turnover because unobserved worker heterogeneity is not directly controlled. My second empirical strategy that analyzes job turnover involves estimation of a fixed-effect Cox proportional hazard model (known as the fixed-effect partial likelihood model, Chamberlain, 1985) using WES. I analyze the impact of explicitly taking into account unobserved heterogeneity on the propensity to change jobs.

The analysis using WES cannot distinguish between inter-firm and intra-firm job mobility for Waves 1–4 (Fall 1997–2001) because the WES survey questions on job tenure for these waves only refer to length of time worked in the position held, not employer tenure. However, for the period spanning Winter 2002–2004 when information was collected on employer tenure, I find that the lion's share of job-to-job transitions occurred between firms rather than promotion within firms. Thus, my third and final empirical strategy to analyze turnover utilizes MES. Using MES, I estimate a hazard model of worker-firm separations for the sample of jobs previously filled by former/current welfare recipients. The model includes direct measures of wage growth prospects (both chances of within-job pay raises and chances of promotion) from employer reports, as well as starting wage, whether job provides OJT, job skill requirements, employee and firm characteristics. The differences in specification between the WES and MES analyses of turnover due to the different variables at disposal in each data set, allow new and different insights from each analysis.

#### *4.3.2. WES Job Transition Summary Statistics*

The first sample I use in my analysis of job transitions consists of the 653 respondents that were employed at some point between Waves 1 and 5 of the WES. The 653 respondents held a total of 2,416 primary jobs over this period (Fall 1997 to Winter 2004). Of these jobs, 321 (13%) were censored because they were still in progress at the Wave 5 interview. Fifty-nine percent ($N = 1{,}418$) of the jobs ended in transitions to nonemployment, while

28% ($N = 677$) ended via voluntary job changes. Furthermore, the overwhelming majority of these voluntary job-to-job changes were between firms rather than due to promotion within the same employer. As observed in WES during the 2002–2004 period, less than 10% of women experienced promotions within the firm while working at their most recent employers.

In Table 5, I present means on overall monthly transitions out of jobs, as well as those into nonemployment and other jobs. The results are also shown separately by educational attainment. The results show that the monthly probability of a transition out of a job averages about 7.1% for the WES sample. The median job duration is seven months; only about a third (32.6%) of jobs lasted a year or more. Examining job turnover rates by education, we see significantly higher monthly transition rates out of jobs among high school dropouts relative to those with a high school diploma or GED, and especially higher turnover relative to those with some post-secondary education. These differences in turnover rates by education are driven by differences in the incidence of job-to-nonemployment transitions by education. Job-to-job transition rates do not differ significantly by

***Table 5.*** Job Transition Summary Statistics by Education.

| | All | Dropout | GED | HS | Post HS |
|---|---|---|---|---|---|
| *Job turnover* | | | | | |
| Monthly incidence rate | 0.071 | 0.096 | 0.075 | 0.066 | 0.056 |
| Duration of job (months): | | | | | |
| 25th percentile | 3 | 2 | 3 | 3 | 4 |
| Median | 7 | 5 | 7 | 9 | 10 |
| 75th percentile | 17 | 12 | 14 | 17 | 23 |
| One-year survival probability | 0.326 | 0.240 | 0.292 | 0.354 | 0.411 |
| *Job-to-job turnover* | | | | | |
| Monthly incidence rate | 0.023 | 0.024 | 0.024 | 0.022 | 0.023 |
| Duration of job (months): | | | | | |
| 25th percentile | 12 | 12 | 12 | 13 | 12 |
| Median | 28 | 26 | 26 | 27 | 30 |
| 75th percentile | 63 | 56 | 76 | 80 | 61 |
| One-year survival probability | 0.739 | 0.735 | 0.702 | 0.756 | 0.739 |
| *Job-to-nonemployment turnover* | | | | | |
| Monthly incidence rate | 0.048 | 0.072 | 0.051 | 0.045 | 0.034 |
| Duration of job (months): | | | | | |
| 25th percentile | 4 | 3 | 3 | 4 | 6 |
| Median | 10 | 7 | 10 | 12 | 16 |
| 75th percentile | 32 | 19 | 28 | 34 | 56 |
| One-year survival probability | 0.450 | 0.337 | 0.426 | 0.477 | 0.564 |

education. Job transitions observed in the sample are disproportionately comprised of job-to-nonemployment transitions, as opposed to voluntary job-to-job transitions, which are associated with wage gains (see wage growth estimates).[30]

### *4.4. Dependent Competing-Risks Model of Job Turnover Using WES.*

#### *4.4.1. Specification*

A competing-risks hazards model is used to distinguish between three types of job discontinuations: voluntary job-to-job mobility, employee-initiated job-to-nonemployment, and involuntary (employer-initiated) job-to-nonemployment transition. By using a competing-risks model of turnover, I can allow the determinants of job transitions to vary between job spells that end by a voluntary job change and those that end by a movement out of the workforce or end involuntarily (laid-off/fired). This allows me to test whether the variables I use to explain job duration have different effects on the propensity to leave jobs for different reasons.

Nearly all women in the sample experience more than one job spell over the observation period. The durations of jobs contributed by the same woman may be correlated because of unobserved individual characteristics that influence the duration of each of a woman's job spells. If ignored, the correlation between observations may lead to underestimation of standard errors owing to a reduction in the effective sample size. Random effects are therefore incorporated in the model to allow for unobserved heterogeneity between women. These random effects are defined at the individual level and represent unobserved individual-level characteristics that influence the hazard of a job ending at each month of a given job spell, and for each job spell.

I analyze determinants of monthly job transitions in the three-way competing-risks framework (where risks are voluntary job change, involuntary job separation, and employee-initiated movement to nonwork) using a multinomial probit specification of the hazard. Specifically, I specify the hazard – i.e., the probability that woman $i$ leaves job $j$ for reason $r = 1, 2, 3$, during month $t$, given that the woman has remained in the job the previous $(t-1)$ months—as

$$h_{ijr}(t) = \beta_r \mathbf{X}_{ij}(t) + \Gamma_r \text{TenureDummies} + u_{ir} + \varepsilon_{ijr}(t) \quad (r = 1, 2, 3) \qquad (4)$$

In this model, the variables in $\mathbf{X}$ are individual-specific and do not differ across alternatives. Estimated coefficients will therefore represent the effect of a given variable on the value of new job relative to its effect on the value on the current job, or the effect of this variable on the value of nonemployment relative to its effect on the value of the current job. The level of **X** is set at wave $T$ for months between wave $T$ and $(T+1)$, $(T=1, 2, 3, 4)$, for all variables except the county monthly unemployment rate, which corresponds with the observation month, and the set of job task variables which correspond with the job tasks performed on jobs held between wave $T$ and $(T+1)$. I use a similar set of explanatory variables (vector **X**) as was used in the WES wage model. In order not to place restrictions on the functional form of the relationship between job tenure and the hazard of leaving a job, I enter 10 dummy variables consisting of eight monthly dummies for the first eight months, a dummy for months 9–12, and an annual variable for year two (tenure greater than two years is the reference category). Woman-level unobserved variables are represented by a woman-specific random effect, $u_{ir}$, which is assumed to follow a normal distribution with zero mean.

A common yet very restrictive assumption in the analysis of competing risks is to assume that the latent survival times are independent, conditional on covariates. In this context, this involves treating the woman-specific random effects, $\boldsymbol{u}_i = (u_{i1}, u_{i2}, u_{i3})$, as uncorrelated across the different types of discontinuation. This means that a woman with a higher propensity toward leaving a job for reason $r$ does not tell us anything about her propensity toward leaving a job for any of the other reasons. This assumption of Independence of Irrelevant Alternatives (IIA), however, is unlikely to be true if certain characteristics of job transition types make two of them more similar than the others. Dependency between competing risks and shared unobserved risk factors may be accommodated by permitting the random effects $\boldsymbol{u}_i$ to be correlated across different types of discontinuation.

In light of these considerations, a multinomial probit specification is utilized to allow for flexible correlation structures across alternatives. An assumption of joint normality on the errors (trivariate normal distribution – $(u_{i1},u_{i2},u_{i3})$ in (1) implies a multinomial probit for the estimation of these turnover equations. The residual terms $\varepsilon_{ijr}(t)$ are assumed to be uncorrelated and to follow standard normal distributions. (footnote: The estimation was carried out using full-information likelihood, as implemented in aML (see Lillard and Panis (2000) for details of the estimation procedure).

I first estimate this version of the model of job transitions, which specifies unobserved worker heterogeneity as a random effect, and then estimate a fixed-effect Cox proportional hazard model (discussed in the next section) to examine the effects of explicitly controlling for unobserved heterogeneity on the propensity to leave jobs.

I have tested the hypothesis that the three-way dependent competing-risks model is inappropriate and that a simple duration model or a two-way independent competing-risks model is preferred, which does not distinguish between involuntary job changes and employee-initiated movements out of the workforce, or voluntary job changes, and/or the dependency between the types of discontinuation. The data reject these options. I highlight a few of the results of the competing-risks model of *monthly* job transitions below.[31]

*4.4.2. Competing-Risks Hazard Results*

The competing-risks hazard estimates are displayed in Table 6. An inspection of the correlation coefficients of the multinomial probit shows the relevance of the multinomial probit specification of the hazard in correctly estimating the probability of voluntary and involuntary job discontinuation. Recall that the woman-specific random effects allow for the possibility that some component of the unobservable value of a new job or of nonemployment may persist over time for the same individual. Table 6 presents the estimated standard deviations of the woman-specific random effects in the hazards equations for the different types of job discontinuation and the correlations between these random effects. These results provide evidence that indicate that time-persistent individual unobservables and the dependency between risks are both important in these job turnover equations. The estimated standard deviations of each random effect and the correlations between them are significantly different from zero. The economic interpretation of the correlations across job discontinuation types is that the worker differentiates between the alternative routes of discontinuation, and that women with an above-average probability of discontinuation via voluntary job-to-job changes tend also to have a below-average probability of discontinuation via job-to-nonemployment transitions (either voluntarily or through being laid-off/fired). This is an important result that emerges from the richer model, which violates the restrictive assumptions of independent competing-risks models of turnover that have been used in previous research, and suggests ignoring unobservable correlations across alternatives may lead to erroneous inferences of the determinants of job dynamics.

