1997

Short-Term Employment Persistence for Welfare Recipients: The "Effects" of Wages, Industry, Occupation and Firm Size

Timothy J. Bartik
W.E. Upjohn Institute, bartik@upjohn.org

Upjohn Institute Working Paper No. 97-46

Short-Term Employment Persistence for Welfare Recipients: The "Effects" of Wages, Industry, Occupation, and Firm Size

Timothy J. Bartik
Senior Economist
W. E. Upjohn Institute for Employment Research
300 S. Westnedge Avenue
Kalamazoo, MI 49007
(616) 385-0433
bartik@we.upjohninst.org

June 1997

The research for this paper was conducted with financial assistance from the Russell Sage Foundation (R.F.# 85-96-17), and the Rockefeller Foundation (RF 94063 #9), as part of the project "Jobs for the Poor: Can Labor Demand Policies Help?" The opinions, findings, and conclusions in this paper are those of the author and do not necessarily reflect the views of the Russell Sage Foundation, the Rockefeller Foundation, or the Upjohn Institute. I thank Wei-Jang Huang, Claire Black, and Babette Schmitt for their assistance in preparing this paper. I also appreciate comments on a previous draft of this paper from seminar participants at the Upjohn Institute and the Federal Reserve Bank of Philadelphia.

Abstract

Using data from 13 years (1983-95) of the March Current Population Survey, this study examines how the types of jobs held by welfare mothers during the preceding year affects their employment and earnings at the time of the March interview. The estimates suggest that the wages of last year's job affect current employment and earnings, but the effects of wages are more modest than might be expected. The industry and occupation of last year's job make a great deal of difference, with industry being more important than occupation. The industries with the most positive effects on current employment are hospitals and educational services; jobs held last year in the temporary help industry are negatively correlated with current employment. The size of the firm employing a welfare recipient last year has no effect on March's employment or earnings. These results suggest that welfare-to-work programs should consider efforts to target higher-wage jobs or jobs in industries such as hospitals or educational services.

Short-Term Employment Persistence for Welfare Recipients: The "Effects" of Wages, Industry, Occupation, and Firm Size

INTRODUCTION

> "In contrast to the failed training programs of the past, a job, most any job, has shown itself capable of generating the earnings growth which will make welfare reform a reality."
>
> (Carlos Bonilla, Chief Economist, Employment Policies Institute, testimony before the U.S. House Committee on Economic and Educational Opportunities, January 18, 1995)

> "Policy should, perhaps, concentrate more on keeping people off welfare than on getting them off once. It may be relatively easy to get many people a low-paying job, but the job may not be sustainable as a source of economic provision."
>
> (Bane and Ellwood, p. 65)

> "Neither program administrators, evaluators, nor academics have looked closely at job retention."
>
> (Berg, Olson, and Conrad, p. 3)

The American public and politicians express strong support for getting welfare recipients to work. One rationale for this position is that getting a job may be a step forward toward a welfare recipient's long-term success. But will any job contribute to long-term success? Or must the job obtained be a "good job," or at least not too bad a job? The long-term effects of getting a job might depend on many job characteristics: wages, on-the-job training, promotion possibilities, personnel practices, and the job's match to its holder's skills.

Job quality is an important issue for welfare-to-work programs and job training programs for welfare recipients. These programs provide job development services, job placement services, and job training that will lead to particular types of jobs for their welfare recipient clients. Should these programs target particular types of jobs for their clients, and if so, what types? The job quality issue is also relevant to wage subsidy programs or economic development programs that seek to create better job opportunities for disadvantaged persons. Should these programs subsidize any job, or focus on particular types of jobs?

An important part of the long-term effects of a welfare recipient getting a job is determined by short-term job retention. Short-term job retention is amazingly low among welfare recipients. For example, at one welfare-to-work program, Project Match, researchers found that 46 percent of the program's clients lost their first job by three months, 60 percent by six months, and 73 percent by 12 months.[1] These problems with short-term job retention contribute to the extremely high welfare recidivism rates among women leaving welfare: one study found that 27 percent of those leaving welfare returned within six months (Blank and Ruggles 1994). This Blank and Ruggles study of welfare recidivism concluded that ". . . if post-program assistance is provided to reduce recidivism, the crucial period is the first six months following the end of the program. Most women for whom jobs or income changes will not be permanent will return to public assistance within that period." A study by Abt Associates found statistically significant correlations between relatively short-term measures of labor market success and long-term success in a welfare-to-work training program (Zornitsky and Rubin 1988). For example, whether an individual was employed three months after training completion was significantly positively correlated with the net earnings gains attributable to the program over the entire two-and-a-half-year follow-up period.

Despite the importance of short-term job retention and the frequent discussion of job quality as a factor in job retention, there has been little research on this topic. A few studies have examined

[1]Berg, Olson, and Conrad (1992). This paper cites similarly high job loss rates in other welfare-to-work programs. For example, the Enterprise Jobs program had a 31 percent job loss rate one month after the job was started and 73 percent by six months later. The Massachusetts ET program, which is widely considered a highly successful welfare-to-work program, found that 12 to 16 months after a job was started, 62 percent of the program participants were no longer at their original job.

the influence of wages on job retention (see next section), but there has been little research examining the effects of other job characteristics on job retention for disadvantaged persons.

This study makes some attempt to fill this gap in the research literature. Using data from 13 years (1983-95) of the March Current Population Survey (CPS), this study focuses on single mothers who, during the year before the March interview, were on welfare at least part of the year and were employed at least part of the year. The study estimates how the probability of a single mother being employed at the time of the March interview is influenced by characteristics of the job held during the preceding year. The job characteristics examined include not only wage rates, but also the job's occupation, industry, and firm size. One fourth of the sample (the outgoing rotation group) also reports data for March weekly earnings and wage rates. For these persons, this study also estimated how characteristics of jobs held last year affect March weekly earnings and wage rates.

The big advantage of investigating the job retention issue using the March CPS, compared with other possible data sets, is its large sample size. The data set used in this study has information on over 6000 welfare recipients who held a job during the preceding year. This large sample size allows this study to estimate more accurately the effects of occupation, industry, and other job characteristics at a finer level of detail.

The biggest disadvantage for this study of using the March CPS is the limited information available on the timing of welfare receipt and job holding. A job retention study would ideally consider individuals on welfare who then at some point got a job, and it would analyze the determinants of their labor market outcomes some fixed amount of time later. In the present study, using the March CPS, we only know that the single mothers in our sample were at some point in the preceding year receiving welfare and at some point employed. These individuals could have had the job first, then lost the job and gone on welfare. In addition, using the March CPS it cannot be determined what time elapsed between when the job was first held last year and the March interview. The job could have been first held last year anywhere between three months before the March interview (December of the previous year) and 14 months (January of the previous year). Even with these timing problems, however, this study's estimates still are of interest. The effect of past jobs on future employment prospects for disadvantaged persons is an important issue, above and beyond the job retention issue. If certain jobs help improve later labor market outcomes by providing more skills, self-confidence, a better reputation among other employers, better job contacts, or through other means, this is important.

The estimates in this paper suggest that the wages of last year’s job matter to this year’s employment and earnings, but the effects of wages are more modest than might be expected. The industry and occupation of last year’s job have a great deal of influence on this year’s employment and earnings, with industry being more important than occupation. The size of the firm employing a welfare recipient last year has no effect on this year’s employment and earnings. The industries that have the most positive influence on this year’s employment and earnings are hospitals and educational services. In contrast, as one might expect, jobs held last year in the temporary help industry are negatively correlated with this year’s employment. Among the occupations that have negative effects on this year’s employment are handlers and laborers, and cashiers.

An important limitation of this study’s findings is that it is unclear why certain types of jobs matter to later labor market outcomes. This study’s estimates cannot reveal whether the characteristics of jobs matter or whether the results are due to unobserved characteristics of individuals who obtain those types of jobs.[2] For many purposes, however, it is of interest to simply know what types of jobs are associated with later success. Whether that success is due to the job or the person may be a secondary issue. For example, welfare-to-work programs could benefit from simply knowing that certain types of jobs are more strongly associated with later success. The program can then improve performance by targeting those types of jobs. Targeting jobs includes placing individuals in those types of jobs and providing the training needed for success in those types of jobs.

THEORY AND PREVIOUS RESEARCH ON JOB CHARACTERISTICS AND JOB RETENTION FOR DISADVANTAGED GROUPS

Why might job characteristics be associated with job retention for welfare recipients? One might expect job retention problems to arise from some mismatch between firms and the workers they hire. Firms may have expected skills that the workers did not provide. Workers may have expected job characteristics that the employer did not provide.

To give greater content to this discussion, it is useful to examine the types of jobs that are held by welfare recipients. As shown in Tables 1 and 2, welfare recipients are employed in the types of jobs one would expect: jobs with relatively low formal educational requirements that pay low wages. Although these jobs have low requirements for skills acquired through formal education, most of these jobs do require considerable skill. In particular, many of these jobs require skills dealing with people, particularly customers. However, the exact nature of the daily activities and "output" of these

[2] Although, as will be seen below, the models used control for observed characteristics of the individuals in the sample, the models cannot control unobserved individual characteristics that may be correlated with job characteristics. The present paper does not attempt to use instrumental variables to correct for this problem. Such instruments would need to be correlated with job characteristics, but uncorrelated with unobserved individual characteristics. Finding good instruments of this kind is difficult.

Table 1

Table 1
15 Leading Occupations of Sample of Welfare Recipients

Occupation	Percentage of Sample
Cashiers (276)	9.8
Nursing aides (447)	6.7
Waitresses (435)	6.3
Maids (449)	4.3
Cooks (436)	4
Janitors (453)	3.9
Secretaries (313)	2.8
Child care (466)	2.6
Household cleaning (407)	2.1
Assemblers (785)	1.8
Miscellaneous food preparation (444)	1.7
Textile machine operators (744)	1.7
Bartenders (434)	1.5
Miscellaneous sales (274)	1.5
Household child care (406)	1.5
Total of 15 leading occupations	52.1
	of sample of 6,720 welfare recipients from 1983-95 March Current Population Survey

Notes: This table is derived from simple tabulations of occupations of employed welfare recipients from 1983-95 March Current Population Survey. Individuals are in sample if they are single mothers, between the ages of 16 and 64, who received welfare during the previous year and were employed during the previous year. In addition, individuals were excluded from the sample if earnings and weeks worked the previous year were "allocated" by the Census Bureau. These occupational categories are the 3-digit categories used by the Census Bureau; the 3-digit category number is given in parentheses. Tabulations are unweighted, as it is unclear whether Census Bureau weights are appropriate after the exclusions for allocated observations.

jobs varies quite a bit from job to job. What types of mismatches cause the most job retention problems for welfare recipients? There is considerable qualitative research on this topic, from case studies that interview welfare recipients and their employers. This case study research shows that high turnover results less from problems with “hard” skills (reading skills, math skills, specific vocational skills) than problems with “intangible” skills. These intangible skills include getting to work consistently on time and getting along with customers, co-workers, and supervisors.

