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# IRP Discussion Papers

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## DISABILITY TRANSFERS AND EARLY RETIREMENT: A CAUSAL RELATIONSHIP?

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Disability Transfers and Early Retirement: A Causal Relationship?


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## Abstract

During the decade 1968-1978, the labor force participation rate of older male workers decreased substantially. Simultaneously, the number of recipients of disability transfers grew rapidly. The simultaneous movement of these time series has prompted assertions of causality. We empirically test this assertion, employing a utility maximization choice framework and a two-stage empirical model involving modified least squares and probit maximum likelihood.

We conclude that an increase in generosity and/or eligibility leniency of disability transfer programs has been a statistically significant, but quantitatively small, determinant of the decrease in labor force participation--no more than 25-30 percent. And, because the response is concentrated among older, more severely disabled men, we conclude that the impact of more generous and lenient disability transfer programs on national output is relatively small.

Finally, since these findings run counter to earlier results, we attempt to identify the sources of the difference in estimated responses.

Disability Transfers and Early Retirement: A Causal Relationship?

## 1. INTRODUCTION

Many western industrialized countries have recently experienced both a substantial decrease in the labor force participation of older workers and a rapid growth in disability transfer programs. Table 1 characterizes these patterns during the 1968-1978 decade for seven countries. In the United States, for example, the number of disability transfer recipients rose at a rate of 7 percent per year during this period. From 1959 to 1980, the labor force participation rate of males aged 45-59 fell from 96 percent to 88.5 percent. Changes of this magnitude are unique for both variables.

The simultaneous movement of these time series has prompted assertions of causality (Parsons, 1980a, 1980b; Leonard, 1979). Increased benefits per recipient in disability programs, it has been suggested, have made recipiency status more attractive than work for numerous older workers with some health problems. And, worker choice to cease work prior to the standard retirement age has been facilitated by a reduction in the stringency with which eligibility criteria in these programs have been applied.

Indeed, real recipient benefits in disability programs have increased during the 1970s.[1] And, there is evidence that eligibility criteria have been applied more leniently. However, neither of these changes is a sufficient basis on which to attribute primary responsibility for the decrease in older worker labor supply to changes in the level and availability of disability benefits. Numerous other changes in the labor

Table 1

Patterns of Decrease in Older Male Labor Force Participation Rates and Disability Program Growth, 1960s to 1970s, by Country

| | Percentage Change in Ratio of Older to Prime-Age Worker Participation Rates, 1960s to 1970s[a] | Annual Rate of Growth of Disability Program Recipients, 1968 to 1978 | Annual Rate of Growth of Real Disability Program Expendidures, 1968 to 1978 |
|---|---|---|---|
| France | - 7.4% | - 1.3% | - 1.3% |
| Italy | -15.5 | 8.1 | 12.7 |
| Netherlands | -14.8 | 11.3 | 18.6 |
| Sweden | - 9.5 | 5.2 | 11.7 |
| United Kingdom | - .2 | 2.0 | .5 |
| United States | -12.5 | 7.0 | 6.3 |
| West Germany | -15.4 | 2.5 | 5.3 |

Source: R. Haveman, V. Halberstadt, and R. Burkhauser, Public Policy toward Disabled Workers: Cross-National Analyses of Economic Impacts (Cornell: Cornell University Press, forthcoming).

[a]In general, the age range for older male workers is 45 to 64. However, data for some of the countries includes older workers somewhat outside this age range. Prime age refers generally to ages 18 to 45.

market for older workers occurred during the same period that disability transfers and older worker nonparticipation were rising: youths and women entered the labor market in unprecedented numbers during this period; although labor demand rose rapidly throughout the period, unemployment remained high; the pressure on males to continue working decreased as spouses increased their contribution to household income; social security retirement benefits became more generous and available at age 62, freeing savings for earlier retirement; and public attitudes became far more accepting of retirement prior to age 65. The observed decrease in older male participation is explained by some complex interaction of these (and other) exogenous factors over the period.

In this paper, we estimate the responsiveness of older male labor supply to the generosity of disability transfers. These estimates provide a test of the assertion that the recent decline in labor force participation can be "largely explained by the social welfare transfers, particularly Social Security benefit payments" (Parsons, 1980a, p. 130).

In Section 2, we present our model of the labor supply decision of older men. The model suggests that expected disability transfers and expected labor market income are the primary determinants of the work-transfer recipiency choice. The data are described and the results presented in Section 3. They are interpreted and related to those of others in Section 4. Section 5 draws conclusions.

## 2. A MODEL OF WORK STATUS CHOICE

Our model begins with the standard assumption of utility maximization where individuals face a choice between either the labor market option or the disability transfer recipiency option. The income flows associated with each option determine the well-being experienced in each option, together with other sources of utility, such as the utility of time spent in leisure and the stigma cost associated with public transfer recipiency.

Thus, utility in the labor market option is

$$U_L = U_L(LE + N, \bar{H}), \tag{1}$$

where LE is the income flow in the labor market option, N is nontransfer, nonwage income, and $\bar{H}$ is the hours of market work. In analogous fashion,

$$U_D = U_D(DT + N, 0) \tag{2}$$

is the utility in the disability transfer option, where DT is the income flow in the disability transfer option, and $\bar{H} = 0$. The partial derivatives of both functions with respect to $\bar{H}$ are negative and with respect to income are positive.

We approximate the utility functions by assuming that they are linear in their arguments. Hence, the utility-maximizing individual follows the decision function

$$\begin{aligned} I^* &= U_L(LE + N, \bar{H}) - U_D(DT + N, 0) \qquad (3) \\ &\cong \alpha(LE + N) - \gamma(DT + N) + \omega X + V, \end{aligned}$$

where X is a vector of parameters of the utility function, and V is a random error term with a zero mean measuring tastes and other unobserved variables. Given this rule,

$$I = \begin{cases} 1 \text{ if } I^* > 0 \\ 0 \text{ if } I^* \leq 0 \end{cases}$$

where 1 represents the labor market option and 0 represents the disability transfer option.