Both the involuntary job separation hazard and employee-initiated job-to-nonemployment hazard remain high through the first seven months of the job before gradually declining over the remainder of the job spell. This familiar pattern of the hazard has been observed in previous work (see, for example, Farber (1998), or Holzer and LaLonde (2000)). The process of gaining information about the quality of the job match early in jobs, as well as worker heterogeneity, are common explanations of the pattern. The

***Table 6.*** Dependent Competing-Risks Hazard Model of Job Turnover (MNP) with Random Effects.

| Explanatory Variables | Multinomial Probit Coefficient Estimates | | |
|---|---|---|---|
| | Involuntary job separation | EE-initiated job-to-nonemployment transition | Voluntary job-to-job transition |
| | (1) | (2) | (3) |
| *Job tenure (reference category: Tenure >2 years)* | | | |
| Month 1 | 0.3669 *** | 0.1040 | 0.0036 |
| | (0.1008) | (0.0651) | (0.0658) |
| Month 2 | 0.5469 *** | 0.2354 *** | −0.1642 ** |
| | (0.1070) | (0.0654) | (0.0749) |
| Month 3 | 0.4572 *** | 0.2303 *** | −0.1535 ** |
| | (0.1051) | (0.0696) | (0.0755) |
| Month 4 | 0.3947 *** | 0.2809 *** | −0.2726 *** |
| | (0.1105) | (0.0688) | (0.0804) |
| Month 5 | 0.3233 *** | 0.2070 *** | −0.1631 ** |
| | (0.1230) | (0.0733) | (0.0803) |
| Month 6 | 0.4562 *** | 0.1416 * | −0.0426 |
| | (0.1191) | (0.0748) | (0.0793) |
| Month 7 | 0.3964 *** | 0.1808 ** | −0.3814 *** |
| | (0.1232) | (0.0787) | (0.0962) |
| Month 8 | −0.0397 | 0.0558 | −0.1302 |
| | (0.1581) | (0.0929) | (0.0981) |
| Months 9–12 | 0.2965 *** | 0.2250 *** | 0.1344 ** |
| | (0.0892) | (0.0531) | (0.0540) |
| Year 2 | 0.2397 *** | 0.0679 | 0.0469 |
| | (0.0891) | (0.0514) | (0.0449) |
| *Labor market demand conditions* | | | |
| Unemployment rate | 0.0621 *** | −0.0241 ** | 0.0258 *** |
| | (0.0164) | (0.0095) | (0.0095) |
| *Human capital variables* | | | |
| HS Grad/GED (reference category: HS dropout) | −0.3175 *** | −0.1155 * | −0.0336 |
| | (0.1212) | (0.0594) | (0.0474) |
| Some post-secondary education | −0.4121 *** | −0.2163 *** | −0.0062 |
| | (0.1484) | (0.0668) | (0.0522) |
| Years of full-time work experience | −0.0143 | −0.0112 | 0.0102 ** |
| | (0.0164) | (0.0077) | (0.0046) |
| Years of part-time work experience | −0.0115 | −0.0022 | 0.0006 |
| | (0.0200) | (0.0081) | (0.0055) |
| *Job skill variables* | | | |
| Reading/writing | 0.0056 | −0.0644 * | 0.0802 * |
| | (0.0701) | (0.0408) | (0.0425) |

***Table 6.*** (*Continued*)

| Explanatory Variables | Multinomial Probit Coefficient Estimates | | |
|---|---|---|---|
| | Involuntary job separation | EE-initiated job-to-nonemployment transition | Voluntary job-to-job transition |
| | (1) | (2) | (3) |
| Computer | −0.0395 | 0.0613 | −0.0019 |
| | (0.0737) | (0.0435) | (0.0454) |
| Math | 0.2594 *** | 0.0077 | 0.0534 |
| | (0.0727) | (0.0408) | (0.0471) |
| Gauges/dials/instruments | −0.0763 | 0.0182 | −0.0054 |
| | (0.0610) | (0.0351) | (0.0362) |
| Customer communication | −0.2981 *** | −0.0812 * | −0.0124 |
| | (0.0723) | (0.0423) | (0.0526) |
| Supervise co-workers | −0.1548 ** | −0.0802 ** | −0.0820 ** |
| | (0.0673) | (0.0401) | (0.0404) |
| *Other job characteristics* | | | |
| Ln(Wage) | 0.1406 | 0.0229 | −0.1513 ** |
| | (0.0982) | (0.0552) | (0.0591) |
| Health insurance | 0.0408 | −0.1026 *** | 0.0085 |
| | (0.0558) | (0.0348) | (0.0381) |
| Full-time | 0.0329 | −0.0461 | −0.0124 |
| | (0.0603) | (0.0393) | (0.0426) |
| *Occupation (Reference category: Service)* | | | |
| Professional/managerial/ technical | −0.0172 | 0.0585 | −0.0746 |
| | (0.1258) | (0.0710) | (0.0679) |
| Sales | −0.0616 | 0.0530 | 0.0136 |
| | (0.0902) | (0.0527) | (0.0494) |
| Clerical | 0.1266 | −0.0383 | 0.0263 |
| | (0.1099) | (0.0658) | (0.0636) |
| Operator | 0.2848 *** | 0.1604 *** | −0.1032 |
| | (0.0930) | (0.0584) | (0.0644) |
| Craft | 0.0694 | 0.1873 | −0.1973 |
| | (0.2106) | (0.1345) | (0.1321) |
| Laborer | 0.2074 | 0.1654 ** | 0.0830 |
| | (0.1268) | (0.0719) | (0.0920) |
| *Demographic variables* | | | |
| Black | 0.1332 | 0.0219 | 0.0388 |
| | (0.1317) | (0.0601) | (0.0428) |
| Age 25–34 | −0.0628 | −0.0972 | −0.0514 |
| | (0.1559) | (0.0725) | (0.0518) |
| Age ≥ 35 | −0.0438 | −0.2025 ** | −0.1490 ** |
| | (0.2221) | (0.0981) | (0.0731) |

***Table 6.*** *(Continued)*

| Explanatory Variables | Multinomial Probit Coefficient Estimates | | |
|---|---|---|---|
| | Involuntary job separation | EE-initiated job-to-nonemployment transition | Voluntary job-to-job transition |
| | (1) | (2) | (3) |
| Married/cohabiting | −0.0132 | 0.0543 | 0.0058 |
| | (0.0789) | (0.0411) | (0.0402) |
| Child 0–2 years | −0.0009 | 0.0459 | 0.1320 ** |
| | (0.0771) | (0.0437) | (0.0517) |
| Child 3–5 years | 0.1098 * | −0.0887 *** | 0.0394 |
| | (0.0612) | (0.0339) | (0.0425) |
| *Health-related variables* | | | |
| Pregnant | −0.0090 | 0.2388 *** | −0.1881 *** |
| | (0.0968) | (0.0486) | (0.0632) |
| Work-limiting (physical) health condition | 0.0709 | 0.0922 ** | −0.0567 |
| | (0.0727) | (0.0417) | (0.0473) |
| Child health problems | 0.0648 | 0.0658 | 0.0582 |
| | (0.0822) | (0.0467) | (0.0572) |
| Mental health condition | 0.1950 *** | 0.2133 *** | 0.0496 |
| | (0.0654) | (0.0404) | (0.0446) |
| Domestic violence (past year) | 0.0755 | 0.0889 ** | −0.0538 |
| | (0.0748) | (0.0445) | (0.0520) |
| Lack access to a car | 0.2856 *** | 0.2170 *** | −0.0214 |
| | (0.0688) | (0.0452) | (0.0432) |
| Constant | −3.9924 *** | −1.6566 *** | −2.0815 *** |
| | (0.3118) | (0.1562) | (0.1601) |
| *Standard Deviations and pairwise correlations for woman-level random effects* | | | |
| Involuntary job separation equation | 1.0494 *** | | |
| | (0.1170) | | |
| EE-initiated job-to-nonemployment equation | −0.1347 * | 0.5079 *** | |
| | (0.0795) | (0.0295) | |
| Voluntary job-to-job equation | −0.3323 ** | −0.4207 ** | 0.1409 *** |
| | (0.1550) | (0.1765) | (0.0419) |

*Note:* Asymptotic standard errors in parentheses. Significance: *10%;**5%; ***1%.

job-to-job hazard follows a noticeably different pattern as it declines gradually through the seventh month, before increasing significantly between months nine through twelve, and declining thereafter. This pattern may be the result of the fact that the majority of the jobs this less-educated sample of women is able to obtain lack career ladders and/or provide limited learning opportunities that can increase wages, and thus for them, job changes are a more important source of wage growth than for other workers (see wage growth estimates).