Table 2
15 Leading Industries of Sample of Welfare Recipients

Industry	Percentage of Sample
Eating and drinking places (641)	16.4
Nursing and personal care (832)	5.6
Private household services (761)	4.2
Hotels and motels (762)	4.1
Grocery stores (601)	3.7
Elementary and secondary schools (842)	3.6
Department stores (591)	3.1
Personnel supply services (731)	2.9
Hospitals (831)	2.8
Services to dwellings and buildings (722)	2.4
Child day care services (862)	2.2
Miscellaneous social services (871)	2
Colleges and universities (850)	1.8
Apparel and accessories (151)	1.8
Health services (840)	1.7
Total of 15 leading industries	58.1
	of sample of 6,720 welfare recipients from 1983-95 March Current Population Survey

Notes: This table is derived from simple tabulations of industries of employed welfare recipients from 1983-95 March Current Population Survey. Individuals are in sample if they are single mothers, between the ages of 16 and 64, who received welfare during the previous year and were employed during the previous year. In addition, individuals were excluded from the sample if earnings and weeks worked the previous year were "allocated" by the Census Bureau. These industry categories are the 3-digit categories used by the Census Bureau; the 3-digit category number is given in parentheses. Tabulations are unweighted, as it is unclear whether Census Bureau weights are appropriate after the exclusions for allocated observations.

Consider the evidence from 50 interviews conducted with participants in the New Chance program, which provided young welfare mothers with preparation for getting a GED and job placement help (Quint, Musick, and Ladner 1994). Quint, Musick, and Ladner concluded that

> With only a few exceptions, the respondents in this study did not leave their jobs because of inability to perform the required tasks . . . The difficulties of many young women in the workplace might rather be described as relational— dealing with supervisors, with fellow workers, with apparently arbitrary rules, and with favoritism and discrimination. (p. 61)

Quint, Musick, and Ladner tell the story of one woman who was given a week's suspension from her nursing home job because she was late for work. Her lateness occurred because her boyfriend drug dealer was in jail and couldn't get her kids off to school for her:

> Delores resented her week's suspension and seemed to think that her supervisor should excuse her lateness because she believed she had a good reason for that lateness . . . She exemplifies this comment by one New Chance staff member: 'They [the program enrollees] think a good excuse for not doing something is as good as doing it.' (p. 48)

A similar picture emerges from interviews conducted by Berg, Olson, and Conrad (1992) with 58 participants and their employers in Project Match, a welfare-to-work program for residents of the Cabrini-Green neighborhood in Chicago. According to these researchers,

> We did not find that technical inability to do a job was a primary factor accounting for job loss. In 9 out of 58 cases, employers complained the worker did not have the skills to do some part of their job, usually running a cash register. There were only four cases where the inability to perform the work contributed to losing the job within six months. However, even in most of these cases, clearly many factors contributed to the job loss—it was not just a skill deficiency problem. For example, an 18 year old counter clerk not only had trouble filling orders and running a cash register, her supervisor also felt she chronically made personal phone calls, was absent frequently, could not get along with her co-workers, and was perhaps stealing from the register. The worker, in turn, felt the supervisor was prejudiced and unbearably demanding. (p. 14)

Berg, Olson, and Conrad found that the problems causing job loss include absenteeism and punctuality, questioning orders or "having an attitude" with supervisors, and general difficulties getting along with supervisors and co-workers.

A study by Mathematica Policy Research mentions similar job retention problems (Haimson, Hershey, and Rangarajan 1995). This study describes the operations of the Postemployment Services Demonstration (PESD), which provides intensive case management assistance to welfare recipients to avoid or respond to job loss. According to the study,

> Failure to comply with work schedules was a relatively common reason for job loss cited by staff members and clients. According to one case manager, one client was fired from a temporary clerical job in a health clinic because she made no effort to conform to her work schedule, frequently arrived late, and often left early for no apparent reason. (p. 69)

Clients also had trouble dealing with supervisors:

> One client acknowledged that it was difficult to go from simply being "in charge" of her household to being "bossed around" by others at the job. PESD clients often entered the workplace as the newest, least experienced employee, and several noted the difficulty they had assuming a subordinate role. (p. 70)

Welfare recipients also had troubles dealing with customers: "In one extreme example, a client lost her job when she was so offended by a customer that she assaulted him physically" (p. 70). Finally, the PESD study also mentions the problems some welfare recipients have with learning to use cash registers.

These job retention problems of welfare recipients may occur in part because of the large differences between the daily activities of unemployed welfare recipients and the daily activities expected of workers in low-wage jobs. The usual daily activities of an unemployed welfare recipient consist of child care and home care, with no supervisors or co-workers. An unemployed welfare recipient largely controls her own schedule. Many low-wage jobs involve intense supervision and lots of pressure to deal continually with customers and co-workers. Many long-term welfare recipients also lack self-confidence, which makes it more difficult to deal with an unfamiliar, high-stress work environment. According to the PESD study,

> One client told her case manager that she had quit her job as a word processor because she felt "out of her league," overpaid for her skills, and under qualified compared with her co-workers. Another client sought support from her case manager because she felt overwhelmed in her soda shop job when her co-worker stepped outside for a cigarette break and left her alone behind the counter. (p. 72)

Jobs are more likely to be retained by welfare recipients in some occupations and industries. Occupations and industries differ in their pressure for timely completion of tasks, the strictness of supervision, and the number of interactions with co-workers or customers. Occupations or industries also differ in whether the skills required have much in common with child care or home care. Some occupations and industries may better tolerate substandard performance while the new worker adjusts to the job. Finally, higher wages or benefits are likely to make an otherwise bad job easier to endure.

Why don't employers restructure low-education jobs to increase job retention? There are employer policies that can reduce worker turnover. Employers could devote more resources to screening prospective workers. Employers could be more tolerant of poor performance, firing fewer workers, and offering on-the-job training to incumbent workers rather than hiring replacements. Employers could offer higher wages instead of intensive supervision, as workers may work harder if the work is better compensated ("efficiency wage theory").

Presumably, employers do not adopt these policies for most low-education jobs because these policies are more costly than the status quo. Screening for "people skills" may be difficult. It is difficult, without expensive background checks, to make a reasonable prediction about how well a job applicant will get along with customers, co-workers, and supervisors. Replacements may be readily available for many (not all) of these low-education jobs, as people skills are developed through life experience rather than education and training. For many of these low-education jobs, intensive supervision is more feasible than it is for many high-education jobs. For example, it is easy to see whether a cashier at a fast-food restaurant is doing a good job: a supervisor can observe the length of the queue of customers waiting to order, listen to the cashier's conversations with customers, and check whether the register is "short" at the end of the shift. Determining the quality of output of a college professor is likely to be more difficult, certainly in the short-term and probably in the long-term.

Some employers in these low-education jobs may find it in their interest to reduce turnover, if any of the factors mentioned above are altered. For example, if the job involves greater job-specific skills, making it more difficult to find replacement workers, employers will be more motivated to try to retain their current workers. The production process varies greatly across the industries in Tables 1 and 2, and also across different-sized firms. Hence, employer policies that affect job retention will vary quite a bit.

Why do welfare recipients and other disadvantaged workers take jobs that may quickly be lost? Part of the explanation is that welfare recipients may often make mistakes in pursuing job opportunities when dealing with an unfamiliar world, the world of work. Mistakes will occur because the quality of many low-education jobs varies enormously with the skill and sensitivity of the supervisor. This is difficult to ascertain before the job starts. In the Project Match study, Berg et al. mention that supervisors varied enormously in their tolerance of absenteeism and their understanding of the challenges faced by welfare recipients. For example, some supervisors took a hard line on dress codes, whereas others would allow welfare recipients some time to get the money needed to buy the required "uniforms" for the job.

Finally, welfare recipients, and others with low educational levels and low technical skills, may have relatively few alternatives. If education and technical skills are lacking, a person's opportunities may be limited to jobs emphasizing people skills.

Little quantitative research exists on what job characteristics affect job retention for welfare recipients and other disadvantaged groups. Most studies find that higher wages increase job retention. Some studies find positive effects of wages on job retention or negative effects on welfare recidivism (Nightingale et al. 1991; Berg, Olson, and Conrad 1992; 9to5 Working Women Education Fund

1993; Pavetti 1993). In contrast, a study of federal "on-the-job-training" (OJT) programs in Kalamazoo found no statistically significant relationship between the starting wage and the probability of being employed 13 weeks after completing OJT (Bartik, Houseman, and Thies 1993).

Only two studies, to my knowledge, have explicitly examined the effects of job characteristics other than the wage on job retention. Bartik, Houseman, and Thies' study suggested that OJT participants placed at small employers (fewer than 100 employees) were significantly more likely to be employed at follow-up than those placed with larger employers. OJT participants placed in "processing and machining" occupations were less likely to be employed at follow-up, although this estimate was only marginally significant. A study by Leete (1996) found few strong relationships between the occupation and industry of the first job and subsequent employment over a five-year period. Her study was based on 500 welfare recipients in the National Longitudinal Survey of Youth (NLSY).

MODEL AND DATA

The models estimated are probit, tobit, and selection-bias corrected regressions using data on individuals. The data come from 13 March Current Population Survey data files, from 1983 through 1995. The up to 20,830 individuals included in the models are all single mothers who were on welfare sometime during the year preceding the March CPS interview. The dependent variables are measures of the individual's labor market situation as of the March interview. The independent variables of most interest are characteristics of the job held during the preceding year. Control variables include state and year dummies and individual demographic characteristics.

The estimating equation can be written as

$$Y_{jst} = B_0 + B_x{}'X_{jst} + B_eE_{jst-1} + B_{occ}OCC_{jst-1} + B_IIND_{jst-1} + B_wW_{jst-1} + B_hH_{jst-1} + U_{jst}$$

Individuals in the sample were interviewed in March of year t. To be in the sample, persons must have received welfare at some time between January and December of year t - 1. Y_{jst} is some labor market outcome, as of March of year t, for individual j living in state s in March of year t. The labor market outcome for which data are available for the full sample is a zero-one dummy for whether the individual is employed as of the week preceding the March interview. For one-fourth of the sample, the "outgoing rotation group" of the CPS, data are also available for other measures of labor market success as of March. Hence, some models use as dependent variables the individual's real weekly earnings as of March, usual weekly hours as of March, and hourly wage rate (if employed) as of March. X_{jst} includes state dummies, year dummies, and variables describing the individual's education, age, race, and family situation. E_{jst-1} is a zero-one indicator for whether the individual was employed during the calendar year preceding the March interview. OCC_{jst-1} is a vector of zero-one dummies for whether the individual's longest job during the preceding year was in a particular occupational classification. IND_{jst} is a vector of zero-one dummies for whether the individual's longest job during the preceding year was in a particular industrial classification. W_{jst-1} is the natural logarithm of the individual's calculated hourly wage rate during the preceding year. H_{jst-1} is the usual weekly hours the individual worked during the preceding year. U_{jst} is the disturbance term.

As the above discussion implies, the model includes all single mothers on welfare during the preceding year, including those who never held a job. This allows comparison of the effects of working in particular occupations or industries, or at jobs that offer particular wage rates or weekly hours, with the effect of simply working at an average job. In addition, including the full sample increases the precision in estimating the effects of control variables.

The vector of occupation dummies and the vector of industry dummies, each sum up to the dummy variable for whether the individual worked the preceding year. Each individual who works must work at some occupation and industry. Estimation requires some restriction. The usual restriction is to drop one industry and one occupation from estimation. The coefficients on the excluded industry and occupation are implicitly set equal to zero. The estimated effects of included industries and occupations than represent effects compared to the excluded industry and occupation.

