Centre d'Etudes de Populations, de Pauvreté et de Politiques Socio-Economiques
International Networks for Studies in Technology, Environment, Alternatives and Development

IRISS Working Papers

IRISS-C/I

An Integrated Research Infrastructure in the Socio-economic Sciences

Determinants of Labor Market Outcomes of Disabled Men Before and After the Americans with Disabilities Act of 1990

by

Chung Choe

IRISS Working Paper Series 2009-07 July 2009

Determinants of Labor Market Outcomes of Disabled Men Before and After the Americans with Disabilities Act of 1990

Chung Choe
CEPS/INSTEAD

Abstract The study compares the labor market experience of men with disabilities before and after the Americans with Disabilities Act of 1990. The handful of studies that have focused on the wage impact of disabilities have either not fully incorporated the probability of employment into the analysis or have not correctly decomposed the wage differences in light of selectivity corrections. After estimating a two-stage model of the probability of employment followed by a wage equation for men with and without disabilities, I use Newman and Oaxaca?s (2004) method to correctly decompose the distributions. In addition, I also perform a similar analysis to explain the differentials in employment rates between the non-disabled and disabled. The analyses are performed for samples before and after the passage of the Americans with Disabilities Act of 1990. The results from studies of the Survey of Income Program Participation (SIPP) of 1984, 1990, 1996 and 2001 indicate that the employment and wage gaps between the disabled and the non-disabled have risen sharply over time, both before and after the passage of the ADA. Most of the rise prior to the ADA was attributable to arise in differences that cannot be explained with measurable factors. Nearly all of the rise in the gaps in the 1990s, however, is attributable to factors that can be measured. The unexplained differential has held relatively constant during that period.

Reference IRISS Working Paper 2009-07, CEPS/INSTEAD, Differdange, Luxembourg

URL http://ideas.repec.org/p/irs/iriswp/2009-07.html

(CEPS/INSTEAD internal doc. #07-09-0476-E)

DETERMINANTS OF LABOR MARKET OUTCOMES OF DISABLED MEN BEFORE AND AFTER THE AMERICANS WITH DISABILITIES ACT OF 1990[1]

Chung Choe
Research Economist
CEPS/INSTEAD, B.P. 48, Differdange
L-4501, Luxembourg
Phone: (352) 585 855 582
Fax : (352) 585 560
Email: chung.choe@ceps.lu

First Draft: April 2005
This Draft: June 2008

ABSTRACT

The study compares the labor market experience of men with disabilities before and after the Americans with Disabilities Act of 1990. The handful of studies that have focused on the wage impact of disabilities have either not fully incorporated the probability of employment into the analysis or have not correctly decomposed the wage differences in light of selectivity corrections. After estimating a two-stage model of the probability of employment followed by a wage equation for men with and without disabilities, I use Newman and Oaxaca's (2004) method to correctly decompose the distributions. In addition, I also perform a similar analysis to explain the differentials in employment rates between the non-disabled and disabled. The analyses are performed for samples before and after the passage of the Americans with Disabilities Act of 1990. The results from studies of the Survey of Income Program Participation (SIPP) of 1984, 1990, 1996 and 2001 indicate that the employment and wage gaps between the disabled and the non-disabled have risen sharply over time, both before and after the passage of the ADA. Most of the rise prior to the ADA was attributable to arise in differences that cannot be explained with measurable factors. Nearly all of the rise in the gaps in the 1990s, however, is attributable to factors that can be measured. The unexplained differential has held relatively constant during that period.

Keywords: Labor Market Discrimination, Disabilities, and the Americans with Disabilities Act

JEL Classification: I1, J15, J71

---

[1] I am grateful to Manuela Angelucci, Marjorie Baldwin, Price Fishback, Alfonso Flores-Lagunes, Keisuke Hirano, Ronald Oaxaca, Paul Rhode and seminar participants at The University of Arizona for their helpful comments. I would also like to thank David Brightwell for his editorial assistance. All errors are mine.

1. Introduction

On July 26, 1990, the Americans with Disabilities Act (ADA) was legislated to protect the civil rights of persons with disabilities. The ADA was expected to increase the employment and wages of people with disabilities. Although the anti-discriminatory law was enacted to ensure equality of opportunity for persons with disabilities, promote their economic self-sufficiency, and encourage independent living, researchers find that the ADA had little impact on the labor market experience of individuals with disabilities, or a slight negative effect on their employment opportunities. The raw data from Survey of Income and Program Participation (SIPP hereafter) shown in figures 1 and 2 also indicate that since the introduction of the ADA relative socioeconomic status of the disabled has worsened in terms of earnings and employment participation. In particular, the difference in employment participation between non-disabled and disabled has significantly increased after the ADA (Figure 1). Moreover, although the decline of relative wages between 1984 and 2001 is not as significant as the relative employment, it is evident that workers with disabilities face a larger hourly wage gap after the ADA than before (Figure 2). These data do not control for the difference in average individual characteristics between the non-disabled and the disabled. The emphasis in this paper is to examine how much of the declines can be explained by measurable factors and how much by unexplained differentials.

Several empirical studies (DeLeire 2000, 2001; Acemoglu and Angrist 2001; Beegle and Stock 2003) investigate how the ADA affects the labor market experience of the disabled. In terms of the employment rate, DeLeire (2000) and Acemoglu and Angrist (2001) find that the ADA contributes to an increase in the unemployment rate of the disabled. In contrast, Beegle and Stock (2003) consider various state-level antidiscrimination laws prior to the ADA and present new evidence on the effects of disability discrimination laws. They find that disability discrimination laws are associated with lower relative earnings of the disabled, with slightly lower labor force participation rates among the disabled, but the laws are not associated with lower relative employment rates for the disabled once they control for pre-existing employment trends among the disabled. There is some research on wage differentials between individuals with disabilities and ones without disabilities in the U.S. labor market. Schumacher and Baldwin (2000) find an increase in wage differential between people with and without disabilities between 1990 and 1993. On the other hand, Moon and Shin (2006) show that estimated effects of the ADA on dollar-valued well-being measures (i.e., wages and total personal income) of men with disabilities are sensitive to the measurement of disability in use. The ADA effects on dollar-valued well-being measures of disabled men are found to be larger and more statistically significant for objective measures than for a self-reported measure of disability.

A fundamental assumption underlying the ADA is that disabled individuals retain low economic status in part due to discrimination in the labor market and lack of access to employment opportunities. While many researchers (Johnson and Lambrinos 1985, Baldwin and Johnson 1994, 2000) examine the labor market experience of persons with disabilities with emphasis on the discrimination perspective, few studies attempt to evaluate the impact of the ADA from the discrimination perspective. DeLeire (2001) finds that the discriminatory component of the wage gap did not fall after the introduction of the ADA, but the study has not paid attention to the impact of the ADA on employment participation of the disabled.

There are several contributions of this study. First, I contribute to the literature on the impact of the ADA with direct analyses on the changes in unexplained differentials (discrimination and the residual effects) for the disabled in terms of both employment rates and wage differentials. Second, I apply a newly suggested decomposition methodology by Neuman and Oaxaca (2004) that can be applied to decompose the actual wage differentials when the Heckman sample selection model is utilized. Third, this study includes a broader time period before and after the ADA. I use information from the SIPP 1984, 1990, 1996, and 2001, allowing comparisons to cover a longer time span before and after the passage of the ADA.[2] Finally, disability may be a socially acceptable and convenient rationalization of absence from the labor market. Accordingly the literature has been concerned about 'justification bias' or the endogeneity of self-assessed health measures. I utilize relatively more objective measures of disability in this study.

The results shown here are different from the results of previous studies on the impact of the ADA on the labor market performance of the disabled. Consistent with previous work, I also find that there was no improvement in both employment opportunities and the wage for the disabled even after the introduction of the anti-discriminatory law. However, in the decomposition analyses where I control for a number of characteristics of the non-disabled and disabled, I find interesting results not found by the previous studies. Although the unexplained differentials for employment rates between the non-disabled and disabled had increased, there are no significant changes in the relative portion of the unexplained components over time. Furthermore, although I do not find an apparent decline in the unexplained portion of the wage gap, the relative portion of the unexplained components has significantly narrowed in the post-ADA. If the negative productivity effects of poor health on labor market performance have not changed over time, the ADA was successful to the extent in reducing wage discrimination against people with disabilities in the U.S. labor market.

2. Econometric Framework

This study focuses on explaining how observed and unobserved factors affect the differentials in employment opportunities and earnings between the non-disabled and the disabled. Using the Heckman sample selection model, I estimate both labor supply and wage equations for the two

[2] Previous studies allowed insufficient time periods in the evaluation of the ADA. For example, DeLeire (2001) utilized SIPP 1984 and 1993 to evaluate the impact of the ADA on the changes in wage discrimination against people with disabilities.

groups with data from the Survey of Income and Program Participation (1984, 1990, 1996, and 2001). Since there is a selection correction term in the Hackit model, it is inappropriate to use the decomposition methods that have been commonly applied to estimate the extent of discrimination.[3] In this paper, a newly suggested decomposition method (Neuman and Oaxaca, 2004), which is applicable to the wage decomposition of selectivity-corrected wage equations, is applied to divide the total wage gap into the explained and unexplained components[4]. Along with the estimation of unexplained components of wage differentials for the disability, I investigate changes in the impact of unexplained components on differences in employment opportunities before and after the ADA.

2.1 Estimating Employment Participation and Wage

The wages earned by employed workers (the observed wages) are biased measures of the wages receiving by all labor force participants because some of the influences on wages also determine whether or not individuals participate in the labor force. The bias may be substantial in the estimation of earnings functions for persons with disabilities because many disabled persons are not employed. Heckman's sample selection model can correct for this bias in the earning functions. I, therefore, use the model to estimate the wage and employment status coefficients of both non-disabled and disabled.

Let us first consider probit equations which are the first step in the Heckit model. I follow the traditional labor force participation model in assuming that an individual decides upon whether or not to enter the labor market on the basis of a comparison between the employer's

[3] However, while most of the previous studies applied a traditional decomposition method to decompose the selection corrected wage differentials into the explained and unexplained differentials (discrimination and residual components), I decompose the actual wage differential by applying a new decomposition technique.
[4] In the discrimination articles, people normally call the unexplained part 'discrimination', which is not explained by the difference of characteristic variables between groups.

wage offer and his or her reservation wage. There is a large differential in the employment participation rates between the non-disabled and the disabled. The low employment participation of the disabled could be due to in part to high reservation wages associated with certain types of disability as a consequence of disability income transfers and the extra demands on time and energy required to participate in the labor force. Low employment rates might also be due to low market wage rates offered to the disabled as a consequence of lower levels of productivity and/or employer discrimination (Kruse and Schur, 2003). To examine the relationship between offer and reservation wage, we begin with the specification of the human capital-based wage offer equations, which may be written as:

(1) $$W_{ij}^{O} = \beta_j X_{ij} + v_{ij} \quad (j = nd,\ d)$$

where W_{ij}^{O} denotes the logarithm of the offer wage, X_{ij} is a vector of determinants of wages for individual i of type j, β_j is the associated parameters vector, and v_{ij} is an error term following a normal distribution. nd and d stand for non-disabled and disabled respectively. The reservation wage is determined as follows:

(2) $$W_{ij}^{R} = \alpha_j Z_{ij} + \varepsilon_{ij} \quad (j = nd,\ d)$$

where the vector Z incorporates human capital variables as well as factors influencing the value of time (for example, presence of children, level of exogenous income, and difficulties of moving about with a disability.). We do not directly observe the reservation wage, which is a latent variable, but we do observe the indicator variable I, where $I = 1$ if $W_{ij}^{O} \rangle W_{ij}^{R}$ and 0 otherwise. Thus, the probability that an individual i works is:

(3) $$\mathrm{Prob}\left(W_{ij}^{O} \rangle W_{ij}^{R}\right) = \mathrm{Prob}\left(\beta_j X_{ij} - \alpha_j Z_{ij} \rangle \varepsilon_{ij} - v_{ij}\right)$$

Assuming that v_{ij} and ε_{ij} are normally distributed, the composite error $\left(\varepsilon_{ij} - v_{ij}\right)$ is also normally distributed with variance σ_j^2. Thus, the probability individual i works may be written as:

$$(4) \qquad \mathrm{Prob}\left(W_{ij}^{O} \rangle W_{ij}^{R}\right) = \mathrm{Prob}\left(u_{ij} \langle \frac{\beta_j X_{ij} - \alpha_j Z_{ij}}{\sigma_{uj}}\right) = \Phi\left(\gamma_j H_{ij}\right)$$

where Φ is the cumulative normal density function, u_{ij} is distributed following a standard normal distribution, γ_j is the combined vector of parameter β_j and α_j, and H_{ij} is the associated combined vector of X_{ij} and Z_{ij}. The labor force participation (employment) equation is estimated by a probit specification.