One of the most insightful results of the turnover analysis is the sensitivity of these women's job transition patterns to changes in labor market demand conditions. The results indicate significant effects of the monthly unemployment rate, which is used as a measure of local labor market demand conditions. We find that a one percentage-point increase in the local unemployment rate increases the hazard of being laid-off/fired by about 12%. On the other hand, a one percentage-point increase in the local unemployment rate decreases the probability of an employee-initiated transition into nonemployment by about 4%. The differential effect of the unemployment rate by type of job separation is expected. One reason for the latter result is that it decreases in job availability increases the costs of job-to-nonemployment transitions (or, alternatively stated, increase the value of maintaining employment) by decreasing the expected (monthly) re-employment probability.

The results from the analysis indicate that individuals with lower levels of education have higher transition rates out of jobs. By distinguishing transition rates from jobs into nonemployment from transitions to new jobs, I find that the higher job transition rates for the least-educated individuals result primarily from higher rates of both involuntary job separations and employee-initiated job-to-nonemployment transitions.

Individuals working in jobs requiring reading/writing on a daily basis are significantly more likely to experience voluntary job changes (job mobility), which are associated with wage gains, and have significantly lower transition rates into nonemployment. My previous analyses of the determinants of wage growth have revealed that individuals working in jobs requiring reading/writing on a daily basis experienced significantly higher wage growth (as well as wage levels) between waves across all job transition types (job stability, job mobility, and job instability), and that a primary route of advancement was through changing jobs. Thus, the present evidence of lower quit rates into nonemployment and higher job-to-job transition rates among individuals working in jobs requiring reading/writing (on the order of about 15%) is consistent with the following story. Individuals working in jobs requiring more cognitive skills and in jobs providing more learning opportunities, and thus more wage growth, are also more likely to receive job offers from superior wage offer distributions in the future (controlling for the wage). This has the effect of both reducing the likelihood of voluntary transitions out of the labor force and increasing the hazard of voluntarily leaving the current job for another.

Individuals working in blue-collar occupations (operator/laborer) were more likely to experience involuntary job separations. Full-time work experience is positively associated with job-to-job transitions (job mobility), while part-time work experience has insignificant effects on both job-to-nonemployment and job-to-job transition rates. The wage of the job as of the most recent wave is negatively associated with job-to-job transitions. Individuals working in jobs providing employer-sponsored health insurance have lower rates of employee-initiated job-to-nonemployment transitions.

Given the relatively high prevalence of health-related conditions among this sample of women, I also include a set of health-related variables in the model to attempt to better understand the causes of the high incidence of job instability. (The sample means for these health-related measures are displayed in the last set of rows of the first column of Appendix Table B1). The results indicate that individuals with physical health limitations had higher job-to-nonemployment transition rates. The results also indicate that individuals with mental health conditions, mothers with children who have health problems, and women who suffered domestic violence within the past year, had higher rates of job-to-nonemployment transitions. As expected, child bearing is a significant predictor of job turnover as we see that being pregnant and having pre-school aged children (0–2 years old) each significantly increases rates of job turnover.

### *4.5. Fixed-Effect Cox Proportional Hazard Model Using WES*

#### *4.5.1. Empirical Strategy*

Do jobs (as opposed to workers in them) have different turnover behavior? It is very difficult to sort out "person" from "job" effects in the above analysis of job turnover. With wages and other characteristics held constant, individuals working in jobs requiring particular job skills are shown to have significantly lower job turnover rates than individuals working in jobs not requiring these job skills. Why? There are two possible explanations: (1) jobs requiring more cognitive skills reduce worker's propensity to quit the job by providing greater learning opportunities (human capital investment opportunities – training (informal/formal)), thereby offering more potential to experience within-job wage growth; (2) the job turnover – job skills relationship reflects a selection effect whereby workers are sorted by ability resulting in unobserved worker quality differences across jobs of different skill requirements (e.g., underlying unobserved heterogeneity among workers affecting the propensity to quit, such as "stick-to-it-iveness"). The analysis below seeks to disentangle these two possible causes – i.e., whether the skill requirements of jobs affect job turnover behavior of workers (job-specific effect), or whether differences in job turnover rates across jobs of different skill requirements are being driven by unobserved worker characteristics (i.e., person-specific effects are observed indirectly via the types of jobs individuals hold).

My empirical strategy involves exploiting the longitudinal dimension of the WES data to estimate a fixed-effect Cox proportional hazard model (known as the fixed-effect partial likelihood approach Chamberlain, 1985) of job turnover, distinguishing between involuntary job separations, voluntary job-to-job transitions, and employee-initiated job-to-nonemployment transitions. I have information on two or more complete job spells for almost all of the WES respondents (so selection bias should not be a concern), along with job skills used during periods in which different jobs were held. In essence, the fixed effect partial likelihood approach uses only information about the rank ordering of job spell lengths within individuals, and asks how that ordering may depend on variations in the explanatory variables. There is a significant amount of within-person changes across the periods in job skills used.[32] Use of Cox's fixed-effect partial likelihood approach eliminates all individual-specific factors (and thus the selectivity bias) by comparing job turnover behavior of the same worker in jobs held of differing skill requirements, thereby isolating the behavioral impact of the skill content of jobs. I relate the results from the turnover analysis with those from the wage growth analysis, and I use the job skill requirements to proxy the role of a worker's wage growth prospects in predicting turnover.

To be more specific, suppose that for worker $i$ we have $n_i$ spells (ordered by their increasing length) and that the duration for each spell is denoted $t_{ij}$, where $j$ stands for the spell number. Assuming all spells for the same person are independently distributed given her heterogeneity parameter, I can write the hazard functions as

$$\lambda_{ij}(t) = \exp(\beta' \mathbf{X}_{ij}(t) + a_i)\lambda_{i0}(t),\ j = 1, \ldots, n_i; i = 1, \ldots, N \tag{5}$$

Then it can be shown that the partial log-likelihood function is equal to[33]

$$L_p = \sum_{i=1}^{N} \sum_{j=1}^{n_{i-1}} \ln \left( \frac{\exp\left(\beta' \mathbf{X}_{i(y)}(t_{i(j)})\right)}{\sum_{k=j}^{n_i} \exp\left(\beta' \mathbf{X}_{i(k)}\left(t_{i(j)}\right)\right)} \right) \tag{6}$$

where the denominator corresponds to the risk set of worker *i*. Note that both $\alpha_i$ and $\lambda_{i0}$ do not appear in Eq. (6). Although all biases caused by unobserved individual heterogeneity are removed using Chamberlain's extension of Cox's partial likelihood method, the problem of biases caused by unobserved job-match heterogeneity remains.

#### *4.5.2. Fixed-Effect Hazard Results*

The exponentiated coefficients from the fixed-effect Cox proportional hazard model are presented in Table 7. I find that workers' probability of being laid-off/fired is 26% lower when working in jobs requiring reading/writing and computer skills on a daily basis relative to their probability while working in jobs not requiring these skills.[34] On the other hand, workers' probability of being laid-off/fired is significantly higher when working in jobs requiring use of arithmetic (including making change) on a daily basis relative to their probability while working in jobs not requiring these skills. These results are consistent with employer incentives to concentrate layoffs on workers with the lowest levels of firm-specific human capital (Devereux, 2000). The previous findings using MES documented significantly greater provision of OJT opportunities in jobs requiring reading/writing, which may signal greater firm investments in the worker and enable workers in these jobs to accumulate greater levels of firm-specific human capital.

The results also indicate that workers' probability of voluntary movements out of the workforce is significantly less likely when individuals work in jobs requiring reading/writing skills, which serve to proxy wage growth opportunities. The results also indicate that when individuals work in jobs that require supervisory responsibilities, their job turnover rates decline relative to their turnover rates when working in jobs not requiring these responsibilities. This finding is consistent with predictions from the theory of turnover, if skills accumulated on the job that lead to supervisory responsibilities are fairly firm-specific.

The estimated effects of labor market demand conditions are robust to explicit controls for unobserved individual heterogeneity. The economic downturn significantly increased workers' probability of being laid-off/fired; and significantly reduced workers' quit rate into nonemployment, indicating that workers are less likely to quit if jobs are scarce in their local community. We find that a one percentage-point increase in the local unemployment rate increases the hazard of being laid-off/fired by 7.7%, and decreases the probability of an employee-initiated transition into nonemployment by 7.1%.