Equation (3) could be estimated if all of the right-hand side variables were observed. The expected coefficient signs are positive for LE and negative for DT, if leisure is a normal good. But a difficulty is raised by the fact that the income flows (LE, DT) are observed only if the respective choice was made. Hence, we need to explicitly or implicitly determine LE for those with I = 0 and DT for those with I = 1. Equations (4) and (5) describe the determination of LE and DT as a function of variables $\underline{Z}$, including exogenous permanent characteristics of individuals expected to influence labor market and disability transfer income flows, and the characteristics of labor and disability transfer markets describing the terms on which the respective flows are available. In this representation we simplify and let LE represent LE + N and DT represent DT + N.

$$LE_j = \beta_1' \underline{Z}_j + \varepsilon_{1j} \tag{4}$$

$$DT_j = \beta_2' \underline{Z}_j + \varepsilon_{2j} \tag{5}$$

Since $\underline{Z}_j$ is assumed to be exogenous, $E(\varepsilon_{ij} \mid \bar{Z}) = 0$ for $i = 1,2$.

From this, we can write the model as a simultaneous equation system in (6), (7), and (8).

$$LE_j = \beta_1'\underline{Z}_j + \varepsilon_{1j} \quad \text{iff } I_j^* > 0 \tag{6}$$

$$DT_j = \beta_2'\underline{Z}_j + \varepsilon_{2j} \quad \text{iff } I_j^* \leq 0 \tag{7}$$

$$\begin{aligned} I_j^* &= (\alpha\beta_1 - \gamma\beta_2)'\underline{Z}_j + (\alpha\varepsilon_{1j} - \gamma\varepsilon_{2j}) + \omega'\underline{X}_j + v_j \\ &= \beta_3'\underline{Z}_j + \omega'\underline{X}_j + \varepsilon_{3j} \end{aligned} \tag{8}$$

where $\beta_3 = (\alpha\beta_1 - \gamma\beta_2)$, $\varepsilon_{3j} = \frac{1}{\sigma^{2*}} (V_j - \alpha\varepsilon_{1j} - \gamma\varepsilon_{2j})$, and $\sigma^{*2} = E(V_j - \alpha\varepsilon_{1j} - \gamma\varepsilon_{2j})^2$.

The selection rule presumes that individuals know the outcome should either option be chosen, implying that individuals have engaged in search activity in both options, and have achieved a long-run equilibrium. The selection equation, however, recognizes that for some individuals search may be incomplete so that the realized income flow in an option may fall short of or exceed the ex ante estimate of expected income. The equation also reflects cost of application and the discretionary role of employers and administrators to the extent they depend on observed characteristics $Z$.

Since $LE_j$ and $DT_j$ are involved in the decision process but our observation of them depends on the final choice, the observed values are truncated (limited dependent or censored). Hence, OLS estimates of these variables will yield biased estimates. However, given sample separation, we observe the final choice. Hence, $\beta_1$, $\beta_2$, $\varepsilon_1^2$, and $\varepsilon_2^2$ are identified and can be consistently estimated by a two-stage method involving modified least squares and probit maximum likelihood.

This, then, is an example of a "switching regression" which has been discussed by Heckman (1976) and Lee (1979). Indeed, our model is precisely that of Lee, who has shown that the system can be estimated by the following maximum likelihood procedures. The relevant linear likelihood function is

$$L = \prod_{j=1}^{J} \left(\int_{-\psi_j}^{\infty} f_1(LE_j - \beta_1' \underline{Z}_j, \varepsilon_{3j}) d\varepsilon_{3j}\right)^{I_j} \times$$

$$\left(\int_{-\infty}^{-\psi_j} f_2(DT_j - \beta_2' \underline{Z}_j, \varepsilon_{3j}) d\varepsilon_{3j}\right)^{1-I_j}, \tag{9}$$

where $\psi = \beta_3' \underline{Z}_j + \underline{w}'\underline{X}_j$ and $f_1$ and $f_2$ are joint normal density functions for $\varepsilon_{1j}$, $\varepsilon_{3j}$ and $\varepsilon_{2j}$, $\varepsilon_{3j}$ respectively. However, to insure identification, some of the variables in $\underline{Z}_j$ are excluded from the decision function. Hence, we break $\underline{Z}_j$ into two parts; $\underline{Z}_j[\underline{O}_j;\ \underline{W}_j]$, where $\underline{W}_j$ is a vector of exogenous variables included in the $LE_j$ and $DT_j$ predictions but not directly included in the decision function. Hence, (4) and (5) become, respectively,

$$LE_j = \beta_{10}' \underline{W}_j + \beta_{11}' \underline{O}_j + \varepsilon_{1j} \tag{10}$$

$$DT_j = \beta_{20}' \underline{W}_j + \beta_{21}' \underline{O}_j + \varepsilon_{2j}. \tag{11}$$

With this modification, the likelihood function becomes

$$L = \prod_{j=1}^{J} \left(\int_{-\psi}^{\infty} f_1(LE_j - \beta_{10}' \underline{W}_j - \beta_{11}' \underline{O}_j, \varepsilon_{3j}) d\varepsilon_{3j}\right)^{I_j} \times$$

$$\left(\int_{-\infty}^{\psi_j} f_2(DT_j - \beta_{20}' \underline{W}_j + \beta_{21}' \underline{O}_j, \varepsilon_{3j}) d\varepsilon_{3j}\right)^{1-I_j}. \tag{12}$$

We have chosen to derive estimates from the two-stage probit procedure for heuristic reasons, and because the estimates from maximum likelihood procedures dependent on numerical iterative procedures rest on the availability of good initial estimates in highly nonlinear models. This two-stage probit procedure utilizes modified least squares in the first stage and probit maximum likelihood in the second.

