The Returns to Education and Basic Skills Training for Individuals with Poor Health or Disability

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THE RETURNS TO EDUCATION AND BASIC SKILLS TRAINING FOR INDIVIDUALS WITH POOR HEALTH OR DISABILITY

Abstract

This paper examines linkages between disability and health status and the returns to education and basic skills training. It bases analyses on two separate data sources: wave 3 from the 1993 panel of the Survey of Income and Program Participation (SIPP) and the 1992 National Adult Literacy Survey (NALS).

The data sets have been used to estimate standard wage equations with education and basic skills training among the independent variables. The NALS data set allows us to control for prose, quantitative, and document literacy. The wage equations rely on Heckit corrections for labor force participation, and we stratify by sex. We also estimate the wage equations stratifying by disability status (also with an appropriate econometric correction) to permit the coefficient estimates on all the regressors to vary by disability status. Overall, we find that the returns to education for individuals with a disability or poor health are positive, although of moderate size and equal to the returns for the nondisabled population. The findings suggest supply side policy options that maintain or improve access to and retention in educational opportunities are indicated. Basic skills training seems to be especially advantageous for some individuals.

INTRODUCTION

In 1990, the U.S. Congress passed legislation perceived as a hallmark in the quest by disabled individuals for equal access to labor market opportunities. The Americans with Disabilities Act (ADA) mandates accommodations and provides civil rights protection to the disabled. It is arguably too soon to make a final judgement about this legislation, but many studies suggest it has had, at best, limited success (See Burkhauser and Daly, 1996; Oi, 1996). The evidence suggests that it may have lengthened retention moderately, but it has had little impact on labor force entry or earnings. Furthermore, early evidence suggests that the ADA might have had the unintended consequence of reducing employment rates of the disabled, consistent with a hypothesis of employer discrimination (DeLeire, 2000).

Because its primary intent is to expand the number of employment opportunities for disabled individuals, the ADA may be characterized as a demand-side intervention.[1] Numerous education, training, and rehabilitation programs operate on the supply side of the labor market. Their intent is to enhance the skills and knowledge of disabled workers, which would increase their productivity and employability. The returns to education and to general basic skills training for the disabled population are indicative of the potential efficacy of such supply-side interventions. If the rates of return to education, training, or rehabilitation are large, then it might be argued that there is an underinvestment in such interventions. If the rates are low, then expanding these human capital interventions as a way to improve employment or earning may not be indicated. Our empirical work finds that the returns for disabled workers are somewhat in between. They are positive, indicating that access to and participation in education and training are important for disabled individuals, but they are not so large as to argue for substantial increases.

While the main focus of the paper is on the education returns for individuals with poor health or disability, the paper also compares the returns for disabled workers to those for the nondisabled population. Theoretically, we hypothesize that the returns for disabled individuals will be lower, *ceteris paribus*. However, empirically identifying the returns to education for individuals with poor health or disability is quite difficult. In general, individual productivity in the labor market depends on health status and education (proxying for human capital), among other things. A health condition that impairs an individual's ability to perform his/her work obviously diminishes his/her productivity by definition (the marginal contribution of health status is positive). But in a *ceteris paribus* framework, is there any reason to believe that a health

[1] Of course accommodations may be expensive. If they raise the quasi-fixed costs of employment (see Oi 1962), they may depress employment demand.

impairment diminishes the marginal productivity of a unit of education (i.e., is the second derivative with respect to health and education negative)?

Theoretically, it seems to us that the answer is probably “yes” for most individuals. Just as poor health diminishes the efficiency with which one accomplishes a task, it also diminishes the efficiency in how one applies a unit of education toward the accomplishment of a task. However, empirically, we may find higher returns. As discussed below, selection issues along several dimensions of unobserved variables may confound any estimates of returns. For example, it may be the case that workers in poor health or with a disability differ from nondisabled workers in motivation; they may be far more motivated. Consequently the estimated return to education would be biased upward. Aside from selection bias, there are other reasons to anticipate that educational returns for disabled individuals are higher than for the nondisabled. It may be the case that individuals with poor health who participate in the labor market may have a comparative advantage in their educational credentials and sort themselves into jobs where education affects productivity much more than health status. It may also be the case that barriers to full accessibility of educational opportunities has resulted in underinvestment by individuals with disabilities and observed returns are therefore inframarginal.

Finally, any analysis of the labor market outcomes for individuals with poor health or disability must acknowledge the heterogeneity of this population with respect to health status. Considerable variation exists in type of impairment, severity of condition, age at onset, prognosis for recovery, and access to health care resources. Obviously, in the empirical work, our definition of disability is limited by the information available in our two data sets. We attempt to examine the stability of the results with respect to the definition of disability, but as a general caveat, we simply do not have the information available to pinpoint the variation in returns to education and training with respect to the variation in condition.

The next section of this paper discusses the labor market experiences of the disabled population. Virtually all data sets and all studies document the poor labor market performance and outcomes of the disabled population relative to the nondisabled, and this study is no exception. Next we present and discuss previous evidence on the returns to education for the disabled population. Here the evidence is mixed; some studies find returns to education for the disabled that are higher than for the nondisabled, and others find the opposite. That section is followed by a brief presentation of our three increasingly sophisticated empirical specifications, which encompass a discussion of the complex nature of the selection on unobserved characteristics for this population. We then discuss our data sources followed by a presentation of the empirical results. Finally, we conclude with findings and recommendations.

EXISTING EVIDENCE ON LABOR MARKET CHARACTERISTICS OF THE DISABLED

Kruse (1997) presents a detailed summary concerning people with disabilities who have employment potential. He defines employment potential based on detailed disability information garnered from the 1992 and 1993 panels of the SIPP (Survey of Income and Program Participation). He estimates that 18.4 percent of the total population between the ages of 15 and 64 have disabilities, and he calculates that this group has an employment rate of 51 percent, compared with 75 percent for the nondisabled.[2] In regression analyses of employment, Kruse uses the standard technique of a first-stage probit model to explain the probability of being disabled, then using the resulting inverse Mills ratio in a regression model for employment. Having a disability is significantly negative in the employment regression, suggesting that unobserved or unmeasured characteristics explain the lower employment rates. These characteristics might include ability to work, access to jobs, discrimination, and possibly diminished returns to human capital. It is the final consideration that is the focus of this paper. DeLeire (2000) tackles a related topic, employment and earnings of the disabled pre- and post-ADA using data from the Survey of Income and Program Participation. He finds that post-ADA employment rates for the disabled are 7.2 percentage points lower than before the passage of ADA, a decline during a time period that the disabled employed's wages did not change.

Ettner, Frank, and Kessler (1997) examine the importance of psychiatric disorders on labor market outcomes including employment, hours, and income. They analyze data from 1992 on men and women from the National Comorbidity Survey. They find strong evidence that employment rates are reduced by about 11 percentage points for both men and women with psychiatric disorders. They also find that psychiatric disorders are associated with significant declines in income but only limited reductions in hours, implying that the disorders affect wages which reflect reductions in on-the-job productivity.

Mitchell and Burkhauser (1990) examine the relationship between arthritis and earnings by using a simultaneous equations approach to disentangle the effect on wages and hours. They find a strong link between arthritis and earnings, but they note that arthritis affects wages differently from hours and has different impacts on men and women. Education plays a complicated role in these results. Hendricks, Schiro-Geist, and Broadbent (1997) study the linkage between disability and employment outcomes for those who have had the opportunity to pursue both a university education and rehabilitation services. Their

[2]When he focuses on the non-severely disabled, the employment rate increases to 74.1 percent.

data include students who graduated from the University of Illinois between 1948 and 1993 who participated in rehabilitation services for long-term disabilities while at the university, an "intervention" that is relatively early in their working careers. The authors estimate that the salary gap between the disabled and nondisabled workers in 1992 was 8.3 percent when regression analyses are used to control for individual and human capital characteristics.