*Table 7.* Exponentiated Coefficients from Fixed-Effect Cox Proportional Hazard Model of Job Turnover Using WES.

| Explanatory Variables | Job Turnover: With Control for Heterogeneity (Workers w/2 or more Spells) | | |
|---|---|---|---|
| | Involuntary job separation | EE-initiated job-to-nonemployment transition | Voluntary job-to-job transition |
| | (1) | (2) | (3) |
| *Job skill variables* | | | |
| Reading/writing | 0.7407* | 0.8382* | 1.1225 |
| | (0.1607) | (0.1036) | (0.1783) |
| Computer | 0.7236* | 1.2916* | 1.0178 |
| | (0.1664) | (0.1711) | (0.1475) |
| Math | 2.0219*** | 1.1118 | 1.0124 |
| | (0.5228) | (0.1420) | (0.1500) |
| Gauges/dials/instruments | 0.8082 | 0.9947 | 1.0170 |
| | (0.1638) | (0.1098) | (0.1433) |
| Customer communication | 0.7477 | 1.0184 | 0.9735 |
| | (0.1849) | (0.1471) | (0.1828) |
| Supervise co-workers | 0.8081 | 0.7547** | 0.7927 |
| | (0.1907) | (0.0915) | (0.1279) |
| *Labor market demand conditions* | | | |
| Unemployment rate | 1.0769* | 0.9292** | 1.0051 |
| | (0.0566) | (0.0287) | (0.0374) |
| *Other job characteristics* | | | |
| Ln(Wage) | 1.3882 | 1.1095 | 0.6367** |
| | (0.5997) | (0.2180) | (0.1208) |
| Health insurance | 1.2582 | 0.8817 | 0.9218 |
| | (0.2455) | (0.0998) | (0.1222) |
| Union | 1.3421 | 0.8855 | 0.8785 |
| | (0.3920) | (0.1796) | (0.1633) |
| Full-time | 1.0814 | 0.8791 | 0.8827 |
| | (0.2413) | (0.1020) | (0.1187) |
| *Human capital variables* | | | |
| Years of full-time work experience | 2.4355*** | 2.5440*** | 1.1486 |
| | (0.7274) | (0.3924) | (0.1960) |
| Years of part-time work experience | 2.3733*** | 2.6084*** | 1.0965 |
| | (0.7600) | (0.4165) | (0.2198) |
| Pregnant | 0.9580 | 1.2365* | 0.7277* |
| | (0.2208) | (0.1502) | (0.1353) |
| Log-likelihood | −239.2687 | −989.3010 | −492.3998 |
| Observations | 29,485 | 29,485 | 29,485 |
| Subjects (Jobs) | 2,415 | 2,415 | 2,415 |
| Failures | 289 | 1,128 | 677 |

Robust standard errors in parentheses. * Significant at 10% (one-tailed test); ** significant at 5%; *** significant at 1%.

### *4.6. Results from Job Turnover Analysis using MES*

The results from the hazard model of worker-firm separations using MES are presented in Table 8. The overall pattern of the MES turnover results are similar to those yielded using WES. The results indicate that, controlling for starting wages, jobs that offer greater wage growth opportunities have significantly lower turnover rates. In particular, jobs that provide chances for merit-based within-job pay raises (above cost of living increases), jobs that have good or excellent chances of promotion upward mobility (assuming good performance), and jobs requiring reading/writing skills on a daily basis, all have substantially lower turnover rates in a given week. Jobs that provide OJT opportunities also had significantly lower turnover rates in a given week – these effects became statistically insignificant only after the inclusion of the variables capturing employer reports of wage growth prospects of the job. On the other hand, individuals working in jobs requiring computer skills and individuals with prior occupation-specific work experience have significantly higher turnover rates than individuals that do not possess these skills or experience. These results are not inconsistent, however, with results from the previous analyses above, since acquiring computer skills and experience may enable individuals to sample from better (outside) wage offer distributions in the future, thereby increasing job mobility. The effects of the other job skills are statistically insignificant. As was found using WES, high school graduates had significantly lower turnover rates than high school dropouts. The results indicate, as expected, that having work performance-related problems (either problems with absenteeism, work attitude, or job skills) significantly increases the hazard of worker-firm separations.

After inclusion of the starting wage, wage growth, and job skill variables, the effects of occupation variables became insignificant. The MES results indicate that jobs that provided employer-sponsored health insurance benefits had significantly lower turnover rates. This finding is not necessarily inconsistent with the previous finding that women in the WES sample were more likely to experience involuntary job separations when working in jobs that offer employer-provided health benefits, because we cannot disaggregate employer-initiated and employee-initiated job separations in the MES turnover analysis. Somewhat surprisingly, part-time jobs did not have significantly higher turnover rates after the inclusion of the variables that affect wage growth prospects.

The MES results indicate that firms that were neither within 0.3 miles of public transit nor within 30 min of downtown, had significantly higher rates

***Table 8.*** Worker-Firm Separation Hazard Estimates Using MES.

| Explanatory Variables | Worker-Firm Separation |
|---|---|
| *Job characteristics* | |
| Starting wage | 0.1431** |
| | (0.0639) |
| Health insurance | −0.6451** |
| | (0.2864) |
| Offers chance of within-job pay raise (assuming good performance) | −0.9819*** |
| | (0.2890) |
| Offers good/excellent promotion prospects (assuming good performance) | −0.6478*** |
| | (0.2753) |
| Offers on-the-job training | −0.2879 |
| | (0.2725) |
| Part-time | 0.1275 |
| | (0.3145) |
| *Job skill variables* | |
| Reading/writing | −0.5434** |
| | (0.2517) |
| Computer | 0.6136** |
| | (0.3154) |
| Math | 0.1973 |
| | (0.2767) |
| Customer communication | −0.1084 |
| | (0.3594) |
| *Occupation (Reference category: Service)* | |
| Sales | 0.1831 |
| | (0.3832) |
| Clerical | −0.0354 |
| | (0.3893) |
| Blue-collar | 0.0739 |
| | (0.4817) |
| *Employee characteristics* | |
| High school Diploma/GED | −0.6451** |
| | (0.3140) |
| Prior occupation-specific work experience | 0.4886* |
| | (0.2581) |
| Training/skill certification | −0.2691 |
| | (0.2512) |
| Work performance-related problem | 0.7677*** |
| | (0.2445) |
| *Firm characteristics* | |
| % Employees unionized | −0.0079* |
| | (0.0054) |

**Table 8.** (*Continued*)

| Explanatory Variables | Worker-Firm Separation |
|---|---|
| Firm size (Reference Category: $\geq 100$ Employees) | |
| 1–19 employees | 0.5853* |
| | (0.3466) |
| 20–99 employees | 0.4446* |
| | (0.3213) |
| Not within 0.3 miles of public transit nor within 30 min of downtown | 0.3042* |
| | (0.2424) |
| *Job tenure* | |
| Ln(Tenure) | 0.5644* |
| | (0.4543) |
| $(\text{Ln(Tenure)})^2$ | −0.1175 |
| | (0.1369) |
| Log-likelihood | −396.8297 |
| Observations | 3,694 |
| Subjects (Jobs) | 418 |
| Failures | 106 |

*Note:* Regressions also include metropolitan area dummies and a constant term. Robust standard errors are in parentheses.
*Statistically significant at the 0.10 level (one-tailed test).
**Statistically significant at the 0.05 level.
***Statistically significant at the 0.01 level.

of job turnover. This result suggests that job accessibility may play a role in predicting job turnover. The results on the other variables indicate that large firms ($\geq 100$ employees) and firms with greater fractions of unionized employees have lower job turnover rates.

### *4.6.1. Multinomial Endogenous Switching Model of Wage Growth*

A final aim of this paper is to analyze wage differentials between job stayers and voluntary and involuntary job movers after taking into account the endogeneity of these job mobility decisions. The final empirical specification involves the estimation of a multinomial endogenous switching model of wage growth to attempt to address the endogeneity between job transitions and wages/wage growth. In particular, I specify a multinomial switching regression model, which allows the joint estimation of a quadrivariate selection process that accounts for the type of job transition and four wage change equations conditional on each type of transition with the appropriate selection corrections. These estimates are then used to predict a woman's change in wages for the four potential job transition types – job stability, voluntary job mobility, employee-initiated job instability, and involuntary (employer-initiated) job instability. By comparing potential wage growth in each transition type, I am able to estimate the relative returns of job stability, mobility, and the costs of having a spell of nonemployment. I also investigate whether wage differentials with job transitions vary significantly by job skill requirements.

The details of the endogenous switching model estimation procedures follow the work of Garcia-Perez and Sanz (2004) and are contained in Appendix B. The first-stage selection process of the type of job transition experienced between waves is specified as a multinomial probit model. The estimation of the model is highly computationally intensive and is estimated using aML. The exclusion restrictions used for identification of the model involve the exclusion of the following variables from the wage change equation: the presence of pre-school aged children, marital status, whether became pregnant over the year, whether experienced domestic violence over the year, mental or physical health conditions, and whether any children with a health condition.

I estimate four wage change equations, one for each job transition type, to allow the marginal effects of the explanatory variables of the woman's wage growth to depend on the type of job transition. For example, the effects of changes in work experience reflect the sum of the returns to experience and returns to tenure for individuals who experienced job stability; and they capture the sum of the returns to experience and the change in the job match component for individuals who experienced the relevant type of job change. To test for the endogeneity of the switching model, the parameters of interest are the covariances of the error term of each wage change equation with the error term of the selection equations.

The results are presented in Tables 9 and 10.[35] I first inspected the results of the correlation structure of the error terms and the likelihood ratio test for the endogenous switching model with respect to the exogenous one, which is a restricted case. The likelihood ratio test together with the correlation parameters reveal that there is evidence of non-random selection, and thus, if we omit the effects of unobservables, predicted wage growth with job mobility, job stability, and the wage penalty with job instability would be inconsistently estimated.