In order for this model to be identified:

(1) not all variables in the LE and DT equation can be in the final stage decision function [as presented in (12)],

(2) and either

(a) there exists no covariance between the residuals of the income flows, i.e., $cov(\varepsilon_1, \varepsilon_2) = 0$ or

(b) there exists no covariance between the error term of the decision function and the error terms of LE and DT, i.e., $cov(\varepsilon_1, V)$, $cov(\varepsilon_2, V) = 0$.

With this formulation, the estimates from the two-stage probit analysis will be strongly consistent, and the error terms can be shown to be asymtotically normally distributed (Lee, 1979).

The particular form of the two-stage probit model which we estimate is designed to reflect both the complexity of the disability transfer system, and that of the process by which individuals are determined to be eligible for benefits. We assume that each individual takes as the value of $LE_j$ and $DT_j$ the expected value of observed labor earnings and disability transfers of individuals with similar characteristics.

Estimation of these flows is not straightforward, however, because, as stated above, individuals are observed to have only labor earnings or disability transfers as a result of their decision. Given the self-selection of these groups, direct estimation of (6) and (7) will not yield consistent estimates of $\underline{\beta}_1$ and $\underline{\beta}_2$. Following Heckman (1974, 1979), we assume that $\varepsilon_j = (\varepsilon_{1j}, \varepsilon_{2j})$ has a bivariate normal distribution and that $\varepsilon_j$ is independent of $\varepsilon_j'$ for $j \neq j'$ (assumption 2, above). Given the selection rule and the normality assumption, the appropriate regression functions for (6) and (7) are

$$E(LE_j \mid \underline{z}_j, I^* > 0) = \underline{\beta}_1'\underline{z}_j + E(\varepsilon_{1j} \mid \underline{z}_j, I^* > 0)$$

$$= \underline{\beta}_1'\underline{z}_j + E(\varepsilon_{1j} \mid \varepsilon_{3j} > -\underline{\beta}_3'\underline{z}_j)$$

$$= \underline{\beta}_1'\underline{z}_j + \frac{\sigma_{13}}{\sigma_{33}^{1/2}} \lambda_{1j}(-\underline{\beta}_3'\underline{z}_j/\sigma_{33}^{1/2}) \tag{13}$$

$$E(DT_j \mid \underline{z}_j, I^* < 0) = \underline{\beta}_2'\underline{z}_j + E(\varepsilon_{2j} \mid \underline{z}_j, I^* < 0)$$

$$= \underline{\beta}_2'\underline{z}_j + E(\varepsilon_{2j} \mid \varepsilon_{3j} < -\underline{\beta}_3'\underline{z}_j)$$

$$= \underline{\beta}_2'\underline{z}_j + \frac{\sigma_{23}}{\sigma_{33}^{1/2}} \lambda_{2j}(-\underline{\beta}_3'\underline{z}_j/\sigma_{33}^{1/2}), \tag{14}$$

where $\lambda_1(s) = \phi(s)/1 - \Phi(s)$ and $\lambda_2(s) = -\phi(s)/\Phi(s)$. The final equality in equations (13) and (14) is based on the formula for the mean of a truncated normal random variable.

The parameters in equations (13) and (14) are estimated in three steps. Let $D_j = 1$ if $I^* > 0$ and $D_j = 0$ if $I^* < 0$. Using equation (8),

$$P(D_j = 1 \mid \underline{z}_j) = P(\varepsilon_{3j} > -\underline{\beta}_3'\underline{z}_j \mid \underline{z}_j) = 1 - P\left\{\frac{\varepsilon_{3j}}{\sigma_{33}^{1/2}} < \frac{-\underline{\beta}_3'\underline{z}_j}{\sigma_{33}^{1/2}}\right\}. \tag{15}$$

Performing the probit regression implied by (15), we obtain consistent estimates of $\underline{\beta}3/\sigma_{33}^{1/2}$, denoted $\hat{\underline{\beta}}3/\sigma_{33}^{1/2}$. With $\hat{\underline{\beta}}3/\sigma_{33}^{1/2}$, we next construct estimates of $\lambda_{ij}(\cdot)$ (the inverse Mill's ratio), which we label $\hat{\lambda}_{1j}(\cdot)$ and $\hat{\lambda}_{2j}(\cdot)$. Finally, with the $\hat{\lambda}(\cdot)$ variables, the OLS regressions of $LE_j$ on $\underline{Z}_j$, $\hat{\lambda}_{1j}(\cdot)$ and $DT_j$ on $\underline{Z}_j$, $\hat{\lambda}_{2j}(\cdot)$ are estimated over the appropriate subsamples. This procedure provides consistent estimates of $\underline{\beta}1$, $\underline{\beta}2$, $\frac{\sigma_{13}}{\sigma_{33}^{1/2}}$, and $\frac{\sigma_{23}}{\sigma_{33}^{1/2}}$.