Loprest et al. (1995) use the first wave of the Health and Retirement Survey to examine the importance of gender and disabilities on employment outcomes. They find that the type of disability measure chosen for the analysis is important to the findings, and they find significant differences in occupational choices by disability status. Two disability measures that rely on functional limitations and health impairments have significant and negative affects on the employment outcomes. Stern (1989) uses two data sets, the 1978 Survey of Disability and Work and the 1979 cohort of the Health Interview Survey. He estimates a simultaneous equations model of endogenous reported disability and labor force participation, using symptoms or diseases as instruments for disability. He finds that his two self-reported health status measures (the work-limiting condition measure and the overall health status measure) serve as good proxies for estimating the effect of disability on labor force participation. His estimation results show that each measure of disability plays an important role in explaining variation in labor force participation.

Bound, Schaenbaum, and Waidmann (1995) use the first wave of the Health and Retirement Survey to study race and education differences in disability status and labor force attachment. They find that measures of current health status are strong predictors of disability status and employment for men aged 50B61. Also, they find that a substantial portion of the racial employment gap observed in middle-aged men can be explained by differences in health status and functional ability. They also find that the middle-aged man's occupation affects the manner in which he will adapt to the onset of a disability, and in fact, the occupation itself explains a good portion of the tendency to self-identify as disabled.

Overall, these studies support the somewhat unsurprising finding that disabled individuals are less likely to work, and when they do work, they tend to earn lower wages. The studies also highlight differences across sex and type of disability, as well as the significance of the age of onset of disability.

EVIDENCE ON THE RETURNS TO EDUCATION FOR DISABLED INDIVIDUALS

The existing literature on the effects of discrimination on employment outcomes for the disabled versus nondisabled populations contain relevant information concerning the importance of education on wages. Baldwin and Johnson (2000, 1995, 1994), O'Hara (2000), and Johnson and Lambrinos (1985) examine the importance of discrimination in wages or employment for disabled individuals.[3] Each study reports estimates of wage equations run separately by disability status, yielding estimates of the returns to education for disabled and nondisabled samples.

Johnson and Lambrinos (1985) examine wage discrimination against handicapped men and women using the 1972 Social Security Survey of Disabled and Nondisabled Adults. They focus on *handicap*, which is a "disadvantage resulting from an impairment or a disability. Hence, an impairment subject to prejudice is a handicap, whether or not it is disabling." (p. 265) Their estimates of the returns to education for non-handicapped men are 0.054, while they find handicapped men generate a 0.040 return. The returns for non-handicapped and handicapped women are 0.037 and 0.020, respectively. So, in their regressions using the natural logarithm of the wage, they find lower overall returns to education for women, and lower returns for the handicapped.

Baldwin and Johnson (1995) estimate that the returns to education for nondisabled women to be 0.054, while it is 0.014 (and not significant) for disabled women. The disability measures used by the authors were derived using principal components analysis to construct three functional limitation variables from the 12 variables measured in wave 3 of the 1984 SIPP. Baldwin and Johnson (1994) focus on men using wave 3 of the 1984 SIPP and estimate returns to education equal to 0.059 for nondisabled men, 0.055 for disabled men, and 0.023 for handicapped men. (In this study, the term *disabled* means existence of impairments that are subject to little or no prejudice; *handicapped* means impairments subject to greater prejudice.) The study again used principal components analysis to construct their disability and handicapped measures. Baldwin and Johnson (2000) focus on men with disabilities using wave 3 of the 1990 panel of the SIPP and use the stratification of less prejudicial (LP) versus more prejudicial (MP) to denote impairments that are likely to generate less or more prejudice, respectively, rather than the handicapped versus disabled delineation used in their earlier studies. They find returns to education for the nondisabled, the LP impairments, and the MP impairments to equal 0.045, 0.044, and 0.053, finding a difference only for the disabled group with the impairments most likely to face prejudice in the workplace.

O'Hara (2000), using the 1990 full SIPP panel, focuses on the possibility of disabled women facing two sources of discrimination: from their disabilities and their sex. He also incorporates information regarding job changes over time into his analyses. He finds estimates of the returns to education equal to 7.0 percent for women workers with no disabilities, and to 6.0 and 9.0 percent for LP and MP disabled

[3] In this literature, the use of the word disabled differs from ours. These studies distinguish between the terms *disability*, *impairment*, and *functional limitation*. See, for example, Baldwin and Johnson (2000).

women workers. Hotchkiss (2000) estimates annual wage equations using Current Population Survey data from the years 1981 through 1999 and focuses on differences over time between the disabled and nondisabled populations. While her focus is not specifically on providing estimates of the differential effects of education on wage outcomes, her results indicate that the returns to education for the disabled are greater than those returns for the nondisabled, although this differential has narrowed over time.

The evidence seems to be mixed about the relative returns to education for disabled (or handicapped) individuals relative to their nondisabled counterparts. About half of the studies find a lower return and about half find a higher return. It is notable that the latter are the more recent studies.

DATA DESCRIPTIONS

Data from two population surveys have been used: the Survey of Income and Program Participation (SIPP) and the 1992 National Adult Literacy Survey (NALS). These two survey data sets differ fundamentally in the two key focal points of this paper: measurement of education and measurement of disability.

Basic criteria were imposed on both data sources to produce analyses samples that would be as comparable as possible. In both data sets, only individuals aged 25–62 were included in order to minimize problems associated with modeling formal human capital investment decisions or retirement decisions, both of which are joint with the employment choice. Additionally, the self-employed were excluded due to the difficulty in measuring wage returns to education when the wage reflects returns to both physical and human capital.[4]

The SIPP data come from the third interview of the 1993 Panel (called wave 3) that covers the time period September through December 1993. This SIPP contains detailed disability status measures that were designed to be consistent with the ADA (Americans with Disabilities Act of 1990) definition of disability. The topical module contains detailed information that encompass five categories of disability: instrumental activities of daily living (IADLs, such as going outside the home, preparing meals, or doing housework.), activities of daily living (ADLs, such as bathing, dressing, or eating), other functional disability

[4]Unfortunately, excluding the self-employed results in relatively more employed disabled individuals being dropped from the samples than nondisabled persons. As Kruse (1997) reports, employed people with disabilities are somewhat more likely to be self-employed than employed nondisabled people. Also reported in Kruse, the employed nondisabled are somewhat more likely to be in school than the employed disabled, so we lose disproportionately more nondisabled persons by the schooling restriction.

(difficulties in performing specific functional activities such as seeing, hearing, or climbing stairs), chronic conditions (such as autism, learning disabilities, or heart disease), and the more standard measure of disability, a self-reported assessment of the existence of a physical or mental condition that limits type or intensity of work that one can perform.[5] Basing our choice on the need for compatible measures for the two data sources, we define disability status using the self-reported response to the question concerning work-limiting conditions.[6]

The purpose of the 1992 National Adult Literacy Survey (NALS) was to measure the nature and extent of literacy among the adult population in the United States The Educational Testing Service (ETS) used the opportunity to develop a unique definition and measure of literacy using three scales: prose literacy, document literacy, and quantitative literacy. The data from this survey have several advantages for the purpose of estimating returns to education for an adult population. First, the extensive measures of literacy can be used to control for contemporaneous cognitive ability and, to some extent, for educational quality. An individual's cognitive ability at the time of participation in the educational system, presumably correlated with the cognitive ability at the time of the survey, helps to determine the effectiveness of the education. Furthermore, learning depreciates over time, and it is likely that the rate of depreciation varies with individuals. Having a contemporaneous assessment of cognition controls for this depreciation. Finally, it is likely that adult cognitive abilities are positively associated with the quality of their educational experiences.