Table 10 presents predicted wage returns to voluntary job mobility, evaluated at sample means and evaluated at different levels of selected job skill variables. A comparison of the results previously presented with those shown in Table 10 reveal that if we do not consider the self-selection

**Table 9.** Endogenous Switching Model Estimates of Wage Growth.

| | Dependent Variable: First-Difference of Log of Real Hourly Wages ($1999) | | | |
|---|---|---|---|---|
| | Wage change equation w/job stability | Wage change equation w/vol. job mobility | Wage change equation w/ee-initiated job instability | Wage change equation w/ involuntary job instability |
| ΔFull-time work experience | 0.0004 | −0.0353 | 0.0337 | −0.0136 |
| | (0.0407) | (0.0415) | (0.0274) | (0.0485) |
| ΔPart-time work experience | −0.0264 | −0.0569 | 0.0358 | −0.0373 |
| | (0.0448) | (0.0441) | (0.0348) | (0.0570) |
| ΔReading/writing | 0.0461* | 0.0732** | −0.0148 | 0.0583* |
| | (0.0290) | (0.0332) | (0.0243) | (0.0367) |
| ΔExperience using reading/writing | 0.0459 | 0.0773* | 0.0233 | 0.0184 |
| | (0.0442) | (0.0513) | (0.0398) | (0.0562) |
| ΔComputer | −0.0100 | −0.0219 | 0.0332 | 0.0231 |
| | (0.0377) | (0.0360) | (0.0274) | (0.0430) |
| ΔExperience using computer | 0.0240 | 0.0396 | −0.0642 | −0.0388 |
| | (0.0550) | (0.0746) | (0.0452) | (0.0722) |
| ΔMath | 0.0867** | 0.0128 | 0.0257 | −0.0194 |
| | (0.0354) | (0.0425) | (0.0269) | (0.0407) |
| ΔExperience using math | −0.0038 | −0.0262 | 0.0323 | 0.0057 |
| | (0.0417) | (0.0500) | (0.0335) | (0.0523) |
| ΔGauges/dials/ instruments | −0.0262 | 0.0296 | 0.1149*** | 0.0027 |
| | (0.0270) | (0.0343) | (0.0207) | (0.0420) |
| ΔExperience using gauges/dials/ instruments | 0.0121 | 0.0671 | 0.0133 | −0.0215 |
| | (0.0447) | (0.0545) | (0.0393) | (0.0552) |
| ΔCustomer communication | −0.0168 | −0.0523 | −0.1154*** | −0.0972** |
| | (0.0390) | (0.0448) | (0.0263) | (0.0391) |
| ΔExperience using customer communication | 0.0010 | 0.0143 | 0.0660** | 0.0381 |
| | (0.0473) | (0.0506) | (0.0293) | (0.0537) |
| ΔSupervise co-workers | 0.0301 | −0.0096 | −0.0458* | −0.0435 |
| | (0.0337) | (0.0407) | (0.0244) | (0.0434) |
| ΔExperience supervising co-workers | −0.0324 | 0.0057 | −0.0414 | −0.0407 |
| | (0.0496) | (0.0931) | (0.0493) | (0.0939) |
| ΔOccupation index | | 0.0959*** | 0.1250*** | 0.1350*** |
| | | (0.0331) | (0.0281) | (0.0319) |
| ΔUnion | | 0.0248 | 0.1646*** | 0.1284** |
| | | (0.0464) | (0.0345) | (0.0544) |
| ΔFull-time | −0.0512 | 0.0601 | 0.0362 | 0.0530 |
| | (0.0340) | (0.0398) | (0.0238) | (0.0379) |
| | 0.0131 | 0.0098 | −0.0034 | −0.0053 |

***Table 9.*** *(Continued)*

| | Dependent Variable: First-Difference of Log of Real Hourly Wages ($1999) | | | |
|---|---|---|---|---|
| | Wage change equation w/job stability | Wage change equation w/vol. job mobility | Wage change equation w/ee-initiated job instability | Wage change equation w/ involuntary job instability |
| ΔUnemployment rate | (0.0156) | (0.0147) | (0.0070) | (0.0149) |
| Constant | −0.0359 | 0.1933* | 0.0968 | −0.0739 |
| | (0.0672) | 0.1057) | (0.0712) | (0.1097) |
| *Correlations of error terms across job turnover (T.O.) and wage change* equations | | | | |
| Correlation (T.O. mobility equation, wage J-stability equation) | −0.1574 | | | |
| | (0.3508) | | | |
| Correlation (T.O. EE instability equation, wage J-stability equation) | −0.4634*** | | | |
| | (0.1727) | | | |
| Correlation (T.O. layoff equation, wage J-stability equation) | 0.4692** | | | |
| | (0.2112) | | | |
| Correlation (T.O. mobility equation, wage J-mobility equation) | | −0.4158*** | | |
| | | (0.1486) | | |
| Correlation (T.O. EE instability equation, wage J-mobility equation) | | −0.6009*** | | |
| | | (0.1797) | | |
| Correlation (T.O. layoff equation, wage J-mobility equation) | | 0.3543 | | |
| | | (0.2854) | | |
| Correlation (T.O. mobility equation, wage EE Instability equation) | | | −0.6304** | |
| | | | (0.2949) | |

**Table 9.** (*Continued*)

| | Dependent Variable: First-Difference of Log of Real Hourly Wages ($1999) | | | |
|---|---|---|---|---|
| | Wage change equation w/job stability | Wage change equation w/vol. job mobility | Wage change equation w/ee-initiated job instability | Wage change equation w/ involuntary job instability |
| Correlation (T.O. EE instability equation, wage EE Instability equation) | | | −0.6020***<br>(0.1089) | |
| Correlation (T.O. Layoff equation, wage EE instability equation) | | | −0.0033<br>(0.3032) | |
| Correlation (T.O. mobility equation, wage layoff equation) | | | | −0.3491<br>(0.6143) |
| Correlation (T.O. EE instbility equation, wage layoff equation) | | | | −0.8710***<br>(0.1662) |
| Correlation (T.O. layoff equation, wage layoff equation) | | | | −0.1527<br>(0.2149) |
| Log-likelihood | −2421.13 | −2476.61 | −2611.21 | −2341.84 |

*Note:* Asymptotic Standard Errors in Parentheses. Significance: ***1%; **5%; *10% (one-tailed test).

problem we will considerably underestimate the wage returns to job mobility. The results indicate the estimated wage differentials are largest when we use involuntary job instability as the comparison group, as we find wage returns to mobility of 29.5%. Furthermore, workers who experience voluntary job changes without intervening spells of nonemployment earn around 22.9% more than if they had stayed at the same job. After accounting for differences in work experience accumulated over the period, there are not significant wage differences between voluntary job mobility and employee-initiated job instability.

***Table 10.*** Multinomial Endogenous Switching Model Estimates of Wage Return to Voluntary Job Mobility: Evaluated at Sample Mean and at Different Levels of Selected Job Skill Variables.

| | | Wage Returns to Voluntary Job Mobility |
|---|---|---|
| All evaluated at sample means | *Counterfactual* | |
| | Job stability | 0.2291 |
| | EE-initiated job instability | 0.0155 |
| | Involuntary job instability | 0.2950 |
| *Job skills* | | |
| Additional years of experience using reading/writing | Job stability | 0.2461 |
| | EE-initiated job instability | 0.0426 |
| | Involuntary job instability[a] | 0.4052 |
| No use of reading/writing on job | Job stability | 0.2147 |
| | EE-initiated job instability | −0.0114 |
| | Involuntary job instability | 0.2696 |

[a]This involuntary job instability counterfactual estimate assumes the woman is unable to secure a job requiring reading/writing skills immediately following layoff. Other variables were held at sample means.

These wage differentials with job transitions between waves vary significantly by the skill content of work experience, in much the same ways that the previous analyses have shown. In particular, wage returns to mobility (relative to job stability and instability) tend to be the largest for jobs requiring the use of reading/writing. The results indicate that when an individual's job-to-job changes involve the accumulation of additional experience using reading/writing skills, wage returns are 24.6% higher than returns experienced by continual usage of those job skills while holding the same job. On the other hand, the wage penalty is 40.5% for being laid-off or fired from a job that required reading/writing skills and failing to secure a job requiring these skills following the lay-off (relative to the wage gains with job mobility while accumulating experience using these skills).

## 5. SUMMARY AND CONCLUSION

In this paper, I used survey data from employers and longitudinal data from former/current welfare recipients covering the period 1997-early 2004 to analyze the relationship between job skills, job changes, and the evolution of wages. The results indicate that average wage growth masks considerable heterogeneity in within- and between-job wage growth. Differences in job skill requirements explain a significant portion of the observed heterogeneity in wage growth. I provide evidence that jobs of different skill requirements differ in their prospects for earnings growth, independent of the workers who fill these jobs. This contradicts some previous studies that have concluded that heterogeneity in permanent rates of wage growth among jobs is empirically unimportant (Topel, 1991; Topel & Ward, 1992; Abowd & Card, 1989). I have shown that, in terms of wage differentials, reading/writing skills, in particular, substantially increase wages not only through mere use, but also via experience using these skills, because these jobs offer more on-the-job training opportunities (formal/informal), and thus greater wage growth potential. This result was robust to explicit controls for unobserved heterogeneity related to wage levels and wage growth, as evidenced in the first-difference fixed effect and double-difference wage growth estimation results.

Computer usage is associated with relative pay differentials over non-computer-users. The association of computer usage with higher pay remains, even after controlling for many other sources of pay variation, thus replicating the similar findings of Krueger (1993) and others. However, unlike previous studies, the evidence here suggests that the large and significant effects of computer skill observed in the cross-sectional results do not reflect the true return of computer skills (i.e., the productivity enhancing effect of computers in the workplace), but rather is a result of the job sorting process through which workers with greater ability are systematically selected into jobs requiring computer skills. In the longitudinal dimension, the wage premium associated with computer skills disappears (both the immediate returns as well as the returns to computer usage experience). These results highlight the importance of using longitudinal data to isolate the true return to job skills, which was difficult to address by Krueger (1993) or DiNardo and Pischke (1997) using only cross-sectional information on workers.

