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WITHIN GROUP "STRUCTURAL" TESTS OF LABOR-MARKET DISCRIMINATION: A STUDY OF PERSONS WITH SERIOUS DISABILITIES

David S. Salkever
Marisa E. Domino

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ABSTRACT

Labor-market discrimination measures are usually derived from between-group comparisons of market outcomes for favored vs. disfavored groups, controlling for productivity-related individual characteristics. When the disfavored group is heterogeneous, one can relate variations in discrimination intensity to market outcomes within the disfavored group. We use this approach to test for employment and wage discrimination against persons with various types of disabilities. Measures of "social distance" and employer judgements of "employability" are controls for the intensity of discrimination. In a national sample of adults with serious disabilities, employment discrimination effects are in the "wrong" direction, however, and wage effects are unstable. Thus, variability in labor market outcomes among different types of disabilities is not explained well by variations in discrimination intensity correlated with social distance and employer attitudes. We conjecture that differences in available support services by type of disability may help to explain this variability.

David S. Salkever
Department of Health Policy
and Management
The Johns Hopkins University
School of Hygiene and Public Health
624 N Broadway
Baltimore, MD 21205
and NBER
dsalkeve@phnet.sph.jhu.edu

Marisa E. Domino
Department of Health Policy
and Management
The Johns Hopkins University
School of Hygiene and Public Health
624 N Broadway
Baltimore, MD 21205

Introduction

Empirical studies of discrimination have played a major role in the formulation of policy, both by documenting the need for remedial programs and in evaluating the results of these programs. While some of these empirical studies have taken a carefully controlled "audit" approach (e.g., Kenney and Wissoker, 1994; Ayres and Siegelman, 1995) most have used available data sets and measured discrimination by comparing between-group differences in economic outcomes, controlling via regression analysis for other relevant variables.

The great majority of studies of labor-market discrimination, in particular, have used this approach. To measure labor-market discrimination, a measure of labor-market success, Y, is regressed on a vector of productivity-related characteristics, X, in separate regressions for the favored and disfavored groups, denoted by subscripts F and D. Where b_F and b_D are the estimated parameter vectors, the observed difference of Y_F-Y_D is decomposed into (1) a difference due to productivity differences (i.e., X_F-X_D) and (2) a discriminatory residual reflected in the difference in the estimated parameters (b_F-b_D). The discriminatory residual represents the estimated effect of discrimination.[1]

The identification of this residual as a discrimination effect may be problematic however (Holzer, 1994). For example, suppose the linear models $Y_F = b_F X_F$ and $Y_D = b_D X_D$ are correctly specified for each group but the vector X omits a productivity-enhancing characteristic, z.

[1]References to this literature and more details on the methods employed are provided in Oaxaca and Ransom (1994). They also discuss alternative regression approaches that pool the data for the two groups. Another valuable discussion of estimation methods, in the context of an application to wage diferentials by gender, is provided by Gyimah-Brempong, Fichtenbaum and Willis (1992). Their discussion focuses on potential problems with assuming that b_F equals the "nondiscrimnatory" wage parameters and alternatives to this assumption. In our empirical work described below, this assumption is not necessary since we focus on within-group estimates.

If the average value of z is larger in the favored group, we will overestimate the effect of discrimination even though z is uncorrelated with all elements of X within each group.

A second problem can arise when 1) the range of variation of an element of X, X_i, is different between the two groups and 2) the effect of X_i on Y is approximately linear within groups but non-linear across the range of observed data of both groups combined. In this case, the estimates of b_F are unbiased for Group F but the computed discrimination effect contains specification error.[2]

To avoid (or at least mitigate) these problems, an alternative strategy for measuring discrimination examines variations in labor-market outcomes within a heterogeneous disfavored group. If this heterogeneity implies variations in the intensity of discrimination, and an empirical correlate of intensity, I, is available, we can test the importance of discrimination directly by regressing Y_D on X_D and I. The estimated coefficient of I serves as a measure of discrimination.[3] An additional advantage of this strategy is that it may provide more direct "structural" evidence about the mechanisms through which discrimination works. For example, while employers' attitudes have been cited as a cause of discrimination for some groups of workers, direct tests of this mechanisms have yet to be conducted (Holzer, 1994). If measures of within-group variability in these attitudes were available, these measures could be related to observed within-group differences in labor-market success to determine the importance of this particular source of discrimination.

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[2]Note that the pooled-regression approach explored by Oaxaca and Ransom (1994) is also subject to these problems.

[3]A recent example of this approach is Telles and Murguia (1990). A related (and also atypical) approach is to use data on I across all individuals to estimate the regression model of labor-market success. For recent examples, see Hamermesh and Biddle (1994) and Biddle and Hamermesh (1995).

A disadvantage of this method, however, is that empirical data on I are rarely available. In many contexts (e.g., gender bias, racial bias), heterogeneity within the disfavored group with respect to the characteristics that is the object of discrimination is not observed.

An interesting case for applying the within-group approach to measuring discrimination is persons with disabilities. Several authors have argued persuasively that the intensity of discrimination varies within this group according to a measure of "social distance" developed by Tringo (1970). As Baldwin and Johnson (1994) observe, a pertinent reason for employing this social distance measure is that it corresponds closely to the "taste" for discrimination that is at the core of Becker's (1971) theoretical analysis of discrimination. Other potentially interesting measures of discrimination also vary within this group. In particular, Yuker (1987) has reported wide differences in employer attitudes about "employability" for different disability groups.