There are two distinct purposes in the estimation of the probit model. First, it estimates the bias correction term / selectivity variable that corrects for sample selection bias. Second, using the method suggested by Even and McPherson (1990), it enables the difference between average employment rates for the two groups to be decomposed into those attributable to differences in human capital related characteristics and those related to unexplained components.

Most explanatory variables in probit equations are included in the wage equations as well. However, in order to estimate an economically valid correction term, we need exclusion restrictions. I use non-labor income and various family structures in the employment decision equation and exclude them from the wage equation. This assumes that those variables play a role in determining whether individuals participate in the labor force or not, but do not directly affect the wages of workers. For example, it seems reasonable to assume that the presence of children and positive spouse's earnings are far more likely to influence whether a person enters the labor force than it is to influence the offered wage after they have entered.[5]

The Heckman two-stage procedure is adopted. The probit estimates on the employment decision are used to create the selectivity variable (inverse Mills ratio), λ, which is then included as an additional regressor in the wage equation which is estimated by OLS. Consequently, the sample selection corrected wage equation may be written as follows:

[5] Kidd et al. (2000) and Baldwin and Johnson (2000) used exogenous income and nonwage income and three marital status dummies for exclusion restrictions, respectively. According to Pencavel (1986), a married man with his spouse present is much more likely to be in the labor force than a man with a different marital status. Greater nonwage income is associated with lower participation.

(5) $$E\left(W_{ij}^{O} \middle| I \rangle 0\right) = \beta_j X_{ij} + \theta_j \lambda_{ij}$$

where $\theta_j = \rho_j \sigma_{u_j}$, $\lambda_{ij} = \phi(\gamma_j H_{ij}) / \Phi(\gamma_j H_{ij})$, and $\phi(\bullet)$ is the standard normal density function. These parameters are estimated for both the non-disabled and the disabled group. The sample selection variable corrects the bias that is caused by the absence of information on offered wages to non-workers. For this lambda, the previous studies (Baldwin 1992, 1994, 2000, Kidd et al. 2000, and Jones et al. 2006) on the labor market discrimination against individuals with disabilities have not applied an appropriate decomposition technique. However, Neuman and Oaxaca (2004) suggest a decomposition method which can be applicable under some conditions when the bias correction term is included in the wage equation.[6] The details are discussed in Section 2.3.

2.2 Estimating the Unexplained Causes of Employment Differentials

The results in the first step are used to measure the extent to which unobserved factors influence the difference in employment rates for disabled and non-disabled workers. However, the common decomposition methods to be used in estimating wage discrimination cannot be implemented for the probit model because of the non-linearity. Even and McPherson (1990) suggest a method that enables the difference between the average participation rate for the two groups to be decomposed into that attributable to differences in human capital related characteristics and the unexplained component. The unexplained residual combines the extent to which the disabled face discrimination and also the extent to which there are unmeasured aspects of productivity.

[6] Neuman and Oaxaca (2004) suggest three different decompositions under several relatively strong assumptions. Although none of those present authoritatively identifies the "correct" decomposition, it might be better to apply one of the methods to estimate discrimination, considering our different situations.

The details of the two equation probit method are as follows. Define non-disabled (disabled) characteristics as $H_{nd}\left(H_d\right)$, the probit estimates as $\hat{\lambda}_{nd}\left(\hat{\lambda}_d\right)$ and sample size as $n_{nd}\left(n_d\right)$. The unexplained differential between the employment rates of the disabled and non-disabled (UNEXP),

$$\text{(6)} \qquad UNEXP = \left(1/n_d\right)\sum_{i=1}^{n_d}\Phi\left(H_{id}\,\hat{\gamma}_{nd}\right) - \left(1/n_d\right)\sum_{i=1}^{n_d}\Phi\left(H_{id}\,\hat{\gamma}_d\right).$$

The corresponding measure of the gap explained by the difference between non-disabled and disabled measured characteristics (EXP) is:

$$\text{(7)} \qquad EXP = \left(1/n_{nd}\right)\sum_{i=1}^{n_{nd}}\Phi\left(H_{ind}\,\hat{\gamma}_{nd}\right) - \left(1/n_d\right)\sum_{i=1}^{n_d}\Phi\left(H_{id}\,\hat{\gamma}_{nd}\right).$$

Even and McPherson's suggestion is an application of Oaxaca (1973)'s wage decomposition for a continuous variable applied to probit model. The advantage of this method is that it allows us to control for non-disabled/disabled differences in education, experience, health conditions, family structures, level of unearned income, and all measured factors likely to be correlated with the tendency to participate in employment. However, given the possibility of omitted variables, in particular the extent and severity of the disability and its impact on labor productivity in the current setting, the usual caveat applies in interpreting the residual component. The unexplained component is likely to reflect the role of uncaptured differences in tastes and productivity in addition to the possibility of employment discrimination. Furthermore, we need an additional assumption that measured characteristics are determined exogenously without being affected by the disabilities. For instance, if poor health conditions discourage the disabled from attaining higher education, we will confront identification problems in our decomposition of employment differentials into the explained and unexplained components.

2.3 Estimating Unexplained Components in Wage Differentials

To measure the extent of wage discrimination against people with disabilities, we need to choose among various decomposition techniques. Beginning with the simple decomposition technique developed by Oaxaca (1973), there are several versions of decomposition methods (Cotton, 1988; Neumark, 1988; Oaxaca and Ransom, 1994). There has always been a divergence from the initial decomposition method, since there has been disagreement about what constitutes the nondiscriminatory wage structure. Among several alternatives, we would choose a decomposition method suggested by Neuman and Oaxaca (2004). Their method divides the total wage differential into the explained and unexplained portion when the Heckit model is used for wage equations. In that methodology, we assume that the nondiscriminatory wage structure is the observed wage structure for non-disabled men. This choice is reasonable because men with disabilities are a small fraction of the employed labor force.

Neuman and Oaxaca (2004) suggest the following decomposition method under some assumptions:[7]

(8)

$$W_{nd} - W_d = \underbrace{\overline{X}_d\left(\hat{\beta}_{nd} - \hat{\beta}_d\right) + \hat{\theta}_{nd}\,\hat{\lambda}_d^{0} - \hat{\theta}_d\,\hat{\lambda}_d}_{\text{UNEXP}} + \underbrace{+\left(\overline{X}_{nd} - \overline{X}_d\right)\hat{\beta}_{nd} + \hat{\theta}_{nd}\left(\hat{\lambda}_{nd} - \hat{\lambda}_d^{0}\right)}_{\text{EXP}}$$

where $\hat{\lambda}_d^{0} = \sum_{i=1}^{N_d} \hat{\lambda}_{id}^{0} \Big/ N_d$, and $\hat{\lambda}_{id}^{0} = \phi\left(H_{id}^{'}\,\hat{\gamma}_{nd}\right) \Big/ \Phi\left(H_{id}^{'}\,\hat{\gamma}_{nd}\right)$.[8] Equation (8) states that the gross wage differential is the sum of the wage difference in offer wages that is attributable to the

[7] In Neuman and Oaxaca (2004), several methods to deal with the selection bias correction term are suggested. Among a few alternatives, we would choose the most encompassing way to view discrimination. This suggestion is to regard both difference in γ parameters from the probit selection equation for employment and differences in the wage effects of selectivity (θ) as manifestations of discrimination. Differences in the values of the employment determining variables ($H^{'}$) between the disabled and the non-disabled would be treated as nondiscriminatory endowment effects. The first assumption has been claimed by several previous researchers (see Baldwin and Johnson, 1992, 1994, and 2000 for the details), and the second one is also normally assumed in the discrimination literature. In regards to the last assumption, I assume that labor market discrimination does not affect the employment determining variables.

part of the unexplained differentials (discrimination and residual effects) and the wage differential due to the difference in productivity. The terms $\left[\hat{\theta}_{nd}\,\hat{\lambda}_d^0 - \hat{\theta}_d\,\hat{\lambda}_d\right]$ and $\left[\hat{\theta}_{nd}\left(\hat{\lambda}_{nd} - \hat{\lambda}_d^0\right)\right]$ in the first and second brackets respectively are the key parts that allow us to do the correct decomposition when the lambda, selectivity correction term, is included in the wage equations.[9]

3. Definition of Disability and Data

There is no single commonly accepted, straightforward definition of disability. Different researchers define disability in various ways because it is a fairly subjective issue. However, it is an important step to define disability at the beginning of each of the disability studies since the disabled population rates are not only quite different depending on the definition, but also the definition may influence the results of studies and how they are interpreted.

There are two main ways to determine the existence of a disability from survey data. First, a disability can be self-assessed. In data sources like the National Health Interview Survey (NHIS), Current Population Survey (CPS), and the Survey of Income and Program Participation (SIPP), an individual assesses his/her own condition, and whether the condition affects the capacity to undertake work, without any reference to outside standards. For example, the 2001 SIPP includes questions such as "*Do you have a physical, mental, or health condition that limits the kind and amount of work you can do?*" Although this type of question has the advantage of asking for direct information on work ability and is extensively used in labor market analysis

---

[8] In order to check how equation (8) has been derived and alternative decomposition methods, see Neuman and Oaxaca (2004).

[9] When the selectivity correction term is not dealt appropriately, the estimation of wage decomposition would be biased. Since this new method has been suggested recently, most of previous studies (Baldwin and Johnson, 1992, 1994 and 2000; Kidd et al., 2000; Jones et al., 2006) decomposed the sample selection bias adjusted wage differentials in lieu of the actual wage differentials. In case of DeLeire (2001), he applied Tobit model to estimate the wage equations so that he could avoid encountering having the inverse Mills ratio. However, it is well known that Tobit model results in biased estimates.

(Kidd et al., 2000, Acemoglu and Angrist, 2001, and DeLeire, 2000), it is subjective and there may be social and economic incentives to misreport disability status (Bound, 1991 and Currie, 1999). Second, empirical studies use self-reported information on specific heath conditions or more objective measures of health. Although such observations are less likely to suffer from the bias of disability reporting, the information on disability tends not to be as closely related to limitations on work and thus suffers from measurement errors (Bound, 1991).[10] Among the various measures as described in Jones (2005), I use self-reported functional limitations to define the disabled group in this study.