This paper's empirical work uses two alternate restrictions that yield coefficient estimates with more meaningful interpretations.[3] One restriction sets the weighted sum of all the occupation coefficients to zero, where the weights are the proportion of those working in the sample who are employed in each occupational classification. The analogous restriction is also used for the industrial coefficients. Using these restrictions, the estimated coefficient on each occupation measures the effects of being employed in that occupation, relative to being employed in the "average occupation." A person employed in this average occupation would be partially employed in each occupation, with the amount of their partial employment in each occupation equal to the sample proportion in each occupation. A similar interpretation applies to the coefficients for each industry. Because of these restrictions, the coefficient on the dummy variable for whether the person worked last year also has a more meaningful interpretation. This coefficient is the effect of working last year for a mythical average person who was employed in the "average" occupation and industry. In addition, in the actual estimation, the wage variables and hours variables are measured as deviations of the individual's wages and hours from the sample averages of these variables. This means that the effects of the "worked" dummy can also be interpreting as working at the job that offers "average" wages and "average" usual hours.[4]

[3]These restrictions are suggested by Suits (1984) and Kennedy (1985). These restrictions are not substantive.

[4]Note also that the wage variable is defined as equal to zero for those not working at all last year. This definition is not substantive; the worked dummy coefficient will simply measure the effect of working and having a defined average wage rather than no measured wage.

For the full sample, the dependent variable is a zero-one dummy for whether the individual is employed in March. This model is estimated using probit, which assumes a normal distribution of the disturbance term. A simpler model to use would have been a linear probability models, but the linear probability model ignores the discrete character of the dependent variable. Linear probability models have been shown to be particularly inappropriate when many of the independent variables of interest are also discrete variables, such as the worked variable or the occupation and industry dummies (Maddala 1983; Greene 1993). An alternative to probit is logit, but researchers usually find little substantive differences between probit and logit. In addition, a probit model is more consistent with the estimation strategies used for the other dependent variables, which assume a normal distribution of the disturbance.

For one-fourth of the sample, the so-called "Outgoing Rotation Group" of the CPS, information is available on their usual weekly earnings and usual weekly hours. This allows the calculation of a wage rate for those with positive usual weekly hours. Models were also estimated with three other dependent variables: March values of usual weekly earnings, usual weekly hours, and the natural logarithm of the wage rate. For the usual weekly earnings and usual weekly hours, estimation was done using a tobit regression model. The tobit regression model allows for the truncation of the earnings and hours dependent variables at zero and assumes a normal distribution of the disturbance term.

For the wage rate model, estimation should take account of the selection of the sample: only those working as of March are included. For this model, I used the standard "heckit" or Heckman two-stage censored regression model (Greene 1993). This model requires specifying a probit model for the probability of working. The second-stage regression model, with the wage rate dependent variable, is "corrected" for selection bias by including an additional regressor that reflects the probability of working for each observation, derived from the probit model (the "Mill's ratio"). Heckit models can be estimated more accurately if some variables that are in the probit model are excluded from the second-stage regression equation. I use the standard exclusion that the number of children of the mother is assumed to affect the probability of working, but not the wage rate if working.

No attempt is made to correct for endogeneity of the occupation, industry, and other characteristics of the individual's job last year. Presumably, even though the model controls for numerous observed individual characteristics, there will be some correlation between unobserved characteristics of individuals in the disturbance terms and the various job characteristics. Unobserved characteristics may lead to individuals choosing certain types of jobs or being chosen by employers for certain types of jobs.

This endogeneity limits the interpretation that can be given to the "effects" of last year's job characteristics on March labor market outcomes. The estimates cannot be interpreted as the pure effects of job characteristics. The estimates can be said to have some unknown bias if viewed as attempts to estimate these pure effects. Rather, the estimates reflect both effects of the job characteristics and effects of the types of people who tend to be employed in jobs with those characteristics.

Although knowing whether the job itself matter is important for policy, knowing that some combination of the job and personal characteristics associated with the job matters is still useful for welfare-to-work policymakers. If certain types of jobs are associated with short-term labor market success, then welfare-to-work policymakers still might want to target those types of jobs for their client. However, welfare-to-work policymakers in this case would need to make sure that clients placed in jobs have the tangible and intangible characteristics needed for success in that type of job. Just being placed in the job may not be enough.

More on data selection and description

The data are selected from 13 March Current Population Survey data tapes, from March 1983 to March 1995. The data selection began with 1983 because there were big changes in the occupational classifications used in the Current Population Survey from 1982 to 1983; reconciling the old and new systems is difficult.[5]

Individuals were selected for the estimation sample if they were a female family head, age 16 to 64, were on some kind of public assistance in the previous year, were unmarried or married with spouse absent, and had at least one child 17 years old or younger. In addition, sample selection required that earnings and weeks worked in the previous year not be "allocated" (i.e., made up by the Census Bureau because the individual did not answer that question), and March employment status not be allocated. Furthermore, I dropped observations where last year's average hourly wage seemed implausible. This average hourly wage was calculated as last year's real earnings divided by the product of weeks worked and usual weekly hours (i.e., an imputed value for annual work hours). Specifically, observations were dropped if the individual worked last year, but the calculated real wage last year was less than $1 per hour (in 1995 dollars), or the calculated real wage was greater than $50 and imputed annual hours were less than 500.

Finally, for the estimation involving March's weekly earnings, hourly wage rate, and weekly hours, observations were dropped from estimation if March weekly earnings was allocated or if the hourly wage rate seemed implausible. The March hourly wage rate was assumed to be implausible if it was less than $1.50. The highest observed real wage in March was $36.42, so no observations were dropped because March wages were "too high."

---

[5]There were also minor changes in the occupational and industrial classification systems used in the CPS from 1991 to 1992, but it is relatively easy in this case to reconcile the old and new systems, at the cost of a very slight aggregation of relatively few occupational and industrial categories.

Table 3 presents means and standard deviations for most of the variables used in the empirical work. (Occupation and industry definitions will be discussed in a later section). These numbers give a good picture of the sample. The sample individuals are young, averaging 30 years of age. Education levels are generally low. Forty-five percent are high school dropouts, and fewer than 2 percent have a college degree. The sample is more heavily minority than the general population, but still includes a significant number of whites: 36 percent non-Hispanic white, 36 percent black, 24 percent Hispanic, and 4 percent of other races. The number of children present is not large, about two on average, with one under age six. About 3/4ths of the sample live in a metropolitan area, slightly above the U.S. average. About 30 percent of the sample worked at some

Table 3
Descriptive Statistics on Variables Used in Research
(Omitting Occupation and Industry Dummies)

Variable	Mean	Standard Deviation
Control Variables:		
Age	30.4	8.1
0 years of schooling (0-1 variable)	0.006	
1-8 years of schooling (0-1 variable)	0.135	
9-11 years of schooling (0-1 variable)	0.318	
1+ college years, no degree (0-1 variable)	0.159	
4 years of college, degree (0-1 variable)	0.013	
Post-graduate degree (0-1 variable)	0.002	
Black (0-1 variable)	0.355	
Hispanic (0-1 variable)	0.235	
Other non-white race (0-1 variable)	0.037	
Number of own children, ages 0-5	0.91	0.89
Number of own children, ages 6-17	1.18	1.17
MSA residence (0-1 variable)	0.758	
Worked last year (0-1 variable)	0.304	
ln(real wage rate per hour last year—1995 dollars) = ln[real earnings/(weeks worked*usual weekly hours)]	1.637 (based on 6,338 observations) [exp(1.637) = 5.14]	0.571
Usual weekly work hours last year	31.5 (based on 6,338 observations, those who worked last year)	12.0
Dependent Variables:		
Employed in March (0-1 variable)	0.178	
Employed in March, for those who worked last year	0.478 (6,338 observations)	
Usual weekly earnings in March (includes zero March earnings)	$30.97 (5,006 observations)	$87.94
Usual weekly earnings in March, for those who worked last year	$92.89 (1,433 observations)	$133.48
Usual weekly work hours in March (includes zero March hours)	4.64 (5,006 observations)	11.75
Usual weekly hours in March, for those who worked last year	13.61 (1,431 observations)	16.89
ln (real wage rate in March)	1.802 (764 observations) [exp(1.802) = $6.06]	0.384
ln (real wage rate in March), for those who worked last year	1.818 (640 observations) [exp(1.818) = $6.16]	0.384

Notes: Except where indicated, all descriptive statistics are based on 20,830 observations. Control variables also included age squared, complete vectors of state of residence and year dummies, and occupation and industry dummies. Size of firm where employed last year also tested in some specifications. Omitted category in education variables is "high school graduate only." Omitted category in race variables is "non-Hispanic white." Last year's real wage and work hour variables were actually entered in regression as deviations of original variables from mean values.

time during the preceding year. The natural logarithm of the hourly wage rate at those jobs averaged 1.64, or about $5.14 per hour, and usual weekly hours at those jobs averaged around 31 hours. There was a great deal of variation in hourly wage rates, with a standard deviation of about 57 percent. The percentage employed in March was around 18 percent. Forty-eight percent of those who worked last year were also employed in March, and about 5 percent of those who did not work last year were employed in March. Even without doing any formal estimation, it seems fairly clear that being employed last year has an extremely strong relationship to whether the individual is working in March.

Average real hourly wages were 16 percent higher in March than for the previous year, or a natural log of 1.80, corresponding to a real hourly wage rate of $6.06. This makes sense because we are selecting a sample that is especially "down on its luck" in the preceding year.

Occupation and industry categories

One key issue is how to define the occupation and industry classifications used in the analysis. As Table 1 revealed, welfare recipients have fairly large representation in some relatively detailed occupations and industries. On the other hand, there are some larger occupational and industrial categories in which welfare recipients are seldom represented.[6] For research purposes, we would like to use as detailed categories of occupations and industries as possible, but with a sufficient sample size for each category to allow precise estimation. For some occupations and industries, we clearly have a large enough sample to justify going to the 3-digit level. In other cases, the occupational and industrial categories must be fairly aggregate to allow for reasonably precise estimation. Finally, the

[6] The Appendix presents tables that show occupational and industrial distributions of welfare recipients in this study's sample, using the "standard" census occupation and industry categories, at the 1-digit and 2-digit levels of detail.

procedures used for categorizing industries and occupations must be reasonably "objective." If too much subjective judgment by the researcher is involved, some readers might get suspicious that the categories have been picked to reach a predetermined result.

I decided to estimate a set of rules for aggregating and disaggregating occupations and industries based on the percentage of the sample in the resulting categories. I started with all occupations (industries) combined. The procedure at the first stage attempts to disaggregate to the "major occupation (industry) group" level, at the second stage to the "detailed occupation (industry) recode" level, and at a third stage to the 3-digit level. At each stage, I picked out all individual occupations (industries) if they were greater than some cutoff percentage, x percent. The remaining occupations (industries) were then combined. If these remaining occupations (industries) summed to greater than x percent of the total sample, then this categorization was accepted as an intermediate possible categorization. If the remaining occupations (industries) did <u>not</u> sum to more than x percent, then one of three options was chosen. Option 1 was not to break down the broader category at all. Option 2 was to group the remaining occupations (industries) with whichever one of the more detailed categories in that broad category those remaining occupations (industries) seemed to be most similar. Option 3 was to group the remaining occupations (industries) in a broad miscellaneous category. Which of these three options was chosen was based on my judgment about which option would minimize differences within categories and maximize differences across categories. In the groupings actually used, I have tried to describe fully all the subjective judgments made. After performing this procedure at the first stage, I then went on to the second stage, and then to the third stage. The resulting occupation and industry categories disaggregate to a more detailed level the more welfare recipients are employed in a given type of occupation or industry. All occupational and industrial categories used, by design, have more than x percent of the total sample.