The within-group approach is also attractive in the case of persons with disabilities because the interpretation problems of the between group approach are potentially serious. In comparing persons with and without disabilities, it is important to include health-related differences in functional capacities in the vector X. Available measures of these functional capacities, however, are often very limited in survey data, thus raising concerns about omitted-variable bias in between-group discrimination measures. The range of variation of these measures will also have little overlap between nondisabled and disabled groups, since nondisabled persons (almost by definition) do not have serious functional limitations. This opens up the possibility of the second identification problem noted above. Reinforcing this possibility is the fact that measures of health problems and functional limitations will tend to have very little variance in samples of nondisabled persons, making it difficult to estimate the corresponding elements of b_F precisely.

Finally, it is important to examine the possible influence of labor-market discrimination on persons with disability because the "between-group" differences are so large. For example, Burkhauser, Haveman and Wolfe (1993) have reported that earnings of working-age men with disabilities as of 1987 were less than half of the corresponding figure for men without disabilities; moreover, they find this relative disadvantage has been increasing over time, especially for men who are nonwhite and those with less than a high school education. Evidence that particular "structural" mechanisms of discrimination can explain this differential in labor-market success would be of considerable interest for social policy.

Previous Research

An early and comprehensive "between-group" study of labor-market discrimination and adults with disabilities was carried out by Fechter and Thorpe (1977).[4] Using data from the 1967 Survey of Economic Opportunity, they estimated discrimination effects on labor force participation, hours worked, weeks worked, hourly earnings and weekly earnings for persons age 17 to 64 who reported having a chronic impairment/health problem. (Crude comparisons of employment rates for those in the labor force showed minimal differences between disabled and nondisabled groups so employment discrimination was not examined separately.) For both men and women, discrimination effects on participation were just under 20 per cent of the participation rate for the disabled group. For men, other effects ranged from 10 per cent of hours worked to 32 per cent of weekly earnings. For women, effects were generally larger, up to 62 per cent for weekly earnings. Weeks, hours and earnings effects were also estimated controlling for occupation and industry; this resulted in considerably smaller discrimination effects, especially for women. Fechter and Thorpe also analyzed seven different categories of impairments/health problems separately, finding wide variations among categories with the largest effects for neurological disorders (males and females) and circulatory disorders (females).

Subsequent between-group analyses by Johnson and colleagues (cited below) made major improvements to the Fechter-Thorpe between-group analysis. First, they recognized the need to include health variables to control for health-related productivity differences. Second, they included selectivity corrections in their estimated wage functions. Results of these analyses

[4] Fechter and Thorpe also cite several earlier studies which, while not explicitly focused on discrimination, used empirical approaches similar to theirs. See, in particular, Grossman and Benham (1974) and Luft (1975).

indicated relatively small wage discrimination effects, on the order of 10 to 15 per cent of the nondisabled wage using 1984 SIPP data (Baldwin and Johnson, 1992 and 1994).

Johnson and Lambrinos (1987) advanced an important hypothesis about within-group discrimination differences, namely, that Tringo's "social-distance" scale of prejudice among nondisabled persons against those with disabilities should correlate with the degree of discrimination. The scale is based on nine ordered responses about willingness to associate with persons with various health problems and impairments. The responses range from the least prejudiced ("would marry") to aversion ("would keep away from") to extreme prejudice ("would put to death"). If the scale is correlated with employer prejudice (i.e., degree of "distaste" for a disabled worker), more intense discrimination would be expected against persons whose impairments or health problems correspond to higher values of the scale.

Empirical support for this hypothesis is offered in three studies; two are "between-group" studies and only one (Johnson and Lambrinos, 1987) directly estimates a social-distance discrimination effect. Baldwin and Johnson (1994) divide their data on disabled men in the 1984 SIPP into two groups, 550 "disabled" and 116 "handicapped." The "disabled" group includes eight health problems not included in Tringo's study and the five problems with the lowest values for the Tringo scale. The "handicapped" groups include ten other problems with higher Tringo scale values. Estimated wage discrimination effects (controlling for experience and occupation) were 11.8 per cent and 14.7 per cent of the nondisabled wage respectively. The difference between these discrimination effects is very small, but its direction is consistent with differences in intensity of discrimination implied by the Tringo scale. (A statistical test of this difference is not given.) The authors also present roughly analogous results for the 1972 Social Security Survey of Disabled and Nondisabled Adults. The corresponding discrimination differentials in wages are 4.5 per cent and 5.3 per cent for "disabled" and "handicapped" men respectively.

Johnson and Baldwin (1993) estimate a single wage regression for the 1984 SIPP combining data on males, females, disabled and nondisabled workers. They also include scale variables (2=unable, 1=limited, 0=no limit) for functional limitations in six activities (lifting heavy objects, climbing stairs, mobility outside of home or work, speaking intelligibly and hearing others, walking long distances, and reading newspapers). Other health variables are dummies for seven different impairment groups. The ranking of the coefficients for these seven dummies is then correlated with the Tringo scale rankings. This is a rather approximate test, compromised by the fact that 3 of the 7 dummy variable coefficients are not significant. Rank correlations with the Tringo scale were high for conditions with significant coefficients but significant at only the 10 per cent level when the three insignificant coefficients were included in the rankings. The authors view this as only weak support for the intensity of wage discrimination hypothesis. They then replicate the rank correlation calculations replacing the Tringo scale with a scale based on employer attitudes about "employability" of different types of disabilities (Yuker, 1987) and find stronger correlations, leading them to conclude that intensity of employer prejudice does influence wage discrimination.