The SIPP increased the number of questionnaire terms relevant to health conditions as the survey continued from 1984 through 2001. In this paper, I evaluate labor market performance of individuals with disabilities before and after the ADA. To be consistent with the definition of disability across time, I need to rely on common questions. The 1984 SIPP, which includes the least number of functional limitation questions, is used as the lowest common denominator. Table 1 displays the list of questions that are used to define disabilities in this study. I define an individual to have a disability if the respondent answers 'yes' to at least one of the questions regarding sensory disability, physical disability, or activity limitation.

The four different cross sectional data from the Survey of Income and Program Participation 1984, 1990, 1996, and 2001 are used in this study to estimate the impact of the ADA on the labor market experience of individuals with disabilities. The core questionnaire provides detailed information on the respondents' income sources, demographic characteristics, and participation in various cash and non-cash benefit programs for each individual in every month. The topical module that supplements each core file collects different information in each wave so that I merge the topical module that includes information on functional limitations with core files. The notable difference between SIPP and other survey data is that it includes both detailed

[10] I admit that although the functional limitations are highly correlated with self-reported work limitations, we cannot guarantee that those with functional limitations report the work limitations, vice versa.

information on health-related characteristics and socioeconomic status. Considering the timing of the passage of the ADA and the timing of the collection of the SIPP surveys, we can definitely use SIPP 1984 to reflect the labor market prior to the ADA, and both SIPP 1996 and SIPP 2001 to evaluate the labor market in the post-ADA period. However, we need to be careful how we interpret the results from SIPP 1990. The Americans with Disabilities Act (ADA) was legislated in 1990 to protect the civil rights of persons with disabilities. After enactment in 1990, the ADA covered employers with 25 or more employees starting in 1992, and employers with 15 or more employees starting in 1994. The issue is whether the markets might have changed in anticipation of the adoption of the ADA during 1990 before the law is legally effective.[11] Since this is difficult to determine, it is preferable to say that SIPP 1990 reflects a market that is in the process of adapting to the new law.

I restrict the sample to the men between the ages of 18 and 62 who are not enrolled in school to avoid gender discrimination effects and the restrictions focus only on individuals who are at working age. As the SIPP contains different sample units across years, the total number of observations varies. I define employment participation if the individual is an employee with a positive wage for the reference month (Figure 1 and Table 2). The hourly pay variable for Equation (5) is based on usual weekly pay divided by usual hours (Figure 2 and Table 3). After creating the hourly wage rates, I drop workers whose hourly earnings are either less than 2 or more than 200 dollars among those employed for the reference month.

The detailed definitions of explanatory variables used in this study are presented in Appendix 1. I apply the usual Mincer measure to infer labor market experience (maximum potential experience) as age – years of education – 5. Particularly, for those without a high school degree, I assume that they enter the labor force at age 17. I also incorporate dummies indicating the different level of educations. In addition, dummies are included for health status in both

[11] Ransom and Oaxaca (2005) provide an example for the possibility that people can change their behavior even before the enactment of the ADA.

employment participation and wage equations. Occupation and industry variables are included in the wage equations.

As explained in the previous section, we need exclusion restrictions to correct for the selection bias in wage equations. Unearned income and various family structure variables are included in the employment equation but excluded from the wage equation. These are expected to influence the reservation wages, but not the offered wages. Finally, while dummy variables for union membership and part-time work status are included in wage equations, they cannot be included in the employment equations because such information is unavailable for those who are not employed.

4. Estimation Results

Tables 2 and 3 provide summary statistics of all the major variables used in the empirical analysis for employment participation and wage equations. As shown in Figure 3, according to the definition of disability in this paper, the percentage recorded as disabled has fallen by two or three percentage points from a starting value of around 12 percent in 1984 to slightly less than 10 percent in 2001.[12] Employment participation rates rose from 76.6 percent for the non-disabled men in 1984 to 85.2 percent in 1996 before declining by 3 percentage points by 2001 (Table 2). For people with disabilities, employment rates have consistently decreased from 56 percent to 41percent so that the differences in employment rates between the non-disabled and disabled have increased from 21 percentage points to 41 percentage points over the study period (Figure

[12] In contrast with the U.S. results, Jones et al. (2006) found that the percentage of disabled in the UK has increased by six or seven percentage points over the period 1997-2004. However, we should be careful to compare results across different studies because as previously mentioned each study applies a different criterion to define disability. They defined disabled as individuals who have a self-reported long-term illness (12 months or more).

1).[13] This is an indication of a possible negative effect from the ADA that is also noted in other studies (DeLeire, 2000 and Acemoglu and Angrist, 2001).

In 1984 the hourly earnings of those with disabilities was 93.9 percent of the wage for the non-disabled. The relative hourly pay of the disabled decreased to 93 percent in 1990, 86.9 percent in 1996, before rising to 90.4 percent in 2001 (Figure 2). On the basis of these raw means, the evidence seems to suggest that the relative position of the disabled has moved in a negative direction in terms of both wages and employment opportunities since the introduction of the ADA.

However, the raw data do not control for individual characteristics. It is necessary to implement more sophisticated analyses to estimate the real impact of the ADA, controlling for the difference in individual characteristics between the non-disabled and the disabled.

It is also worth noting several important differences in the means of other explanatory variables. The non-disabled on average have higher educational attainments than the disabled. However, the non-disabled have shorter labor market experience, because disability tends to be associated potentially with age.[14] In Table 3, we compare the difference between non-disabled and disabled in terms of the distributions of occupation and industry. The disabled are under-represented relative to the non-disabled in the high paying managerial and professional occupations and over-represented in manual occupations, which is one explanation for their lower wage levels. However, we do not find notable differences in the employment shares in each of industry between the groups.[15] Moreover, the disabled are more likely to be employed part-time than the non-disabled. Both groups show increases in the proportion of part-time workers after

---

[13] It should be noted that these results depend on the definition of disability and definition of employment status in this study.

[14] The measurement error issue relevant with using potential experience as a proxy for labor market experience is probably larger for the disabled group because they are more likely to have had absences from the labor market for their poor health conditions. See Regan and Oaxaca (forthcoming) for more discussion regarding the measurement error issue in potential experience and its implication for wage decomposition.

[15] More sophisticated analysis will be carried out in the Section 4.3 regarding the comparison of the occupation distributions for the two groups.

the enactment of the ADA. In line with expectations, a higher proportion of disabled workers self-report their health status as fair or poor rather than better health conditions. Finally, while there is no significant change in the amount of nonwage income among the non-disabled across different time periods, the unearned income for the disabled has increased from $300 in 1984 to $693 per month in 2001.[16] I conjecture that more recipients of disability program benefits after the ADA could be a possible reason for this appearance.

Equation (4) and (5) are estimated for non-disabled and disabled group for four cross sectional data sets, before and after the ADA, to evaluate the impact of the Act on the U.S. labor market. Table 4 presents estimation results for employment participation, which are selection equations in the Heckman model. The regression results of wage equations for each of the groups are displayed in Table 5. The explanatory variables such as educational attainments, experience, and health conditions are anticipated to influence both offer wages and reservation wage. Using the estimation results from the Heckman sample selection model, we do decomposition analysis as presented in equations (6) and (7) for employment differentials and in equation (8) for wage differentials between the non-disabled and the disabled (Tables 6 and 7).

4.1. Employment Participation Equations

The employment participation probit estimates are provided in Table 4. In all cases, Likelihood Ratio tests unambiguously reject the null hypothesis that the coefficients in each regression are jointly insignificant. Turning to the coefficient estimates, most findings are in accordance with expectations. For both the non-disabled and the disabled, higher education attainment increases

[16] Although unearned income has not been adjusted for the inflation rate, we can find that it increased relatively faster among disabled than non-disabled. In addition, it also increased much faster than the increase of hourly pay for the same period. As presented in estimation results in Table 5, the nonwage variable is the most critical factor in explaining the employment participation decision regardless of disability status. In that sense, higher unearned income was supposed to increase the reservation wage and this would affect the increase of the unemployment of the disabled.

the probability of being employed. However, the marginal effect of each education variable is stronger for the disabled, indicating the particular importance of obtaining higher education among the disabled. There are also strong experience effects, with positive and negative signs on the linear and quadratic terms, respectively observed in all cases. Whites are more likely to be employed, while unmarried males are less likely to be employed than those with dependents without spousal earnings (the omitted group). As shown in the results, unearned income has pronounced negative effects on labor force participation. In theory non-wage income increases reservation wages, regardless of health status. People who report better health are more likely to be employed as expected.[17]

4.2. Sample Selection Corrected Wage Equations

In general, it seems that earnings are determined in a similar fashion for disabled and non-disabled workers (Table 4 and 5). Similarly with the results in probit regressions, F tests reject the null hypothesis that all the coefficients are zero. Moreover, the overall fit of the wage specification is relatively good with R-squareds ranging from .24 to .41.

The potential maximum experience and education variables[18] make significant positive contributions to higher wages for both the disabled and non-disabled persons. Although a few coefficients for those variables are statistically insignificant at a traditional significance level for the disabled group, the signs of coefficients are still consistent with usual predictions. Whites and union members typically earn more, while part-time workers have lower hourly earnings.

Relative to service occupation (omitted group), all of the other jobs except “laborer” pay better wages. In particular, individuals in the professional and managerial occupations receive the

[17]We may have to be careful with this interpretation. As many studies issued, unemployed individuals may report poor health conditions to justify their work status. Furthermore, responses may not be independent of the labor market effects we want them to explain. For example, it is possible that health conditions can be deteriorated when unemployed.

[18] Those who attain high school degree are used as a comparison group.

highest earnings. The industry dummies have a fairly consistent effect across the sub-groups, with higher wages given the omitted group (agriculture, forestry, and fisheries). Although both occupation and industry dummies provide significant explanatory power for both groups with a similar pattern, these variables do not provide good explanations for the variation of wage levels among people with disabilities in the 2001 SIPP. More interesting transition is found in the coefficients of industry and occupation dummies regardless of disability status. The magnitudes of the coefficients decrease with a few exceptions and loose explanatory power in recent survey years. It is also worthwhile to note that self-reported health conditions have pronounced effects on wages for both the non-disabled and the disabled, although several are not statistically significant. Workers who self-reported worse health earned lower incomes, although many coefficients of health status for those with disabilities are statistically insignificant.

Sample selection into employment does not have substantial effects on the earnings of the disabled. The sample selection correction parameter in the earning functions is statistically insignificant for the disabled workers in every sample except the one in 1984.[19] Given that most of the coefficients of the selection correction term are statistically insignificant, the results are little affected by whether or not a correction is made for sample selectivity.

4.3. Decomposition Results of the Differentials in Employment and Earnings

Tables 6 and 7 represent the set of decomposition results for both the employment and the wage differentials. Equations (6) and (7) outline the probit decomposition of Even and McPherson (1990). The gaps of employment participation between the non-disabled and the disabled have increased over time. The main question addressed by this research is to what extent the employment participation rate differential is due to unexplained components (discrimination and

[19] This result is inconsistent with Baldwin and Johnson (1994), which utilizes the same data, SIPP 1984, in their analysis. They report a significant negative lambda coefficient for the non-disabled implying that not-employed men with above average wage offers have more valuable opportunities outside the labor force.

the residual effects) and productivity related characteristics. Although the difference in employment participation between the two groups has increased over the period 1984-2001, the reasons for the rise vary for different time periods.

Between 1984 and 1990, the year the ADA was adopted, the gap in employment left unexplained after controlling for the factors in the regression analysis, has risen markedly from 6.5 percent in 1986 to over 14.9 percent in 1990. This rise explains most of the overall difference in employment levels between the two groups. After 1990, however, the unexplained differential does not show a rise, as it stayed at 14.4 percent in 1996, and again in 2001.