This procedure was applied for two different "cutoff levels" of x: 10 percent and 2.5 percent.[7] Tables 4 and 5 show the resulting occupational and industrial categories and give some descriptive statistics for these categories. In the empirical section of the paper, the 2.5 percent categories are used in the reported estimates with the March employment dependent variable. The 10 percent categories are used in the reported estimates with the earnings, hours, and wage rate dependent variables, for which only a much smaller sample is available.

Tables 4 and 5 show large differences in March employment probabilities for welfare recipients, depending on which occupation or industry she was employed in last year. There also are some significant differences across occupations and industries in wage rates, however, and it is certainly possible that wage differences could explain any occupation or industry differences in March employment probabilities. In addition, Tables 4 and 5 reveal both similarities and diversity in the types of jobs obtained by welfare recipients. The jobs generally are low-wage, with low formal education requirements, and most of the jobs involve considerable interaction with customers and co-workers. On the other hand, the specific tasks required vary greatly across these occupations and industries.

[7]The choice of 10 percent and 2.5 percent as cutoffs was based on a rough preliminary calculation of likely standard errors on the resulting industry and occupation dummies. If we just did a regression using those employed last year, with a dummy variable for whether employed in March as a dependent variable and a single discrete independent variable, the standard error of the coefficient on that discrete variable would be equal to the standard deviation of the March employment discrete variable, divided by the standard deviation of the single discrete independent variable, multiplied by one over the square root of the sample size (the number of those employed last year). As we add other independent variables, the standard error on any independent variable will be given by a similar calculation, except now the standard deviations of both dependent and independent variables should be the standard deviation after adjusting for all the other independent variables. That is, the standard deviations in the calculation should be for the residuals from regressing both the dependent and independent variable considered on all the other independent variables. Absent information to the contrary, it is not unreasonable to think that the ratio of the adjusted standard deviations will be of similar size to the ratio of the unadjusted standard deviations. Using unadjusted standard deviations and the sample size, the predicted standard error in these data with a discrete industry or occupation dummy with a mean of 0.10 is 0.021, or about 2 percent. For a discrete industry or occupation dummy with a mean of 0.025, the predicted standard error is 0.040, or about 4 percent. Going to more detailed industry or occupation dummies that have means closer to 1 percent would push standard errors up to around 0.063. Based on these calculations, 2.5 percent seemed about the minimal amount of employment in an industry or occupation needed to tell anything useful. At this detail level, we can determine industry or occupation effects with an accuracy of about plus or minus 8 percent in the effects of the industry or occupation on the March employment percentage. Although these calculations are crude, the actual standard errors were reasonably close to these predicted levels.

Table 4
Occupation Categories Used in Analysis

10% Category Name	2.5% Category Name	Occupation codes included	Relation to Census categories	Examples of occupations	% of sample	Mean real wage in sample	Mean March employment probability
All occupations					100	$6.12	0.478
Sales		243-285	Major occ group		14.8	$5.74	0.438
	Cashiers	276	3-digit occ	Cashiers	10.2	$5.58	0.414
	Other sales	243-285, except 276	Major occ group minus 3-digit occ	Sales workers, other commodities; street and door-to-door sales; supervisors and proprietors, sales occupations	4.6	$6.09	0.490
Administrative support		303-389	Major occ group		16.6	$6.85	0.526
	Secretaries	313-315	Sum of 3 3-digit occupations	Secretaries; typists; stenographers	4.1	$7.06	0.542
	Other admin. support	303-389, except 313-315	Major occ group minus 3 occupations	Receptionists; general office clerks; bookkeepers; teacher aides; data entry keyers; file clerks; stock clerks	12.5	$6.78	0.520
Food services		433-444	Detailed recode group		16.6	$5.33	0.457
	Waitresses	435	3-digit occ	Waitresses	6.5	$5.41	0.468
	Cooks	436	3-digit occ	Cooks	4.1	$5.01	0.405
	Other food service	433-444, except 435, 436	Recode minus 2 occs	Bartenders; food counter and fountain; kitchen workers	6.1	$5.46	0.479
Other services		445-469	Sum of 3 detailed recode groups		20.8	$6.02	0.491
	Health aides	445-447	Sum of 3 3-digit occs	Nursing aides; dental assistants	7.9	$6.57	0.508
	Maids	449	3-digit occ	Maids	4.3	$5.31	0.452
	Cleaning	453, 448	Sum of 2 3-digit occs	Janitors; supervisors, cleaning services	4.0	$5.85	0.464
	Child care	466	3-digit occ	Child care	1.8	$5.26	0.496
	Other personal service	450-469, except 453, 466	3 Recode groups minus some 3-digit occs.	Welfare aides; hairdressers	2.8	$6.25	0.533

Table 4
(continued)

10% Category Name	2.5% Category Name	Occupation codes included	Relation to Census categories	Examples of occupations	% of sample	Mean real wage in sample	Mean March employment probability
Machine operators/ inspectors		703-799	1 Major occ group		10.3	$5.88	0.452
	Machine operators	703-779	Recode group	Textile sewing machine operator; packaging machine operator; laundering & dry cleaning machine operator; pressing machine operator	6.6	$5.84	0.468
	Assemblers/ inspectors	783-799	2 Recode groups	Assemblers; production inspectors	3.7	$5.96	0.422
Miscellaneous		All other not in above			20.8	$6.67	0.488
	Professional	43-199	Major occ group	Social workers; teachers, pre-K and K; teachers, elem.; R.N.; teachers, secondary schools; post secondary teachers	3.4	$7.33	0.620
	Private household service	403-407	Major occ group	Private HH cleaners & servants; child care workers, private HH	3.5	$5.92	0.438
	Handlers/ laborers	864-889	Major occ group	Hand packers and packagers; laborers, except construction; stock handlers & baggers	3.7	$5.78	0.319
	Misc.	All other not in above		Farm workers; managers and administrators; bus drivers; butchers and meat cutters; truck drivers; grounds keepers; chemical lab technicians; guards & police, except public svc.; LPNs	10.3	$7.03	0.521

Notes on occupational table: Occupation codes reported are official Census Bureau occupational codes, as summarized in documentation for March 1995 CPS. Some minor aggregations to a few 3-digit categories were made to reconcile the 1983-91 and 1992-95 occupational categories, which are slightly different (see Appendix). Major occupational group, occupation recodes, and 3-digit occupations are the three levels of detail (with detail going from 14 major occupations to 52 occupation recodes to 500 3-digit occupations). The specific 3-digit occupations listed as examples in the fifth column are listed in order of percentage of this sample employed in each occupation. The occupations listed as examples in all cases sum to more than 50 percent of the corresponding category. All descriptive statistics listed are for the full sample used in the regressions with an employment status in March dependent variable, and are based on a sample of 6,338 employed welfare recipients last year. All descriptive statistics listed are unweighted, as it is unclear whether the CPS-provided weights are appropriate in a sample that drops many observations with allocated variables or implausible wage rates. The procedure to create these two systems of classification is as described in the text. The 10 percent classification required no judgments about regrouping occupations, but could be done simply mechanically. The 2.5 percent classification required the following specific judgments about regrouping occupations: sales representative was grouped in with other sales to form other sales category, rather than being grouped with cashiers, in order to preserve separate cashiers category, as cashiers is biggest 3-digit occupation; for administrative support, computer operators and records processing were grouped with other administrative support, and stenographers and typists in with secretaries; for cleaning, because the cleaning supervisors category was very small, I grouped it together with janitors in a somewhat broader category; finally, child care ends up being a separate category because this classification procedure was originally done before observations were dropped for having implausible wages last year. In this original breakdown, child care occupations were greater than 2.5 percent of the sample. As it turned out, child care occupations have a disproportionate number of implausible, usually very low wages, and this occupational category dropped to only 1.8 percent of the final sample. It was kept as a separate category in the belief that there is special interest in seeing whether child care, which clearly has much in common with the usual home activities of welfare recipients, leads to greater employment retention.

Table 4
(continued)

Table 5
Industrial Categories Used in Analysis

10% Category Name	2.5% Category Name	Industry codes included	Relation to Census categories	Examples of industries	% of sample	Mean real wage last year	Mean March employment probability
All industries					100%	$6.12	0.478
Eating & drinking places	Eating & drinking places	641	3-digit industry	Eating and drinking places	16.8	$5.21	0.434
Rest of retail trade		590-691, except 641	Major industry minus 3-digit industry		13.9	$5.82	0.448
	Grocery stores	601	3-digit industry	Grocery stores	3.9	$5.79	0.478
	Department stores	591	3-digit industry	Department stores	3.2	$5.80	0.446
	Rest of retail trade	590-691, except 641, 601, 591	Major industry minus 3 3-digit industries	Apparel accessory stores, except shoe; retail bakeries; gasoline service; drug stores; direct sales; variety stores; sporting goods; auto and home supply	6.8	$5.85	0.432
Personal service/private household service		761-791	Major industry group		10.7	$5.70	0.461
	Hotels/ motels	762	3-digit industry	Hotels/motels	4.2	$5.49	0.455
	Rest of personal service	770-791	Recode group minus 3-digit industry	Laundry, cleaning, and garment services; beauty shops	2.6	$5.64	0.530
	Private household service	761	3-digit industry; also recode group	Private household services	4.0	$5.96	0.422
Health services		812-840	2 Recode groups		11.6	$7.08	0.552
	Hospitals	831	3-digit industry; also recode group	Hospitals	2.9	$8.24	0.640
	Nursing and personal care facilities	832	3-digit industry	Nursing and personal care facilities	5.8	$6.39	0.497
	Other medical services	812-830, 840	Recode group minus 3-digit industry	Health services n.e.c.; offices of physicians; offices of dentists	2.9	$7.27	0.574
Prof, social, & educ. services		841-893	3 Recode groups		12.5	$6.33	0.563
	Educational services	842-860	Recode group	Elementary and secondary schools	5.9	$6.47	0.637
	Social services, other prof. services	841, 861-893	2 Recode groups	Child day care services; social services, n.e.c.; membership organizations; residential care facilities; research, development & testing	6.6	$6.20	0.495

Table 5
(continued)