Johnson and Lambrinos (1987) used data on disabled adults from the 1972 Social Security Survey of Disabled and Nondisabled Adults and estimated separate wage regressions for men and for women. A health index variable is included to control for productivity-related variations in impairments and health problems and the Tringo scale is included directly as an explanatory variable. Thus, effects of intensity of discrimination are estimated directly by the coefficient of the Tringo scale. Results show a significant negative coefficient on the Tringo scale for men and essentially no effect for women. The findings are interpreted as confirmation of the intensity of discrimination hypothesis for men and evidence that attitudes toward different impairments for women do not influence their wages.

While Johnson and Lambrinos provide the only direct estimate to date of the "social-distance" effect on wage discrimination, they did not report corresponding estimates for employment discrimination. The fact that their model only used a single health index (albeit derived from a long list of symptoms, limitations and problems) which did not significantly affect wages also raises concerns about possible bias in their discrimination result due to omitted dimensions of health status. Finally, since their model also controls for occupation and work experience, a smaller discrimination effect could be expected based on the findings of Fechter and Thorpe (1977).

The present study extends the Johnson and Lambrinos work in directly estimating the "social-distance" discrimination effect. An important contribution of this study is that it examines "discrimination" effects on employment as well as wages; this is of interest since employment differentials account for most of the shortfall in average earnings for persons with disabilities relative to the nondisabled. The study also includes relatively detailed health information on functional limitations, and it employs a large recent data set on persons with relatively severe disabilities. Finally, extending the Johnson and Baldwin study, we compare our results for social distance with those obtained with a scale based on employer rankings of employability.

Study Population

Data used for our analyses were from the 1990 National Consumer Survey of People with Developmental Disabilities and Their Families (NCS). The NCS was a face-to-face interview survey developed by Temple University and the National Association of Developmental Disabilities (DD) Councils (Temple University, 1990) and administered to more than 15,000 persons nationwide by the state DD Councils. Persons with developmental disabilities were identified mainly through advocacy organizations and sampled in most states according to a four disability-group proportional sampling strategy recommended by Temple University.[5] Survey respondents were included in the sample for the present study if (i) they were at least 20 years of age at the time of the survey, (ii) had a primary disability that was assigned a social distance score, and (iii) were not missing values for any of the relevant explanatory variables. These inclusion criteria resulted in a sample of 6686 persons.[6]

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[5] The recommended sampling strategy was 42% mental retardation, 34% physical disabilities, 15% sensory disabilities, and 9% emotional disabilities.

[6] Some state DD Councils used procedures that deviated from the guidelines and the content of the survey instrument. As a consequence, no usable data were available in this study for respondents from 8 states: Delaware, Iowa, Kansas, Minnesota, New Jersey, New York, Oregon, and South

Dependent Variables

The definitions and names of variables used in the analysis are shown in Table 1. In stage 1 of the analysis, the dependent variable used for measuring discrimination effects is a competitive employment dummy (COMPETV). This takes on a value of one for respondents who identified themselves at the time of the interview as working full- or part-time but not receiving either sheltered, supported, or other employment services. In stage 2 of the analysis, the dependent variable is the log of the hourly wage (LOG_WAGE) for the 696 competitively employed respondents with reported wage data and data on all other variables in the analysis.[7] The hourly wage was calculated by dividing each respondent's reported gross pay for the week prior to the survey by her reported hours of working in "an average week". This computation yielded average wage values that were rather low, reflecting possible survey reporting errors, including errors in classifying respondents as competitively employed when their employment was not competitive.[8]

Since the interviewing process was carried out within each state by that state's DD Council, we examined the wage data by state to determine whether potentially erroneous very low values were more common in some states than others. This was indeed the case, with eleven states showing hourly wage levels of under $2.00 for more than two-thirds of the competitively employed respondents.[9] Thus, employment and wage models were estimated both with those eleven states included and with them excluded.

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[7]Wage data were not reported for approximately 200 respondents who were competitively employed.

[8]Other possible explanations of low values or a downward bias in reported wages are 1) that some respondents were reporting casual "underground" employment (e.g., yard work for a neighbor) for which their hourly pay may have been very low and 2) that some respondents reported net rather than gross wages.

[9]The eleven states were Arizona, Illinois, Indiana, Kentucky, Maine, Michigan, Mississippi,

Explanatory Variables

Explanatory variables are also defined in Table 1. Variables in both stages of the analysis consisted of demographic, educational, and functional limitations variables that might explain both the likelihood of working, and the productivity and wages of those who were employed. Demographic variables included: dummies for gender and race/ethnicity, age in years, and age squared. A series of indicator variables (MOST_ED1 through MOST_ED9), controlled for the type of setting where the respondent received most of their education, with a regular classroom setting in a regular school as the comparison category. In addition, a second set of dummy variables indicated whether the respondent ever attended high school, college, trade or vocational school, or graduate school.