In this model, disability transfer programs are viewed as influencing participation decisions through their impact on expected income flows. From (13) and (14), we obtain estimates of $LE_j$ and $DT_j$--designated as $\widehat{LE}_j$ and $\widehat{DT}_j$--which are expected income flows in the labor market and disability transfer options. These can be used in a nonlinear probit equation to estimate the elasticity of labor force participation with respect to disability program generosity.

$$P(D_j = 1 \mid LE_j, DT_j) = \Phi(\delta\widehat{LE}_j + \eta\widehat{DT}_j) + \varepsilon_{4j}. \tag{16}$$

This approach to modeling the work-disability transfer choice reflects the complexity of the transfer system, which complexity renders infeasible more standard approaches to labor supply modeling involving explicit nonlinear budget constraint specifications (Hausman, 1981). In the United States there is no single disability transfer program. Instead, several interdependent programs, each with its own budget set and eligibility criteria, provide cash and in-kind support to working-age people with handicaps. Some of these programs are income-conditioned (e.g., SSI); others are not (e.g., Veterans Compensation). Some of these limit earnings (e.g., SSDI and SSI); others do not (e.g., Workers Compensation). For some programs, eligibility depends on past work history (e.g., SSDI); for others, eligibility depends on the nature of the impairment and its cause (e.g., Workers Compensation and Black Lung); for still others, the presence of the impairment is sufficient to confer benefits (e.g., Veterans Compensation). The cost of applying for benefits is very high in some programs (e.g., SSDI); application cost for others is effectively zero. Any person with a health problem can receive benefits from a number of the programs simultaneously, depending on widely disparate coverage and eligibility provisions. Indeed, benefits awarded in one program often automatically confer eligibility for benefits in another. Moreover, the system is ill-defined, so that information regarding the availability of benefits from the several interdependent programs, and the conditions under which benefits can be received, is poor.

In addition to the complex and interdependent nature of the disability transfer option, the process by which individuals seek and are accepted for status in either the labor market or disability transfer recipiency options is not well understood. It involves both those who ultimately determine access to income flows in these options--employers and transfer program administrators, each with their own objectives and decision rules--and individuals with their own unique characteristics and objectives.[2] Our model--a reduced-form approach--attempts to accommodate this complexity and to thereby avoid the specification biases likely to accompany its structural alternative.

In estimating this model, several alternative measures of $\hat{LE}_j$ and $\hat{DT}_j$ can be specified as proxies of $LE_j$ and $DT_j$. Each represents a different assumption regarding how individuals form their expectations of outcomes contingent on choices. In one formulation consistent with (6)-(8), $\hat{LE}_j$ can be represented by $E(LE_j \mid \underline{Z}_j, I^* > 0)$. (An analogous representation exists for $DT_j$.) In an estimation using the selectivity term in predicting income flows, the individual's expectation is based on the outcomes of those with identical observed characteristics who have chosen the labor market option. It reflects the selection process, such that some individuals with given characteristics are, and others are not, successful in that option. An alternative estimation would not use the selectivity term for prediction. In this case, an individual's expected outcome in an option is based on the observed income flows of those with like characteristics who are in each of the two options. This procedure neglects the fact that some individuals participate in an option while others do not, and implicitly assumes that all individuals can successfully participate in that option at some level. The results presented below reflect the first estimation procedure; their robustness is tested by estimates based on the second procedure.

## 3. DATA AND MODEL SPECIFICATION

Estimation of the model employs data on men aged 45-62 in 1978 from the Michigan Panel Study of Income Dynamics.[3] The perspective is that the choice of work or transfers is reversible and that the decision reflects income flows for the year under analysis, as well as taste and stigma factors. While the choice of work status in the latest year--1978--is the focus of the study, the panel character of the data allows construction of variables related to past earnings, occupational mobility (including downward changes), and the duration of impaired status. (The specific variables employed are described in Appendix 1.)

The disability measures used are designed to capture both the duration and the intensity of impairment. The major disability transfer programs are designed to provide support for those unable to participate in "substantial gainful activity." Duration and intensity of health problems are also likely to influence earnings. The current extent of disability is likely to affect the probability of both working and receiving disability transfers. It is measured by a variable indicating the percentage of lost functional capabilities. Both measures are based on information collected in 8 of the 11 years of the survey.[4]

Our estimates are based on the model presented in Section II. Equation (15), which is used to predict the probability of being in the labor market, is estimated using the full sample. Being a labor market participant is defined as having either earned income or unemployment benefits greater than zero and no disability-related transfers or having disability transfers greater than zero but earnings in excess of $3360.[5] Its complement is defined as having disability transfers (except Workers' Compensation) greater than zero and earnings less than $3360.[6]

The independent variables included in (15) reflect those demand- and supply-side characteristics of both the labor market and the disability transfer recipiency "market" which are likely to affect the presence of an individual in either group. Past experience (five years earlier)[7], education, and disability status capture the individual's perception of his potential work capacity and productivity, as does age. They also describe important determinants of eligibility for disability transfers. Marital status and the presence of children reflect the income requirements of the household. The unemployment rate, downward occupational change, and region reflect individual employment opportunities, and hence the likelihood of both obtaining a job and gaining eligibility for disability transfers.

Region also proxies the differential application of eligibility determination criteria. Veteran's status indicates eligibility for military-related disability benefits. Past usual occupation proxies disability pension coverage and past earnings. Race enters to capture the effect of potential labor market discrimination in constraining employment opportunities and as a determinant of eligibility for disability transfers. Religion is entered as a taste variable.

Equations (13) and (14) are estimated by OLS procedures over those in the appropriate subgroup [$I^* > 0$ for (13); $I^* \leq 0$ for (14)]. These equations are used to predict the expected income flow under the two options. The matched inverse Mill's ratio from the estimation of (15) is included as an independent variable to correct for potential selectivity bias. In the labor market income equation $\frac{e^{-\hat{P}^2/2}}{\sqrt{2\Pi} \cdot \hat{P}}$ is used; its complement, $\frac{-e^{-\hat{P}^2/2}}{\sqrt{2\Pi}\ (1-\hat{P})}$, is used in the disability transfer equation. The other independent variables in (13) and (14) include those in the first step probit except the taste variables, unemployment rate, and downward occupational change.