10% Category Name	2.5% Category Name	Industry codes included	Relation to Census categories	Examples of industries	% of sample	Mean real wage last year	Mean March employment probability
Manufacturing		100-392	2 Major industry groups		12.3	$6.24	0.479
	Durable goods	230-392	Major industry group	Electrical machinery and equipment; motor vehicles; furniture; misc. fabricated metal products; medical and dental instruments; machinery, except electrical.	4.3	$6.64	0.529
	Nondurable goods	100-222	Major industry group	Apparel, except knit; meat products; canned, frozen and preserved fruits and vegetables; printing; miscellaneous food preparations; misc. plastic products	8.0	$6.03	0.451
Misc.		All other than listed above			22.2	$6.53	0.453
	FIRE (finance/ insurance/real estate)	700-712	Major industry group	Real estate, incl. real estate insurance ofcs; insurance; banking	2.8	$7.02	0.601
	Personnel supply services	731	3-digit industry	Personnel supply services	3.0	$5.58	0.337
	Rest of business/ repair services	721-760, except 731	Major industry group minus 3-digit industry	Services to buildings; business services.	4.5	$5.84	0.468
	Public admin.	900-991	Major industry group	Admin. of human resource programs; justice, public order, & safety; general government, n.e.c.	2.9	$8.20	0.484
	Misc.	All other than listed above		Misc. entertainment and recreation services; agricultural production; construction; bus service; groceries and related products; veterinary services; trucking services	9.0	$6.29	0.427

Notes on industrial table: Industry codes reported are official Census Bureau industrial codes, as summarized in documentation for March 1995 CPS. Some minor aggregations to a few 3-digit categories were made to reconcile the 1983-91 and 1992-95 industrial categories, which are slightly different (see Appendix). Major industrial group, industry recodes, and 3-digit industries are the three levels of detail (with detail going from 14 major industries to 46 industry recodes to 236 3-digit industries). The specific 3-digit industries listed as examples in the fifth column are listed in order of percentage of this sample employed in each industry. The industries listed as examples in all cases sum to more than 50 percent of the corresponding category. All descriptive statistics listed are for the full sample used in the regressions with an employment status in March dependent variable, and are based on a sample of 6,338 employed welfare recipients last year. All descriptive statistics listed are unweighted, as it is unclear whether the CPS-provided weights are appropriate in a sample that drops many observations with allocated variables or implausible wage rates. The procedure to create these two systems of classification is as described in the text. The specific judgement calls for the 10 percent classification are as follows: health services was grouped together even thought this was two recodes; manufacturing was grouped together even though this was two major groups. The specific judgement calls for the 2.5 percent classification are as follows: repair services was combined with business services, except personnel supply services, to get an "all other business services" category, rather than being placed in miscellaneous category or being grouped with personnel supply services, in order to preserve the distinctive personnel supply services category; other professional services were combined with social services largely on grounds that these are both very diverse categories compared with educational services category.

Firm Size

For six of the CPS data tapes (1988-89, 1992-95), information is available on the size of the firm of the individual's longest job last year. Firm size might affect job retention and earnings growth for welfare recipients. Small and large firms, even in the same industry and for the same occupation, would have different production processes and personnel policies.

Some specifications included firm size, described by a complete set of dummies for different firm size categories. Table 6 gives descriptive statistics for the distribution of welfare recipients by size class of firm.

Table 6
Distribution of Employed Welfare Recipients By Size Class of Firm

Size class of firm	Percentage of welfare recipients employed in that size class of firm
Less than 25 employees	29.4%
25-99 employees	15.3
100-499 employees	15.9
500-999 employees	5.7
1000 or more employees	33.7

Notes: Sample size is 3,277 employed welfare recipients from the following March CPS tapes: 1988-89, 1992-95.

RESULTS

Table 7 presents results for a probit model with a zero-one indicator for March employment as a dependent variable. The reported model includes the complete set of control variables listed in Table 3. The model also includes a complete set of both occupation and industry dummies, defined using the 2.5 percent classifications. The reported model does not include dummy variables for size of firm employing the individual last year.

The reported model is one of eight estimated with a March employment status dependent variable. Models were estimated using both the 10 percent and 2.5 percent classifications, and with either occupation dummies separately, industry dummies separately, or both industry and occupation dummies. In addition, two models were estimated that added the firm size dummies to the 10 percent and 2.5 percent models with both occupation and industry dummies.

Why was the particular model in Table 7 chosen to be reported out of the eight models estimated? Both industry and occupation effects on March employment are potentially of policy interest. Furthermore, we would like to know the effects of industry of employment last year, holding occupation constant, and vice versa. We would like if possible to get the maximum amount of detailed information on industry and occupation effects; the 2.5 percent classification gives reasonably precise results.

From a formal statistical perspective, one could argue for a variety of models. Chi-squared tests indicate that the greater industry and occupational detail of the 2.5 percent occupation/industry model was significantly better than the 10 percent occupation/industry model.[8] Chi-squared tests also indicate that the occupation and industry dummies in the reported model are each separately statistically significant.[9] Other statistical criteria yield other model choices. The Akaike Information Criterion, which seeks to choose a model that minimizes out-of-sample prediction error, prefers the 2.5 percent industry-only model out of the models estimated.[10] The Schwartz Bayesian Criterion, which seeks to choose a model that minimizes the posterior odds of choosing the wrong coefficients, prefers the 10 percent industry-only model out of the models estimated.[11] However, these criteria do not address the issue of the policy interest in learning more about the effects of both occupation and industry, at as fine a level of detail as possible.

---

[8]The value of the chi-squared test statistic, with 24 degrees of freedom, is 72.92, which has a probability of less than .005.

[9]Chi-squared for industry dummies is 67.70, probability less than 0.0001. Chi-squared for occupation dummies is 29.49, probability = 0.0303.

[10]The six models and their values of the AIC, which we want the maximum value of, are OI 2.5 percent: -6893.4; OI 10 percent: -6905.9; I 2.5 percent: -6891.3; I 10 percent: -6902.3; O 2.5 percent: -6909.7; O 10 percent: -6915.3. The I 2.5 percent is the "best" AIC model, but the OI 2.5 percent model is a relatively close second.

[11]The values of the Schwartz Bayesian Criterion for the six models are OI 2.5 percent:-7346.2; OI 10 percent: -7263.4; I 2.5 percent: -7276.58; I 10 percent: -7239.9; O 2.5 percent: -7291; O 10 percent: -7248.9. The I 10 percent model is clearly preferred.

Firm size was dropped from the reported models. When firm size is added, the vector of firm size variables is clearly statistically insignificant.[12] Furthermore, the point estimates imply effects of firm size that are substantively small.[13] Finally, including the firm size variables implies that we must drop slightly over half the observations, as firm size is only available in six of the thirteen CPS tapes included in this study. Reducing the number of observations so much seems an excessive price to pay for adding variables that seem to have little effect.

As shown in Table 7, if a welfare mother worked last year, her probability of employment in March increases from 6 percent to 48 percent. The wage rate of last year's job had highly statistically significant effects but of more modest magnitude than might be expected. A doubling of the wage rate—say from $5 to $10 per hour—would only increase the percentage employed the next March by about 3.6 percent, from 47.8 percent to 51.4 percent.[14] The individual wage is no doubt

---

[12]In the 2.5 percent occ/ind model, the chi-squared test statistic for adding the size variables is 0.25, which has a probability of 0.9930.

[13]In the 2.5 percent occ/ind model, the following are the estimated marginal effects and standard errors: size lt 25: 0.006 (t=0.31); size 25-99: -0.007(t=-0.25); size 100-499: -0.004 (t=-0.14); size 500-999: 0.013 (t=0.31). The omitted category is size 1000 and above. These marginal effects are calculated by multiplying the probit coefficients by 0.478, and so are only approximate calculations for the discrete effects of a change to a different size class, calculated at the mean March employment probability for those working last year of 0.478.

[14]A doubling of the wage rate would increase the natural logarithm of the wage rate by ln(2) = 0.693. The numbers in the table show the marginal effect of increasing the wage rate, evaluated for an individual whose original probability of being employed in March is at the sample mean for those employed last year of 0.478. Multiplying the reported marginal effect of 0.0517 times 0.693 = 0.0358, which will be an approximation to the actual discrete effect of increasing the wage rate by that discrete amount.

Table 7
Effects of Last Year's Work Activity and Various Job Characteristics
on Probability of Employment this March,
for Single Mothers Receiving Welfare Last Year

Variable	Effect on March Employment Probability	
Worked last year (0-1 variable)	0.421	(60.23)
Average wage rate last year	0.0517	(4.37)
Usual weekly hours last year	-0.00049	(-0.84)

Industry categories (0-1 variables):			Occupation categories (0-1 variables:		
Miscellaneous	-0.053*	-2.36	Miscellaneous	0.026	(1.22)
Durable goods	0.076*	(2.12)	Professional	0.049	(1.30)
Nondurable goods	0.011	(0.38)	Cashiers	-0.052*	(-2.09)
Eating and drinking places	-0.022	(-0.91)	Other sales	0.008	(0.24)
Grocery stores	0.051	(1.39)	Secretaries	0.030	(0.89)
Department stores	0.006	(0.16)	Other administrative support	0.005	(0.27)
Rest of retail trade	-0.025	(-0.91)	Private household services	0.155	(1.59)
FIRE (finance/insurance/real estate)	0.088*	(2.21)	Waitresses	-0.000	(-0.01)
Personnel supply services	-0.128*	(-3.29)	Cooks	-0.063	(-1.75)
Rest of business/repair services	-0.000	(-0.00)	Other food service	0.007	(0.25)
Hotels/motels	-0.003	(-0.06)	Health aides	0.025	(0.77)
Rest of personal services	0.030	(0.70)	Maids	-0.008	(-0.18)
Private household services	-0.174	(-1.96)	Cleaning	-0.014	(-0.39)
Nursing, personal care	0.017	(0.47)	Child care	0.020	(0.40)
Other medical services	0.048	(1.18)	Other personal services	0.051	(1.21)
Educational services	0.118*	(4.12)	Machine operators	-0.002	(-0.07)
Social svcs/other personal svcs	-0.014	(-0.50)	Assemblers, inspectors	-0.058	(-1.49)
Hospitals	0.135*	(3.45)	Handlers, laborers	-0.135*	(-3.88)
Public administration	-0.021	(-0.55)			

Notes: Numbers in parentheses are ratios of coefficient estimates to standard errors; coefficient estimates should asymptotically be distributed normally. Estimated effects with ratios of coefficient to standard error estimates of greater than 2 in absolute value are marked with asterisk. Estimates are derived from probit specification, with 0-1 dependent variable for whether the individual is employed in March. Sample is all single mothers who were on welfare previous year, from March Current Population Survey, 1983-95. Control variables include age, age squared, six 0-1 variables for years of education, three 0-1 variables for race, two variables for number of own children of various ages, 0-1 variable for whether resided in metropolitan area, complete vector of 0-1 variables for state of residence, complete vector of 0-1 variables for year of observation. Effects in table for 0-1 variables are change in probability of March employment, for discrete change in variable from 0 to 1, evaluated using March employment probability of 0.478 as baseline, which is mean March employment probability for those employed last year. For "worked last year" variable, change from 0 to 1 is evaluated, but ending up at 0.478 employment probability. Occupation and industry variables each together sum to worked last year variable. Restrictions are imposed to make these occupation and industry coefficients estimable. Specifically, weighted sum of occupation variable coefficients is constrained to equal zero, where weights are proportion of sample in each occupation. Similar restriction is imposed on industry coefficients. Hence, occupation and industry effects are effects of that occupation or industry relative to mythical "average" occupation or industry, in which an imaginary individual was partially in each occupation or industry, with partial employment weights equal to sample averages. Estimation also defines average wage rate last year and usual weekly hours last year variables as deviations from sample averages. Hence, the effect of worked last year should be interpreted as effects for individual in average occupation and industry, and being paid average wages and working average work hours. Effects in table for wage and usual weekly hour variables are marginal effects evaluated at March employment probability of 0.478.

subject to considerable measurement error, which will bias its coefficient towards zero. But it seems unlikely for there to be enough measurement error for the effect of wages on March employment probabilities to be impressively large. The effect of usual weekly hours at last year's job is not only substantively small, but also statistically insignificant.