Twelve dummy variables measured the functional limitations of the respondent in terms of two levels of need ("substantial" and "a little") in each of six areas: (i) self-care, (ii) receptive and expressive language, (iii) learning, (iv) mobility, (v) making decisions, and (vi) capacity for independent living. A variable reflecting the number of disabling conditions reported by the survey respondent was also included (NUM_COND). The primary condition reported by the respondent was assigned a Tringo social distance score (SOC_DIST), as applied by Johnsen (1993) to the NCS survey, and included in both stages of the analysis. The primary condition was also assigned an employability rank score (EMPLABL) as reported by Johnson and Baldwin.[10]

Montana, New Mexico, Ohio and Washington.

[10]Individuals were assigned scores based on their reported primary disability. Disabilities assigned social distance scores were: epilepsy, blindness/severe visual impairment, deafness/severe hearing impairment, mental retardation, severe emotional disorders, speech/language impairments, autism, cerebral palsy, deafness and blindness, head injury, multiple sclerosis, muscular dystrophy, orthopedic impairments, spina bifida, spinal cord injury, and other neurologic impairments. Employability rankings were available for the first six of these disabilities.

A second set of explanatory variables was allowed to enter the first stage probit equation, but were excluded from the second stage of the analysis. These variables consisted of measures that could affect labor market participation, but are assumed to be unrelated to productivity on the job. Regressors in this set include the number of persons in the respondent's family (NUM_FAM), the number of times the respondent had changed addresses in the previous five years (MOVES), a dummy variable indicating whether the respondent had ever been married (EVER_WED), and a series of dummy variables indicating membership in a consumer advocacy group for the respondent (RESP_ADV), a member of the respondent's household (HH_ADV), or a member of the respondent's immediate family(FAM_ADV). Other variables included only in stage 1 were interactions between the female gender dummy variable and 1) the number of persons in the respondent's family (FAM_FEML) and 2) the ever-married indicator (MAR_FEML).

Variable means for observations in the study sample appear in the first column of Table 2. Fifteen percent of the sample was coded as competitively employed. The average age of sample respondents was almost 35 years old, 46.6% were female, 81.6% white, 12.2% hispanic, and 2.6% black. About half the sample received most of their education in a special school, or in a special class in a regular school (MOST_ED1 and MOST_ED3), ten percent attended a residential facility for persons with disabilities (MOST_ED8), and just over one percent attended a residential facility for persons with mental illness (MOST_ED9). On average, respondents reported more than 2 disabling conditions (NUM_COND), and the majority required substantial assistance in several areas of functioning. Thus, the disabilities of the study population are quite substantial.[11]

Statistical Methods

The statistical methods correspond to those employed in a number of other recent employment and wage studies. The probability of employment is analyzed using standard

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[11]For further information on the characteristics of NCS survey respondents, see Salkever (1994) and Temple University (1990).

maximum likelihood multiple probit regressions. The wage regressions use Heckman's (1979) two-step method to control for selection effects of labor market participation. In particular, the inverse of the Mill's ratio for each competitively employed respondent in the wage regression is calculated from the probit employment probability coefficients. Then, the log wage regression is estimated by ordinary least-squares, including the inverse Mill's ratio as an explanatory variable. Since the variance for each observation in the wage regression will be a function of the value of the selectivity variable (Cogan, 1977; Nakamura et al., 1979), variances of coefficients were estimated using White's (1980) heteroskedasticity-consistent method.

Regression Results

The full-sample employment probability regression is reported in the first two columns of Table 3. Results for many of the explanatory variables are significant and consistent with expectations or prior research. The age variables are highly significant and indicate a maximum employment probability at age 45. Among the race/ethnicity variables on the BLACK is significant at conventional levels. Results for the education dummies show strongly positive coefficients for college and graduate school, and a significantly negative coefficient for education in a resource room of a regular school (MOST_ED4). The functional limitations dummies are usually negative and significant and a greater need for assistance usually implies a more negative impact on the employment probability. (An exception is the results for the two mobility limitation dummies.) The number of disabling conditions reported (NUM_COND) also has a strong negative impact on employment probability.

The coefficient of the social-distance measure of discrimination is significant but the sign of the coefficient is positive rather than negative as expected. At a minimum, our result does not provide evidence of employment discrimination based on social distance.

The wage regression reported in columns 3 and 4 of Table 3 does show a strongly negative wage coefficient for social distance. The coefficient value implies a difference in wages between the most preferred disability (blindness/severe visual impairment, with a social distance score of 0.6969) and the least preferred disability (emotional disorders, with a social distance score of

1.4194) of almost 54 per cent of the most preferred wage level. This differential is considerably larger than the difference between "disabled" and "handicapped" groups reported by Baldwin and Johnson (1994).

Results for the education variables in the wage regression show significant positive coefficients for higher education levels, but the interpretation of the strong positive coefficient for MOST_ED9 (residential school for mental illness/behavior problems) is unclear. Functional limitations and NUM_COND again show strong negative effects. The pattern of age effects has the expected shape but shows a peak at age 21, so in fact the age effect is essentially negative. This is confirmed in columns 5 and 6 where we show the results of a more parsimonious specification. Note that with the reduced set of explanatory variables, social distance has an even larger negative effect on wages.