From the OLS equations, expected labor market income and expected disability transfer recipiency income are predicted for each individual in the sample. As stated above, two sets of estimates are made, reflecting alternative assumptions regarding the formation of income expectations. The first set of income flows are based upon the income equations with $\hat{\lambda}_{ij}$. A second set ignore the fact that some individuals choose to participate in an option and others do not. In this case, income equations without $\hat{\lambda}_{ij}$ are used for prediction.

Equation (16) posits a choice between two work status options dependent on income flows in the two options and (in an extended model) the stigma costs of not working. Proxies for stigma costs are used which imply that these costs are greater the younger the worker, the less severe his current health problem, the greater the number of persons dependent on him, and the smaller the volume of his independent asset income. The final form of (16) was estimated including a set of variables included in (15) but not in (13) and (14). Hence, the final estimates of response to expected income flows are consistent with a full maximum likelihood specification (Lee, 1979).

## 4. EMPIRICAL RESULTS

The reduced form probit equation corresponding to equation (15) is shown in Table 2. Persons with greater intensity and duration of disablement (CUMDSEV) are less likely to have earned income. It is the dominant variable. Most of the other determinants are insignificant, except age above 59, veteran's status, and being unmarried and without dependent children, all of which are negatively related to being in the

Table 2

Probit Equation for Selectivity Correction: Dependent Variable Is Labor Market Participation

| Explanatory Variables | | |
|---|---|---|
| CONSTANT | -346.8 | (0.9) |
| CUMDSEV | -344 | (3.1)* |
| $(\text{CUMDSEV})^2$ | .65 | (0.5) |
| % Disabled | -1.59 | (1.3) |
| $(\text{\% Disabled})^2$ | .08 | (0.1) |
| AGE78 | .05 | (0.5) |
| Age spline 52 | .04 | (0.4) |
| Age spline 59 | -.35 | (2.2)* |
| Education | .54 | (1.5) |
| Ed spline 8 | .03 | (0.2) |
| Ed spline 11 | .18 | (0.9) |
| DWHITE | .28 | (1.1) |
| UnRate78 | .003 | (0.1) |
| DPROT | -.82 | (2.0)* |
| DCATH | -.66 | (1.4) |
| DJEW | -.41 | (1.4) |
| DSESDOWN | -.31 | (1.3) |
| NMARNK | -.86 | (2.2)* |
| MARNK | -.32 | (1.1) |
| KIDS1878 | -.01 | (0.1) |
| Spouse work | .23 | (1.0) |
| Parents wealthy | -.06 | (0.2) |
| Other household income | -.00003 | (1.5) |
| DSOUTH | -.38 | (1.1) |
| DWEST | .05 | (0.1) |
| DNC | -.06 | (0.2) |
| Veteran | -.42 | (1.9)* |
| Age × educ. | -.01 | (1.8) |
| DPROF | 70.27 | (0.9) |
| DMANAG | 4.83 | (1.0) |
| DClerical Sales | 7.47 | (0.9) |
| DCRAFT | 46.28 | (0.9) |
| DOPERATIVE | 36.04 | (0.9) |
| DFARM | -259.90 | (0.9) |
| DMISC | 39.12 | (0.9) |
| OCCLIM | 29.67 | (0.9) |
| Experience in 73 | -.01 | (0.3) |
| 2 x Log likelihood ratio | 514.2 | |
| No. of observations | 964 | |

Note: t-statistics are given in parentheses.
*Significant at the .05 level.

labor market group. Religion, as a proxy for tastes, has a significant influence on the probability of having labor income.

The reduced-form equations used to estimate expected income in each status, corresponding to equations (13) and (14), are shown in Table 3.[8] For predicting income if one is a disability transfer recipient, the extent of current disability has a large though not quite significant positive effect. Duration and intensity of disability are not significant, suggesting that once one is found to be eligible for benefits, it is current inability to function in the labor market which is the basis for determining the amount of transfers. The nonlinear relationship of current disability to transfers may indicate that those with severe handicaps have a reduced likelihood of earning more than the income cutoff. Need (as measured by being either married or unmarried and without dependent children) has the expected negative sign. Benefits are, in part, based on family size. Prior earnings, as measured by usual occupation, have some influence.[9] Race is significant in predicting disability-related income flows, suggesting either racial differences in application propensity or discrimination in benefit awards. Age is also important, possibly reflecting prior earnings. South is significant, and implies that lower disability benefits are paid in the South or that more stringent eligibility rules are applied, or that prior earnings on which some transfer benefits depend are lower in the South. Finally, the negative coefficient on education suggests that eligibility determination reflects vocational opportunities. The selectivity term is not significant.

The labor market income equation has few unexpected coefficients. The positive effect of education, of having wealthy parents, and the

Table 3

Ordinary Least Squares Regressions for Predicting Income Flows under the Labor Market [Equation (13)] and Disability Transfer Recipiency [Equation (14)] Options