The effects on March employment of the industry of last year's job are generally greater than the effects of the occupation of last year's job. The industry variables are collectively more statistically significant than the occupation variables. Furthermore, there are more industry effects that are substantively large in absolute value. Job retention for welfare recipients is affected more by an industry's personnel practices than by differences in personnel practices for different types of jobs within the same industry.

The industries with the largest positive, and statistically significant, effects on March employment probabilities are (in order of magnitude of effect): hospitals; educational services; finance/insurance/real estate; and durable goods manufacturing. The temporary help industry has the most negative effects on March employment probabilities.

The magnitude of these industry effects is quite large relative to the effects of wages. A number of industries increase or reduce March employment probabilities by over 0.07. Hospital industry employment last year increases the March employment probability by 0.135, from 0.478 to 0.613. It would take an increase in the wage rate of around thirteenfold to increase March employment probabilities by a similar amount. It should be recalled also that these industrial effects are estimated controlling for individual wages on last year's job. It seems unlikely that these industrial effects could be attributable to wages.

Fewer of the occupation effects are large once one controls for industry and wages. The only two statistically significant occupation effects are for cashiers and handlers/laborers. Both occupations are estimated to significantly reduce the March employment probability compared to the average industry.

Any job last year must be in a particular industry and occupation, by definition. All industrial/occupational combinations are not equally likely, and in many cases a worker's industry and occupation are highly correlated. To take an extreme example, all workers in the private household service occupation are also in the private household service industry, and 87 percent of those in the private household service industry are also in the private household service occupation. The effects reported in Table 7 (which show the effects for someone in a particular industry [occupation], compared to the average industry [occupation], for someone who is in the "average" industry [occupation]) may sometimes be misleading. One should pay some attention to the industry/occupation pairs that are most likely to occur. The effects of any industry/occupation pair can be calculated by adding up the industry/occupation coefficients. Calculating the standard error of that combination requires knowing the variance/covariance matrix of the coefficients.[15]

Table 8 reports estimated effects and ratios to standard errors for each and every pair of the 342 possible industry/occupation pairs (18 occupations times 19 industries) that has more than 1 percent of the sample. Together, these 26 industry/occupation pairs comprise over 60 percent of the sample. As Table 8 shows, the estimates imply significantly negative effects on employment of being a cook or cashier in eating and drinking places. Being a cashier in the rest of retail trade also has negative effects. Administrative support staff and professionals in the educational services industry are significantly more likely to be employed in March. Administrative support personnel in the FIRE industry are also significantly more likely to be employed in March. Both industry and occupation clearly make a difference. For example, waitresses in eating and drinking places are not significantly less likely to be employed in March, unlike cooks or cashiers in eating and drinking places, and cashiers in grocery stores

[15] Actually, because these are discrete effects, the actual effect of an industry/occupation pair differs slightly from adding the two separate discrete effects together, but simply adding the two will give a quite close approximation.

are not significantly less likely to be employed in March, unlike cashiers in eating and drinking places or the rest of retail trade.

For a more limited sample, the "outgoing rotation group" of the March CPS, data are also available on March usual weekly earnings, weekly work hours, and average wage rate. Table 9 reports estimates when earnings, work hours, and wage rates in March are used as dependent variables. As described in the methodology section, the earnings and hours estimating equations are estimated using tobit techniques. The wage rate equation is estimated using Heckman's two-stage method of correcting for selection bias in a regression equation.

To allow comparisons across the dependent variables, Table 9 reports estimated effects in percentage terms. Effects are reported as a percentage of the mean value of the dependent variable for sample members who worked last year.[16] The percentage effect on earnings of an independent variable should <u>approximately</u> equal the sum of its percentage effects on work hours and hourly wages, because weekly earnings is the product of work hours and hourly wages. Table 8 also includes the percentage effects of all variables on the March probability of employment. A comparison of the percentage effect of a variable on March employment, with its percentage effect on March weekly work hours, suggests how the variable affects weekly work hours for those working. The percentage effect on total work hours should approximately equal the sum of the percentage effect on the probability of working

[16]The effects for the tobit equations are percentage effects on the actual dependent variable, not the latent dependent variable that is truncated at zero.

Table 8
Estimated Effects on March Employment Probabilities and Ratios to Standard Errors, For 26 Occupation/Industry Combinations that Employ More than 1% of Sample

Occupation and Industry	Percent of Sample	Effect (Ratio to Standard Error)	
Waitresses/eating and drinking places	5.9%	-0.023	(-0.91)
Health aides/nursing industry	4.3	0.041	(-1.50)
Other food occs/eating and drinking places	4.2	-0.015	(-0.55)
Machine operator/nondurable goods	4.0	0.009	(0.33)
Misc. occupation/misc. industry	3.6	-0.028	(-1.11)
Private household svc occ and industry	3.5	-0.025	(-0.71)
Cooks/eating and drinking places	3.0	-0.084*	(-2.63)
Maids/hotels and motels	3.0	-0.011	(-0.32)
Cashiers/eating and drinking places	2.8	-0.074*	(-2.52)
Cashiers/grocery stores	2.7	-0.002	(-0.05)
Cashiers/rest of retail trade	2.4	-0.077*	(-2.56)
Other sales occs/rest of retail trade	2.0	-0.017	(-0.51)
Cleaning occs/rest of business repair svcs.	1.8	-0.014	(-0.37)
Other admin. support occ/educational svcs.	1.7	0.123*	(3.95)
Other admin. support occ/misc. inds	1.6	-0.048	(-1.74)
Assemblers and inspectors/durable goods	1.6	0.017	(0.44)
Other adm. supp./FIRE	1.5	0.094*	(2.36)
Health aides/other medical svc. inds.	1.4	0.072	(1.75)
Cashiers/department stores	1.3	-0.046	(-1.18)
Other personal service/social & other svcs.	1.3	0.037	(0.87)
Professionals/educational svcs.	1.2	0.165*	(4.05)
Assemblers and inspectors/nondurables	1.1	-0.047	(-1.17)
Machine operators/durable goods	1.1	0.074	(1.86)
Other adm. supp./public administration	1.1	-0.016	(-0.40)
Other adm. supp./rest of bus & repair svcs.	1.0	0.005	(0.14)
Child care occ/social & other svcs.	1.0	0.006	(0.13)
Total of 26 occupation/industry combinations	60.1% of sample		

Note: These effects are measured from a model with both occupational and industry dummies, but no interaction terms between occupation and industry. Hence effects are based on sum of occupation and industry coefficients. Effects are measured as change in probability of employment in March for someone employed last year in that occupation/industry combo, compared to individual in "average" occupation and industry last year. Effects are measured at mean March probability of employment of 0.478 for those employed last year. Number in parentheses is ratio of sum of coefficients to standard error of that sum, calculated from variance/covariance matrix of probit index function coefficients. The coefficient sum should be asymptotically distributed normally. If the ratio is greater than two in absolute value, the corresponding effect is marked with asterisk.

plus the percentage effect on average work hours for those working. The percentage effects of an independent variable on hours, minus the percentage effect on March employment probabilities, should approximately equal the percentage effects on hours for those working in March.[17]

Table 9 reports results for one specification, with 10 percent industry/occupation dummies but no firm size dummies. This specification is one of eight possible specifications that were tried. The other specifications varied in whether both industry and occupation were included, in using the 10 percent or 2.5 percent level of detail, and in whether firm size dummies were included. Firm size dummies were dropped because they were always both statistically and substantively insignificant. Estimates at the 2.5 percent level of classification yielded estimates that were extremely imprecise. The AIC and SBC model selection criterion both agreed that the industry-only, 10 percent classification level was optimal for the hours and earnings estimating equations. The AIC and SBC model selection criterion both indicated that the occupation-only, 10 percent classification level was optimal for the wages estimating equations. The inclusion of both industry and occupation dummies allows both industrial and occupational effects to be analyzed in a comparable way for all dependent variables.

The estimates suggest that whether one worked last year has huge effects on March weekly earnings. Almost all these effects are due to effects of working last year on usual March weekly work hours. Almost all these work hour effects are due to effects on the probability of being employed in March. Wage rate effects on March usual weekly earnings are much larger in percentage terms than are effects on the March employment probability. Doubling the wage rate of the job held last year is

[17]In theory, one could directly estimate an equation with a variable equal to weekly work hours for those working and missing for those not working. This would require "heckit" estimation, as the sample of those working is a selected sample. However, good heckit estimates require excluding some variables from the regression equation that are in the selected equation. It is almost impossible to think of a variable that would plausibly affect the probability of working, yet not also affect the hours one would work if one was working.

Table 9
Percentage Effects of Last Year's Work Activity,
Wage Rate, Usual Work Hours, and Occupation and Industry,
on This March's Employment, Weekly Work Hours, Wage Rate,
and Weekly Earnings, for Single Mothers Receiving Welfare Last Year

Variable	Percentage effect on March employment probability		Percentage effect on March weekly work hours (includes zero March work hours)		Percentage effects on March hourly wage rate		Percentage effect on March real weekly earnings	
Worked last year (0-1 variable)	85.5%*	(28.68)	89.6%*	(13.92)	4.5%	(0.94)	92.2%*	(14.65)
Usual weekly work hours last year (change of 20 work hours)	-2.2%	(-0.94)	20.4%*	(2.85)	8.7%*	(3.34)	23.8%*	(3.27)
Wage rate last year (doubling of wage rate)	8.5%*	(5.01)	16.3%*	(3.12)	20.7%*	(10.39)	30.2%*	(5.70)
Occupation categories (0-1 variables):								
Sales	-1.5%	(-0.36)	5.0%	(0.40)	-7.1%	(-1.70)	1.0%	(0.08)
Administrative support	5.2%	(1.55)	5.7%	(0.57)	5.9%*	(1.82)	10.0%	(0.97)
Food services	0.6%	(0.14)	0.9%	(0.07)	-1.7%	(-0.38)	-0.7%	(-0.05)
Other services	-1.0%	(-0.31)	-2.2%	(-0.24)	-2.4%	(-0.79)	-7.4%	(-0.81)
Machine operators/inspectors	-3.0%	(-0.55)	4.8%	(0.30)	-7.1%	(-1.26)	1.8%	(0.11)
Miscellaneous occupations	-1.1%	(-0.40)	-8.6%	(-1.08)	8.5%*	(2.94)	-1.1%	(-0.14)
Industry categories (0-1 variables):								
Eating and drinking places	-8.3%	(-1.75)	-7.7%	(-0.57)	0.1%	(0.01)	-8.1%	(-0.59)
Rest of retail trade	-5.5%	(-1.28)	-14.1%	(-1.17)	-1.4%	(-0.30)	-18.8%	(-1.54)
Personal services/private household services	-0.1%	(-0.03)	-2.9%	(-0.24)	-6.1%	(-1.57)	-5.9%	(-0.50)
Health services	15.0%*	(3.53)	36.1%*	(2.60)	-1.9%	(-0.48)	37.0%*	(2.62)
Professional/ social/educational services	12.6%*	(3.30)	16.3%	(1.42)	6.5%	(1.78)	25.3%*	(2.12)
Manufacturing	4.0%	(0.80)	8.1%	(0.54)	4.4%	(0.80)	11.0%	(0.72)
Miscellaneous industries	-7.3%*	(-2.60)	-13.0%	(-1.67)	-1.0%	(-0.37)	-14.0%	(-1.80)