The primary reason for the rise in the total employment gap after 1990 is explained by an increase in the difference in employment explained by differences in the mean characteristics of the disabled and non-disabled. After rise from only 14.2 to 15.2 percent between 1984 and 1990, the explained differential in employment rose to 26.9 percent in 1996 and stayed at roughly that same level (26.1%) in 2001.

Thus, it appears that between 1984 and the passage of the ADA most of the rise in employment differentials between the disabled and the non-disabled was explained by a rise in the unexplained differential. After the passage of the ADA, the employment differential continued to rise, but for a different reason. Either due to differences in employers' hiring practices after the ADA or other changes during the 1990s, the increase in the employment differential was driven more by an increase in the measured differences between the disabled and the non-disabled.

The set of decomposition results of wage differentials in Tables 6 and 7 come from applying the decomposition method suggested by Neuman and Oaxaca (2004). Standard errors for the estimates of decompositions are calculated via the bootstrap method. Let us first focus on the wage differences between two sub-groups shown in raw data and how they have changed. Average hourly wages in 1984 are $10.62 for non-disabled men and $9.97 for men with disabilities. Both groups experienced hourly pay increase as time goes by. However, the nominal wage difference between the non-disabled and the disabled has increased over time.

Contrary to the decomposition results regarding employment differences, the wage decomposition analysis in Tables 6 and 7 indicates that there has been a significant change in wage differences attributed to between-group differences in productivity-related characteristics and an unexplained portion which is discrimination and residual effects. The unexplained components of the log wage differential has not risen so dramatically, as it has risen from .037 in 1984 to .055 in 1990, fallen to .039 in 1996, and risen again to .052 in 2001. If the relative unobserved productivity of the disabled who obtained jobs has not changed over time, it does not appear that the extent of wage discrimination in 2001 is any worse than it was in 1990 just as the ADA was being passed, although it may have been worse than in 1984 and 1996.

In 1984 when the overall differential in wages was low at 3.7 percent, the decomposition of the wage shows that the entire differential is attributable to the unexplained differential. By 1990 the wage differential had risen to 6.5 percent in 1990s, but by that point a slightly smaller percentage of the differential, 85 percent, was attributable to the unexplained component. By 1996, six years after the ADA was passed, the wage differential had risen to 9.1 percent, largely due to a rise in differences between the disabled and non-disabled that can be explained with measureable characteristics. The explained differential rose to 5.2 percent, while the unexplained difference fell back to 3.9 percent. Thus the unexplained differential by 1996 accounted for only 43 percent of the overall differential. Between 1996 and 2001 the overall wage differential rose again to 11.4 percent, this time because both the unexplained and the explained differential both increased. As a result, the unexplained differential accounted for 46 percent of the overall differential.

The results show that the gap between the disabled and the non-disabled increased sharply both for the probability of being employed and for the wage paid between 1990 the year that the ADA was passed and 1996 and 2001. In both cases nearly all of the rise in the differential is attributable to a sharp increase in the segment of the gap that can be attributed to factors that can be measured. This result is partly consistent with the British study conducted by Jones et al, (2006). It is also somewhat consistent with the ADA evaluation by DeLeire in 2001, who argues that the ADA was unsuccessful at preventing discrimination. The unexplained differential has not fallen since 1990 for employment and fell temporarily only in 1996 before rising again to the 1990 level in 2001.

Table 6 also decomposes the explained component of wage differentials into sub-components.[20] While the negative contributions of labor market experience to the explained wage differentials has narrowed, the effects of education do not show a significant change in transition. Regarding experience, the relative average age of the disabled men has decreased (Table 3), and the coefficient values on experience variable decreased (Table 5). These two changes both led to a decrease in the explained differential attributable to experience to -.0826 in 1990, -.0628 in 1996, and -.0471 in 2001.

The results also suggest that occupation and health condition differences play a major role in earning differences between the non-disabled and disabled. Difference in occupations and health conditions help explain why the wage differential is so large. The non-disabled tend to be in higher paying occupations, which explain .027 in the log wage differential between the non-disabled and disabled in Table 6 in 1984, 1990, and 2001, and .024 of the differential in 1996. The non-disabled also tend to have better health, which contributes to explaining .0299 of the log wage differential in 1984. Tables 2 and 3 show that the number of disabled persons reporting fair or poor health has risen relative to the number of non-disabled persons with fair or poor health in Tables 2 and 3. The increase in poor health among the disabled relative to the non-disabled is one

[20] As shown in Oaxaca and Ransom (1999), the estimated separate contribution to the unexplained portion of the wage decomposition causes the identification problems. The estimates are not invariant with respect to the choice of reference groups, and a similar identification problem applies to continuous variables.

of the reasons why the log wage differential explained by the difference in health rises to .0357 in 1990, 0.0483 in 1996, and .0418 in 2001.[21]

The last two rows in Tables 6 and 7 represent the decomposition of wage differentials into the explained and unexplained differentials without controlling for occupation and industry variables. This should provide important checks because the disabled may choose certain occupations and industries, either voluntarily or involuntarily, which they would not choose unless they are disabled. Mullay and Sindelar (1992) report that alcohol dependence reduces the probability that a man is in a management, administrative, and technical or professional occupation. These are the highest paying jobs.

Previous studies did not attempt to examine the effects of self-selection in the choice of occupation and industry among the disabled. If workers with disabilities involuntarily settle for specific occupations because of labor market discrimination, the estimate of the unexplained wage differentials should be underestimated. Prior to the implementation of decomposition analysis without occupation and industry dummies, it is worth investigating how much occupation dissimilarity exists between the non-disabled and the disabled. The distribution of the non-disabled and disabled men across occupations is reported in Table 3. Occupations in the labor market are somewhat segregated. In 1984, for example, whereas workers without disabilities are relatively more likely to hold professional jobs, ones with disabilities are more likely to work in semi-skilled jobs. A convenient way to summarize the level of segregation is to use the dissimilarity index, D. This index is widely attributed to Duncan and Duncan (1955), who described some of its properties. Using the Duncan index, the trend in occupation dissimilarities

[21] The results are somewhat consistent with previous studies. DeLeire (2001) finds that the detrimental effect of health on earnings did decline among the work-limited disabled over the period 1984-93, but no significant changes among the only functionally limited disabled.

in the U.S. is .14, .12, .10, and .10 in 1984, 1990, 1996, and 2001, respectively.[22] Interestingly the inequality of occupation distributions was improved in post-ADA. As expected, the percentage of the unexplained differential is larger than when occupation and industry are controlled, but the difference is not at a significant level. More importantly, the unexplained differentials have still decreased before and after the ADA.

As noted above, in terms of the actual differences in wage and employment between the non-disabled and the disabled, individuals with disabilities by 2001 were much less likely to be employed relative to non-disabled people than they were in 1984. The disabled who had jobs also experienced a larger gap in their earnings relative to the non-disabled. Based on decomposition analysis, non-trivial portions of both employment and wage differentials are attributable to the unexplained components. The unexplained components are somewhat difficult to interpret in the current context. Although we attempted to control for the impact of poor health upon productivity by including self-assessed health status in our analysis, it is difficult to adequately control for the impact of disability upon productivity. However, if we assume that the effects of unobservable health characteristics on the unexplained differential are constant across different time period, we may be able to interpret the unexplained components in the traditional manner. Although the ADA prohibits employees from discriminating in employment against individuals with disabilities, we do not find any improvements in employment opportunities among the disabled after the introduction of the ADA. On the other hand, a significant improvement was found in the reduction of the unexplained wage differential.

[22] The Duncan index is defined as $D = \frac{1}{2}\sum_{i=1}^{K}\left|p_i^{nd} - p_i^{d}\right|$, where p_i^d is the proportion of all disabled men in occupation i and p_i^{nd} is the proportion of all non-disabled men in job i. The dissimilarity index is bounded between 0 and 1. Proportional representation of non-disabled and disabled in all job categories would yield a value 1. D has a convenient interpretation – it is equal to the fraction of the disabled (or the non-disabled) that would have to change occupations in order for the proportions of the non-disabled and the disabled in each occupation to be equal.

5. Concluding Remarks

In this analysis I made several adjustments to earlier work in the field. First, I applied an alternative definition of disability which is more objective compared to other studies. Second, I decomposed the actual employment and wage differentials using a newly suggested decomposition technique to deal with the selection correction term, in lieu of the selection bias adjusted wage differential. Finally, I evaluated the impact of the ADA by utilizing a longer period of sample 1984 to 2001.

Between 1984 and 1990, the year in which the ADA was established, the gap in employment rates between the non-disabled and the disabled rose 50 percent from 20.8 percent to 30.2 percent. Meanwhile, the gap in wages nearly doubled from 3.7 percent to 6.6 percent. In both cases, nearly all of the rise in the gap was attributable to a rise in factors that were not measured in the analysis. To the extent that unmeasured features of productivity did not change during this period, the rise in the gap might be attributable to an increase in discrimination against the disabled that is unrelated to productivity differences.

From the passage of the ADA in 1990 through 1996 and on to 2001 the gap in employment rates and wages between the non-disabled and the disabled rose further. The employment probability gap rose another 50 percentage points from 30.2 percent to 40.6 percent, and the wage gap nearly doubled again from 6.6 percent to 11.4 percent. This change, however, was not due to a rise in the unexplained differential. During the period the ADA has been in force, therefore, the increase is primarily attributable to differences that are based on measurable factors.

In deciding how to discuss these findings with respect to the timing of the passage of the ADA, it is important to interpret the unexplained differentials carefully. Some component of the unexplained differential could be due to discrimination against the disabled that is not related to their productivity in the workplace. However, the fact of the disability typically places obstacles to productivity for the disabled that are not easy to quantify, so the extent of economic discrimination measured by the unexplained differential might be smaller than in the case of racial or gender discrimination. In this paper, I included self-reported health status to control for the productivity difference between the non-disabled and the disabled. Even so, the included variables may still be insufficient to control for the productivity difference. The results that I have described might be interpreted as upper bounds within which the true measure of employment and wage discrimination is likely to fall.

The ADA appears to have been associated with a halt in the rise of unexplained differences, a part of which might be economic discrimination, in the 1990s. But the disabled apparently still face increasing challenges based on measurable factors that have led to an increasing gap in their employment and wages relative to the non-disabled.

REFERENCES

1. Baker, M., M. Stabile and C. Deri (2001): "What Do Self-reported Objective Measures of Health Measure?," NBER Working Paper 8419.
2. Baldwin, Marjorie and William G. Johnson (1992): "Estimating the Employment Effects of Wage Discrimination," *Review of Economics and Statistics,* 74(3): 446 – 455.
3. Baldwin, Marjorie and William G. Johnson (1994): "Labor Market Discrimination against Men with Disabilities," *Journal of Human Resources,* 29(1): 1-29.
4. Baldwin, Marjorie and William G. Johnson (2000): "Labor Market Discrimination against Men with Disabilities in the Year of the ADA," *Southern Economic Journal,* 66(3): 548-566.
5. Bound, John (1991): "Self-reported versus Objective Measures of Health in Retirement Models," *Journal of Human Resources,* 26(1), 106 – 138.
6. Currie, Janet (1999), "Health, health insurance, and the labor market," *Handbook of Labor Economics,* Volume 3, Edited by O. Ashenfelter and D. Card.
7. Cutler, David M., Mary Beth Landrum, and Kate A. Stewart (2006): "How Do the Better Educated Do It? Socioeconomic Status and the Ability to Cope with Underlying Impairment," NBER Working Paper 12040.
8. Duncan, Otis D. and Beverly Duncan (1955): "A Methodological Analysis of Segregation Indexes," *American Sociological Review,* 10(2): 210-217.
9. DeLeire, Thomas (2000): "The Wage and Employment Effects of the Americans with Disabilities Act," *Journal of Human Resources,* 35(4): 693-715.
10. DeLeire, Thomas (2001): "Changes in Wage Discrimination against People with Disabilities: 1984-93," *Journal of Human Resources,* 36(1): 144-158.
11. Ermisch, John F. and Robert E. Wright (1994): "Interpretation of negative sample selection effects in wage offer equations," *Applied Economics Letters,* 1: 187-189.
12. Even, William E. and David A. MacPherson (1990): "Plant Size and The Decline of Unionism," *Economics Letters,* 32: 393 – 398.