Table 4 shows analogous results obtained when the social distance score is replaced by employer ratings of "employability" for six different disabilities (where a lower ranking implies greater "employability"). In this case as well the discrimination measure is significant with an unexpected positive sign. Persons whose primary disability is ranked as less employable are in fact <u>more</u> likely to be employed. In the wage equations (columns 3 through 6), the expected negative effect is observed only when a large number of insignificant or marginally significant explanatory variables are excluded from the model (columns 5 and 6). The fact that the employability measure shows a weaker wage effect than the social distance measure is at variance with the earlier finding of Johnson and Baldwin (1993).

Findings in Table 5 show the sensitivity of our social distance results to excluding data points from the "low wage" states where data errors may have been more problematic. With this exclusion, social distance coefficients in both employment and wage regressions are substantially smaller and not significant. Of course, significance levels for a number of other coefficients are also reduced as this exclusion lowers the sample size by about one third.

Discussion

Our analysis of a social distance measure of discrimination for persons with serious disabilities has yielded decidedly mixed evidence. Our employment probit results indicate that persons whose disabilities place them at a greater social distance from the nondisabled are actually more rather than less likely to be employed. On the other hand, our wage regressions show some evidence of larger discrimination effects than had been reported previously. This may be due to at least several factors. First, our data set includes a relatively large number of individuals with serious disabilities. Second, we have not controlled for occupation, industry and work experience. Thus, our wage discrimination estimates include discrimination effects on occupational attainment and job tenure.

The reader should not view the reported discrimination results as very robust, however. An alternative measure of discrimination based on employer views of "employability" produced somewhat weaker evidence of wage discrimination and replicated the unexpected positive employment effect. Exclusion of data from low-wage states (where data quality was more problematic) also weakened both the negative wage effect and the positive employment effect.

In conclusion, while variability in labor-market success among persons with disabilities is substantial, our results do not confirm that discrimination according to social distance is an important explanation for this variability. Similar conclusions hold for variations in perceived "employability" by employers.

Further research should explore alternative causes for this variability which may confound observed effects of discrimination according to social distance. For example, it has often been observed (e.g., Berkowitz, 1987) that many of the agencies that assist persons with disabilities in finding (and keeping) jobs are organized along disability-specific lines and serve only persons with specific types of disabilities.[12] The result may be that service systems to promote employment are

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[12] One example of this is the Federally-supported Vocational Rehabilitation (VR) program. As of 1990, 26 states had two VR agencies, one for the blind and one for all other persons with

much better developed for some groups than others.[13] If some of the groups best served are also those for which social distance scores are high, our empirical findings may result from differences in available services diluting "pure" discrimination effects.

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disabilities.

[13]Another possible result of this arrangement is that persons with multiple disabilities who are more difficult to serve may "fall through the cracks" between the agencies (Ridgely et al., 1990; Salkever and Domino, 1996).

References

Ayres, Ian and Siegelman, Peter. (1995). "Race and gender discrimination in bargaining for a new car," The American Economic Review, 85(3):304-321.

Baldwin, Marjorie and Johnson, William G. (1992). "Labor market discrimination against women with disabilities," Unpublished paper, Department of Economics, East Carolina University.

Baldwin, Marjorie and Johnson, William G. (1994). "Labor market discrimination against Men with disabilities," The Journal of Human Resources, 29(1):1-19.

Becker, Gary S. (1971). The Economics of Discrimination, University of Chicago Press (Chicago: IL).

Berkowitz, Edward (1987). Disabled Policy: America's Programs for the Handicapped. Cambridge University Press (New York: NY).

Biddle, Jeff E. and Hamermesh, Daniel S. (1995). "Beauty, productivity and discrimination: Lawyers' looks and lucre," Paper presented at the NBER Summer Institute, Cambridge, Massachusetts, July 1995.

Burkhauser, Richard V., Haveman, Robert H. and Wolfe, Barbara L. (1993). "How people with disabilities fare when public policies change," Journal of Policy Analysis and Management, 12(2):251-269.

Cogan, John. (1977). Labor supply with time and money costs of participation. R-2044. Santa Monica Cal.: The Rand Corporation.

Fechter, Alan E. and Thorpe, Charles O. Jr. (1977). "Labor market discrimination against the handicapped: An initial inquiry," Working paper no. 3610-1, The Urban Institute, Washington, DC.

Grossman, Michael and Benham, Lee. (1974). "Health, Hours and Wages" in Mark Perlman, ed., The Economics of Health and Medical Care. John Wiley & Sons (New York: NY).

Gyimah-Brempong, Kwabena, Fichtenbaum, Rudy, and Willis, Gregory (1992), "The effects of college education on the male-female wage differential," Southern Economic Journal, 58(3):790-804.

Hamermesh, Daniel S. and Biddle, Jeff E. (1994). "Beauty and the labor market," The American Economic Review, 84(5):1174-1194.

Heckman, James J. (1979). "Sample selection bias as a specification error", Econometrica 47:153-161.

Holzer, Harry J. (1994). "Black employment problems: New evidence, old questions," Journal of Policy Analysis and Management, 13(4): 699-722.

Johnsen, Matthew C. (1993). "Income, disability and earned income for persons with developmental disabilities". Presented at the Annual Meeting of the American Public Health Association, San Francisco, CA, October 1993.