In addition to the literacy measures, the NALS has several education and basic skills training measures that help refine the standard continuous years of education variable. The disability and health status information available in the NALS is much more limited than what is found in the SIPP, however. Disability is measured in NALS as the same sort of self-assessment of a work-limiting condition as in the SIPP. Finally, the NALS has fairly limited and unsophisticated questions about wage rates, employment or

[5]See Pezzin and Schone (1999) for an example of an application of the IADL and ADL disability measures.

[6]Using both the SIPP and the NALS, we also experimented with an alternative more broadly defined disability measure that combines the self-reported assessment measure with other more specific types of disability or poor health. Our overall empirical results were not altered by the use of this alternative measure and so are not reported in text or tables.

unemployment characteristics, and family income. The wage measure is weekly earnings, which are not as useful as hourly wages that can be constructed within the SIPP.[7]

Descriptive means for each variable in both data sets appear in tables 1–4.[8] To the extent possible, similar variables in the two data sets were defined in the same way. Table 1 displays SIPP variable means for men using four subgroups of the data: the employed nondisabled, the non-employed nondisabled, the employed disabled, and the non-employed disabled. Table 2 presents SIPP variable means for women, while tables 3 and 4 report the same variable means for men and women from the NALS.

SIPP data include 8,567 nondisabled employed men; 1,452 nondisabled, not employed men; 1,196 disabled men who work; and 1,044 disabled men who are not currently working. Table 1 shows that nondisabled men are younger than the disabled men, and those working (regardless of disability) tend to be younger than those not working. Working nondisabled men have the most education at 13.60 years, while their nonworking counterparts have 12.88 years of education. Disabled men have less education than either group of nondisabled men, with those working having 12.60 years of education and those not working having 11.17 years of education. Simply looking at education would suggest that the disabled would have lower wages. The disabled are less likely to be married, and the not-employed disabled are more likely to be nonwhite. Nonworkers have less monthly family income (that excludes own earned income) than workers, but the disabled non-workers have more family income than the not working nondisabled. This might be due to the receipt of disability-tied transfers, differences in family structure, or the aforementioned difference in age. The final two rows of table 1 show hourly wages and hours. For hourly wages, nondisabled men earn higher hourly wages, $14.69 an hour versus $12.02 an hour. Weekly hours follow the same pattern, with the nondisabled working more hours per week (a difference of over three hours per week or about 7 percent.)

The patterns in table 2 are largely the same as for the men; the major differences are in family structure and family income. For women, not working is associated with having more young children in the household. Also, despite the older mean age of the disabled group, they tend to have less family income.

[7]The NALS is a cross-section and we are using the SIPP data as a cross-section as well. Burkhauser and Daly (1999) point out that cross-sectional analyses of economic outcomes for disabled individuals may suffer bias because a cross-section will have a disproportionate share of individuals with disabilities of long duration. If such individuals have poorer labor market experiences and returns to education than average, then the returns to education will be biased downward.

[8]Both the SIPP and the NALS means are weighted to correct for any unintended non-randomness in the data collection as well as the systematic non-randomness in the NALS arising from its survey structure that intentionally over-samples specific subgroups of the population (for example, minority groups).

Finally, as expected, the hourly wages for the women repeat the pattern shown for the men, with lower hourly wages for the disabled women ($10.97 an hour versus $8.75 an hour) and lower weekly hours worked.

Variable means for the men and women in the NALS data are presented in tables 3 and 4. For the most part, the patterns revealed here mirror those shown in the SIPP data. The detailed education information in the NALS data follow the same trend as has the continuous years of education measure. That is, the disabled are substantially less likely to have earned a bachelor's degree and also score a lesser percentage correct on the three broad tests of literacy. Interestingly, the differences in literacy scores between working and nonworking individuals is much larger for the disabled population. Tables 3 and 4 present means for three types of literacy scales for men and women. The differences in these means for disabled individuals between those who are working and those not working is over 10 percent in five of the six cases (and 7.5 percent in the other case.) None of these differences is as great as 10 percent for nondisabled individuals. This suggests that literacy may be a substantial correlate for employment among disabled individuals.

The NALS also contains information about the primary language spoken at home. There is no substantive difference between the disabled and the nondisabled in the percentages who speak English as their primary language in the home. Additionally, dispelling any impressions that immigrants display greater tendencies towards disability, the disabled (both working and not working) are less likely to be immigrants. Finally, weekly earnings are, on average, lower for the disabled workers, but since this is a weekly figure, we cannot know what portion of this difference is due to lower hourly wages versus lower weekly hours worked.

EMPIRICAL SPECIFICATIONS OF THE WAGE EQUATION IN THE PRESENCE OF MULTIPLE TYPES OF SELECTIONS

The empirical work is based on the standard human capital wage equation as developed by Mincer (1974). The wage equation, written out below, relates the calculated wage (which is an hourly wage in SIPP constructed by dividing earnings on the primary job by hours on the primary job, and is reported weekly earnings in NALS) to individual measures of human capital, demographic control variables, job characteristic variables, and regional controls. The wage is included in its natural logarithmic form so that the resulting estimated coefficients are more easily interpretable as percentage returns to education. A limitation in the NALS is that wages are measured as weekly earnings, so the returns to education may include the impact on weekly hours. Equation (1) presents a linear estimable specification of this basic model:

$$(1) \qquad \ln W_i = a_1 + B_1' X_i + B_2 D_i + B_3 ED_i + B_4 D_i * ED_i + e_i$$

where	W_i	=	hourly (or weekly) wage of individual i
	X_i	=	vector of characteristics describing individual i that are thought to be related to wages
	D_i	=	1, if individual i has a disability (or vector of health status variables); 0 otherwise
	ED_i	=	years of education that have been completed by individual i
	a_1, B_1, B_2, B_3, B_4	=	parameters to be estimated
	e_i	=	standard error term

The parameter of most interest is B_4. If it is negative, then the returns to education for the nondisabled population, i.e., B_3, exceed the returns for the disabled population. Unfortunately, there are several econometric complexities that influence the B_4 coefficient. These complexities arise from unobserved heterogeneity between the disabled and nondisabled observations in our data sets. Equation (1) assumes orthogonality between the regressors and the error term, but there are at least three sources of potential bias that may confound the differential estimated returns. They are unobserved heterogeneity, or systematic differences, in the following characteristics:

(i) labor force participation and employment behavior

(ii) declaration of health status/disability

(iii) education.

All three characteristics may be influenced by individual psychosociological variables such as motivation, initiative, self-esteem, or locus of control. If disabled individuals face greater barriers to access, for example because of physical limitations or because of adverse discrimination, then those individuals with disabilities who are in the labor force, employed, or have high educational attainment may be the most motivated. They may have the greatest levels of initiative or self-esteem. If motivation or initiative are also positively correlated with wages, as they undoubtedly are, then the coefficients on disability status and on the disabilityBeducation interaction term will be biased upward.

Economic models of individual labor force participation behavior and of educational attainment theorize that these choices are investments made in order to reap future returns. As such, the individual optima depend on the future orientation of the choice makers and on the value of alternative choices. These factors may again be a source of unobserved heterogeneity between the disabled and nondisabled workers. Future orientation, or equivalently the discount rate, may vary significantly across the disabled and nondisabled populations. For the former, it may be the case that labor force participants and persons with high levels of education have strong future orientation, i.e., low discount rates. Again this will bias the returns to education to the extent that future orientation is positively related to wages.