| Explanatory Variables | Labor Market Participation | Disability Transfer Recipiency |
|---|---|---|
| CONSTANT | -6492.2 (0.4) | 26239.7 (2.4) |
| CUMDSEV | -8599.4 (0.8) | -3370.6 (1.0) |
| $(CUMDSEV)^2$ | -768.3 (0.04) | 1643.5 (0.6) |
| % Disabled | -3604.3 (0.7) | 7164.1 (1.4) |
| $(\% \text{ Disabled})^2$ | 416.7 (0.1) | -5328.0 (1.3) |
| AGE78 | 203.2 (0.7) | -445.5 (2.1)* |
| Age spline 52 | -193.0 (0.6) | 430.2 (1.5) |
| Age spline 59 | -498.7 (0.7) | -620.9 (1.3) |
| Education | 2208.7 (2.2)* | -2047.2 (2.1)* |
| Ed spline 8 | -3031 (0.5) | 200.1 (0.6) |
| Ed spline 11 | 2002.2 (3.9)* | 258.3 (0.4) |
| DWHITE | 976.2 (1.0) | 1578.8 (2.6)* |
| NMARNK | -5706.3 (3.5)* | -2366.6 (2.4)* |
| MARNK | 1285.9 (1.3) | -2139.2 (2.6)* |
| KIDS1878 | 182.5 (0.5) | -332.3 (1.3) |
| Spouse work | -2223.9 (2.9)* | -5.0 (0.01) |
| Parents wealthy | 3823.3 (3.4)* | 2600.5 (0.3)* |
| Other household income | -.03(0.6) | -.02 (0.3) |
| DSOUTH | -1752.3 (1.8) | -1753.8 (2.5)* |
| DWEST | -425.78(0.4) | -1818.1 (1.4) |
| DNC | 548.6 (0.6) | -293.7 (0.3) |
| Veteran | 297.7 (0.4) | 349.8 (0.6) |
| Age × educ. | -36.4 (2.10)* | 38.8 (2.2)* |
| DPROF | 4793.0 (2.6)* | 221.5 (0.1) |
| DMANAG | 9383.6 (5.8)* | 652.8 (0.5) |
| DClerical Sales | 4647.9 (2.6)* | 2554.7 (2.0)* |
| DCRAFT | 5556.7 (3.8)* | 1377.8 (1.5) |
| DOPERATIVE | 4479.5 (3.0)* | 1923.7 (2.3)* |
| DFARM | -2293.1 (1.0) | -2110.4 (1.5) |
| DMISC | 5998.9 (1.8)* | 4371.7 (2.9)* |
| Experience in 73 | 123.1 (1.2) | 44.3 (1.1) |
| $\lambda$ | 3863.0 (1.1) | -365.3 (0.4) |
| No. of observations | 841 | 123 |
| $R^2$ | .36 | .62 |

Note: t-statistics are given in parentheses.
*Significant at the .05 level.

pattern of occupation results are all those which economic theory predicts. The negative effects of having a working spouse and being in the South are also expected. The insignificance of disability is somewhat surprising. However, the signs are negative, as expected. And, again, the selectivity term is not significant.

The probit estimates in Table 4 correspond to equation (16), and indicate the role of disability transfers--their accessibility and level --and labor income in affecting the work status choice of older men. Results are based on the measure of the expected income flow in each status, and unemployment rate, tastes as proxied by religion, downward occupation change, and a measure of health limitations of those in the individual's usual occupation (a measure of the opportunity of continuing to work). These are the additional variables used in equation (15) but not included in equations (13) and (14) and ensure consistency with the underlying maximum likelihood estimation model.

In both the simple and extended forms of the model, expected income in the disability transfer option is negatively and significantly related to the decision to participate in the labor market. The extent of disability (which captures a form of stigma costs) has the expected sign and is statistically significant; the other variables in the extended model suggest there is little additional impact of stigma. The elasticity of labor force participation with respect to $\widehat{DT}_j$ is small. In the simple model, the elasticity of labor force participation with respect to disability transfer income $(\widehat{DT\lambda})$ is -.0005 (t-statistic = 7.6); in the extended model, -.0003 (t-statistic = 5.7). Thus, while the responses to the incentives implicit in disability transfers--increased leniency in eligibility or more generous benefits--are verified and statistically

Table 4

Stage-Three Probit Estimates of the Determinants of Work Status Choice

| | Simple Model[a] Coefficient (t-statistic) | Extended Model[a] Coefficient (t-statistic) | $\overline{X}$ | $\sigma$ |
|---|---|---|---|---|
| Expected labor market income | .45 (10.7)* | .42 (8.9)* | \$14,695 | 8550 |
| Expected disability transfer recipiency income | -.49 (7.6)* | -.41 (5.7)* | \$ 6,067 | 2729 |
| Percent currently disabled | | -.87 (2.8)* | .17 | .35 |
| Age | | -.02 (0.9) | 52.9 | 5.0 |
| Not married and no children under 18 (0, 1) | | .77 (1.97)* | .081 | .27 |
| Constant | .83 (1.0) | 2.30 (1.2) | | |
| (2 x Log likelihood function) | 596 | 612 | | |

Note: For the dependent variable: $\bar{x} = .872$; $\sigma = .33$.

*Significant at .05 level.

[a]Both models also include a set of 6 variables included in the first-stage probit equation, but not included in the income regressions. These variables are Protestant (0, 1), Catholic (0, 1), Jewish (0, 1), Decreasing occupational status (0, 1), Disability incidence in usual industry, and Unemployment rate.

significant, their quantitative significance is not substantial in any of the models.

These estimated elasticities are smaller than those of previous studies. For this reason among others, tests of the validity of the estimates are in order. By comparing the predicted results to the actual participation-nonparticipation decision of the older workers in the sample, a measure of the accuracy of our estimates is obtained. Of the 841 observations in the sample who are participants, 821 are predicted by the third-stage probit equation to have a probability of more than .5 of being participants. Of the 123 nonparticipants in the sample, 108 have a predicted probability of more than .5 of being nonparticipants. Thus, our predictions are correct for 96.4 percent of the sample. Our estimate of the labor force participation rate in the sample is also accurate. While the actual rate (weighted) is 91.37 percent, the predicted probability for our sample is 91.30. The predicted value deviates from the actual by only -.07 percent. The implied accuracy of the predictions suggests that our model does accurately distinguish the significant determinants of the labor force participation decision.[10] And it lends confidence to our conclusion that an increase in expected disability benefits is a significant determinant of the decrease in labor force participation of older workers, but that this factor accounts for only a relatively small portion of the decrease.