13. Jones, Melanie K. (2005): “Disability and the Labour Market: A Review of the Empirical Evidence,” WELMERC Discussion Paper Series, vol. 2005-04.

14. Jones, Melanie K., Paul L. Latreille, and Peter J. Sloane (2006): “Disability, Gender, and the British Labour Market,” *Oxford Economic Paper,* 58: 407-449.

15. Kidd, Michael P., Peter J. Sloane, and Ivan Ferko (2000): “Disability and the Labour Market: an Analysis of British Males,” *Journal of Health Economics*, 19: 961-981.

16. Kruse, Douglas and Lisa Schur (2003): “Employment of People with Disabilities Following the ADA,” *Industrial Relations*, 42: 31-64.

17. Madden, David (2004): “Labour Market Discrimination on the Basis of Health: An Application to UK Data,” *Applied Economics,* 36: 421-442.

18. Moon, Sangho and Jaeun Shin (2006): “The Effect of the Americans with Disabilities Act on Economic Well-being of Men with Disabilities,” *Health Policy*, 76: 266-276.

19. Mullahy, J. and J. Sindelar (1992), “Effects of Alcohol on Labor Market Success: Income, Earnings, Labor Supply and Occupation,” Alcohol Health and Research World 16: 134-139.

20. Neuman, Shoshana and Ronald L. Oaxaca (2004): “Wage Decomposition with Selectivity-Corrected Wage Equations: A Methodological Note,” *Journal of Economic Inequality,* 2(1): 3-10.

21. Oaxaca, Ronald L. (1973): “Male-Female Wage Differentials in Urban Labor Markets,” *International Economic Review,* 9: 693-709.

22. Oaxaca, Ronald L. and Michael Ransom (1994): “On Discrimination and the Decomposition of Wage Differentials,” *Journal of Econometrics,* 61: 5-21.

23. Oaxaca, Ronald L. and Michael Ransom (1999): “Identification in Detailed Wage Decompositions,” *Review of Economics and Statistics*, 81(1): 154-157.

24. Oaxaca, Ronald L. and Michael Ransom (2005): “Intrafirm Mobility and Sex Differences in Pay,” *Industrial and Labor Relation Review*, 61: 5-21.

25. Pencavel, John (1986), “Labor Supply of Men: a Survey,” *Handbook of Labor Economics*, Volume I, Edited by O. Ashenfelter and R. Layard.

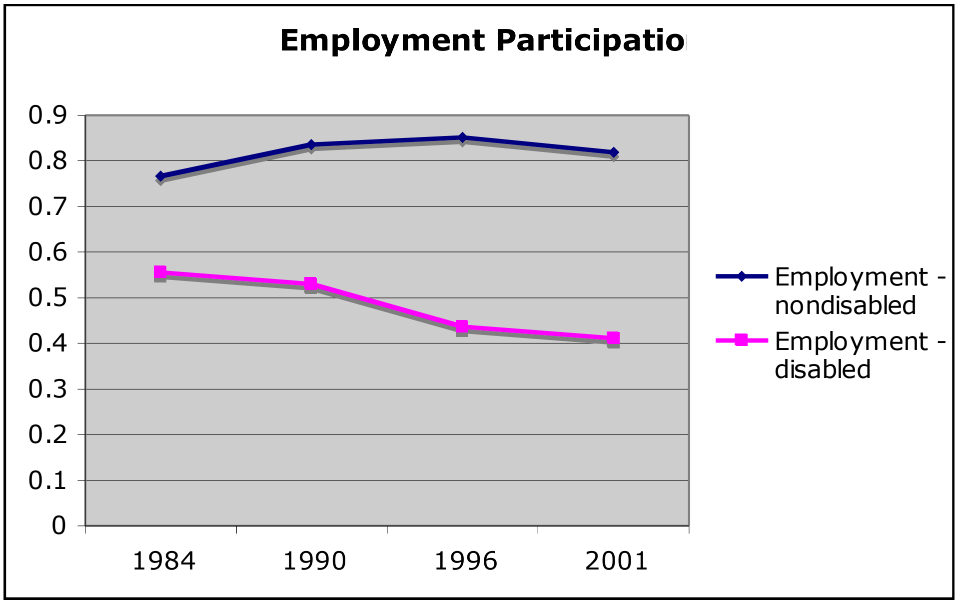
26. Regan, Tracy L. and Ronald L. Oaxaca (forthcoming): “Work Experience as a Source of Specification Error in Earnings Models: Implications for Gender Wage Decompositions,” *Journal of Population Economics*

27. Schumacher, Edward J. and Marjorie L. Baldwin (2000): “The Americans with Disabilities Act and the Labor Market Experience of Workers with Disabilities: Evidence from the SIPP,” Working Paper 0013, East Carolina University, Department of Economics.

28. Wilson, Sven E. (2001): “Work and the Accommodation of Chronic Illness: A Re-examination of the Health-Labour Supply Relationship,” *Applied Economics*, 33: 1139-1159.

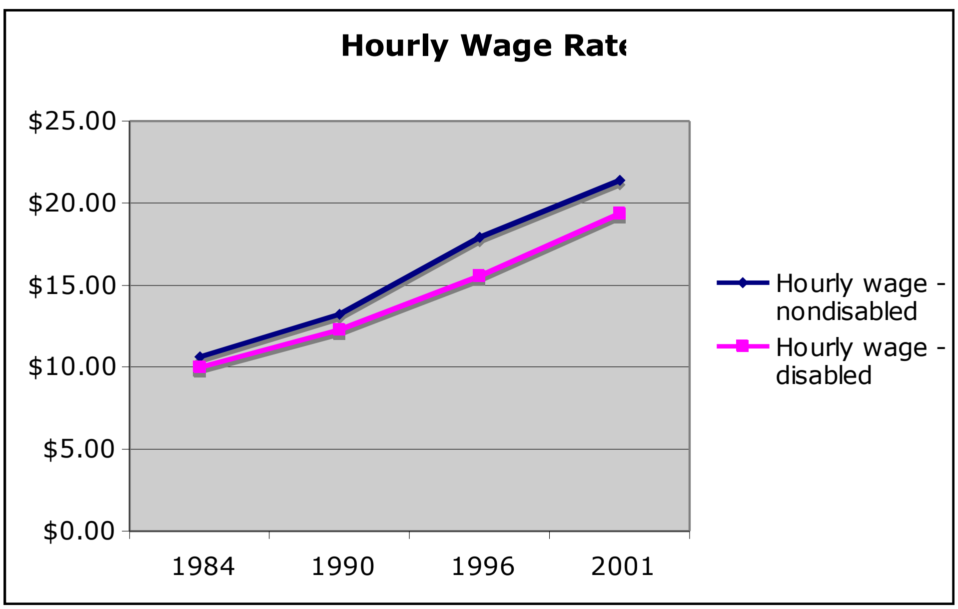
29. Wittenburg, David and Sandi Nelson (2006): “A Guide to Disability Statistics from the Survey of Income and Program Participation,” Cornell University.

Figure 1: Comparison of Employment Participation between Non-disabled and Disabled



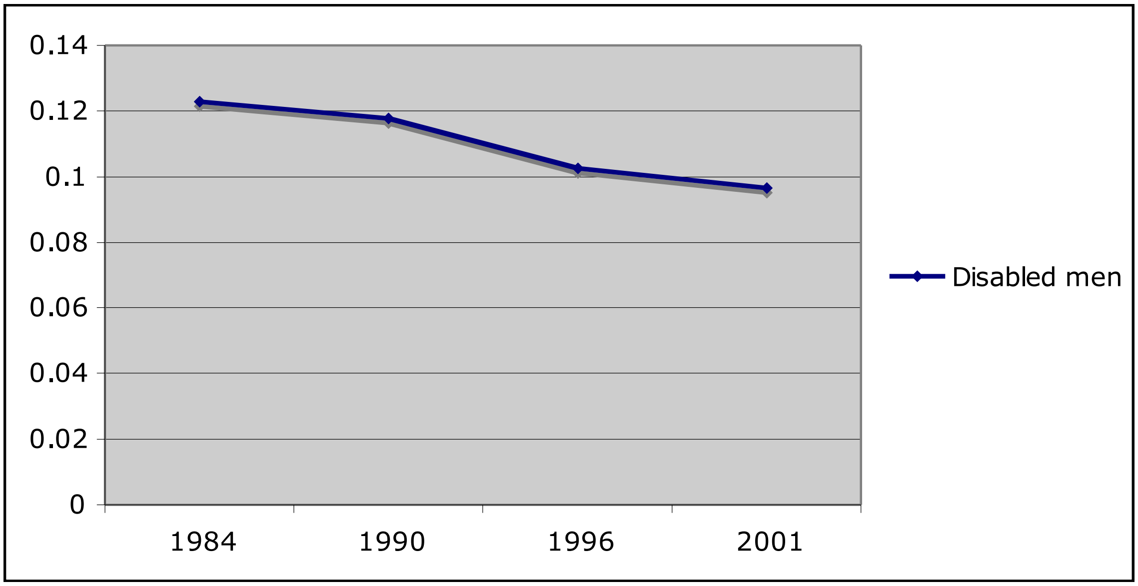
Note: data sources from SIPP 1984, 1990, 1996, and 2001.

Figure 2: Comparison of Wage Rate between Non-disabled and Disabled



Note: data sources from SIPP 1984, 1990, 1996, and 2001.

Figure 3: Disability Rates in the U.S. 1984 - 2001



Note: data sources from SIPP 1984, 1990, 1996, and 2001.

Table 1: Disability Quesionnaire from the 1984 SIPP

Sensory disability

Does … have any difficulty seeing words and letters in ordinary newspaper print even when wearing glasses or contact lenses if … usually wears them?

Does … have any difficulty hearing what is said in a normal conversation with another person?

Does … have any trouble having his/her speech understood?

Physical disability

Does … have any difficulty lifting and carrying something as heavy as 10 lbs., such as a full bag of groceries?

Does … have any difficulty walking for a quarter of a mile - about 3 city blocks?

Does … have any difficulty walking up a flight of stairs without resting?

Activity limitation: ADL (activities of daily living)

Does … need help from others in looking after personal need such as dressing, undressing, eating or personal hygiene?

Does … have any difficulty getting around inside the house by yourself?

Does … have any difficulty getting into and out of bed by yourself?

Activity limitation: IADL (instrumental activities of daily living)

Does … have any difficulty getting around outside the house by yourself?

Because of your health, does … need help to do light housework such as washing dishes, straightening up, or light cleaning?

Does … need help to prepare meals for yourself?

Note: SIPP data have included additional questions relevant to personal health status as they come to more recent data. Hence we should be based on the questions in the 1984 SIPP to compare the results across different time points.