Similarly, a relatively high opportunity cost of labor force participation because of attractive non-earned income alternatives will dampen such participation and, consequently, employment. Disabled individuals have transfer income opportunities in the Social Security Disability Income (SSDI), Supplemental Security Income Disability Income (SSIDI), and, arguably, in worker's compensation. SSDI and SSIDI have experienced accelerated growth in beneficiaries over the last couple of decades, suggesting that take-up rates are growing. The presence of such alternatives increases the likelihood that the individuals who are eligible for them, but who are in the labor force and working, have relatively lucrative wage opportunities because those with less-lucrative wage opportunities choose to not work and receive public benefits.[9]

Finally, the data sources have self-reported health status and disability measures. The declaration of such indicators may be a source of measurement error and heterogeneity. If an individual's health condition is not observable by the data collector, then the respondent has a choice to make about whether to report the condition.[10] Generally, there are no incentives or disincentives in a national survey like SIPP or NALS to influence reporting behavior systematically, but the individual may still misreport. Individuals who are not participating or who do not have high levels of educational attainment may report a health condition obstacle. On the other hand, individuals who are working and have high levels of education may not perceive their health condition to be an obstacle or disability and therefore not report it.

[9]See Haveman and Wolfe (2000) for an in-depth discussion of the relationship between disability policies and labor market behavior for the disabled.

[10]This will be the case for most surveys. For example, if the data are collected by telephone or if a single respondent provides information for a family or household, the individuals who are collecting the information will be unaware of poor health or disabilities. Furthermore, a health condition or disability may be internal and unseen even when the data collector is interacting personally with the individual.

To isolate unbiased education returns requires some attention to these sources of unobserved heterogeneity. We address the labor force participation and employment heterogeneity through the standard technique of estimating a preliminary employment equation in order to construct an inverse Mills ratio term that will serve as a statistical correction when estimating wage equations only for those individuals with observed wages (i.e., for those currently working) (Heckman, 1974). The basis of our empirical work relies on the following empirical specification of the probit model, in which the continuous latent variable p_i* (reflecting preferences for paid work) is expressed as the observed discrete employment outcome:

(2) EMP_i = 1 if $p_i^* > 0$

= 0 otherwise

where p_i^* = $a_2 + C_1'Y_i + C_2ED_i + u_i$

EMP_i = 1 if individual i participates in the labor force and has positive, earnings/wages; 0 otherwise

Y_i = vector of characteristics describing i that are thought to be related to labor force participation

a_2, C_1, C_2 = parameters to be estimated by probit

u_i = standard error term

We then use the predicted inverse Mills ratio for each observation in the sample of workers in equation (1).[11]

Among the X_i variables in equation (1) when estimated with the NALS data is participation in basic skills training, which for many labor market participants, has a substantial payoff (Hollenbeck, 1999). This measure of human capital investment is not often available in employment-related data sets, but for adult workers, particularly those with lower levels of educational attainment, such training may be a means for significantly improving one's skills.[12] It should be recognized, however, that like education, its effects on wages may be skewed by unobserved heterogeneity.

[11]Variables that are included in the estimation of (2) but not (1), thus helping to identify it, include the presence of other earners in the household, nonearned family income, receipt of transfer income, and number of children in the household.

[12]The variable that we are using is the response to the question "Have you taken part in a program other than in

The wage (1) and employment (2) equations are somewhat restrictive in that they assume that the coefficients on all variates other than education are identical for disabled and nondisabled workers, save for an intercept shift. It is, however, possible that the entire wage structure (i.e., all wage equation parameter estimates) varies by disability status. Recognizing this possibility, a more general estimation strategy to follow is to assume that employment behavior and wage determination mechanisms are totally separate for the disabled and nondisabled populations. Empirically, this means estimating equation (1) with the Heckit selection term (but without the variable D) and (2) separately for disabled and nondisabled samples of working adults. The hypothesis being tested here is that B_3 for the disabled sample is less than B_3 for the nondisabled population.

Stratifying the samples into their disabled and nondisabled subgroups using the self-reported disability status indicator is a reasonable approach to test for structural differences in employment and wage behavior. However, as noted earlier, reporting disability may be endogenous. A more sophisticated estimation strategy attempts to control for the potential endogeneity of the disability indicator, D_i, by explicit modeling of the presence of a (self-reported) disability. We implement this strategy by using the disability status indicator as an endogenous switching mechanism. We treat it as endogenous because the probability of self-reporting disability is itself an outcome determined by both personal characteristics and state characteristics. Among the explanatory variables that we use to explain and identify disability status are state variations in the take-up rate of SSI and SSDI, state variations in access to medical care for pregnancies from 1969 (which influences the quality of birth outcomes and therefore adults' potential productivity), and state variations in industrial accident rates and smoking rates.

The precise model is a two-step endogenous switching regression model as described by Maddala (1983). To present this procedure in text, we start by repeating equation (1) in a simplified way, writing it out twice for the disabled and nondisabled groups (where *D* represents disabled and *N* represents nondisabled):

(3) $$\ln W_{Di} = B_D X_{Di} + e_{Di}$$

(4) $$\ln W_{Ni} = B_N X_{Ni} + e_{Ni}$$

regular school in order to improve your *basic skills,* that is, basic reading, writing, and arithmetic skills within the past year?"

The underlying switching mechanism is determined by a probit disability model. In Equation (5) below, d_i^* is a continuous latent variable describing underlying propensities to report oneself as disabled and D_i is the observed disability status.[13]

(5) $D_i = 1$ if $d_i^* > 0$

$= 0$ otherwise

where $d_i^* = \gamma Z_i + \varepsilon_i$

Z_i = vector of characteristics describing *i* that are thought to be related to the likelihood of reporting a work-limiting disability

γ = vector of parameters to be estimated by probit

ε_i = error term

In Maddala's terminology, Regime 1 (equation 3) holds as long as $\gamma Z_i \geq \varepsilon_i$ and Regime 2 (equation (4)) holds as long as $\gamma Z_i < \varepsilon_i$, and e_i is correlated with e_{Di} and e_{Ni}. According to Maddala, due to these error correlations, the model is known as a switching regression model with endogenous switching. Because the sample separation is based on reported disability status, which is an observed indicator, Maddala shows that a maximum likelihood probit model can be used to estimate the parameters in gamma.[14] Finally, Maddala derives the full specification for the switching wage regressions above that includes a "correction" term for each of the two wage equations to adjust for the endogenous stratification on disability status. This full specification includes terms constructed from the results of the disability probit model written out in equation (5).

(6) $$\ln W_{Di} = B_D X_{Di} + \sigma_D \omega_{Di} + e_{Di}$$

(7) $$\ln W_{Ni} = B_N X_{Ni} + \sigma_N \omega_{Ni} + e_{Ni}$$

where $\omega_{Di} = \dfrac{\phi(\gamma' Z_i)}{\Phi(\gamma' Z_i)}$

[13] Of course, it is also likely that the labor force participation outcome is correlated with the disability outcome. An appropriate correction for these joint problems would be to estimate the 0–1 LFP probit jointly with the 0–1 disability probit equation using a full bivariate probit model. Unfortunately , due to weaknesses inherent in identifying such highly correlated outcomes, the bivariate probit model proved to be inestimable in our small NALS samples. However, using the bivariate probit model to construct joint correction terms for use in the wage equation does work for the SIPP, and produces results comparable to the results achieved using the two separately run probit correction models.

[14] This model assumes that because gamma is estimable only up to a scale factor, var(e_i) = 1.

$$\omega_{Ni} = \frac{-\phi(\gamma' Z_i)}{[1-\Phi(\gamma' Z_i)]}$$

$\sigma_{D,N}$ = parameters to be estimated

ϕ, Φ = standard Normal pdf and cdf.