Johnson, William G. and Baldwin, Marjorie. (1994). "The sources of employment discrimination: prejudice or poor information" in David Saunders, ed., Advances in Employment Issues, JAI Press (Greenwich, CT).

Johnson, William G. and Lambrinos, James. (1985). "Wage discrimination against handicapped men and women," The Journal of Human Resources, 20(2):264-277.

Johnson, William G. and Lambrinos, James. (1987). "The effect of prejudice on the wages of disabled workers," Policy Studies Journal, 15(3):571-590.

Kenney, Genevieve M. and Wissoker, Douglas A. (1994). "An analysis of the correlates of discrimination facing young Hispanic job-seekers," The American Economic Review, 84(3):674-683.

Luft, Harold S. (1978). Poverty and Health: Economic Causes and Consequences of Health Problems. Ballinger Publishing Company (Cambridge: Massachusetts).

Nakamura, Masao, Nakamura, Alice and Cullen, Dallas. (1979). "Job opportunities, the offered wage, and the labor supply of married women", The American Economic Review, 69:787-805.

Oaxaca, Ronald L. and Ransom, Michael R. (1994). "On discrimination and the decomposition of wage differentials", Journal of Econometrics, 61:5-21.

Ridgely, M.Susan, Goldman, Howard H. and Willenbring, Mark. (1990). "Barriers to the care of persons with dual diagnoses: Organizational and financing issues", Schizophrenia Bulletin, 16:123-132.

Salkever, David. (1994). "Access to vocational rehabilitation services for persons with severe disabilities," The Journal of Disability Policy Studies, 5(2):45-64.

Salkever, David and Domino, Marisa. (1996). "Impact of separate vocational rehabilitation agencies on access to services for developmentally disabled blind persons", Journal of Visual Impairment an Blindness, 90(1):11-20.

Telles, Edward E. and Murguia, Edward. (1990). "Phenotypic discrimination and income differences among Mexican Americans", Social Science Quarterly, 71(4):682-696.

Temple University (1990). The final Report on the 1990 National Consumer Survey of People with Developmental Disabilities and Their Families. Temple University Developmental Disabilities Center in Cooperation with the National Association of Developmental Disabilities Councils: Philadelphia, Pa.

Tringo, John L. (1970). "The Hierarchy of preference toward disability groups", The Journal of Special Education, 4(3):295-306.

White, Halbert (1980). "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", Econometrica, 48:817-838.

Yuker, Harold E. (1987). "The disability hierarchies: Comparative reactions to various types of physical and mental disabilities." Hofstra University, unpublished.

Table 1: Variable Definitions

Dependent Variables	
COMPETV2	Dummy variable indicating whether the respondent was competitively employed
LOG_WAGE	The logarithm of the respondent's hourly wage
Continuous Explanatory Variables	
SOC_DIST	The Social Distance Score, matched by the respondent's primary disability.
EMPLABL	The "Employability Score", matched by the respondent's primary disability.
AGE	The age of the respondent
AGE_SQ	Age squared
NUM_COND	The number of disabilities the respondent reports
NUM_FAM	The number of family members that live at the same address as the respondent
FAM_FEML	The number of family members that live at the same address as the respondent if the respondent is female, zero otherwise
MOVES	The number of times the respondent has changed addresses in the previous five years
0-1 Indicator Explanatory Variables	
WHITE	African-Americans
BLACK	Hispanic Ethnicity
HISPANIC	White or caucasian
FEMALE	Female
MOST_ED1	Received most education in a special residential or day school
MOST_ED3	Received most education in a special class in a regular school
MOST_ED4	Received most education in a resource room at a regular school
MOST_ED6	Received most education in homebound education
MOST_ED8	Received most education in a residential facility for persons with disabilities
MOST_ED9	Received most education in a residential facility for persons with mental illness, challenging behavior
HIGHSCH	Attended high school
TRADE	Attended Trade or Vocational School
COLLEGE	Attended college
GRADSCH	Attended graduate or professional school
SELFDUM	Substantial assistance needed in self care
LANGDUM	Substantial assistance needed in communicating
LERNDUM	Substantial assistance needed in learning new things
MOBLDUM	Substantial assistance needed in personal mobility
CHCEDUM	Substantial assistance needed in making decisions
LIVEDUM	Substantial assistance needed for independent living
SELF1	Some assistance needed in self care
LANG1	Some assistance needed in communicating
LEARN1	Some assistance needed in learning new things
MOBIL1	Some assistance needed in personal mobility
CHOICE1	Some assistance needed in making decisions
LIVE1	Some assistance needed for independent living
RESP_ADV	The respondent is a member of a consumer/advocacy group
HH_ADV	Someone in the respondent's home is a member of a consumer/advocacy group
FAM_ADV	Someone in the respondent's immediate family is a member of a consumer/advocacy group
EVER_WED	Married, Divorced, Separated, or Widowed
MAR_FEML	Female and Married, Divorced, Separated, or Widowed