Table 2: Summary Statistics for Variables in Employment Participation Equations

	Non-disabled				Disabled			
Variables	1984	1990	1996	2001	1984	1990	1996	2001
Employed	0.766	0.836	0.852	0.819	0.556	0.530	0.437	0.411
	(0.0038)	(0.0033)	(0.0026)	(0.0031)	(0.012)	(0.012)	(0.011)	(0.012)
Experience	16.55	16.80	18.44	19.03	27.20	26.07	27.79	27.98
	(0.11)	(0.10)	(0.085)	(0.095)	(0.31)	(0.30)	(0.25)	(0.28)
Experience squared	4.255	4.191	4.724	5.048	9.103	8.329	9.060	9.136
	(0.046)	(0.043)	(0.035)	(0.040)	(0.16)	(0.15)	(0.13)	(0.14)
HS dropouts	0.157	0.141	0.122	0.120	0.394	0.309	0.284	0.235
	(0.0033)	(0.0031)	(0.0024)	(0.0026)	(0.012)	(0.011)	(0.0098)	(0.010)
High school	0.371	0.355	0.339	0.331	0.355	0.376	0.367	0.383
	(0.0043)	(0.0043)	(0.0035)	(0.0037)	(0.011)	(0.012)	(0.010)	(0.012)
Some college	0.241	0.245	0.297	0.295	0.153	0.185	0.251	0.275
	(0.0038)	(0.0039)	(0.0034)	(0.0036)	(0.0086)	(0.0095)	(0.0094)	(0.011)
College	0.231	0.259	0.242	0.254	0.0973	0.130	0.0981	0.107
	(0.0038)	(0.0039)	(0.0032)	(0.0034)	(0.0071)	(0.0083)	(0.0065)	(0.0075)
White	0.871	0.850	0.844	0.828	0.856	0.835	0.801	0.793
	(0.0030)	(0.0032)	(0.0027)	(0.0030)	(0.0084)	(0.0091)	(0.0087)	(0.0098)
Nonwage	1.071	1.377	1.369	1.593	3.001	4.168	5.809	6.932
	(0.034)	(0.048)	(0.037)	(0.046)	(0.12)	(0.19)	(0.20)	(0.40)
Marital 1	0.186	0.211	0.225	0.200	0.151	0.164	0.136	0.120
	(0.0035)	(0.0037)	(0.0031)	(0.0032)	(0.0086)	(0.0091)	(0.0075)	(0.0079)
Marital 2	0.179	0.126	0.119	0.121	0.163	0.109	0.0815	0.0816
	(0.0034)	(0.0030)	(0.0024)	(0.0026)	(0.0089)	(0.0077)	(0.0060)	(0.0066)
Marital 3	0.133	0.159	0.167	0.159	0.178	0.183	0.197	0.212
	(0.0030)	(0.0033)	(0.0027)	(0.0029)	(0.0092)	(0.0095)	(0.0087)	(0.0099)
Marital 4	0.106	0.0761	0.0740	0.0822	0.223	0.160	0.153	0.124
	(0.0028)	(0.0024)	(0.0019)	(0.0022)	(0.0100)	(0.0090)	(0.0078)	(0.0080)
Marital 5	0.0847	0.0762	0.0810	0.0848	0.0461	0.0487	0.0460	0.0575
	(0.0025)	(0.0024)	(0.0020)	(0.0022)	(0.0050)	(0.0053)	(0.0046)	(0.0056)
Marital 6	0.311	0.352	0.334	0.354	0.239	0.335	0.386	0.404
	(0.0042)	(0.0043)	(0.0035)	(0.0038)	(0.010)	(0.012)	(0.011)	(0.012)
H Excellent	0.381	0.392	0.382	0.373	0.109	0.101	0.0597	0.0610
	(0.0044)	(0.0044)	(0.0036)	(0.0038)	(0.0075)	(0.0074)	(0.0052)	(0.0058)
H Very good	0.288	0.348	0.364	0.352	0.151	0.166	0.128	0.124
	(0.0041)	(0.0043)	(0.0035)	(0.0038)	(0.0086)	(0.0091)	(0.0073)	(0.0080)
H Good	0.200	0.217	0.215	0.231	0.263	0.299	0.259	0.263
	(0.0036)	(0.0037)	(0.0030)	(0.0033)	(0.011)	(0.011)	(0.0095)	(0.011)

H Fair	0.0399	0.0381	0.0339	0.0368	0.258	0.261	0.292	0.305
	(0.0018)	(0.0017)	(0.0013)	(0.0015)	(0.011)	(0.011)	(0.0099)	(0.011)
H poor	0.00387	0.00441	0.00537	0.00703	0.219	0.173	0.260	0.248
	(0.00056)	(0.00059)	(0.00054)	(0.00066)	(0.0099)	(0.0093)	(0.0096)	(0.010)
Observations	12,391	12,473	18,448	15,941	1,737	1,664	2,110	1,704

Note: standard deviation in the parenthesis.

Table 3: Summary Statistics for Variables in Wage Equations

	Non-disabled				Disabled			
Variables	1984	1990	1996	2001	1984	1990	1996	2001
Hourly wages	10.62	13.21	17.93	21.41	9.971	12.28	15.56	19.36
	(0.074)	(0.088)	(0.14)	(0.19)	(0.19)	(0.28)	(0.36)	(0.77)
Log of hourly wages	2.302	2.496	2.720	2.877	2.264	2.430	2.629	2.763
	(0.0056)	(0.0055)	(0.0050)	(0.0056)	(0.017)	(0.019)	(0.020)	(0.025)
Experience	16.61	17.13	18.66	19.28	24.85	23.96	25.38	26.41
	(0.12)	(0.11)	(0.087)	(0.099)	(0.40)	(0.38)	(0.37)	(0.43)
Experience squared	4.150	4.163	4.682	5.008	7.736	7.038	7.680	8.262
	(0.050)	(0.045)	(0.037)	(0.042)	(0.20)	(0.19)	(0.18)	(0.21)
HS dropouts	0.139	0.125	0.105	0.103	0.306	0.234	0.167	0.167
	(0.0036)	(0.0032)	(0.0024)	(0.0027)	(0.015)	(0.014)	(0.012)	(0.014)
High school	0.370	0.357	0.338	0.321	0.387	0.374	0.393	0.353
	(0.0050)	(0.0047)	(0.0038)	(0.0041)	(0.016)	(0.016)	(0.016)	(0.018)
Some college	0.242	0.241	0.299	0.303	0.182	0.224	0.302	0.320
	(0.0044)	(0.0042)	(0.0037)	(0.0040)	(0.012)	(0.014)	(0.015)	(0.018)
College	0.248	0.278	0.258	0.273	0.125	0.168	0.139	0.160
	(0.0044)	(0.0044)	(0.0035)	(0.0039)	(0.011)	(0.013)	(0.011)	(0.014)
Union	0.240	0.198	0.160	0.145	0.303	0.252	0.193	0.207
	(0.0044)	(0.0039)	(0.0029)	(0.0031)	(0.015)	(0.015)	(0.013)	(0.015)
White	0.887	0.861	0.859	0.847	0.893	0.900	0.869	0.847
	(0.0032)	(0.0034)	(0.0028)	(0.0032)	(0.0099)	(0.010)	(0.011)	(0.014)
Part time	0.0496	0.0743	0.192	0.190	0.0850	0.0839	0.280	0.316
	(0.0022)	(0.0026)	(0.0031)	(0.0034)	(0.0090)	(0.0093)	(0.015)	(0.018)
Professional	0.234	0.249	0.257	0.278	0.154	0.188	0.169	0.210
	(0.0043)	(0.0042)	(0.0035)	(0.0039)	(0.012)	(0.013)	(0.012)	(0.015)
Clerical	0.202	0.205	0.199	0.201	0.140	0.147	0.187	0.164
	(0.0041)	(0.0040)	(0.0032)	(0.0035)	(0.011)	(0.012)	(0.013)	(0.014)
Service	0.0986	0.104	0.106	0.114	0.101	0.109	0.114	0.136
	(0.0031)	(0.0030)	(0.0025)	(0.0028)	(0.0097)	(0.010)	(0.010)	(0.013)
Skilled	0.208	0.190	0.188	0.175	0.262	0.221	0.218	0.184
	(0.0042)	(0.0038)	(0.0031)	(0.0033)	(0.014)	(0.014)	(0.014)	(0.015)
Semi-skilled	0.165	0.159	0.156	0.137	0.231	0.217	0.210	0.204
	(0.0038)	(0.0036)	(0.0029)	(0.0030)	(0.014)	(0.014)	(0.013)	(0.015)
Labored	0.0928	0.0938	0.0952	0.0941	0.112	0.118	0.102	0.101
	(0.0030)	(0.0029)	(0.0023)	(0.0026)	(0.010)	(0.011)	(0.0100)	(0.011)
Farm	0.0198	0.0228	0.0255	0.0249	0.0332	0.0283	0.0217	0.0171
	(0.0014)	(0.0015)	(0.0013)	(0.0014)	(0.0058)	(0.0056)	(0.0048)	(0.0049)

Mining	0.0140	0.00921	0.00871	0.00804	0.0176	0.0181	0.0152	0.00857
	(0.0012)	(0.00094)	(0.00074)	(0.00078)	(0.0042)	(0.0045)	(0.0040)	(0.0035)
Construction	0.0875	0.0919	0.0941	0.103	0.0850	0.0952	0.0889	0.109
	(0.0029)	(0.0028)	(0.0023)	(0.0027)	(0.0090)	(0.0099)	(0.0094)	(0.012)
Manufacture	0.283	0.251	0.230	0.195	0.374	0.297	0.286	0.241
	(0.0046)	(0.0042)	(0.0034)	(0.0035)	(0.016)	(0.015)	(0.015)	(0.016)
Whole	0.0589	0.0559	0.0570	0.0509	0.0446	0.0465	0.0466	0.0371
	(0.0024)	(0.0023)	(0.0018)	(0.0019)	(0.0066)	(0.0071)	(0.0069)	(0.0072)
Retail	0.141	0.138	0.145	0.150	0.116	0.137	0.118	0.130
	(0.0036)	(0.0034)	(0.0028)	(0.0031)	(0.010)	(0.012)	(0.011)	(0.013)
Finance	0.0439	0.0458	0.0419	0.0467	0.0290	0.0306	0.0293	0.0343
	(0.0021)	(0.0020)	(0.0016)	(0.0018)	(0.0054)	(0.0058)	(0.0056)	(0.0069)
Utility	0.0425	0.0381	0.0343	0.0332	0.0456	0.0340	0.0434	0.0129
	(0.0021)	(0.0019)	(0.0015)	(0.0016)	(0.0067)	(0.0061)	(0.0067)	(0.0043)
Transportation	0.0591	0.0687	0.0613	0.0607	0.0622	0.0714	0.0824	0.0729
	(0.0024)	(0.0025)	(0.0019)	(0.0021)	(0.0078)	(0.0087)	(0.0091)	(0.0098)
Service	0.187	0.215	0.232	0.258	0.140	0.189	0.208	0.269
	(0.0040)	(0.0040)	(0.0034)	(0.0038)	(0.011)	(0.013)	(0.013)	(0.017)
Government	0.0633	0.0633	0.0682	0.0692	0.0528	0.0522	0.0564	0.0686
	(0.0025)	(0.0024)	(0.0020)	(0.0022)	(0.0072)	(0.0075)	(0.0076)	(0.0096)
H Excellent	0.422	0.396	0.384	0.387	0.149	0.145	0.110	0.111
	(0.0051)	(0.0048)	(0.0039)	(0.0043)	(0.011)	(0.012)	(0.010)	(0.012)
H Very good	0.322	0.357	0.378	0.364	0.226	0.249	0.217	0.217
	(0.0048)	(0.0047)	(0.0039)	(0.0042)	(0.013)	(0.015)	(0.014)	(0.016)
H Good	0.213	0.213	0.210	0.221	0.326	0.363	0.350	0.364
	(0.0042)	(0.0040)	(0.0032)	(0.0036)	(0.015)	(0.016)	(0.016)	(0.018)
H Fair	0.0364	0.0324	0.0257	0.0259	0.230	0.178	0.257	0.236
	(0.0019)	(0.0017)	(0.0013)	(0.0014)	(0.014)	(0.013)	(0.014)	(0.016)
H poor	0.00211	0.00182	0.00216	0.00214	0.0684	0.0646	0.0662	0.0714
	(0.00047)	(0.00042)	(0.00037)	(0.00040)	(0.0081)	(0.0083)	(0.0082)	(0.0097)
Observations	9489	10424	15724	13054	965	882	922	700

Note: standard deviation in the parenthesis.