Notes: Numbers in parentheses are ratios of estimated underlying coefficients to standard errors. Estimates should be asymptotically distributed normally. If ratio is greater than 2 in absolute value, corresponding effect is marked with asterisk. Estimates are derived from probit specification for the March employment dependent variable, tobit for work hours and weekly earnings dependent variables, and from regression equation corrected for selection bias for wage dependent variable. All estimates include same control variables as in Table 7 and Table 3, except that wage equation drops variables for number of own children. For all occupation and industry dummies, estimated effects are effects of being in that occupation or industry, compared to being in "average" occupation or industry. These effects are evaluated at mean value of working in March of 0.478 for those working last year. Effects are converted to percentage effects, for employment, hours, and earnings dependent variables, by using sample mean values of dependent variables for those working last year: 0.478 for employment in March, 13.6 hours for work hours, and $92.89 per week in earnings. For wage rate dependent variable, which is natural logarithm of real wage rate, effects are converted to actual percentages. For worked last year variable, effect evaluated is change from one to zero. For usual weekly hours last year variable, calculated effects are for change of 20 hours per week. For wages last year variable, calculated effect is for change in natural logarithm of wages last year of 0.693, where 0.693 = ln(2.0). So change considered is doubling of hourly wage. Calculated effects are extrapolation of marginal effects, where all marginal effects are calculated from mean March employment probability of 0.478. The changes in hours and wage variables are both a little less than a two standard deviation change (see Table 3).

associated with increasing usual weekly earnings in March by over 30 percent. The effect on earnings is large, even though the effect on the March employment probability is so modest, for two reasons. First, increasing last year's wage rate is associated with substantial increases in the March wage rate. Second, an increase in last year's wage is associated with greater March work hours for those working. Increasing usual weekly work hours also has large positive effects on March earnings: an increase from 20 to 40 work hours per week last year is associated with an increase in March earnings of over 20 percent. Most of this effect of usual hours last year on March weekly earnings appears to be due to increases in March weekly work hours for those working.

Industry effects are much more important than occupation effects for earnings and work hours. This appears to be partially due to using the 10 percent level of classification, as occupation effects also diminish in importance for the March employment status dependent variable. On the other hand, for wage rates in March, last year's occupation appears to be much more important than last year's industry.

The industry effects on earnings are consistent with what was previously discovered about industry effects on March employment probabilities. The industries with the largest positive effects on March earnings are health services (which includes hospitals) and the professional/social/ educational services aggregation. A substantial portion of both of these earnings effects is due to effects on the March employment probability. Health services employment last year is also associated with an increase in March weekly work hours for those already working. The professional/social/educational services industry is associated with higher March wages. These industry effects hold last year's wage rate constant, so these industry effects on March wages reflect effects on the probability of getting a wage increase.

The occupational variables have no effects on weekly earnings or work hours that are even close to statistical significance. The occupational categories do have some statistically significant effects on the hourly wage rate. Part of the difference in statistical significance between the wage equation and the earnings and work hours estimating equations is that standard errors, expressed in percentage terms, are considerably smaller in the wage equation than in the earnings and work hour estimating equations. Standard errors in the wage equation for the occupational categories and industrial categories are often less than 5 percent. In the earnings and hours equations, standard errors are often greater than 10 percent. Apparently there is considerable “noise” in how many hours people work and in their earnings that cannot be explained by the variables in the model, whereas there is less unexplained noise in the wage equation. Even the March employment status equation, which has a much larger sample size than does the wage equation, has standard errors similar in size to those of the wage equation.

The wage equation's findings suggest that employment last year in administrative support occupations tends to increase March wages. Because this estimation controls for average wages last year, the interpretation is that administrative support occupations are more likely to lead to wage increases between last year and March than is the average occupation. Administrative occupations also seem to increase the March employment probability. On the other hand, employment last year in sales occupations or in food services occupations appears to be associated with lower March wages, controlling for last year's wages.

Interpretation

One of the most important issues is how to interpret all these “effects” of working at a job with a particular set of characteristics last year. Are these true effects of getting a particular job, or do these effects reflect differences in unobserved characteristics of individuals who tend to get particular jobs?

Several arguments can be offered that these effects are, at least in part, true effects. First, industry effects tend to be greater than occupation effects. One would expect unobservable personal characteristics to be more important in sorting persons across occupations than across industries. If all the estimated effects were due to unobservable personal characteristics, the occupation effects should be stronger.

Second, the effects of last year’s wage rate tend to be relatively modest, particularly on whether someone is employed. One would expect last year’s wage rate to be significantly higher for individuals who, for unobservable reasons, have higher productivity. The modest effects of the wage rate suggests that the effects of unobservable personal characteristics must be modest, particularly on whether an individual is employed in March.

Third, the effects of whether one worked at all last year, and the industry one worked in, tend to be greater on March employment status and work hours and less on the March hourly wage rate. One would expect unobservable personal characteristics to have important effects on the March wage rate. This suggests that at least some of the effects of working last year, and of working in a particular industry, are true effects.

Finally, many of these effects of last year's employment activities on March employment and earnings are huge. This increases the chance that these effects are to some extent true effects and not simply a reflection of unobservable personal characteristics.

Assume that these effects of last year's employment activities are to some extent true effects. Speculative reasons can be offered for why these effects occur.

Whether someone worked last year may lead to human capital accumulation. Both general and firm-specific human capital may be accumulated. This worker has the advantage of being a known quantity to the employer. By continuing to employ this worker, the employer avoids hiring and initial training costs that may result in a new worker who is no more productive.

Higher wage jobs may have persistent wage advantages, based on how firms have chosen to compensate that job relative to other wages available in the market. These higher wages lead to greater job retention. The effects of wages may be relatively modest because job retention may depend much more on a wide variety of firm-specific personnel practices—how jobs are supervised, what kind of OJT the firm provides, etc.

The usual weekly hours last year may tend to persist because jobs tend to be defined by firms as either part-time or full-time. Full-time jobs may be more likely to lead to wage increases, controlling for last year's wages. The lack of any effect of usual weekly hours on job retention may reflect the pros and cons of higher weekly hours from the perspective of single mothers. Full-time jobs may be better jobs, but part-time jobs may be more consistent with fulfilling other family responsibilities.

Several speculative reasons can be offered for the industry and occupation effects. Temporary help employment is of course temporary, and handler/laborer occupations may in many cases also be casual jobs. Cashiers must have some technical skills and be able to handle pressures for accuracy. Hospitals and the educational services industry may have more in common with the regular activities of many welfare recipients. These industries, durable manufacturing, and finance/ insurance/real estate may have less pressure for dealing with customers. Durable manufacturing industries, hospitals, and educational services may be more likely to offer benefits, which are not measured in these data. Secretaries and other administrative support occupations may have less pressure for dealing with customers. Furthermore, such occupations may tend to have more defined career ladders and involve acquiring more firm-specific skills while on the job. In contrast, cooks and other food service occupations may be relatively high pressure occupations that require constantly dealing with the changing needs of customers.

CONCLUSION

These results demonstrate that there are large correlations between a welfare mother's employment activity in one year, and her employment, wage rate, and earnings the next year. What is most important about last year's employment activity is whether any occurred, with welfare mothers who work in one year being much more likely to work the next year. The characteristics of the job also matter a great deal: its wage, usual hours, industry, and occupation.

The results suggest, but do not prove, that these effects of last year's job characteristics are true effects and are not simply due to who is hired for different jobs. Future research should try to separate the true effects of jobs from the effects of who is placed in jobs. This research would require instruments that shift employment opportunities but are uncorrelated with unobserved personal characteristics.

These results have some important implications for policymakers interested in getting more welfare mothers into jobs and making those jobs sustainable in the long term. The most important implication is that the characteristics of jobs matter. Policymakers should consider efforts to target higher-wage jobs, jobs in the hospitals or educational services industry, and jobs with less customer contact and less intense supervisory pressures. Programs should try to ensure that welfare recipients have the characteristics needed to succeed in whatever types of jobs are targeted.

Finally, whatever programs do in targeting jobs and preparing welfare recipients for those jobs, many welfare mothers will not succeed in retaining those jobs. We need more research on what policy can do to respond to job loss by welfare mothers and other disadvantaged clients of government programs. There are a few programs in existence that attempt to respond to job loss. Project Match, for example, has for many years focused on providing long-term assistance to welfare recipients. Clients are typically helped through many cycles of obtaining a job, losing a job, getting some training, obtaining the next job, etc. Furthermore, the federal government is currently conducting a social experiment (the Postemployment Services Demonstration) that examines the effectiveness of intensive case management in helping increase the job retention of welfare recipients. Whatever the outcome of this social experiment, job retention is such a huge problem that we must continue to consider more creative and effective policy solutions.

References

9to5 Working Women Education Fund. 1993. Welfare to Work: Obstacles to Job Retention: A Survey of Graduates of Federally-Funded Programs in Cleveland and Milwaukee. Cleveland, OH: 9to5 Working Women Education Fund.

Bane, Mary Jo, and D. T. Ellwood. 1994. Welfare Realities: From Rhetoric to Reform. Cambridge, MA: Harvard University Press.

Bartik, T. J., S. N. Houseman, and C. Z. Thies. 1993. "OJT Study: Preliminary Findings," Upjohn Institute for Employment Research presentation, February.

Berg, Linnea, Lynn Olson, and Aimee Conrad. 1992. "Causes and Implications of Rapid Job Loss among Participants in a Welfare-to-Work Program," Working Paper No. 92-1, Center for Urban Affairs and Policy Research, Northwestern University.

Blank, Rebecca M., and Patricia Ruggles. 1994. "Short-Term Recidivism among Public-Assistance Recipients," The American Economic Review 82(2): 49-53.

Greene, William H. 1993. Econometric Analysis, 2nd edition. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Haimson, Joshua, Alan Hershey, and Anu Rangarajan. 1995. "Providing Services to Promote Job Retention," Working Paper, Mathematica Policy Research, Inc., Princeton, NJ, December.

Kennedy, Peter. 1986. "Interpreting Dummy Variables," The Review of Economics and Statistics 68: 174-175.

Leete, Laura. 1996. "Beyond the Dead-End? Labor Market Outcomes among AFDC Recipients," paper prepared for the 1996 Annual Meeting of the Western Economic Association, June.

Maddala, G. S. 1983. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

Nightingale, Demetra Smith, Douglas A. Wissoker, Lynn C. Burbridge, D. Lee Bawden, and Neal Jeffries. 1991. Evaluation of the Massachusetts Employment and Training (ET) Program. Urban Institute Report 91-1. Washington, DC: The Urban Institute Press.

Pavetti, LaDonna A. 1993. The Dynamics of Welfare and Work: Exploring the Process by Which Women Work Their Way Off Welfare, Dissertation, Harvard University, Cambridge, MA.

Quint, Janet C., Judith S. Musick, and Joyce A. Ladner. 1994. Lives of Promise, Lives of Pain: Young Mothers after New Chance, New York: Manpower Demonstration Research Corporation, January.