Results from the wage growth analysis identified job mobility as a critical component of the wage growth process in the less-skilled labor market of this sample of less-educated women. My analysis of the determinants of job transitions underscored the importance of potential wage growth as an important factor affecting job turnover behavior. The turnover analysis underscores the sensitivity of these women's job transition patterns to changes in labor market demand conditions, which ultimately affect wage growth. This work highlights the importance of *jointly* considering processes of turnover along with wage growth when analyzing the labor market experiences of less-skilled workers. The results from the analyses of wage and job dynamics taken together, suggest that jobs requiring more cognitive skills (e.g., reading/writing) reduce worker's (firm's) propensity to quit (layoff/discharge) by providing greater learning opportunities (human capital investment opportunities – firm-specific training (formal/informal)), thereby offering more potential to experience wage growth. The results from the job turnover analyses, which suggest an important role of wage growth prospects in predicting job turnover, are robust to explicit controls for unobserved heterogeneity, as evidenced in the fixed-effect Cox proportional hazard model estimation results.

The results show that factors that predict future wage growth reduce quits as predicted by economic theory. The findings are consistent with an economic model in which workers compare the long-run value of employment opportunities when making quit decisions, which supports recent theoretical work by Munasinghe (2000) on the relationship between wage growth and job turnover. Because of data limitations, most previous work has relied on the assumption that, together with tenure and experience, the wage is a sufficient statistic for future wages. The results of this paper are inconsistent with that assumption both in that the analysis shows an additional predictor of wage growth – job skill requirements (independent of the workers who fill these jobs) – and in that this predictor helps explain quit behavior. The results therefore also point to the importance of developing good longitudinal data sets with information about firm characteristics, job skill requirements, and wages in order to improve our understanding of the wage growth process, particularly for less-skilled workers.

The results have important implications for welfare reform. TANFs work participation mandates have shifted the focus of welfare-to-work programs away from education and training and toward immediate job placement. As this study demonstrates, however, job skills profoundly affect the wage-experience profile, and thus, remain a central ingredient that will determine welfare recipients' ability to attain economic self-sufficiency.

Because most welfare-to-work programs have focused narrowly on job placement, we unfortunately have limited knowledge about how to design and implement programs that promote job retention and job advancement. Analyses that inform and evaluate the likely effects of various post-employment services is an important topic for future research.

The focus of this paper was to analyze the effects of job skills on the wage growth process and job turnover behavior of former/current welfare recipients. Ultimately, an important direction of future research will be to investigate whether particular skills have rising or falling value, analyzed separately by education and gender. This will provide the type of labor market information that may illuminate and inform policy with respect to the skill-supplying institutions.

# NOTES

1. The broader questions of the extent to which the employment problems of the working poor emanate from job skill deficiencies versus a deterioration of job quality for less-educated workers, is a related issue but one beyond the scope of this paper.

2. On the other hand, there is a countervailing effect because job matching is likely a more important component of the earnings of high-skilled workers (e.g., Barron, Berger, & Black, 1997, show that employers spend more resources trying to make good matches for high-skilled workers), which may act to increase the value of their job changes. It is not clear, as a matter of theory, whether job changes are more important for less-skilled workers. Indeed, skill-level differences in the importance of the relationship between job changes and wage growth are borne out empirically. For example, Bartel (1980) finds that less-educated workers had the largest proportion of earnings gains occurring between jobs.

3. A few exceptions are Loprest (1992), Keith and McWilliams (1997), and Abbott and Beach (1994).

4. Notable studies focusing on the wage growth of less-skilled workers include Connolly and Gottschalk (2000), Gladden and Taber (2000), Loeb and Corcoran (2001), Burtless (1995), Moffitt and Rangarajan (1989), Card, Michalopoulos, and Robins (2001).

5. Notable exceptions include (Antel, 1986; Topel, 1991; Mincer, 1986; Bartel & Borjas, 1981).

6. The job task questions were developed from Harry Holzer (1996).

7. Michigan's welfare policies are quite similar to those of many other states. For example, women in Michigan who worked part-time at minimum wage jobs were at the median for monthly net income among 12 states that contained a large portion of the nation's population and about half of the 1998 caseload (Acs, Coe, Watson, & Lerman, 1998 Acs et al., 1998). While the study uses data only from Michigan, the policy and economic conditions in Michigan are broadly representative of the majority of the TANF caseload.

8. For the job turnover analysis, I use information collected at each wave of the WES on the set of job skills used on jobs held over roughly the past year. Some individuals may have used a job skill on a job held in a given year, but not on all the jobs held that are analyzed in that year. Consequently, job skills used do not correspond to jobs held perfectly in all cases (i.e., they are not perfectly aligned). However, I do not believe this to cause a serious mismeasurement issue.

9. Since only about 10% of the sample did not work between waves (and thus lack wage information), selection bias should not be a major concern.

10. Job change and employer change are used interchangeably here due to insufficient data information to distinguish between the two. However, for the period spanning Winter 2002–2004 when information was collected on job and employer

tenure, I find that the lion's share of job-to-job transitions occurred between firms rather than promotion within firms.

11. Involuntary job separations resulting from being laid-off and separations resulting from being fired are grouped together here due to insufficient data information to distinguish between the two.

12. I compared the total number of job transitions with information on the total number of jobs held between waves, as well as information on jobs held concurrently and could account for nearly all primary job changes.

13. This is confirmed empirically in the WES data from self-reported reasons for job separations.

14. See, for example, Lynch (1991) for evidence on the effects of on-the-job training on wage growth and job mobility patterns of female workers.

15. Previous research has documented that most employer-provided training is short and intensive, concentrated during the first four weeks of the job spell (Lynch 1991). Thus, the observed differences in the amount of hours of job training are not likely to be driven by potential differences in job turnover rates between these jobs.

16. Employer reports of potential wage increases for merit and chances for promotion are likely upward-biased, since employers may consider it more socially acceptable to claim that they are willing to offer chances of upward mobility. Still, the differences in these reports provide useful comparisons of the potential for wage growth and chance for promotion in jobs of different skill.

17. The reported coefficients in Columns 1, 2, and 4 of Table 2 are the derivative of the probability with respect to a one-unit change in the particular variable, where the derivatives are evaluated at the sample means of the independent variables.

18. It is important to note that the OJT variable in the Employer Survey reflects the formal aspect of the process by which workers accumulate human capital – certainly, a significant portion of training and the process by which workers accumulate skills is informal, and is thus not captured by the OJT measure. The set of job tasks may pick up the effect of informal training opportunities.

19. The model includes the starting wage and conventional human capital variables as controls, though the coefficient estimates of these variables are suppressed in Table 2. One would not think of wages as an exogenous variable in this setting, but it is of interest to know whether individuals with relatively high starting wages are more likely to receive raises or to be promoted.

20. Only 14.3% of the respondents did not work between Waves 1 and 2, 11.9% did not work between Waves 2 and 3, and only 12.1% did not work between Waves 3 and 4. The WES data contains wage information for the most recent job of each respondent as of the survey interview dates of Waves 1–5, given the individual worked sometime between waves. Since only a small fraction of the sample did not work between waves (and thus lack wage information), selection bias should not be a major concern.

21. These results are consistent with those of Royalty (1998) and Holzer and LaLonde (2000), who found that job-to-nonemployment changes were more frequent than were job-to-job changes among young women with low levels of schooling.

22. Women who were working at Wave 1 were asked if they expected to be working in their current job less than six months, six months to one year, one to two years, or over two years. Sixty-three percent of those working at Wave 1 expected to

be working in the same job at Wave 2, but only 38% actually still worked at the same jobs at Wave 2. The primary reason reported for job separations between Waves 2 and 3 were: 21.3% fired/laid-off; 21.3% job-related quit (includes dissatisfaction with current job, such as inadequate pay, poor working conditions, suboptimal hours, poor job match); 10.3% child care concern; 9.4% health problem; 7.6% transportation problem; 2.7% family problem/pressure; 27.4% other. The large proportion reporting non-job-related reasons (57.4%) is consistent with the substantial job instability experienced by these women. Twenty percent of the women changed from working part-time to full-time on their primary job; 13.5% changed from full-time to part-time; 22.2% remained part-time; and 44.1% remained full-time between successive waves.

23. It is possible that the effects of job skills estimated with equation (3) will be biased if workers that do not use valued job skills have unobserved characteristics that lower not only their wage levels but also their rates of wage growth. For example, if the correct specification is

$$\begin{aligned}\ln(\text{WAGE})_{ijt} = \Gamma\mathbf{Z}_{ijt} + \beta_0\text{EXP}_{it} + \beta_1\text{JOBSKILL}_{ijt} \\ + \beta_2\text{EXP using JOBSKILL})_{ijt} + \alpha_i + \gamma_i t + u_{ijt}\end{aligned} \tag{2'}$$

where the unobserved heterogeneity components can be decomposed into a time-invariant person-specific intercept term ($\alpha_i$) and a person-specific growth term ($\gamma_i$). In this case, to eliminate bias on the estimated return to various job skills, I estimate a double-difference model to account for the person-specific growth effect. This is equivalent to estimating the determinants of changes in wage growth rates (between Wave 1–2 vs. Wave 2–3 vs. Wave 3–4 vs. Wave 4–5) for a given worker. In this model, the estimated return to job skills is identified by contrasting wage growth experienced over a period when the set of job skills used changes for a given worker. This specification is tested to evaluate potential bias from unobserved heterogeneity related to levels of wage growth.

24. Loprest (1992) also controls for occupation transitions using a one-dimensional occupation index in her analysis of wage growth (though her occupation index differs from that developed here). See Shaw (1987) and Sicherman and Galor (1990) for empirical work on occupational mobility.