Estimation of equations (6) and (7) yields consistent parameter estimates.[15]

SUMMARY OF ESTIMATION STRATEGY

All models have been estimated separately for the two different data sets and separately by sex. The latter stratification is useful given the long established literature on wage structure differences by sex. We approach the problem of differentiating the returns to education between the disabled and the nondisabled in two ways. Our initial specification includes both the disabled and nondisabled in a single wage equation that contains a discrete measure of disability status, years of education, and an interaction of disability status with years of education. The coefficient on years of education will be referred to as the returns to education for the nondisabled population. That coefficient plus the coefficient on the interaction term will be referred to as the returns to education for the disabled group. This approach includes the Heckit correction designed to address the problem of estimating wages for workers only.

The second approach (more like what is seen in the discrimination literature) is to stratify the samples by disability status, without correcting this potentially endogenous stratification. We estimate a wage equation for the sample of disabled individuals separately from the wage equation for the nondisabled individuals, thereby producing estimates of the returns to education separately by disability status. The third approach is the switching regression approach described earlier. This permits estimation of the returns to education for disabled separately from nondisabled, as well as allowing all other coefficients to vary by disability status, and permits an appropriate econometric correction for stratifying the samples based on a potentially endogenous disability status indicator.

Our empirical specification ignores any systematic unobserved heterogeneity in education across the disabled and nondisabled population. A justification for this simplification is that in one of our data sets, we

[15]Because generated values of ù are used in the wage equations, the results are heteroscedastic and Maddala describes a weighted least squares estimation procedure to account for this problem. However, each of our two wage equations include two separate generated correction terms, making WLS less feasible. In any event, the results are still consistent and typically, coefficient values in such regressions are not substantively altered by implementing the appropriate econometric correction.

have measures of literacy that proxy for ability.[16] While it is convenient to assume away the education selectivity, we recognize the sizeable returns to education literature that attempts to compensate for the fact that investment in human capital is an endogenously determined outcome variable that is correlated with unobserved ability, so its direct inclusion as a right-hand side regressor can be problematic. This strand of the education literature often relies on institutional features as instrumental variables for individual schooling outcomes. The *a priori* expectation of these studies is that the returns to education estimates obtained from simpler models might be overstating the true returns to education and this might explain some of the rise in these estimates in recent years. These studies are reviewed by Card (2000), who finds that the IV estimates are relatively imprecise, but still at least as large (and sometimes much larger) than the non-IV estimates. This alleviates the concern that the non-IV estimates result in overestimates of the returns to education. There is also a strand of the health/education literature that examines the positive correlation of education and health outcomes. Berger and Leigh (1988) examine potential causes for this correlation and conclude that the direct effect of schooling on health is more important than the effect of unobservables jointly on both outcomes.

ESTIMATES OF THE RETURNS TO EDUCATION AND LITERACY TRAINING

Tables 5 and 6 provide estimates of the returns to education from wage models run on the SIPP and NALS data using our definition of disability, which is an affirmative answer to whether the survey respondent has a health condition that limits her/his ability to work.[17] The entries in the tables are coefficients from a regression on wages (or weekly wages) in logarithmic form so they may be interpreted as percentage effects. The other independent variables in the wage regressions control for other demographic and human capital characteristics, and include the inverse Mills ratio (IMR) from a first stage regression of labor force participation to control for the effect of selecting on positive wages.[18] Note that the SIPP equations use hourly wages as the dependent variable while the NALS equations use weekly earnings.

[16] In any event, our data do not include reasonable correlates for education that are not related to wages for use in a corrective IVE procedure and potential state-level data instruments performed poorly in preliminary runs.

[17] All estimation was repeated using a second more broadly defined disability measure that includes the self-report on disability status plus many additional medical conditions. The empirical findings are not affected by this alternative definition.

[18] The first stage regressions on labor force participation include sex, age, age squared, minority status, marital status, presence of children (SIPP only), region, years of education, current student status, monthly family income excluding own earnings (SIPP), English speaking ability (NALS), immigration status, presence of other earners in

Consequently, results from the latter data set are confounded by the influence of the explanatory variables on hours worked per week.

The first panel in tables 5 and 6 display the estimates under the most restrictive model that relies on a single wage equation (with an interaction term) for both disabled and nondisabled individuals, and a labor force participation correction term estimated over the entire population. In the first table with estimates from the SIPP, the returns to a year of education are estimated to be about 10 percent, with the returns for women (even reduced for disability by about 1.5 percentage points) being much greater than the returns for men. The estimates from NALS in table 6 show a weekly earnings return to a year of education of around 3B4 percent; and again, lower for males and higher for females. The returns to education under this estimation strategy are virtually identical for the disabled and nondisabled individuals in the SIPP, whereas the returns for the disabled workers are about 20 percent higher in NALS (more precisely for female workers in NALS). Table 6 shows a high return to basic skills training of 7B22 percent, although the estimates for the disabled individuals are imprecise. Nevertheless, it is striking that the point estimates of these returns are approximately of the same magnitude as having a bachelor's degree. When one examines means for the two populations, it is clear that the basic literacy of the disabled population is much lower than of the nondisabled population, especially for women. So it is entirely plausible that basic skills training has a substantial payoff.

The results shown in the middle panels of tables 5 and 6 present the returns to education and basic skills training when estimates are derived from wage equations and first-stage labor force participation probits run separately on disabled and nondisabled populations. Using the SIPP data, we find that the returns to education for the disabled population are much higher than the returns for the nondisabled. They are almost 20 percent for the former and 5 percent for the latter. The estimates from the NALS, shown in table 6, tell a different story. The estimated returns to education and basic skills training for the nondisabled population are virtually identical to those in the top panel of the table estimated with the entire sample. Yet the estimated returns for disabled workers are quite different and, in magnitude, lower than in the top panel of the table (except for the estimated returns to basic skills training for disabled males.)

The bottom panel of the tables show the returns to education produced by the full switching model. In other words, the estimates have been generated by explicitly modeling and controlling for disability reporting behavior. Econometrically, the results suggest that disability reporting behavior does add a systematic bias in the SIPP but not in the NALS. The estimated returns to education in the third panel of

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household (NALS), and presence of transfer income (NALS).

table 5 show parity between disabled and nondisabled individuals, as in the upper panel, but quite unlike the results in the middle panel. This is consistent with a positive selection story. Relative to individuals who report no work-limiting disability, those individuals who *do* report such a disability are more likely to have unobservable characteristics associated with higher wage rates. However, an examination of the estimates from the NALS in table 6 shows that the estimated returns to education and basic skills training in the bottom panel of the table are quite similar to those in the middle panel (which are similar in magnitude to the estimates in the top panel for nondisabled workers).

In attempting to reconcile the magnitudes of the estimated returns between the NALS and SIPP data sets, we restricted the models estimated in NALS to have the identical covariates as used in the SIPP estimates (i.e., we deleted literacy scores, basic skills training, and educational degree attainment). The gap between the two sets of estimates given in tables 5 and 6 was approximately 5-6 percentage points (about 3 percent for the NALS and 8-9 percent for the SIPP). The restricted model in NALS resulted in narrowing the gap, but only slightly. The returns to education (not shown in tables) for NALS were approximately 4-5 percent. We conclude that the differences in magnitude between the two data sets stem mainly from use of different dependent variablesBhourly wage versus weekly earnings, entirely different population samples, and random survey and nonsurvey error.

Finally, tables 7 and 8 provide the full set of coefficients for the wage equations estimated using the switching approach. In the SIPP, comparing the first and third columns of coefficients in table 7 shows that the main differences between disabled and nondisabled male workers is in the age-wage profiles and in the impact of current enrollment in education on wages. However, comparing the second and fourth columns shows many differences between the wage determination functions for disabled and nondisabled females. For example, disabled women who are married are estimated to have an 8 percent wage disadvantage, whereas nondisabled married women have a 2 percent disadvantage. There are also substantial differences in the age-wage profile, in residence characteristics (metropolitan status and region), in years of schooling, and in industry and occupations.