Suits, Daniel. 1984. "Dummy Variables: Mechanics V. Interpretation," The Review of Economics and Statistics 66: 177-180.

U.S. House of Representatives. 1995. Committee on Economic and Educational Opportunities. Contract with America: Hearing on Welfare Reform, 18 January 1995 (Serial No. 104-10). Statement of Carlos Bonilla, Chief Economist, Employment Policies Institute. Washington: Government Printing Office, pp. 30-43.

Zornitsky, Jeffrey, and Mary Rubin. 1988. Establishing a Performance Management System for Targeted Welfare Programs, National Commission for Employment Policy Research Report No. 88-14, August.

APPENDIX

Appendix

The occupation and industry codes used by the CPS are slightly different for the 1992-95 period compared with the 1983-91 period. Some aggregation of categories over time was needed for the occupation and industry categories to be completely consistent. In addition, in a few cases the numbering system was changed between 1983-91 and 1992-95.

Changes for Census occupation codes:

1. For the 1992-95 data, the managerial codes 17, 21, and 22 were combined into one category (22) to be compatible with pre-92 data that combined these three occupations. Also, the three child care worker categories 466-468 were combined into one category (466) to be compatible with pre-92 data.

2. For the pre-1992 data: The managerial codes 16-19 were renumbered to conform to 1992-95 data. Telegraph operator (349) was merged into communication equipment operators n.e.c. (353) because telegraph operator was not a separate defined occupation in 1992-95. Occupation 369 was merged into 368, and 437 into 436, in both cases because these occupations were combined after 1992. 463-468 were renumbered to follow the 1992-95 numbering scheme. 633 was renumbered as 628 to match the 1992-95 data. 673 was merged into 674, 794 into 795, and 805 into 804, in all cases because these occupations were merged in the 1992-95 data. 863-867 were renumbered to match the 1992-95 numbering system. 873 was renumbered as 874 to match the 1992-95 numbering system.

Changes for Census industry codes:

1. For pre-1992 data, change the following industry codes:

20 to 12
21 to 20
30 to 31
31 to 32
460 to 450
461 to 451

462 to 452
510 to 532
630 to 623
631 to 630
632 to 631
661 to 662
730 or 732 to 891
740 to 732
742 to 741
801 to 802
802 to 810
892 to 893.

2. For 1992-95, change the following industry codes:

30 to 12
510 to 530
632 or 633 to 640
661 to 682
892 to 891
801 to 741
742 to 750
863 to 862
873 to 881.

These changes make the old and new industry codes as close to consistent as possible.

For information and reference, tables A-1 through A-4 present a complete list of the occupation and industry of the longest job last year for the 6720 individuals in this sample who were employed last year (later exclusions in the analysis for implausible wage rates reduced the number employed in the sample to 6338). These lists use the detailed occupation codes, major occupation group codes, detailed industry codes, and major industry group codes that are used from 1992-95.

Occupations or industries are listed in descending order of the number employed last year in this sample of 6720.

Table A-1
Distribution of Welfare Recipients' Jobs Last Year,
By Detailed Occupation Recodes

Occupation Recode	Detailed Occupation Recode Name	Number Employed Last Year in Occupation	Percent Employed	Cumulative Percentage
29	Food service	1,091	16.2	16.2
22	Other sales	894	13.3	29.5
26	Other administrative support occupations	700	10.4	40.0
31	Cleaning and building service	562	8.4	48.3
30	Health service	514	7.6	56.0
43	Machine operators and tenders, except precision	430	6.4	62.4
32	Personal services	407	6.1	68.4
24	Secretaries, stenographers, and typists	266	4.0	72.4
27	Private household services	245	3.6	76.0
44	Fabricators, assemblers, and hand-working occupations	151	2.2	78.3
42	Other precision production	103	1.5	79.8
46	Transportation	99	1.5	81.3
34	Farm occupations, except managerial	98	1.5	82.7
3	Salaried managers	93	1.4	84.1
45	Production inspectors, testers, samplers, and weighers	88	1.3	85.4
25	Financial records processing	86	1.3	86.7
50	Other handlers, equipment cleaners and helpers	84	1.3	88.0
16	Other professional specialty	80	1.2	89.2
15	Teachers, except postsecondary	78	1.2	90.3
49	Freight, stock, and material handlers	75	1.1	91.4
17	Health technologists and technicians	70	1.0	92.5
51	Laborers, except construction	63	0.9	93.4
35	Related agricultural	55	0.8	94.2
20	Sales supervisors and proprietors	48	0.7	94.9

Table A-1
(continued)

Occupation Recode	Detailed Occupation Recode Name	Number Employed Last Year in Occupation	Percent Employed	Cumulative Percentage
21	Sales representatives, commodities and finance	47	0.7	95.6
28	Protective service	47	0.7	96.3
5	Management related	33	0.5	96.8
14	Librarians, counselors, and college teachers	33	0.5	97.3
13	Health assessment and treating	32	0.5	97.8
23	Computer equipment operators	25	0.4	98.2
38	Construction trades and extractive	16	0.2	98.4
37	Mechanics and repairers	13	0.2	98.6
48	Construction laborers	13	0.2	98.8
6	Accountants and auditors	12	0.2	99.0
19	Technicians, except health, engineering and science	11	0.2	99.1
18	Engineering and science technicians	9	0.1	99.3
4	Self-employed managers	7	0.1	99.4
41	Precision metal working	7	0.1	99.5
33	Farm operators and managers	6	0.1	99.6
40	Supervisors of precision production	6	0.1	99.7
1	Public administration	4	0.1	99.7
39	Carpenters	4	0.1	99.8
9	Natural scientists and mathematicians	3	0.0	99.8
47	Material moving equipment operators	3	0.0	99.8
52	Armed forces	3	0.0	99.9
10	Computer systems analysts and scientists	2	0.0	99.9
36	Forestry and fishing	2	0.0	100.0
7	Architects and surveyors	1	0.0	100.0
12	Physicians and dentists	1	0.0	100.0

Notes: Numerical codes and names come from Appendix B to March 1995 Current Population Survey, "Detailed Occupation Recodes for Longest Job Last Year." Total employed in sample last year is 6720.

Table A-2
Distribution of Welfare Recipients’ Jobs Last Year,

by Major Occupation Group Recodes

Occupation Recode	Major Occupation Recode Name	Number Employed Last Year in Occupation	Percent Employed	Cumulative Percentage
8	Service occupations, except household and protective	2574	38.3	38.3
5	Administrative support, including clerical	1077	16.0	54.3
4	Sales	989	14.7	69.0
11	Machine operators, assemblers, and inspectors	669	10.0	79.0
6	Private household service	245	3.6	82.6
13	Handlers, equipment cleaners, helpers, and laborers	235	3.5	86.1
2	Professional specialty	230	3.4	89.6
9	Farming, forestry, and fishing	161	2.4	92.0
1	Executive, administrative, and managerial	149	2.2	94.2
10	Precision production, craft, and repair	149	2.2	96.4
12	Transportation and material moving	102	1.5	97.9
3	Technicians and related support	90	1.3	99.3
7	Protective service	47	0.7	100.0
14	Armed forces	3	0.0	100.0

Notes: Occupation numerical cod es and names come from Appendix B to March 1995 Current Population Survey, "Major Occupation Group Recodes for Longest Job Last Year." Total employed in sample is 6720.

Table A-3
Distribution of Welfare Recipients' Jobs Last Year,
by Detailed Industry Recodes

Industry Recode	Detailed Industry Recode Name	Number Employed Last Year in Industry	Percent Employed	Cumulative Percentage
32	Retail trade	2025	30.1	30.1
41	Health services, except hospitals	560	8.3	38.5
38	Personal service, except private household	498	7.4	45.9
36	Business services	488	7.3	53.1
42	Educational services	380	5.7	58.8
43	Social services	379	5.6	64.4
35	Private household service	280	4.2	68.6
46	Public administration	198	2.9	71.5
40	Hospitals	189	2.8	74.4
18	Food and kindred products	155	2.3	76.7
21	Apparel and other finished textile products	141	2.1	78.8
28	Transportation	136	2.0	80.8
1	Agriculture	135	2.0	82.8
31	Wholesale trade	125	1.9	84.7
34	Insurance and real estate	118	1.8	86.4
44	Other professional services	115	1.7	88.1
39	Entertainment and recreation services	113	1.7	89.8
33	Banking and other finance	67	1.0	90.8
23	Printing, publishing, and allied industries	65	1.0	91.8
3	Construction	55	0.8	92.6
11	Electrical machinery, equipment, supplies	55	0.8	93.4
20	Textile mill products	43	0.6	94.0
26	Rubber and miscellaneous plastics products	39	0.6	94.6
8	Fabricated metals	37	0.6	95.2
12	Motor vehicles and equipment	33	0.5	95.7
10	Machinery, except electrical	29	0.4	96.1
27	Leather and leather products	27	0.4	96.5
37	Repair services	25	0.4	96.9

Table A-3
(continued)

Industry Recode	Detailed Industry Recode Name	Number Employed Last Year in Industry	Percent Employed	Cumulative Percentage
5	Furniture and fixtures	24	0.4	97.2
15	Professional and photo equipment, watches	24	0.4	97.6
29	Communication	22	0.3	97.9
24	Chemicals and allied products	21	0.3	98.2
22	Paper and allied products	20	0.3	98.5
17	Miscellaneous and not specified durable goods	18	0.3	98.8
16	Toys, amusements, and sporting goods	16	0.2	99.0
4	Lumber and wood products, except furniture	14	0.2	99.2
6	Stone, clay, glass, concrete products	10	0.1	99.4
7	Primary metals	9	0.1	99.5
30	Utilities and sanitary services	9	0.1	99.7
45	Forestry and fisheries	6	0.1	99.7
2	Mining	5	0.1	99.8
14	Other transportation equipment (not motor vehicles or aircraft)	5	0.1	99.9
19	Tobacco manufacturers	4	0.1	100.0
13	Aircraft and parts	3	0.0	100.0

Notes: The numerical industry codes and names for this table are f rom Appendix A to the March Current Population Survey, "Detailed Industry Recodes for Long est Job Last Year." The total employed last year in the sample is 6720.

Table A-4
Distribution of Welfare Recipients' Jobs Last Year,
by Major Industry Group Recodes

Industry Recode	Major Industry Recode Name	Number Employed Last Year in Industry	Percent Employed	Cumulative Percentage
8	Retail trade	2025	30.1	30.1
13	Professional and related services	1623	24.2	54.3
11	Personal services including private households	778	11.6	65.9
5	Nondurable goods	515	7.7	73.5
10	Business and repair services	513	7.6	81.2
4	Durable goods	277	4.1	85.3
14	Public administration	198	2.9	88.2
9	Finance, insurance, and real estate	185	2.8	91.0
6	Transportation, communication, and other public utilities	167	2.5	93.5
1	Agriculture, forestry, and fisheries	141	2.1	95.6
7	Wholesale trade	125	1.9	97.4
12	Entertainment and recreation services	113	1.7	99.1
3	Construction	55	0.8	99.9
2	Mining	5	0.1	100.0

Notes: The numerical industry codes and names used here are from Appendix A to the March 1995 Current Population Survey, "Major Ind ustry Group Recodes for Longest Job Last Year." The total employed in the sample last year is 6720.