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Timothy Waidman, John Bound, and Austin Nichols

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Timothy Waidman
Urban Institute

John Bound
University of Michigan and NBER

Austin Nichols
University of Michigan

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Michigan Retirement Research Center
University of Michigan
P.O. Box 1248
Ann Arbor, MI 48104

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Abstract

The Social Security Disability Insurance (SSDI) system is designed to provide income security to workers in the event that health problems prevent them from working. In order to qualify for benefits, applicants must pass a medical screening that is intended to verify that the individual is truly incapable of work. Past research has shown, however, that the screening procedures used do not function without error. If screening were error-free, it has can be demonstrated that it is socially optimal to distinguish the disabled non-worker from the non-disabled, providing benefits to the disabled. In this paper we first demonstrate that if the errors in the medical screening are too large, it will not be optimal to distinguish the disabled from the non-disabled. Then, we use data on the actual quality of screening to determine first, if segmenting the non-working population is desirable, and second whether the current SSDI system relies too heavily on screening than is justified. Our preliminary conclusion is that while screening is good enough to justify some distinction in benefits, it may not be good enough to justify the size of the benefit offered.

Much of the discussion about social insurance programs centers around the question of the generality of program coverage. Should there be many programs each with its own target population and its own rules for coverage, or should the welfare and tax bureaucracies be combined into one super-program that accomplishes all of the society's redistribution and collective consumption with some sort of negative income tax program? In the history of this literature some economists and policy-makers advocated the negative income tax as a more efficient means of redistribution. More recent work has argued that categorization, or tagging, is more efficient because it can use different incentives for those whose decisions are made differently. For example, Ellwood and Summers (1986) argue that certain groups, like the severely disabled, have very inelastic supplies of labor, while others, like teenagers have very elastic supplies. Since the efficiency losses of subsidies are smaller for those with inelastic supply responses, it makes sense, on efficiency grounds to use different systems of benefits and eligibility requirements for groups like these. Akerlof (1978) presents a more formal treatment of the economics of "tagging." If we determine that a group of individuals has a greater need, Akerlof has shown that if we can "tag" this group, it is optimal, in the social welfare sense, to treat these individuals differently (under his example, a negative income tax) by giving them higher subsidies. This result only holds when the tagging is costless and the characteristic that determines the tag is exogenous to the individual. When the tagging is based on an endogenous characteristic, the optimality of differential treatment becomes an empirical question. Redistributive programs can be considered forms of social insurance when income contains random components. As such, much of the work relevant to social programs with endogenous beneficiary status is done in the context of imperfect information and the provision of insurance. Varian (1980) discusses the choice of an optimal tax system that involves trade-offs of three types of effects: equity, efficiency, and insurance. Redistribution has the effect of reducing the variance in income, an effect that is valued by risk-averse individuals. When moral hazard, adverse selection, and transaction costs problems make private provision of such insurance infeasible there may be a case to be made for public provision of insurance. Specifically, one method of overcoming problems of adverse selection is mandatory insurance, but moral hazard problems may exist in public as well as private provision. While Varian discusses redistributive taxation in general, Diamond and Mirrlees (1978) discuss social insurance specifically with regard to labor force decisions. Under several sets of assumptions, including the existence of moral hazard, they derive the optimal provision of public insurance against loss of earnings ability, where ability to work is treated as a dichotomous variable. Those who are unable to work retire and all others choose whether to retire or work. They find that at the optimal level of provision, individuals are indifferent between working and not working but work when able. Like Diamond and Mirrlees, Crocker and Snow (1986) base their optimal insurance provision on the existence of two (or some finite number of) groups in the population which are imperfectly distinguishable from one another. They find that in private insurance markets, it is optimal to discriminate between the groups, offering different policies based on some observable characteristic (race, sex, etc.) when that characteristic is somehow correlated with the underlying high/low risk distinction. However, if the observation of the intermediate characteristic is costly, there is no unambiguous efficiency gain to discrimination based on that characteristic. Finally, Shavell (1979) obtains the same result for the provision of social insurance finding that it is possible to design a program, under moral hazard, where the usefulness of imperfect information about the care taken by individuals to avoid loss outweighs the risks (to the insurer) involved in using that information. This program involves either ex ante or ex post observation[1] of care taken depending on the value of imperfect information and the number of individuals, among other things.

[1] Ex ante observation is made of all covered by the insurance while ex post observation is made only of claimants.