In table 8, the coefficients estimated with the NALS using the switching model data are displayed. Recall that the NALS has literacy test score data, basic skills training participation, and more educational attainment data than the SIPP. But the patterns of coefficient estimates in table 8 are qualitatively very similar to those in table 7. Relatively few differences can be seen between nondisabled and disabled males in the first and third column of estimates. Region of residence and metropolitan status are the only variables for which the coefficients are significantly different. There are more differences for women. For example, nonwhite disabled women have a 41 percent wage advantage over majority women, whereas nonwhite nondisabled women have but a 10 percent return. Other substantial differences can be found with marital status, metro residence, years of education, and some of the industry and occupational dummies.

CONCLUSIONS

Our findings undergird the importance of supply-side human capital investments for disabled individuals. Estimates of the returns to education and basic skills training are significant for this population. Continued attention on access to and retention in educational opportunities are clearly proscribed.

Four empirical results stand out. First, the returns to a year of education are moderate and statistically significant for both the nondisabled and disabled populations. The SIPP estimates estimates suggest that each year of education returns 8 B 9 percent higher wages, whereas the NALS estimates place the returns in the 3 B 4 percent range for weekly earnings. The literature on the returns to training argues that if there were a significant underinvestment in education or training, then there would be a very high return on that investment. The magnitudes estimated here do not suggest such an underinvestment, but are nevertheless healthy enough to imply that education is a good investment.

Second, the return to a year of education for females is much higher than for males for both disabled and nondisabled individuals. The SIPP estimates of 13 B 15 percent may be indicative of underinvestment in education for women. Obviously disabled women have their disability as an obstacle to investment in education, but women may have child-rearing, child care, or other family-related responsibilities that constrain their educational attainment as well. Our results may signal access to education for disabled women as an important role of public policy.

Third, the estimates seem to indicate that the differential between returns to education for disabled and nondisabled individuals is fairly minimal. Small sample sizes for the disabled population make their estimated returns unstable, but the three panels in each of tables 5 and 6 provide several different estimates of the returns to a year of education, and the differences between disabled and nondisabled workers are most often very slight. The more important point than trying to resolve the relative magnitudes of the returns for disabled and nondisabled populations is that estimates from both data sets are significant and positive for both.

A final important finding from our study is the significant payoff to basic skills training for the disabled population. On average, individuals with a disability or a chronic health condition have much lower levels of literacy (as measured by the three scales in the NALS data) than the nondisabled, and among the disabled population, individuals working have much higher literacy scores than those not working. Basic skills training, presumably in reading and mathematics, seems to have fairly large payoffs in terms of weekly earnings. Given that the monetary costs of this type of training are quite modest (Hollenbeck, 1993), the return on investment is, on average, extremely large.

The estimates that we have reported are subject to the usual caveats of cross-sectional data. Furthermore, they may be subject to serious selection problems cause by the endogeneity of labor force behavior and the potential endogeneity of disability reporting. The latter seemed to be an important consideration in the SIPP, but not in the NALS. In the latter data set, the self-reported disability measure appears to be nearly random, or least cannot be modeled using the information we have available in our data.

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Table 1 **SIPP Variable Means for Men** (Standard deviation in parentheses)

	Nondisabled		Disabled	
	In LF	Not in LF	In LF	Not in LF
Number of observations	8,567	1,452	1,196	1,044
Demographic Characteristics				
Age	40.16	41.68	43.35	46.55
	(9.5)	(11.4)	(10.2)	(10.9)
Education	13.60	12.88	12.60	11.17
	(2.8)	(2.9)	(2.6)	(3.0)
Non-white	0.11	0.16	0.10	0.20
	(0.3)	(0.4)	(0.3)	(0.4)
Number of children ages 0–6	0.40	0.32	0.27	0.24
	(0.7)	(0.7)	(0.6)	(0.6)
Number of children ages 7–17	0.61	0.48	0.53	0.45
	(0.9)	(0.9)	(0.9)	(0.9)
Marital status	0.74	0.60	0.65	0.55
	(0.4)	(0.5)	(0.5)	(0.5)
Number of children	1.01	0.80	0.79	0.69
	(1.2)	(1.2)	(1.1)	(1.2)
Monthly family income, excluding own earnings	$1980.14	$1469.87	$1998.32	$1727.18
	(2474.6)	(2326.4)	(2198.2)	(1718.8)
Regional Characteristics				
Live in metro area	0.76	0.70	0.76	0.70
	(0.4)	(0.5)	(0.4)	(0.5)
South	0.34	0.33	0.33	0.39
	(0.5)	(0.5)	(0.5)	(0.5)
Job Characteristics				
Hourly wage	$14.69	—	$12.02	—
	(9.3)		(8.4)	
Weekly hours	45.35	—	42.17	—
	(10.92)		(12.26)	

Table 2 **SIPP Variable Means for Women** (Standard deviation in parentheses)

	Nondisabled		Disabled	
	In LF	Not in LF	In LF	Not in LF
Number of observations	7,596	3,505	945	1,477
Demographic Characteristics				
Age	40.05	40.63	42.87	45.76
	(9.5)	(10.8)	(9.8)	(11.0)
Education	13.61	12.52	12.80	11.54
	(2.5)	(2.8)	(2.3)	(2.7)
Non-white	0.15	0.17	0.15	0.20
	(0.4)	(0.4)	(0.4)	(0.4)
Number of children ages 0–6	0.32	0.63	0.28	0.34
	(0.7)	(0.9)	(0.6)	(0.8)
Number of children ages 7–17	0.62	0.77	0.62	0.63
	(0.9)	(1.1)	(0.9)	(1.0)
Marital status	0.66	0.75	0.53	0.55
	(0.5)	(0.4)	(0.5)	(0.5)
Number of children	0.95	1.40	0.90	0.97
	(1.2)	(1.4)	(1.1)	(1.4)
Monthly family income,	$2587.21	$2637.13	$2085.83	$2084.78
excluding own earnings	(2557.5)	(2775.5)	(2187.0)	(2328.7)
Regional Characteristics				
Live in metro area	0.76	0.71	0.78	0.70
	(0.4)	(0.5)	(0.4)	(0.5)
South	0.34	0.35	0.34	0.38
	(0.5)	(0.5)	(0.5)	(0.5)
Job Characteristics				
Hourly wage	$10.97	—	$8.75	—
	(7.3)		(5.9)	
Weekly hours	37.94	—	35.48	—
	(11.1)		(11.5)	

Table 3 **NALS Variable Means for Men** (Standard deviation in parentheses)