25. Mincer (1986) pointed out that using all stayers as a comparison group presents selectivity bias, since the within-job wage growth for the type of worker prone to job change/loss may be different from the within-job wage growth in the economy as a whole. The differences may not be entirely controlled by observable characteristics. To control them, Mincer suggested using the following year's job changers/losers as the comparison group. However, because labor market demand conditions change significantly over the period analyzed, this is not a viable strategy here.

26. Baker, Gibbs, and Holmstrom (1994) document considerable variation in wages, as well as in their growth rate, within job grades, suggesting that the prospect of promotion is not the only means of providing incentives that firms use. Abowd et al. (1999) provide evidence showing that starting pay differentials and compensation growth profiles are negatively correlated across jobs; employers offering greater opportunities for compensation growth offer lower starting pay.

27. Empirical evidence supports this assumption. See, for example, the evidence of Baker et al. (1994) showing that those who experience the largest wage growth within a given job level also get promoted rapidly. They find the relationship between wage growth and time to promotion is uniformly negative. Furthermore, they find that promotees are drawn from all parts of the wage distribution within a given job level, suggesting that promotions are determined by factors other than the wage level.

28. As noted by Prendergast (1996), this may be caused by the common bureaucratic rules within firms where each job classification has a wage range that cannot be violated (e.g., job may have 6 grades). Workers who are at the top of their wage grade are generally impeded from future increases, constraining wage growth. Therefore, we would expect that job-to-job transition rates are accelerated by being at the top of a wage grade

29. Jovanovic and Nyarko (1996) stepping stone mobility model predicts that labor will flow from occupations with flat learning curves and into occupations where learning curves are steep, *as long as learning is sufficiently transferable between occupations.*

30. Royalty (1998) and Holzer and LaLonde (2000) find similar turnover patterns for non-college educated, young women in the NLSY using similar definitions of job transitions. However, the job turnover rates among jobs held by the WES sample of respondents are higher than that observed by Royalty, (1998; see her Figures 5 and 7) or Holzer and LaLonde (2000). For example, Holzer and LaLonde (2000) estimate an average weekly transition probability out of a job of about 2% in their sample of less-skilled (noncollege graduates) young workers. As a crude approximation, a 2% weekly transition rate translates into a median job duration of nine months; contrasted with the seven month median job duration found in the WES sample. Similarly, Royalty (1998) reports average annual job mobility (i.e., job-to-job turnover) and job instability (i.e., job-to-nonemployment turnover) rates of 18% and 28%, respectively, among noncollege educated women in the first year of job tenure; significantly lower turnover rates than observed in the WES sample. Additionally, the turnover rates observed in the WES sample are significantly higher than the 39% average annual turnover estimated by Holzer et al. (2001) from employer survey evidence of jobs recently filled by former/current recipients. (Potential sources of bias in their estimates are acknowledged and discussed in their paper).

31. To compute the implied marginal effects of explanatory variables on the hazard from the estimated coefficients of the multinomial probit model, I follow procedures developed in Stern (1989).

32. For example, one-third of workers who did not use reading/writing skills in a previous period did use these skills the next period; conversely, roughly 30% of women who were observed using reading/writing skills in the previous period did not use these skills in the subsequent period – the high prevalence of job instability was a factor that contributed to the latter pattern. Similarly high degrees of changes in job skills used are observed across periods for other job skills examined.

33. See Lancaster, 1990, pp. 268–271. Note that a censored spell must be at least as long as the smallest completed spell in order to contribute anything to the likelihood function.

34. Note that the effect of failing to control for heterogeneity is to bias the coefficients toward zero in a partial likelihood framework (see Lancaster, 1990, p. 304).

However, to the extent that workers with lower quit propensities work in jobs requiring more skills, one would expect that the coefficient should actually be smaller in absolute value when controlling for fixed effects. Thus, it appears that controlling for unobserved heterogeneity in Cox's partial likelihood framework may actually lead to an increase in the estimated coefficient if the effect mentioned above is more than counterbalanced by the removal of a substantial bias toward zero.

35. The first-stage estimates mirror the patterns of results shown for the dependent competing-risks hazard model of job turnover, and are available upon request.

36. Loprest (1992) also controls for occupation transitions using a one-dimensional occupation index in her analysis of wage growth (though her occupation index differs from that developed here). See Shaw (1987) and Sicherman and Galor (1990) for empirical work on occupational mobility.

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# APPENDIX A. MULTINOMIAL ENDOGENOUS SWITCHING MODEL OF WAGE GROWTH

Potential wage changes for a given job transition type can be represented by

$$\Delta \text{Wage}_j = \beta_j \mathbf{X}_j + \varepsilon_j,\ j = 0, 1, 2, 3 \tag{A.1}$$

where $j$ denotes the type of job transition – job stability, voluntary job mobility, employee-initiated job instability, and involuntary job instability. The selection mechanism is described through a latent variable model that captures the propensity of experiencing each of the transition types. We only observe the realization

$$I = k \Leftrightarrow I_k > \max\{I_j\},\ j = 0, 1, 2, 3 \tag{A.2}$$

That is, the worker will be observed experiencing job transition type $k$ if the total value associated with this transition is greater than the value of any alternative transition type. This latent variable model may be interpreted as a reduced form approach, where supply and demand side effects interact and cannot be disentangled. This implies the behavior of workers and the functioning of the labor market jointly determine what job transition type is observed, $I_j$. The estimated coefficients of the explanatory variables therefore capture the joint effect of the preferences of the worker and employer's preferences with regard to the worker's characteristics. Thus, we have

$$\Delta \text{Wage} = \Delta \text{Wage}_k,\ \textit{if}\ I_k = \max\{I_j\}, \quad j = 0, 1, 2, 3 \tag{A.3}$$

I assume that $I_j$ depends on observable characteristics ($Z$) and unobservable factors captured by woman-specific random effects ($u_{ij}$) and a random error component ($v_{ijt}$):

$$I_{ijt} = \alpha_j \mathbf{Z}_j + u_{ij} + v_{ijt} \tag{A.4}$$

In order to jointly estimate the wage change equations and job transition selection process, the likelihood function has to add the information relevant to the wage process and take account of the endogeneity of the job transition selection process. The selection process of the type of job transition experienced between waves is specified as a multinomial probit model with women-level random effects to allow a flexible correlation structure across alternative job transition types. Following Garcia-Perez and Sanz (2004), I estimate the endogenous switching model by full maximum likelihood. The estimation of the model is highly computationally intensive and is estimated using aML.

For ease of exposition, assume below there are only three types of potential job transition types. The likelihood function to be estimated has the following form:

$$\begin{aligned} & L\left(\beta_{j^*}, \alpha_j, \sigma^2_{\varepsilon_j}, \sigma^2_{u_j}, \sigma_{u_j u_k}, \sigma_{\varepsilon_j u_{j^*}} \middle| \Delta\text{Wage}, \mathbf{X}, \mathbf{Z}, I^*\right) = \\ & \prod_{\substack{I_1^*>0,\\ I_0^*>0}} \left[\varphi\left(\Delta\text{Wage}_0\right)\Phi\left(I_1^*>0, I_0^*>0 | \Delta\text{Wage}_0\right)\right] \\ & \prod_{\substack{I_2^*>0,\\ I_0^*>0}} \left[\varphi\left(\Delta\text{Wage}_1\right)\Phi\left(I_2^*>0, I_0^*>0 | \Delta\text{Wage}_1\right)\right] \\ & \prod_{\substack{I_3^*>0,\\ I_2^*>0}} \left[\varphi\left(\Delta\text{Wage}_2\right)\Phi\left(I_2^*>0, I_1^*>0 | \Delta\text{Wage}_2\right)\right] \end{aligned} \tag{A.5}$$

where the term $\varphi\left(\Delta\text{Wage}_j\right)$ denotes the density function of wage changes ($j = 0,1,2$) and $\Phi\left(I^* | \Delta\text{Wage}_j\right)$ is the cumulative distribution function of the bivariate selection process conditional on wage changes.

For each worker I observe one wage change and I have to predict the potential or counterfactual wage change for the alternative job transition types not observed. To illustrate how I compute the relative wage return to voluntary job mobility, the expected wage change experienced by voluntary job changers is described as:

$$E\left(\Delta\text{Wage}_0 | I_1^*>0, I_0^*>0\right) = \beta_0 \mathbf{X}_0 + \frac{\sigma_{\varepsilon_0}}{\left(1-\rho^2_{u_1^* u_0^*}\right)}(\theta_{01}\lambda_1 + \theta_{00}\lambda_0) \tag{A.6}$$

where $\theta_{00}$ and $\theta_{01}$ are functions of the correlations between the error terms of the wage change and job transition selection equations:

$$\theta_{00} = \left(\rho_{\varepsilon_0 u_0^*} - \rho_{\varepsilon_0 u_1^*}\rho_{u_1^* u_0^*}\right),\ \theta_{01} = \left(\rho_{\varepsilon_0 u_1^*} - \rho_{\varepsilon_0 u_0^*}\rho_{u_1^* u_0^*}\right) \tag{A.7}$$

If the selection process is not endogenous then these correlations between the error term of the wage change equation and the error term of the selection equation will be zero and therefore the estimated parameters $\theta_{00}$ and $\theta_{01}$ will also be zero. The terms $\lambda_0$ and $\lambda_1$ control the bivariate process of the probability of experiencing a voluntary job-to-job change relative to remaining in the same job and relative to job-to-nonemployment transition:

$$\lambda_0 = \phi\left(\frac{\alpha_0^* \mathbf{Z}}{\sigma_{u_0^*}}\right)\left(1 - \Phi\left(\frac{-\alpha_0^* \mathbf{Z}}{\sigma_{u_0^*}}\right)\right)^{-1}, \lambda_1 = \phi\left(\frac{\alpha_1^* \mathbf{Z}}{\sigma_{u_1^*}}\right)\left(1 - \Phi\left(\frac{-\alpha_1^* \mathbf{Z}}{\sigma_{u_1^*}}\right)\right)^{-1} \tag{A.8}$$

Thus, the returns to voluntary job mobility can be obtained by taking the difference between the wage equations for the observed job transition type and each of the counterfactuals, which can be computed in the same way.