Table 4: Probit Regressions

Dependent variable: Dummy = 1 if a person is in the employment participation

	Non-disabled				Disabled			
Variables	1984	1990	1996	2001	1984	1990	1996	2001
Experience	0.0455***	0.0804***	0.0714***	0.0676***	0.0210*	0.0573***	0.0261**	0.0112
	(0.0045)	(0.0045)	(0.0040)	(0.0041)	(0.013)	(0.013)	(0.012)	(0.013)
Experience squared	-0.0925***	-0.180***	-0.154***	-0.139***	-0.0515**	-0.139***	-0.0654***	-0.0158
	(0.010)	(0.011)	(0.0094)	(0.0096)	(0.025)	(0.026)	(0.024)	(0.027)
HS dropouts	-0.151***	-0.270***	-0.341***	-0.193***	-0.295***	-0.0511	-0.485***	-0.192**
	(0.039)	(0.042)	(0.037)	(0.039)	(0.083)	(0.088)	(0.083)	(0.094)
Some college	0.00222	-0.0193	0.0215	0.153***	0.176	0.235**	0.0892	0.259***
	(0.036)	(0.038)	(0.031)	(0.032)	(0.11)	(0.10)	(0.082)	(0.088)
College	0.0725*	0.235***	0.226***	0.237***	0.209	0.368***	0.280**	0.455***
	(0.038)	(0.041)	(0.037)	(0.036)	(0.14)	(0.12)	(0.12)	(0.13)
White	0.219***	0.213***	0.325***	0.356***	0.274***	0.380***	0.428***	0.224**
	(0.038)	(0.038)	(0.031)	(0.031)	(0.10)	(0.099)	(0.083)	(0.088)
Nonwage	-0.0609***	-0.0427***	-0.0629***	-0.0490***	-0.116***	-0.0597***	-0.0609***	-0.0566***
	(0.0034)	(0.0022)	(0.0024)	(0.0020)	(0.0084)	(0.0045)	(0.0046)	(0.0045)
Marital 1	0.568***	0.127**	0.0206	0.0330	0.180	-0.0572	0.0961	-0.125
	(0.051)	(0.059)	(0.052)	(0.053)	(0.13)	(0.15)	(0.14)	(0.16)
Marital 3	0.519***	0.131**	0.0720	0.0460	0.186	0.115	0.180	-0.0280
	(0.056)	(0.063)	(0.056)	(0.056)	(0.13)	(0.15)	(0.14)	(0.15)
Marital 4	-0.161***	-0.155**	-0.145**	-0.264***	0.0794	0.0578	0.117	-0.203
	(0.054)	(0.072)	(0.063)	(0.061)	(0.13)	(0.16)	(0.15)	(0.16)
Marital 5	-0.240***	-0.468***	-0.529***	-0.428***	-0.678***	-0.729***	-0.142	-0.427**
	(0.059)	(0.068)	(0.059)	(0.060)	(0.19)	(0.20)	(0.19)	(0.19)
Marital 6	-0.112***	-0.288***	-0.419***	-0.354***	-0.531***	-0.619***	-0.489***	-0.555***
	(0.042)	(0.053)	(0.047)	(0.047)	(0.12)	(0.13)	(0.13)	(0.13)
H Excellent	0.881***	0.122***	0.0958***	0.265***	0.0628	0.144	0.404***	0.348**
	(0.034)	(0.040)	(0.034)	(0.034)	(0.13)	(0.13)	(0.15)	(0.16)
H Very good	0.859***	0.128***	0.191***	0.177***	0.367***	0.434***	0.266**	0.291**
	(0.036)	(0.040)	(0.034)	(0.033)	(0.12)	(0.11)	(0.11)	(0.12)
H Fair	0.378***	-0.291***	-0.536***	-0.503***	-0.367***	-0.574***	-0.438***	-0.570***
	(0.066)	(0.071)	(0.061)	(0.061)	(0.094)	(0.093)	(0.081)	(0.089)
H Poor	-0.300	-1.181***	-1.310***	-1.319***	-1.222***	-1.104***	-1.303***	-1.325***
	(0.19)	(0.19)	(0.14)	(0.14)	(0.11)	(0.11)	(0.098)	(0.11)
Constant	-0.318***	0.394***	0.502***	0.187***	0.598***	0.0923	0.234	0.355
	(0.069)	(0.079)	(0.070)	(0.070)	(0.21)	(0.22)	(0.21)	(0.22)

Observations	12391	12473	18448	15941	1737	1664	2110	1704
Log likelihood	-5646	-4769	-6433	-6393	-817.6	-804.7	-991.4	-836.6
LR chi2	2198	1606	2579	2296	751.3	691.4	908.6	634.5
Pseudo R-squared	0.163	0.144	0.167	0.152	0.315	0.301	0.314	0.275

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Selectivity Corrected Wage Equations

Dependent variable: log of hourly wage rate

	Non-disabled				Disabled			
Variables	1984	1990	1996	2001	1984	1990	1996	2001
Experience	0.0418***	0.0360***	0.0316***	0.0345***	0.0331***	0.0320***	0.0245***	0.0174**
	(0.0016)	(0.0020)	(0.0018)	(0.0020)	(0.0047)	(0.0058)	(0.0068)	(0.0086)
Experience squared	-0.0691***	-0.0568***	-0.0498***	-0.0611***	-0.0494***	-0.0481***	-0.0338**	-0.0253
	(0.0037)	(0.0046)	(0.0042)	(0.0046)	(0.0096)	(0.012)	(0.014)	(0.017)
HS dropouts	-0.113***	-0.122***	-0.137***	-0.109***	-0.128***	-0.118***	-0.0593	-0.147**
	(0.014)	(0.015)	(0.016)	(0.018)	(0.034)	(0.040)	(0.052)	(0.068)
Some college	0.0768***	0.0635***	0.0907***	0.113***	0.0828**	0.140***	0.100**	0.0183
	(0.012)	(0.012)	(0.011)	(0.013)	(0.040)	(0.041)	(0.043)	(0.057)
College	0.287***	0.298***	0.349***	0.394***	0.185***	0.298***	0.277***	0.392***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.055)	(0.054)	(0.064)	(0.086)
Union	0.163***	0.212***	0.192***	0.172***	0.213***	0.252***	0.238***	0.318***
	(0.011)	(0.011)	(0.012)	(0.014)	(0.031)	(0.036)	(0.046)	(0.059)
White	0.127***	0.115***	0.0741***	0.0953***	0.0953**	0.0638	0.0274	0.0843
	(0.014)	(0.013)	(0.013)	(0.014)	(0.044)	(0.051)	(0.053)	(0.064)
Part time	-0.140***	-0.105***	-0.0428***	-0.0232*	-0.165***	-0.111*	-0.0591	-0.0754
	(0.020)	(0.017)	(0.011)	(0.013)	(0.049)	(0.057)	(0.039)	(0.050)
Professional	0.336***	0.347***	0.347***	0.327***	0.335***	0.406***	0.390***	0.185**
	(0.019)	(0.018)	(0.017)	(0.019)	(0.063)	(0.065)	(0.074)	(0.092)
Clerical	0.170***	0.182***	0.163***	0.165***	0.154***	0.270***	0.178***	0.0191
	(0.018)	(0.017)	(0.017)	(0.019)	(0.059)	(0.061)	(0.069)	(0.085)
Skilled	0.149***	0.174***	0.174***	0.131***	0.182***	0.220***	0.225***	-0.0281
	(0.019)	(0.018)	(0.018)	(0.020)	(0.054)	(0.060)	(0.069)	(0.089)
Semi-skilled	0.0361*	-0.00496	0.0508***	0.00116	-0.0238	0.0163	-0.00175	-0.110
	(0.020)	(0.019)	(0.019)	(0.021)	(0.056)	(0.061)	(0.070)	(0.087)
Labored	-0.0181	-0.0312	-0.00489	-0.0104	-0.0501	-0.0230	0.0202	-0.184*
	(0.021)	(0.021)	(0.020)	(0.023)	(0.063)	(0.067)	(0.079)	(0.100)
Mining	0.376***	0.319***	0.287***	0.220***	0.585***	0.470***	0.216	0.181
	(0.049)	(0.053)	(0.053)	(0.062)	(0.13)	(0.14)	(0.18)	(0.30)
Construction	0.289***	0.256***	0.197***	0.190***	0.332***	0.370***	0.135	-0.0506
	(0.035)	(0.033)	(0.030)	(0.035)	(0.089)	(0.10)	(0.13)	(0.19)
Manufacture	0.321***	0.330***	0.242***	0.195***	0.402***	0.361***	0.225*	0.0318
	(0.034)	(0.031)	(0.028)	(0.034)	(0.081)	(0.097)	(0.12)	(0.18)
Whole	0.250***	0.244***	0.232***	0.184***	0.372***	0.343***	0.163	-0.0734
	(0.037)	(0.035)	(0.032)	(0.039)	(0.100)	(0.11)	(0.14)	(0.21)
Retail	0.115***	0.119***	0.0480*	0.000413	0.133	0.151	-0.0268	-0.196

	(0.034)	(0.032)	(0.029)	(0.035)	(0.086)	(0.10)	(0.12)	(0.19)
Finance	0.311***	0.333***	0.286***	0.207***	0.325***	0.295**	0.305**	-0.0189
	(0.039)	(0.036)	(0.034)	(0.040)	(0.11)	(0.13)	(0.15)	(0.22)
Utility	0.358***	0.351***	0.289***	0.251***	0.326***	0.397***	0.329**	-0.0832
	(0.039)	(0.037)	(0.036)	(0.042)	(0.099)	(0.12)	(0.14)	(0.27)
Transportation	0.312***	0.258***	0.235***	0.177***	0.361***	0.407***	0.225*	-0.0805
	(0.037)	(0.034)	(0.032)	(0.038)	(0.094)	(0.11)	(0.13)	(0.20)
Service	0.102***	0.153***	0.118***	0.0683**	0.180**	0.141	-0.00132	-0.192
	(0.034)	(0.032)	(0.029)	(0.034)	(0.086)	(0.099)	(0.12)	(0.19)
Government	0.226***	0.289***	0.261***	0.181***	0.198**	0.409***	0.190	-0.0269
	(0.037)	(0.035)	(0.032)	(0.038)	(0.098)	(0.11)	(0.14)	(0.20)
H Excellent	0.0602***	0.0724***	0.0913***	0.0591***	0.0563	0.0954**	0.130**	0.137*
	(0.016)	(0.012)	(0.012)	(0.014)	(0.043)	(0.046)	(0.061)	(0.079)
H Very good	0.0464***	0.0410***	0.0517***	0.0305**	0.0554	0.0870**	0.0442	0.149**
	(0.016)	(0.012)	(0.012)	(0.013)	(0.037)	(0.039)	(0.048)	(0.062)
H Fair	-0.0462*	-0.0676***	-0.0541*	-0.0654**	-0.0729*	-0.0722	-0.103**	-0.00582
	(0.025)	(0.026)	(0.029)	(0.033)	(0.038)	(0.046)	(0.047)	(0.066)
H Poor	-0.00158	-0.0526	-0.0373	-0.105	-0.0822	-0.0691	-0.336***	-0.0977
	(0.095)	(0.10)	(0.094)	(0.11)	(0.065)	(0.069)	(0.090)	(0.11)
Inverse Mill's ratio	-0.00945	-0.0157	-0.0270	-0.00664	-0.134***	0.0207	-0.00905	-0.0882
	(0.028)	(0.037)	(0.036)	(0.037)	(0.045)	(0.042)	(0.059)	(0.072)
Constant	1.257***	1.472***	1.788***	1.982***	1.340***	1.355***	1.898***	2.466***
	(0.048)	(0.045)	(0.042)	(0.050)	(0.12)	(0.14)	(0.16)	(0.23)
Observations	9489	10424	15724	13054	965	882	922	700
Log likelihood	-5192	-5978	-12200	-10583	-490.2	-491.5	-676.5	-595.7
F test	237.4	258.4	235.8	186.1	22.90	22.85	12.97	9.067
Adj R-squared	0.411	0.409	0.295	0.284	0.389	0.410	0.267	0.244