	Nondisabled		Disabled	
	In LF	Not in LF	In LF	Not in LF
Number of observations	5,087	1,179	171	376
Demographic Characteristics				
Age	39.46	41.43	40.98	46.79
	(9.8)	(11.1)	(9.8)	(10.5)
Education	13.88	13.20	12.42	11.48
	(3.2)	(3.1)	(3.2)	(3.0)
Bachelor's degree	0.30	0.23	0.13	0.08
	(0.5)	(0.4)	(0.3)	(0.3)
Basic skills training	0.02	0.01	0.03	0.01
	(0.1)	(0.1)	(0.2)	(0.1)
Percent correct prose	75.85	73.13	69.78	61.33
	(19.3)	(20.4)	(22.7)	(23.7)
Percent correct document	83.15	80.41	79.06	73.95
	(15.7)	(17.2)	(17.2)	(20.3)
Percent correct quantitative	70.83	67.55	62.80	53.28
	(23.5)	(24.5)	(26.3)	(27.9)
English	0.97	0.96	0.99	0.98
	(0.2)	(0.2)	(0.1)	(0.1)
Immigrant	0.09	0.11	0.03	0.06
	(0.3)	(0.3)	(0.2)	(0.2)
Non-white	0.12	0.18	0.11	0.17
	(0.3)	(0.4)	(0.3)	(0.4)
Marital status	0.74	0.64	0.64	0.58
	(0.4)	(0.5)	(0.5)	(0.5)
Regional Characteristics				
Live in metro area	0.78	0.77	0.75	0.69
	(0.4)	(0.4)	(0.4)	(0.5)
South	0.32	0.33	0.41	0.42
	(0.5)	(0.5)	(0.5)	(0.5)
Job Characteristics				
Weekly wage	\$703.33	—	\$526.0	—
	(805.1)		(938.7)	

Table 4 **NALS Variable Means for Women** (Standard deviation in parentheses)

	Nondisabled		Disabled	
	In LF	Not in LF	In LF	Not in LF
Number of observations	5,472	2,960	205	615
Demographic Characteristics				
Age	39.87	40.29	42.77	47.33
	(9.7)	(10.6)	(9.0)	(10.5)
Education	13.68	12.78	12.96	11.33
	(2.8)	(2.8)	(2.8)	(2.8)
Bachelor’s degree	0.25	0.17	0.18	0.06
	(0.4)	(0.4)	(0.4)	(0.2)
Basic skills training	0.02	0.02	0.02	0.02
	(0.2)	(0.2)	(0.1)	(0.1)
Percent correct prose	76.60	71.74	72.89	62.27
	(17.8)	(20.4)	(19.0)	(25.1)
Percent correct document	83.28	79.74	79.10	69.72
	(14.8)	(16.7)	(17.2)	(21.4)
Percent correct quantitative	68.79	62.45	64.64	49.40
	(22.1)	(25.2)	(23.8)	(28.4)
English	0.98	0.95	0.99	0.98
	(0.1)	(0.2)	(0.1)	(0.2)
Immigrant	0.07	0.10	0.02	0.04
	(0.3)	(0.3)	(0.1)	(0.2)
Non-white	0.14	0.16	0.14	0.22
	(0.3)	(0.4)	(0.3)	(0.4)
Marital status	0.68	0.75	0.63	0.56
	(0.5)	(0.4)	(0.5)	(0.5)
Regional Characteristics				
Live in metro area	0.78	0.78	0.79	0.72
	(0.4)	(0.4)	(0.4)	(0.4)
South	0.35	0.34	0.41	0.38
	(0.5)	(0.5)	(0.5)	(0.5)
Job Characteristics				
Weekly wage	$403.97	—	$374.06	—
	(305.1)		(386.6)	

Table 5 **Returns to Education from a Model of Wages Estimated from the SIPP, by Sex and Total Population**

	All	Male	Female
1) Joint estimation			
Nondisabled	0.086***	0.011**	0.132***
	(0.004)	(0.005)	(0.011)
Disabled	0.086***	0.013	0.115***
	(0.007)	(0.008)	(0.013)
2) Separate without correction			
Nondisabled	0.054***	0.013***	0.108***
	(0.005)	(0.004)	(0.009)
Disabled	0.197***	0.048	0.148***
	(0.028)	(0.035)	(0.047)
3) Separate with switching regression			
Nondisabled	0.078***	0.045***	0.109***
	(0.007)	(0.007)	(0.013)
Disabled	0.073**	0.038	–0.083
	(0.034)	(0.040)	(0.065)

Note: Samples restricted to individuals aged 25–62 with wages. Entries are coefficients from OLS regression of log wages; standard errors are in parentheses. Other independent variables include sex (in "All" column), marital status, age, age squared, minority status, region, residence in metropolitan area, current enrollment, number of children in household, industry and occupation, inverse Mills ratio from first-stage probit regression on labor force participation, and inverse Mills ratio from disability reporting probit (in panel 3). Sample sizes for panel 1 are 9,763 males and 8,541 females. Sample sizes for panels 2 and 3 are 1,196 disabled males; 8,567 non-disabled males; 945 disabled females; and 7,596 non-disabled females. *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.

Table 6 Returns to Education and Basic Skills Training Coefficients from a Model of Wages Estimated from the NALS, by Sex and Total Population

	All	Male	Female
1) Joint estimation			
Returns to education			
Nondisabled	0.031***	0.023***	0.041***
	(0.005)	(0.006)	(0.007)
Disabled	0.038***	0.016	0.050***
	(0.012)	(0.027)	(0.018)
Returns to basic skills training			
Nondisabled	0.068*	0.036	0.126**
	(0.040)	(0.052)	(0.059)
Disabled	0.221	0.256	0.059
	(0.186)	(0.281)	(0.245)
2) Separate without correction			
Returns to education			
Nondisabled	0.033***	0.028***	0.043***
	(0.005)	(0.006)	(0.007)
Disabled	0.032	–0.009	0.017
	(0.034)	(0.057)	(0.048)
Returns to basic skills training			
Nondisabled	0.068*	0.038	0.126**
	(0.040)	(0.051)	(0.058)
Disabled	0.111	0.484	–0.151
	(0.242)	(0.452)	(0.303)
3) Separate with switching regression			
Returns to education			
Nondisabled	0.029***	0.021***	0.040***
	(0.005)	(0.006)	(0.008)
Disabled	0.025	-0.009	0.013
	(0.036)	(0.060)	(0.053)
Returns to basic skills training			
Nondisabled	0.063	0.037	0.120**
	(0.040)	(0.051)	(0.058)
Disabled	0.106	0.461	–0.147
	(0.244)	(0.455)	(0.304)

Note: Samples restricted to individuals aged 25–62 with weekly earnings. Entries are coefficients from OLS regression of log weekly earnings; standard errors are in parentheses. Other independent variables include sex (in total sample column); marital status; age; age squared; minority status; region; residence in metropolitan area; high school graduate; GED; bachelor's degree; current student; prose; document and quantitative literacy test scores; inverse Mills ratio from first-stage probit regression on labor force participation, and inverse Mills ratio for disability reporting probit (in panel 3). Samples sizes for panel 1 are 5,259 males and 5,678 females. Sample sizes for panels 2 and 3 are 171 disabled males; 5,088 non-disabled males; 205 disabled females; and 5,473 non-disabled females. *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.

Table 7 Coefficients from Wage Regressions Estimated Separately with Switching Regression Using SIPP Data (Standard errors are in parentheses)