Table 2: Variable Means

	(1) Probit Model (n=6686)	(2) Wage Models (n=696)	(3) High-wage States (n=403)
Dependent Variables			
COMPETV2	0.150		
LOG_WAGE		0.422	0.949
Explanatory Variables			
SOC_DIST	1.142	1.131	1.082
EMPLABL*	19.856	19.718	
AGE	34.828	35.318	35.069
AGE_SQ	1372.100	1384.100	1377.700
WHITE	0.816	0.809	0.834
BLACK	0.122	0.142	0.112
HISPANIC	0.026	0.022	0.022
FEMALE	0.466	0.474	0.486
MOST_ED1	0.293	0.246	0.261
MOST_ED3	0.210	0.223	0.186
MOST_ED4	0.019	0.014	0.020
MOST_ED6	0.011	0.010	0.017
MOST_ED8	0.102	0.070	0.065
MOST_ED9	0.014	0.013	0.012
HIGHSCH	0.372	0.493	0.561
TRADE	0.086	0.114	0.154
COLLEGE	0.114	0.221	0.323
GRADSCH	0.020	0.073	0.114
SELFDUM	0.319	0.241	0.263
LANGDUM	0.385	0.279	0.280
LERNDUM	0.658	0.557	0.504
MOBLDUM	0.280	0.269	0.333
CHCEDUM	0.788	0.704	0.630
LIVEDUM	0.905	0.862	0.826
SELF1	0.289	0.249	0.243
LANG1	0.268	0.256	0.218
LEARN1	0.234	0.269	0.266
MOBIL1	0.103	0.060	0.069
CHOICE1	0.119	0.129	0.144
LIVE1	0.075	0.101	0.124
NUM_COND	2.115	1.849	1.883
NUM_FAM	1.294		
RESP_ADV	0.252		
HH_ADV	0.216		
FAM_ADV	0.226		
EVER_WED	0.123		
MOVES	1.218		
FAM_FEML	0.623		
MAR_FEML	0.076		

* The sample size was smaller for models using EMPLABL instead of SOC_DIST; n=4801 for the first stage probit, and n=582 for the second stage regression.

Table 3: First-stage Probit and Second Stage OLS Coefficients for Models with "Social Distance" Score

(with t-statistics adjusted for heteroskedasticity)

Variable	First Stage Probit Coefficient	First Stage Probit t-ratio	Second Stage OLS: Coefficient	Second Stage OLS: t-ratio	Second Stage OLS: Coefficient	Second Stage OLS: t-ratio
Constant	-1.369	-4.679	-0.381	-0.207	1.907	3.138
SOC_DIST	0.224	2.008	-1.047	-3.242	-1.350	-5.216
HECKMAN			1.493	1.539	0.324	0.907
AGE	0.036	4.059	0.043	1.484		
AGE_SQ	-.4E-03	-3.929	-0.001	-1.777	-.8E-04	-1.862
WHITE	0.094	0.827	0.262	0.785		
BLACK	0.226	1.834	0.330	0.824		
HISPANIC	-0.110	-0.640	0.403	0.791		
FEMALE	0.004	0.074	0.105	1.12		
MOST_ED1	-0.053	-0.947	0.165	1.126	0.203	1.632
MOST_ED3	0.085	1.484	0.037	0.238		
MOST_ED4	-0.360	-2.163	0.120	0.269		
MOST_ED6	-0.268	-1.266	-0.193	-0.556		
MOST_ED8	-0.080	-1.043	0.043	0.197		
MOST_ED9	0.025	0.147	1.011	2.414	0.916	2.292
HIGHSCH	-0.052	-1.004	0.466	3.276	0.550	4.426
TRADE	0.010	0.142	0.129	0.924		
COLLEGE	0.271	3.766	0.870	3.351	0.693	3.973
GRADSCH	0.793	6.437	1.322	2.377	0.677	2.36
SELFDUM	-0.206	-3.523	-0.541	-2.726	-0.412	-2.96
LANGDUM	-0.091	-1.769	-0.343	-2.338	-0.294	-2.496
LERNDUM	-0.113	-1.596	-0.591	-3.015	-0.500	-2.977
MOBLDUM	-0.139	-2.287	-0.279	-1.328		
CHCEDUM	-0.261	-3.277	-0.563	-1.994		
LIVEDUM	-0.120	-0.946	-0.255	-0.995		
SELF1	-0.053	-1.077	-0.281	-2.102	-0.250	-2.012
LANG1	-0.071	-1.386	0.024	0.183		
LEARN1	0.020	0.274	-0.338	-1.963	-0.376	-2.333
MOBIL1	-0.253	-3.369	-0.230	-0.794		
CHOICE1	-0.242	-2.767	-0.497	-1.804		
LIVE1	-0.086	-0.615	-0.067	-0.257		
NUM_COND	-0.068	-3.410	-0.188	-2.558	-0.125	-2.337
NUM_FAM	0.009	0.542				
RESP_ADV	0.018	0.358				
HH_ADV	-0.072	-1.225				
FAM_ADV	-0.049	-0.847				
EVER_WED	-0.098	-1.020				
MOVES	-0.011	-1.043				
FAM_FEML	-0.009	-0.399				
MAR_FEML	-0.046	-0.389				

Table 4: First-stage Probit and Second Stage OLS Coefficients for Models with "Employability" Score

(with t-statistics adjusted for heteroskedasticity)