To obtain a rough estimate of the contribution of disability program generosity to early retirement, we simulate the effect of a $\pm$ 20 percent change in expected SSDI (including dependents) benefits in the transfer option of each individual in the sample. The results, reported in Table 5, show that a 20 percent change in expected disability income would elicit a change in the labor force participation rate of .64-1.04 percentage points.

This response can be placed in an historical perspective. From 1968 to 1978, the labor force participation rate of males aged 55-64 (45-54) decreased by about 12 (4.5) percentage points. During the same period, average real SSDI benefits per recipient increased 43 percent. Our estimates of behavioral response would imply that this increase in benefit generosity would induce a decrease in the labor force participation rate of, at most, 1.81 percentage points. Hence, much of the observed decrease must be attributed to factors other than the increased generosity of disability benefits.

Table 5

Simulated Effect of Changes in Social Security Disability Transfer Generosity on the Work Effort Choice

| Percent of Predicted Expected Disability Transfer Recipiency Income | Labor Force Participation Rate | Disability Recipiency Rate |
|---|---|---|
| 80 | 92.41 | 7.59 |
| 100 | 91.37 | 8.63 |
| 120 | 90.73 | 9.27 |

The gap between these conclusions and those of Parsons (1980a, 1980b) is very large, and is reflected in the difference between Parsons's elasticity estimate (-.03) and ours (-.0003 to -.0005). We have attempted to ascertain the source of this difference. Because the Parsons estimates are based on a different model from that which we employ, and rest on different data and expected income concepts, we first replicate his estimates using his single equation probit model and our data. Then, in a series of steps, we alter Parsons's model to bring it into conformance with accepted standards for modeling behavioral choices. Alterations in specification and variable definition are made seriatim, and include

1. The addition of control variables (marital status, dependents, other household income, long-term occupation) to supplement the limited selection included by Parsons (welfare benefits, unemployment rate, age, disability status).
2. The introduction of a selectivity correction term to adjust for Parsons's use of a sample containing only observations with an observed wage.
3. The addition of dependent benefits to the primary beneficiary's disability transfer benefits to yield an estimate of total disability transfer benefits.
4. The alteration of Parsons's replacement rate specification by entering the disability benefit numerator and wage rate denominator separately in the probit equation.
5. The multiplication of the disability benefit variable by the probability that an individual will be eligible for the disability benefits, conditional on application, his health status, and other characteristics.[11]

Each alteration in Parsons's specification and procedures moves his model into closer conformity with accepted estimation standards. Each movement toward conformity reduces the estimated elasticity of response. These results are shown in Table 6. The final estimate including all of

Table 6

Elasticities of Labor Force Participation with Respect to Disability Transfers, Various Specifications

| | Elasticity | t-statistic of Coefficient |
|---|---|---|
| 1. Parsons's reported elasticity | -.030 | -2.48 |
| 2. Replication of Parsons using PSID | -.021 | -1.59 |
| 3. (2.) plus additional control variables | -.018 | -1.46 |
| 4. (3.) plus selectivity correction | -.011 | -.92 |
| 5. (4.) plus inclusion of dependents' benefits | -.004 | -.22 |
| 6. (3.) but with split replacement rate | -.013 | -.40 |
| 7. (6.) plus modifications in (3.), (4.), (5.), plus an adjustment for the probability of eligibility | -.0007 | -.13 |

Source: Haveman-Wolfe (1982).

the adjustments yields an elasticity estimate of -.0007 (t-statistic = -.13), a value which is 2.5 percent of that reported by Parsons and very close to the elasticities estimated in this paper.

We address one final question with our preferred estimates from the extended model: Which groups are most responsive to changes in expected disability income? In Table 7 we present the elasticities of labor market participation with respect to expected disability-related transfers and expected earnings at the means of the distributions, and at selected relevant points in the disability, age, and earnings distributions. When the extended equation is used, the elasticities on both of the expected income terms fall substantially. The role of current disability status is important in this comparison; those with current impairments are much more responsive to changes in expected income flows than are the nondisabled. This response presumably reflects eligibility perceptions and program practices, as well as stigma costs. The responsiveness of older persons is somewhat larger than for younger persons. Of particular interest is the result for expected earnings. Persons with earnings (disability transfer) expectations one standard deviation below (above) the mean are much more responsive to changes in transfer income flows than are persons at or above (below) the average. These differences are much larger than those based on any other characteristic and suggest that disability transfer flows are targeted primarily on the older disadvantaged worker population with some health problem. This implies that the disability transfer programs are "target efficient." It also implies a smaller impact of these programs on national output than is implied by the associated reduction in work hours and participation

Table 7

Elasticities of Expected Labor Market Income
and Disability Transfer Recipiency Income

| Variables set at: | Expected Labor Market Income | Expected Disability Transfer Recipiency Income |
|---|---|---|
| Simple equation at means | .0012 | -.0005 |
| Extended equation[a] at means | .0007 | -.0003 |
| Percent currently disabled = 0 | .0004 | -.0001 |
| Percent currently disabled = 100 | .0095 | -.0039 |
| Age = 45 | .0003 | -.0001 |
| Age = 59 | .0012 | -.0005 |
| Expected earnings + $\sigma$ | .0000 | -.0000 |
| Expected earnings - $\sigma$ | 1.3948 | -1.3593 |
| Expected earnings + $\sigma$; Percent currently disabled = 0 | .0000 | -.0000 |
| Expected earnings - $\sigma$; Percent currently disabled = 100 | 2.5370 | -2.4727 |

[a]Other variables in extended equation set at their means.

rates. To the extent that such induced early retirement permits increased employment opportunities for youths and other potential workers, this productivity effect is still smaller.