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Decomposition of Employment and Wage Differentials

	1984		1990		1996		2001	
				Employment differentials				
Employment - non-disabled	0.766		0.836		0.852		0.819	
Employment - disabled	0.556		0.53		0.437		0.411	
Employment differential	***0.2079***		***0.3018***		***0.4134***		***0.4057***	
				Decomposition of employment differentials				
Explained differential	0.1428	(0.0155)	0.1524	(0.0124)	0.2691	(0.0131)	0.2616	(0.0124)
Unexplained differential	0.0651	(0.0179)	0.1494	(0.0161)	0.1442	(0.0156)	0.1441	(0.0153)
				Wage differentials				
Hourly wage - non-disabled	$10.62		$13.21		$17.93		$21.41	
Hourly wage - disabled	$9.97		$12.28		$15.56		$19.36	
Wage Differential	$0.65		$0.93		$2.37		$2.05	
				Decomposition of wage differentials				
Log Wage Differential	***0.0373***		***0.0657***		***0.0910***		***0.1141***	
Explained differential	0.0001	(0.0149)	0.0100	(0.0126)	0.0520	(0.0139)	0.0619	(0.0157)
Unexplained differential	0.0372	(0.0172)	0.0557	(0.0170)	0.0390	(0.0198)	0.0522	(0.0234)
				Components of the explained wage differentials				
Experience	-0.0970	(0.0066)	-0.0826	(0.0056)	-0.0628	(0.0051)	-0.0471	(0.0053)
Education	0.0587	(0.0051)	0.0472	(0.0050)	0.0501	(0.0051)	0.0494	(0.0064)
Occupations	0.0270	(0.0041)	0.0272	(0.0044)	0.0243	(0.0041)	0.0272	(0.0051)
Industry	-0.0136	(0.0037)	-0.0036	(0.0034)	-0.0089	(0.0032)	-0.0028	(0.0034)
Health conditions	0.0299	(0.0101)	0.0357	(0.0085)	0.0483	(0.0102)	0.0418	(0.0121)
Others	-0.0060	(0.0032)	-0.0150	(0.0039)	-0.0033	(0.0033)	-0.0077	(0.0037)
Lambda	0.0011	(0.0039)	0.0012	(0.0049)	0.0043	(0.0067)	0.0012	(0.0086)
				Decomposition of wage differentials without controlling for occupation and industry				
Explained differential	-0.0071	(0.0125)	0.0039	(0.0145)	0.0581	(0.0138)	0.0582	(0.0149)
Unexplained differential	0.0444	(0.0166)	0.0618	(0.0176)	0.0329	(0.0236)	0.0559	(0.0275)

Note: Standard errors are in parentheses; Standard errors are bootstrap estimates from 200 replications.

Table 7: Decomposition of Employment and Wage Differentials: Percentage Changes

	1984	1990	1996	2001
Employment differential	***0.2079***	***0.3018***	***0.4134***	***0.4057***
Explained differential	0.142(69%)	0.152 (50%)	0.269 (65%)	0.261 (64%)
Unexplained differential	0.065 (31%)	0.149 (50%)	0.144 (35%)	0.144 (36%)
Log Wage Differential	***0.0373***	***0.0657***	***0.0910***	***0.1141***
Explained differential	0.000 (0%)	0.010 (15%)	0.052 (57%)	0.0619 (54%)
Unexplained differential	0.037 (100%)	0.055 (85%)	0.039 (43%)	0.0521 (46%)
Total Differential				
Decomposition of wage differentials without controlling for occupation and industry				
Explained differential	-0.0071 (-19%)	0.0039 (6%)	0.0581 (64%)	0.0582 (51%)
Unexplained differential	0.0444 (119%)	0.0618 (94%)	0.0329 (36%)	0.0559 (49%)

Appendix 1: Variable Names and Definitions

Variables	Definitions
	Dependent variables
Log of hourly wages	Monthly earned income divided by (usual hours worked per week)*4
Employment participation	Dummy variable equal to 1 if individual has a positive hourly wage, 0 else
	Human capital variables
Experience	Potential labor market experience (age - years of education - 5)
Exp squared	Experience squared / 100
HS dropouts	High school dropouts
High School	High school graduates (omitted group)
Some College	More than high school degree, but less than 4 year college degree
College	4 year college degree or above
	Occupation variables
Clerical	Clerical occupations
Professional	Professional / managerial occupations
Service	Service occupations (omitted group)
Skilled	Technical occupations
Semi-skilled	Operative occupations
Labored	Laborer
	Industry variables
Farm	Agriculture, forestry, and fisheries (omitted group)
Mining	Mining
Construction	Contruction
Manufacture	Manufacturing
Whole	Wholesale trade
Retail	Retail trade
Finance	Finance, insurance, and real estate
Utility	Public utility
Transportation	Transportation, communications, and other public utilities
Service	Services
Government	Public administration
	Self-reported health status
H Excellent	Excellent health status
H Very good	Very good health status
H Good	Good health status (omitted group)
H Fair	Fair health status
H Bad	Bad health status
	Exclusion restrictions
Nonwage	Monthly unearned income / 100
Marital 1	Married, kids under age 18, and positive spouse earnings
Marital 2	Married, kids under age 18, and no spouse earnings
Marital 3	Married, no kids under age 18, and positive spouse earnings (omitted group)
Marital 4	Married, no kids under age 18, and no spouse earnings
Marital 5	Single with kids under age 18
Marital 6	Single without kids under age 18
	Other variables
White	Dummy variable denoting ethnic group, equals 1 if white
Union	Dummy variable denoting union members, equals 1 if union member
Part-time	Dummy variable denoting part-time workers, equals 1 if work hours per week is less than 35

IRISS Working Papers

The IRISS Working Paper Series has been created in 1999 to ensure a timely dissemination of the research outcome from the IRISS-C/I programme. They are meant to stimulate discussion and feedback. The working papers are contributed by CEPS/INSTEAD resident staff, research associates and visiting researchers.

The fifteen most recent papers

Choe C., 'Determinants of Labor Market Outcomes of Disabled Men Before and After the Americans with Disabilities Act of 1990', IRISS WP 2009-07, July 2009.

Choe C. & Chrite E., 'Internal Migration of Blacks in South Africa: Self-selection and Brain Drain', IRISS WP 2009-06, July 2009.

Raileanu Szeles M. & Fusco A., 'Item response theory and the measurement of deprivation: Evidence from PSELL-3', IRISS WP 2009-05, May 2009.

Bazyl M., 'Factors influencing tenure choice in European countries', IRISS WP 2009-04, April 2009.

Valentova M., 'Employment breaks due to childcare in the Czech Republic. Before and after 1989', IRISS WP 2009-03, March 2003.

Sohn C., Reitel B. & Walther O., 'Cross-border metropolitan integration in Europe (Luxembourg, Basel and Geneva)', IRISS WP 2009-02, February 2009.

Zhelyazkova N. & Valentova M., 'Womens Perceptions of Consequences of Career Interruption due to Childcare in Central and Eastern Europe', IRISS WP 2009-01, January 2009.

Pi Alperin M., 'A comparison of multidimensional deprivation characteristics between natives and immigrants in Luxembourg', IRISS WP 2008-14, December 2008.

Lincaru C., Predosanu G. & Brinza R., 'Process of transition from school-to-work: generator for the initial stage of path dependence in career development', IRISS WP 2008-13, December 2008.

Pavlopoulos D. & Fouarge D., 'Escaping low pay: do male labour market entrants stand a chance?', IRISS WP 2008-12, December 2008.

Abatemarco A., 'Measuring Inequality of Opportunity through Between-Group Inequality Components', IRISS WP 2008-11, November 2008.

Nichols A., 'Trends in Income Inequality, Volatility, and Mobility Risk', IRISS WP 2008-10, November 2008.

IRISS-C/I 10th Anniversary Conference on 'The measurement of discrimination, inequality and deprivation: Recent developments and applications: Book of abstracts', IRISS WP 2008-09, November 2008.

Ayllón S., 'Modelling poverty transitions in Spain: Do attrition and initial conditions really matter?', IRISS WP 2008-08, October 2008.

Neocleous T. & Portnoy S., 'A Partially Linear Censored Quantile Regression Model for Unemployment Duration', IRISS WP 2008-07, September 2008.

Electronic versions

Electronic versions of all IRISS Working Papers are available for download at
http://www.ceps.lu/iriss/wps.cfm

IRISS-C/I is a visiting researchers programme at CEPS/INSTEAD, a socio-economic policy and research centre based in Luxembourg. It finances and organises short visits of researchers willing to undertake empirical research in economics and other social sciences using the archive of micro-data available at the Centre.

What is offered?

In 1998, CEPS/INSTEAD has been identified by the European Commission as one of the few *Large Scale Facilities* in the social sciences, and, since then, offers researchers (both junior and senior) the opportunity to spend time carrying out their own research using the local research facilities. This programme is currently sponsored by the European Community's 6th Framework Programme. Grants cover travel expenses and on-site accommodation. The expected duration of visits is in the range of 2 to 12 weeks.

Topics

The major resource offered to visitors is access to a series of internationally comparable longitudinal surveys on living conditions at the household and individual level. The anonymised micro-data provide information on wages and income, health, education, employment and professional activities, accommodation, social relations,... Comparable micro-data are available for EU countries, Central European countries, as well as the USA. These data offer opportunities to carry out research in fields such as *survey and panel data methodology*, *income distribution and welfare*, *income and poverty dynamics*, *multi-dimensional indicators of poverty and deprivation*, *gender, ethnic and social inequality*, *unemployment and labour supply behaviour*, *education and training*, *social protection and redistributive policies*, *fertility and family structures*, *new information technologies in households and firms*, ...

Who may apply?

All individuals (doctoral students as well as experienced academics) conducting research in an institution within the EU-25 or an FP6 Associated State. IRISS-C/I can be meeting place for groups of researchers working on a joint project. We therefore encourage joint proposals by two or more researchers.

For more detailed information and application form, please consult our website: http://www.ceps.lu/iriss or contact us at

IRISS-C/I, CEPS/INSTEAD
BP 48, L-4501 Differdange, G.-D. Luxembourg
Tel: +352 585855 610; Fax: +352 585588
E-mail: iriss@ceps.lu