	Nondisabled		Disabled	
Variable	Male	Female	Male	Female
Intercept	2.356***	–2.387***	1.925***	–2.739*
	(0.265)	(0.533)	(0.727)	(1.538)
Age	–0.028***	0.134***	–0.001	0.076
	(0.008)	(0.016)	(0.023)	(0.047)
Age^2 (scaled in 00s)	0.047***	–0.158***	0.024	–0.042
	(0.011)	(0.021)	(0.036)	(0.065)
Nonwhite	0.099***	–0.031	0.103	0.087
	(0.024)	(0.020)	(0.079)	(0.060)
Marital status	–0.053	–0.215***	–0.065	–0.763***
	(0.036)	(0.040)	(0.193)	(0.206)
South	–0.122***	–0.156***	–0.152***	–0.090**
	(0.012)	(0.013)	(0.036)	(0.041)
Metro	–0.094***	0.104***	–0.068	–0.118
	(0.017)	(0.023)	(0.059)	(0.076)
Years of schooling	0.045***	0.109***	0.038	–0.083
	(0.007)	(0.013)	(0.040)	(0.065)
Number of children in the household age 0–17	0.019***	–0.159***	0.017	–0.067
	(0.006)	(0.021)	(0.018)	(0.060)
Enrollment	0.139***	–0.222***	0.038	–0.022
	(0.044)	(0.038)	(0.176)	(0.130)
Manufacturing	0.012	0.048	0.033	0.455***
	(0.022)	(0.050)	(0.064)	(0.166)
Transportation and communication	0.065**	0.134**	0.066	0.594***
	(0.027)	(0.054)	(0.078)	(0.174)
Wholesale and retail trade	–0.203***	–0.240***	–0.275***	0.203
	(0.026)	(0.049)	(0.073)	(0.161)
Finance	0.015	0.042	–0.143	0.486***
	(0.035)	(0.050)	(0.109)	(0.175)
Services	–0.195***	–0.197***	–0.338***	0.141
	(0.029)	(0.051)	(0.083)	(0.165)
Professional Services	–0.155***	–0.110**	–0.217***	0.335**
	(0.027)	(0.048)	(0.076)	(0.160)
Public administration	0.006	0.058	0.009	0.497***
	(0.031)	(0.052)	(0.089)	(0.176)
Business and management	0.484***	0.501***	0.585***	0.145
	(0.029)	(0.053)	(0.087)	(0.175)
Technicians	0.425***	0.422***	0.423***	–0.012
	(0.038)	(0.058)	(0.108)	(0.188)
Sales	0.349***	0.288***	0.382***	–0.181
	(0.035)	(0.056)	(0.095)	(0.175)
Administration	0.234***	0.287***	0.220**	–0.123
	(0.033)	(0.052)	(0.086)	(0.166)
Service occupations	0.057	0.110**	0.019	–0.372**
	(0.038)	(0.055)	(0.096)	(0.172)
Construction	0.272***	0.187***	0.298***	–0.281
	(0.026)	(0.057)	(0.069)	(0.181)

Table 7 (Continued)

	Nondisabled		Disabled	
Variable	Male	Female	Male	Female
Transportation	0.146***	0.150**	0.120	–0.289
	(0.029)	(0.064)	(0.076)	(0.192)
Disability reporting mills	–1.340***	0.997***	–0.138	2.365***
	(0.147)	(0.233)	(0.341)	(0.702)
LFP mills	–1.966***	1.401***	–1.032**	0.642
	(0.165)	(0.212)	(0.482)	(0.603)

Note: Samples restricted to individuals aged 25–62 with wages. Entries are coefficients from OLS regressions of log wages. Samples sizes are 8,567 nondisabled males; 7,596 nondisabled females; 1,196 disabled males; and 945 disabled females. Adjusted R^2 statistics are 0.2644, 0.2772, 0.2668, and 0.2406 for the four columns respectively. *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.

Table 8 Coefficients from Wage Regressions Estimated Separately with Switching Regression Using NALS Data (Standard errors are in parentheses)

	Nondisabled		Disabled	
Variable	Male	Female	Male	Female
Intercept	4.631***	4.532***	5.012	6.852*
	(0.329)	(0.295)	(3.325)	(3.713)
Age	0.052***	0.018**	0.080	–0.021
	(0.008)	(0.009)	(0.085)	(0.099)
Age^2 (scaled in 00s)	–0.044***	–0.014	–0.075	0.025
	(0.010)	(0.011)	(0.102)	(0.106)
Nonwhite	–0.020	0.097***	–0.029	0.414**
	(0.028)	(0.025)	(0.265)	(0.164)
Married	0.096***	–0.119***	0.027	0.220
	(0.020)	(0.029)	(0.155)	(0.285)
South	–0.080***	–0.059***	0.056	–0.162
	(0.018)	(0.020)	(0.156)	(0.128)
Metro	0.184***	0.234***	0.382**	0.411***
	(0.021)	(0.023)	(0.176)	(0.157)
Years of education	0.021***	0.040***	–0.009	0.129
	(0.006)	(0.008)	(0.059)	(0.053)
Enrollment	–0.121***	–0.108***	0.176	–0.213
	(0.032)	(0.029)	(0.347)	(0.237)
High school graduate	0.055	–0.022	0.122	0.116
	(0.034)	(0.038)	(0.290)	(0.235)
GED	–0.005	–0.075	–0.378	0.054
	(0.050)	(0.056)	(0.317)	(0.323)
Bachelor’s degree	0.043	0.002	0.376	0.295
	(0.032)	(0.037)	(0.394)	(0.254)
Basic skills	0.037	0.120**	0.461	–0.147
	(0.051)	(0.058)	(0.456)	(0.304)
Percent correct prose	0.032	0.097*	0.622	0.011
responses (scaled in 00s)	(0.050)	(0.058)	(0.446)	(0.361)
Percent correct document	0.176***	0.131*	–0.341	0.508
responses (scaled in 00s)	(0.064)	(0.074)	(0.623)	(0.441)
Percent correct quantitative	0.173***	0.069	0.376	–0.214
responses (scaled in 00s)	(0.044)	(0.048)	(0.353)	(0.287)
Agriculture	0.055	–0.117	–0.917	1.193*
	(0.099)	(0.129)	(0.903)	(0.652)
Transportation and	0.201**	0.261**	–0.566	1.109*
communication	(0.100)	(0.118)	(0.906)	(0.608)
Wholesale and retail trade	–0.075	–0.197*	–1.551*	0.724
	(0.099)	(0.116)	(0.880)	(0.586)
Finance	0.188*	0.102	–0.956	0.701
	(0.103)	(0.117)	(0.922)	(0.604)
Services	–0.096	–0.127	–1.540*	0.610
	(0.098)	(0.114)	(0.883)	(0.572)
Public administration	0.131	0.124	–0.588	1.126*
	(0.103)	(0.119)	(0.900)	(0.607)

Table 8 (Continued)

	Nondisabled		Disabled	
Variable	Male	Female	Male	Female
Professional occupations	–0.100	0.381***	0.237	–1.104
	(0.283)	(0.128)	(0.908)	(0.957)
Business management	0.040	0.618***	0.634	–0.860
	(0.283)	(0.129)	(0.930)	(0.955)
Technicians	–0.326	0.373***	0.474	–0.517
	(0.285)	(0.131)	(0.971)	(0.985)
Sales	–0.216	0.035	0.535	–1.196
	(0.283)	(0.129)	(0.977)	(0.979)
Computer	–0.381	0.110	0.523	–0.892
	(0.290)	(0.132)	(1.103)	(0.977)
Administrative	–0.427	0.087	–0.111	–1.068
	(0.284)	(0.126)	(0.921)	(0.951)
Crafts	–0.271	0.166	0.835	–1.331
	(0.283)	(0.138)	(0.935)	(0.998)
Transportation	–0.457	0.037	0.504	–1.231
	(0.283)	(0.130)	(0.920)	(0.930)
Other services	–0.496*	–0.160	0.160	–1.201
	(0.284)	(0.127)	(0.928)	(0.957)
Farming	–0.568**	—	–0.173	—
	(0.286)		(0.951)	
Disability reporting mills	0.404**	0.274	–0.201	–0.280
	(0.200)	(0.198)	(0.587)	(0.606)
LFP mills	–0.547***	–0.267**	–1.868	–1.576
	(0.144)	(0.106)	(1.516)	(1.041)

Note: Samples restricted to individuals aged 25–62 with weekly earnings. Entries are coefficients from OLS regressions of log weekly earnings. Sample sizes and adjusted R^2 statistics are as follows: 5,088 nondisabled males (0.3830); 5,473 nondisabled females (0.3117); 171 disabled males (0.3073); and 205 disabled females (0.2599). *** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level. — indicates variable omitted.