The present paper attempts to answer questions of coverage in the specific case of Disability Insurance taking into account issues raised by the authors mentioned above. In particular, what system of incentives is most appropriate for the provision of benefits to the disabled? Given that the first step in obtaining disability benefits is the application by the individual who reports himself as disabled, and given that observation of health status by the government is imperfect, what program can the government design that will maximize social welfare? Does it impose a health screen, or does it rely on low benefit levels to induce those who are able to work to remain in the labor force and provide basic support only to those who have no labor force option? If the health screen is only partially effective in screening out the able-bodied and screening in the disabled, should the screen even be used? If the application process is costly either for the applicant or the government, is the program worth having? If there is some threshold level of costs, below which the program is welfare-improving, what is that level?

The overriding goal of this paper is to examine the welfare implications of imperfect medical screening. Stories of able-bodied applicants being awarded disability benefits and deserving applicants being denied have caused concern about both the reliability and validity of DI screening. The designers of DI recognized the difficulty of distinguishing the disabled from the able-bodied and have tried to design a screening process that can identify the truly disabled. Intuitively, one imagines that the reliability and validity of screening would have an impact on the design of the optimal program. This paper uses available evidence on both the reliability and validity of medical screening to determine how an optimal set of programs might be designed to provide income to both the disabled and non-disabled. Given the level of imperfection in the medical screen that is used, does it make sense to make the kinds of distinctions that exist in transfer programs between the disabled and non-disabled?

The Reliability and Validity of Disability Screening

The law defines disability as the inability to engage in substantial gainful activity by reason of a medically determinable physical impairment expected to result in death or last at least 12 months. The worker must be unable to do any work that exists in the national economy for which that worker is qualified by virtue of his age, education, and work experience.

The actual arrangement for awarding DI benefits is complex. A person seeking these benefits applies for them at an office of the Social Security Administration (SSA). Once the federal officials and the applicant have gathered sufficient information to complete the application, it is submitted to a state agency for determination of disability. Disability examiners in this office, working with the aid of vocational and medical consultants, make the initial determination of eligibility for DI.

As a practical matter, SSA asks the state disability determination offices to follow a five-step procedure in determining disability. First, the examiners check to see if the applicant is currently working and making more than $500.00 a month, defined as the "substantial gainful activity" amount. If so, the application is denied. Almost no cases are rejected in this manner, since presumably the SSA field offices have already checked to see if the applicant is working before they send the application to the disability determination office. Second, the state disability examiners determine if the applicant has a severe impairment that is expected to last 12 months or result in death. If not, the application is denied. About 26 percent of all applicants were denied at this step in 1994. Third, the state disability examiners look to see if the impairment is included on a list of impairments defined as disabling by SSA. If the impairment is listed, and if it can be expected to last at least 12 months-medical doctors hired by the state agencies help to make this decision-then the person receives benefits. If the impairment is judged to be the equivalent of one of the listed disabling impairments, then the person also receives benefits. Most recipients are awarded benefits at this stage because their impairment either "meets" or "equals" (21 percent of all applicants in 1994) one of those on the list.

If a decision cannot be reached on medical factors alone, the applicant's residual functional capacity is examined, to see if the person's impairment prevents him or her from meeting the demands of "past relevant work." If not, then benefits are denied. About 20 percent of all applicants were denied at this step in 1994. If so, examiners determine if the impairment prevents the applicant from doing other work. Here vocational factors are considered. If, for example, a person's maximum sustained work capacity is limited to sedentary work and he is at least aged 50 to 54, with less than a high school education and no skilled work experience, then the person would be considered disabled and given benefits. But if the person's previous employment experience includes skilled work, then he or she would not receive benefits. At this point, 11 percent of all applicants were allowed and 22 percent were denied in 1994.

Applicants who are denied benefits can ask for a reconsideration. Their file will then go back to a second team of examiners. Rejected on this reconsideration, an individual may appeal the case to an administrative law judge. Here is the first time that an applicant will actually come face to face with the decision makers. Denied benefits at this stage, an individual may appeal the decision to the Social Security Appeals Council and then to the District Courts.

Only a minority of claims get past the initial hearing (34 percent in 1995), with an even smaller portion getting as far as an administrative law judge (19 percent in 1995). Still, as the proportion of claimants who were initially denied benefits rose during the late 1970s, the proportion of those who appealed also rose. The proportion of initial decisions that were reversed also went up. For the claimants who are either allowed benefits at the initial level or who don't appeal, the process usually takes a few months. For those who appeal through to the administrative law judge, the process can take a year or more.