Variable	First Stage Probit Coefficient	t-ratio	Second Stage OLS: Coefficient	t-ratio	Second Stage OLS: Coefficient	t-ratio
Constant	-1.856	-4.606	-5.642	-2.105	0.270	0.337
EMPLABL	0.034	2.691	0.001	0.021	-0.055	-1.885
HECKMAN			3.970	3.356	1.758	4.364
AGE	0.033	3.238	0.090	2.789		
AGE_SQ	0.000	-3.070	-0.001	-3.032	-.1E-03	-2.188
WHITE	0.244	1.779	0.645	1.3		
BLACK	0.437	2.971	1.064	1.677		
HISPANIC	-0.003	-0.017	0.176	0.257		
FEMALE	-0.010	-0.171	0.036	0.302		
MOST_ED1	-0.091	-1.355	0.126	0.656		
MOST_ED3	0.113	1.660	0.477	2.451		
MOST_ED4	-0.350	-1.719	-0.195	-0.36		
MOST_ED6	-5.249	-0.003				
MOST_ED8	-0.116	-1.363	-0.219	-0.896		
MOST_ED9	-0.047	-0.247	1.164	2.073	1.165	2.299
HIGHSCH	-0.007	-0.112	0.322	1.998	0.369	2.692
TRADE	-0.058	-0.651	0.001	0.006		
COLLEGE	0.060	0.565	0.337	1.202		
GRADSCH	0.909	4.361	3.465	4.27	2.411	6.257
SELFDUM	-0.181	-2.497	-1.061	-4.486	-0.782	-4.206
LANGDUM	-0.067	-1.099	-0.294	-1.777		
LERNDUM	0.017	0.170	-0.339	-1.481	-0.309	-2.571
MOBLDUM	-0.126	-1.625	-0.051	-0.169		
CHCEDUM	-0.116	-0.912	-0.374	-1.412		
LIVEDUM	-0.378	-2.413	-1.582	-3.839	-1.109	-4.638
SELF1	-0.082	-1.449	-0.447	-2.887	-0.304	-2.106
LANG1	-0.079	-1.347	-0.101	-0.656		
LEARN1	0.183	1.777	0.226	0.747		
MOBIL1	-0.252	-2.929	-0.577	-1.697		
CHOICE1	-0.056	-0.397	-0.300	-1.041		
LIVE1	-0.326	-1.926	-1.057	-2.803	-0.667	-2.673
NUM_COND	-0.076	-3.098	-0.279	-2.703	-0.158	-2.107
NUM_FAM	0.009	0.470				
RESP_ADV	-0.065	-1.055				
HH_ADV	-0.060	-0.879				
FAM_ADV	-0.037	-0.555				
EVER_WED	-0.107	-0.848				
MOVES	0.001	0.083				
FAM_FEML	-0.012	-0.492				
MAR_FEML	-0.061	-0.403				

Table 5: First-stage Probit and Second Stage OLS Coefficients for Models with "Social Distance" Score

Sample of High Wage States

(with t-statistics adjusted for heteroskedasticity)

Variable	First Stage Probit Coefficient	t-ratio	Second Stage OLS: Coefficient	t-ratio
Constant	-0.903	-2.534	5.156	3.526
SOC_DIST	-0.043	-0.313	0.004	0.011
HECKMAN			-3.047	-3.348
AGE	0.018	1.692	-0.014	-0.604
AGE_SQ	-.2E-03	-1.595	0.000	0.474
WHITE	0.057	0.421	-0.145	-0.385
BLACK	0.055	0.368	0.053	0.130
HISPANIC	-0.152	-0.726	1.440	3.079
FEMALE	0.002	0.030	0.264	2.240
MOST_ED1	0.001	0.009	0.236	1.491
MOST_ED3	0.008	0.109	0.087	0.536
MOST_ED4	-0.096	-0.488	0.616	2.131
MOST_ED6	-0.026	-0.114	-0.002	-0.006
MOST_ED8	0.002	0.026	0.283	0.948
MOST_ED9	0.147	0.674	0.920	2.385
HIGHSCH	0.002	0.034	0.734	4.576
TRADE	0.102	1.277	-0.279	-1.687
COLLEGE	0.336	3.960	-0.404	-1.244
GRADSCH	0.748	5.558	-1.337	-2.726
SELFDUM	-0.158	-2.139	0.081	0.419
LANGDUM	-0.111	-1.699	-0.075	-0.405
LERNDUM	-0.131	-1.486	-0.017	-0.091
MOBLDUM	-0.141	-1.826	0.102	0.427
CHCEDUM	-0.300	-3.060	0.044	0.152
LIVEDUM	-0.230	-1.499	0.518	2.416
SELF1	0.006	0.089	-0.028	-0.184
LANG1	-0.152	-2.314	0.195	0.968
LEARN1	-0.005	-0.060	-0.209	-1.205
MOBIL1	-0.105	-1.159	0.265	1.012
CHOICE1	-0.289	-2.731	0.375	1.283
LIVE1	-0.108	-0.653	0.299	1.648
NUM_COND	-0.029	-1.187	-0.063	-1.024
NUM_FAM	0.026	1.299		
RESP_ADV	0.135	2.279		
HH_ADV	-0.073	-1.000		
FAM_ADV	0.028	0.397		
EVER_WED	0.065	0.555		
MOVES	0.005	0.431		
FAM_FEML	-0.016	-0.608		
MAR_FEML	-0.086	-0.593		