***Table A1*** Cross-section OLS wages regressions using WES.

| Dependent Variable: Log of Real Hourly Wages ($ 1999) | | | | |
|---|---|---|---|---|
| Explanatory Variables | Mean | (1) | (2) | (3) |
| *Human capital variables* | | | | |
| High school grad/ GED (reference category: high school dropout) | 0.3704 | | 0.0277 | 0.0246 |
| | | | (0.0210) | (0.0208) |
| Some post-secondary education | 0.3406 | | 0.0655*** | 0.0495** |
| | | | (0.0233) | (0.0230) |
| Years of full-time work experience | 4.8077 | | 0.0143*** | 0.0136*** |
| | | | (0.0053) | (0.0052) |
| Full-time work experience squared | 23.1138 | | −0.0004 | −0.0003 |
| | | | (0.0003) | (0.0003) |
| Years of part-time work experience | 3.4115 | | −0.0037 | −0.0020 |
| | | | (0.0065) | (0.0065) |
| Part-time work experience squared | 11.6385 | | 0.0004 | 0.0004 |

***Table A1.*** (*Continued*).

| Dependent Variable: Log of Real Hourly Wages ($ 1999) | | | | |
|---|---|---|---|---|
| Explanatory Variables | Mean | (1) | (2) | (3) |
| *Job skill variables* | | | (0.0004) | (0.0004) |
| Reading/writing | 0.5064 | 0.0531*** | 0.0434*** | 0.0401** |
| | | (0.0163) | (0.0167) | (0.0164) |
| Experience using reading/writing | 0.5982 | 0.0260** | 0.0201* | 0.0190* |
| | | (0.0114) | (0.0114) | (0.0111) |
| Computer | 0.2689 | 0.0815*** | 0.0723*** | 0.0444** |
| | | (0.0182) | (0.0185) | (0.0189) |
| Experience using computer | 0.2626 | 0.0471*** | 0.0391*** | 0.0291** |
| | | (0.0152) | (0.0147) | (0.0142) |
| Math | 0.5867 | 0.0084 | 0.0141 | 0.0134 |
| | | (0.0180) | (0.0177) | (0.0172) |
| Experience using math | 0.7380 | −0.0259** | −0.0237** | −0.0214* |
| | | (0.0116) | (0.0114) | (0.0110) |
| Customer communication | 0.7186 | 0.0130 | 0.0207 | 0.0239 |
| | | (0.0154) | (0.0158) | (0.0156) |
| Experience using customer communication | 1.0279 | 0.0229* | 0.0177 | 0.0144 |
| | | (0.0120) | (0.0119) | (0.0116) |
| Gauges/dials/ instruments | 0.4155 | −0.0745*** | −0.0848*** | −0.0827*** |
| | | (0.0225) | (0.0228) | (0.0225) |
| Experience using gauges/dials/ instruments | 0.4359 | 0.0323*** | 0.0286** | 0.0273** |
| | | (0.0113) | (0.0114) | (0.0112) |
| Occupation index | 1.4123 | | | 0.1244*** |
| | | | | (0.0213) |
| Below 6th grade reading competency | 0.1915 | | −0.0605*** | −0.0500** |
| | | | (0.0224) | (0.0223) |
| Learning disability | 0.1503 | | −0.0524** | −0.0458* |
| | | | (0.0238) | (0.0238) |
| Full-time | 0.6001 | 0.0757*** | 0.0627*** | 0.0626*** |
| | | (0.0161) | (0.0168) | (0.0167) |
| Union | 0.1153 | 0.1786*** | 0.1753*** | 0.1769*** |
| | | (0.0265) | (0.0260) | (0.0256) |
| *Demographic variables* | | | | |
| Child 0–2 years | 0.2974 | −0.0542*** | −0.0289 | −0.0279 |
| | | (0.0174) | (0.0184) | (0.0186) |
| Child 3–5 years | 0.3547 | 0.0014 | 0.0190 | 0.0176 |
| | | (0.0155) | (0.0161) | (0.0162) |

*Table A1.* (*Continued*).

| Dependent Variable: Log of Real Hourly Wages ($ 1999) | | | | |
|---|---|---|---|---|
| Explanatory Variables | Mean | (1) | (2) | (3) |
| Married/cohabiting | 0.2908 | 0.0411** | 0.0459** | 0.0467** |
| | | (0.0193) | (0.0194) | (0.0195) |
| Black | 0.5401 | 0.0213 | 0.0276 | 0.0303 |
| | | (0.0189) | (0.0193) | (0.0191) |
| *Health-related variables* | | | | |
| Work-limiting (physical) health condition | 0.2668 | −0.0613*** | −0.0590*** | −0.0491*** |
| | | (0.0189) | (0.0189) | (0.0188) |
| Mental health condition | 0.2980 | −0.0359** | −0.0329* | −0.0349** |
| | | (0.0173) | (0.0175) | (0.0174) |
| Domestic violence (past year) | 0.1547 | −0.0201 | −0.0095 | −0.0059 |
| | | (0.0199) | (0.0200) | (0.0197) |
| *Labor market demand conditions* | | | | |
| Unemployment rate | 6.18 | −0.0069 | −0.0066 | −0.0076 |
| | | (0.0056) | (0.0057) | (0.0056) |
| Observations | | 2,558 | 2,405 | 2,396 |
| $R^2$ | | 0.1737 | 0.2001 | 0.2180 |

Robust standard errors in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%.
*Note:* Regressions also include a constant term. The median (mean) wage for this sample of former/current welfare recipients is $6.63 ($7.24).

## APPENDIX B. DERIVATION OF OCCUPATION INDEX

In order to control for occupation transitions, I create a one-dimensional occupation index that is designed to capture the amount of human capital needed to work in different occupations (after required training is completed). My construction of the index is adapted from that previously developed by Sicherman and Galor (1990) in their analysis of occupation mobility[36].

The mean levels of human capital needed to work in the various occupations our sample of women are likely to work in are constructed by summing the weighted means of the levels of schooling, previous occupation-specific experience, previous training (or skill certification), and job skills required in order for a worker to be qualified to work in the different occupations. Using the 1997 Michigan Employer Survey (MES), these means by occupation are estimated from employer reports of the requirements of a sample of recently-filled non-college jobs, which constitute a representative sample of the jobs that are available to non-college educated workers in local labor markets over a period of several months (Holzer, 1996). The weights are the estimated coefficients of these variables (level of schooling, previous occupation-specific experience, previous training (or skill certification), and job skill requirements) in a wage regression. Specifically, using the sample of recently-filled non-college jobs from MES, the occupation index is derived by first estimating the following wage regression:

$$\ln(\mathrm{W}_{ijo}) = \mathbf{X}_{ijo}\beta + \alpha\mathrm{ED}_j + \tau\mathrm{POCCEXP}_j + \delta\mathrm{PTRAIN}_j + \mu\mathrm{JOBSKILLS}_j + \varepsilon_{ijo} \tag{B.1}$$

where $\mathbf{X}$ is a vector of observed characteristics, ED is the level of schooling required to be considered for hire, POCCEXP is the degree of previous occupation-specific experience necessary to be considered for hire, PTRAIN is whether the job requires previous formal training or skill certification, JOBSKILLS is a vector of job tasks required on the job, $i$ indexes the individual and $j$ the job.

The mean level of human capital needed to be fully qualified to work in occupation $k$ is given by:

$$\overline{HC_k} = \alpha\overline{ED_k} + \tau\overline{POCCEXP_k} + \delta\overline{PTRAIN_k} + \mu\overline{JOBSKILLS_k} \tag{B.2}$$

The bar over variables in equation (B.2) signifies the mean level of the variable across the sample of non-college jobs in occupation group $k$. The change in occupation index due to occupation transition from occupation $l$ to $m$, or equivalently, the vertical distance between occupations $l$ and $m$ is given by:

$$\Delta\mathrm{OCCINDEX}_{lm} = \overline{HC_l} - \overline{HC_m} \tag{B.3}$$

This occupation index results in the following hierarchical ranking of occupations for non-college educated workers:

(1) Professional/Managerial/Technical
(2) Clerical
(3) Craft
(4) Operative

(5) Service
(6) Sales
(7) Laborer

Data limitations do not allow a more detailed (3-digit) occupational ranking. This ranking is highly correlated with that obtained by the mean levels of schooling and the mean wages per occupation.

Occupation changing is common among the WES sample. At baseline (Wave 1), WES women are concentrated in relatively few occupations, and are least represented in occupations that have the highest probability of requiring previous occupation-specific experience to be considered for hire (Johnson & Corcoran, 2003). By far, service is the occupation containing the largest fraction of respondents, 41%, and followed by 22% working in sales. Using one-digit census-level occupation codes, the average fraction of respondents remaining in the same occupation between successive waves range from only 25–68%. The occupation transition patterns suggest both a significant amount of upward and downward occupation mobility. Some of the occupation changes may be the result of measurement error due to misclassification. The largest occupation transition among our sample is service to sales. This evidence of frequent occupation changing is consistent with human capital theory since individuals who have invested less in occupation-specific skills have less to lose when changing occupations.