The validity of the medical screening involved in determining DI eligibility has always been questioned. During the 1960s the Social Security Administration commissioned several studies to consider this issue. The most ambitious effort was a study conducted by Saad Nagi (1969). Independent panels evaluated the work potential of a sample of SSDI applicants. These panels included doctors, psychologists, and occupational and vocational counselors. They were authorized to enter applicants' homes to conduct any of a variety of tests and to collect any information they felt to be relevant to the case. Moreover, in their deliberations they were not bound by the legal definition of disability.

The teams evaluated applicants on an eight-point continuum ranging from "fit for work under normal conditions" to "not fit for work." As reprinted in Table A.1, Nagi (1969) compares the clinical teams' eight-point evaluations of work capacity to the actual Social Security Administration decisions to provide or deny benefits. Somewhat surprisingly, even among the subsample of people the clinical team judged to be nonborderline cases there is a 30 to 40 percent disparity compared to Social Security evaluation outcomes. For example, of those the clinical team judged to be fit only for work at home, 30.5 percent had been denied benefits. Of those the clinical team judged to be fit for work in specific jobs, excluding former jobs, under normal circumstances, 36 percent received DI allowances.

Nagi (1969) pointed out the limitations of the DI screening process. He argued that because the vast majority of its applicants suffer significant health limitations, the disability determination examiners have considerable difficulty distinguishing the more deserving from the less deserving. They have particular difficulty in evaluating cases that involve either multiple impairments or psychological or vocational components.

There have been substantial changes in the nature of the medical screening used to evaluate disability insurance applicants since Nagi's study. Not only has the Social Security Administration made changes in the criteria used to evaluate disability applicants, but the fraction of individuals appealing decisions substantially increased. As a result, it is unclear to what extent the Nagi study still applies. Still, no similar study has ever been commissioned and so it continues to be the most reliable guide to the accuracy of the medical screening used to evaluate applicants.

Errors in disability determination arise from a number of sources. First of all, even with the same medical information, individuals will differ in their judgments about how debilitating a specific condition is. Even if they do not disagree about the fact they may disagree about the right threshold. These sources of disagreement introduce elements of test-retest error. A second source of error is introduced by whatever discrepancy there is between disability as it is legally and administratively determine and disability as it affect labor market performance. Such discrepancies would arise if there are factors that influence actual disability that the disability determination service fails to take into account (e.g. unobserved components of health) or if there are factors that don't influence actual disability that the disability determination service does take into account (e.g. misinformation about an applicants condition).

In evaluating the empirical evidence it will be useful to work with a simple statistical model, in which SSA screeners consider a component of health, ψ, while Nagi screeners consider ψ, but in addition, consider an orthogonal component, η. Both screeners have a fixed standard for disability, but both have random errors in their evaluations (κ for SSA, ν for Nagi). Thus a DI applicant

$$\text{passes SS screen if } \delta_s = \psi + \kappa > c \tag{1}$$

$$\text{passes Nagi screen if } \delta_n = \psi + \eta + \nu > c_n. \tag{2}$$

We can collapse the data in table A.1 to a 2 x 2 table if we define the bottom 3 Nagi categories as passing the disability screen. Using these data we can calculate the correlation between δ_s and δ_n, but even with one normalization, we are still left with three variances to calculate.

In this model, σ_κ^2 σ_ν^2 are natural measures of the reliability of the two screening regimes. Data obtained by Gallichio and Bye (1980) can be used to get an estimate of σ_κ^2. These researchers gave different SSA evaluators in 8 states the same set of applications, and measured the rate of agreement between them. A simple statistical model of this experiment would posit that an applicant in state s

$$\text{passes screen 1 if } \delta_1 = \psi + \kappa_1 > c_s \tag{3}$$

$$\text{passes screen 2 if } \delta_2 = \psi + \kappa_2 > c_s. \tag{4}$$

Here, we assume that $\sigma_{\kappa_1}^2 = \sigma_{\kappa_2}^2 = \sigma_\kappa^2$. The within state estimate of the correlation between evaluators is 0.912. If we normalize the variance of ψ to 1, this implies that $\sigma_\kappa^2 = 0.52$. If we assume that the screening variability of the Nagi teams is roughly equal to that of the SSA evaluators, we can identify the remaining parameters in the model. Under these assumptions, $\sigma_\eta^2 = 0.84$. Thus, the SSA evaluators considered just over half of the variation in the health considered by the Nagi evaluators when making disability determinations.