## 5. CONCLUSION

These estimates suggest that the increasing relative generosity and/or leniency of disability income transfer programs do have a statistically significant, though quantitatively small, effect on the work effort choices of older workers. They also partially explain the growth in these programs, and identify older low earners with health problems to be most responsive to changes in expected transfer income. Nevertheless, many questions remain unanswered. Little insight is gained into the relative contribution of other variables to the observed decrease in labor force participation rates. While disability benefit generosity has accounted for a relatively modest amount of the reduction, the contribution of changes in tastes for work, changes in social expectations regarding early retirement, changes in the physical demands of occupations, changes in the incidence of impairments, and changes in income from spouses and other sources remains unexplained.

To test the robustness of our results, we have undertaken a variety of alternative specifications, and have reconciled the quite disparate results of other studies with our own. We conclude that the responses of older males to increased disability transfer benefits is statistically significant but quantitatively small. This response is concentrated among older, disabled men who have low expected earnings. It follows that a policy of reducing disability transfers with the objective of increasing labor supply and total output is unlikely to have marked success. Moreover, those persons most likely to be hurt have low earnings capacities and few alternative sources of income support. Hence, retrenchment can be expected to reduce equity without a substantial gain in efficiency.

Notes

[1]From 1957 to 1978, the wage replacement rate in the Social Security Disability Insurance program rose from 30 to 41 percent for the average nonsupervisory manufacturing worker with no dependents; for the same worker with a wife and child, the rate rose from 57 to 68 percent.

[2]If these objectives and rules have changed over time, the analysis at a point in time would reflect both past and current conditions. This is unlikely to be significant in this case, as leniency has increased for most disability programs from their inception to 1978. Since one can reapply if denied, the 1978 data are likely to reflect 1978 rules and objectives.

[3]We exclude workers older than 62, since most are eligible for Social Security early retirement benefits at that age. Inclusion of this group of workers would further complicate the estimation problem and mask the role of disability transfers in the early retirement decisions. Evidence suggests that the availability of disability transfers is less likely to alter the work status of men below 45 years of age. Other researchers have also focused on this older age group.

[4]While there is debate in the literature on the use of self-reported disability (health) information, a recent longitudinal study indicates that self-reports of health are stable over time, highly correlated with medical doctor reports and, in fact, a better predictor of future medical evaluation than the earlier physician assessment (Maddox and Douglas, 1973). Although some researchers (e.g., Parsons, 1982) have argued that self-reported health is endogenous and leads to downward-biased estimates of the responsiveness to disability transfers, replication of his estimates using self-reported disability indicators and the PSID data obtain

estimates similar to his suggesting little evidence of bias due to endogeneity (Haveman and Wolfe, 1982).

[5]The $3360 cutoff was chosen because it is the annual equivalent of the monthly earnings limit in the dominant disability-related transfer program. There are 841 observations in this group.

[6]Disability-related transfers are defined to include benefits from SSDI, Supplemental Security Income (a program of income-tested benefits directed at the blind and disabled), veterans' disability benefits, other disability pensions, and, if disabled, a share of other welfare and help from relatives. There are 123 observations in this group.

[7]Experience five years earlier, rather than as of a more recent date, is used in order to minimize correlation with the residuals. It is included, since experience influences worker productivity and/or wage rates.

[8]The standard errors in these equations are not corrected for the inclusion of $\lambda$, so the levels of significance should be interpreted with caution. We use the equations for predictions and the coefficients would be unaffected by the adjustment.

[9]DMISC includes police and firemen, who tend to have extensive disability pension plans.

[10]We use the model in its extended form in this exercise.

[11]The estimated probability of benefit eligibility is imputed using coefficients from a probit equation explaining the acceptance-denial outcome for a sample of disability benefits applicants.

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# Appendix 1

## Variables Used in Estimates

### Disability Variables

CUMDSEV: negative exponential of years severely disabled 1968-1978, largest weight on 1978;

$(\text{CUMDSEV})^2$: square of Cum Dis Severe;

% Disabled: percent currently disabled, from 0 for no disability to 1 for totally disabled;

$(\%\ \text{Disabled})^2$: square of % Disabled.

### Dependents and Needs Variables

NMARNK: dummy variable = 1 if not married and no children under 18;

DMarried: dummy variable = 1 if currently married;

MARNK: dummy variable = 1 if currently married and no children under 18;

KIDS1878: number of children under 18 in 1978;

Spouse work: dummy variable = 1 if spouse worked in 1977;

Other household income: household income not due to respondent ($000);

Unearned income: income from assets, rent, dividends, interest, and alimony ($000).

### Tastes and Market Opportunities Variables

DPROT, DCATH, DJEW are dummy variables = 1 if person's religion is in each category, omitted category is no religion;

DWHITE: dummy variable = 1 if person is white;

Veteran: dummy variable = 1 if person is a veteran;

DSOUTH, DWEST, DNC (North Central) are dummy variables = 1 if person currently resides in each area, omitted category is East;

OCCLIM: % of male labor force in usual 1 digit industry who are functionally limited;

DPROF, DMANAG, DClerical Sales, DCRAFT, DOPERATIVE, DFARM are dummy variables = 1 if usual occupation is in each category;

DMISC: usual occupation is armed forces or protective services;

AGE78: age in 1978;

Age spline 52: second piece of linear spline corner at 52;

Age spline 59: third piece of linear spline corner at 59;

UnRate 78: area-specific unemployment rate in 1978.

Human Capital Variables

Experience in 73: years of work experience as of 1973;

Education: years of education;

Ed spline 8: second piece of linear spline; corner at 8 years of education;

Ed spline 11: third piece of linear spline; corner at 11 years;

Age × educ.: age times education;

Parents wealthy: dummy variable = 1 if parents well off when person growing up.