However, both the GB data and the Nagi data are obtained on self-selected samples of applicants. We can add an application decision to the model, in which a potential applicant considers both health factors, ψ and η, and non-health factors, υ. He applies for DI benefits if

$$\delta_a = \psi + \eta + \upsilon > c_a. \tag{5}$$

While these data do not allow us to identify the relative importance of non-health factors in the application decision, in other work (Bound, Stinebrickner, & Waidmann,

2002) we have found that about half of the decision to apply is based on factors other than observeable health and disability. Using a trivariate probit, we can jointly estimate the selection equation with the screening decisions. When we account for self-selection, we estimate that the correlation between the Nagi and SSA evaluators is more like 0.64, higher than estimated without accounting for selection, and thus the validity of screening is higher than estimated when we ignored selection. In addition, the correlation between SSA evaluators (and thus the reliability of screening) is also higher (.928 vs. .912) after accounting for selectivity.

In the remainder of the paper we outline an economic model of the SSDI program that allows us to examine the relevance of these findings for the design of the socially optimal program.

A Model of Disability Insurance with Imperfect Screening

Diamond and Sheshinski (1995) have a model of a disability insurance program that can help to answer some of these questions. They show that in a scheme where health is costlessly but imperfectly observable it is still optimal to provide a DI program that screens on the basis of health such that the probability of being accepted onto the program increases with level of disability.[2] Under such a program, those who are most able to work do not apply for DI, some who would work otherwise apply and are accepted while others are rejected and return to work. Still others apply, are rejected and choose to remain out of the labor force regardless. In their model, the optimum is such that the benefits from the disability program are less than the income received by those who work but are greater than the benefits to rejected applicants who remain out of the labor force. It can be shown, however, that if there are costs to the government of observing the health status of applicants then the optimality of providing higher benefits to those who pass a health screen

[2] "Disability" and "Disutility from labor" are indistinguishable from one another.

is ambiguous.[3] Diamond and Sheshinski, therefore leave interesting empirical questions unanswered. By allowing for individual specific costs of application and more carefully modeling the government assessment of individual health status, the model presented here generalizes the Diamond and Sheshinski model and develops an empirical implementation which, we claim, helps answer some of these questions.

Assume that each individual is characterized by realizations on four random variables:

- ψ This represents disutility caused by work which the Social Security Administration calls disability. This is what the medical examiner uses in evaluating the individual's eligibility for Disability Insurance benefits.
- ϵ This variable has several possible interpretations. It represents either disutility from work that is unrelated to health or the component of poor health that is unobserved in the physical examination required by SSA. Thus, while ϵ does not enter into the SSA decision regarding eligibility, it does enter the individual's decision about work and is counted in welfare calculations. In terms of the statistical model presented above, we can think of $\epsilon = \eta + \upsilon$.
- ξ This variable represents the cost, in utility terms, of application for the individual. This cost might be interpreted as either a monetary or a psychic cost or a combination of both. Its monetary component may be the earnings foregone during the period of application (working during the application process is taken as evidence of ineligibility by the Social Security Administration) or the opportunity cost of time involved applying and undergoing medical examination.
- κ We can think of this as deviation from the mean value of the disability screen used by SSA, and could represent the examiners error in measuring "true" health. The individual never actually knows the value of this variable, but knows its distribution, and makes application decisions based on that knowledge.

[3] See the Appendix for this result.

The Individual's Problem

Based on an individual's realization of the first three random variables, he decides whether or not to apply for disability benefits. If he decides not to apply or applies and is rejected, he must decide whether or not to work. If the individual does not work and does not receive disability benefits, he receives benefits from a program that has no health criteria for its beneficiaries. We model the application and work decisions as follows. Each of the three states of the world has its own level of consumption. Workers receive C_a; DI recipients receive C_d; and the rest receive C_b.[4] In utility terms, a non-applicant has utility

$$U^{na} = \max\{v(C_b), v(C_a) - \theta\} \tag{6}$$

where $\theta = \exp\{\psi + \epsilon\}$ and $v(\cdot)$ is a function such that $v'(\cdot) > 0$ and $v''(\cdot) < 0$. An applicant who is accepted has utility

$$U^{di} = v(C_d) - \xi \tag{7}$$

while an applicant who is rejected has utility

$$U^{rej} = \max\{v(C_b), v(C_a) - \theta\} - \xi. \tag{8}$$

As discussed above, the individual does not know the value of κ that will apply in his particular case, but based on his knowledge of its distribution, he knows

$$\text{Prob(Application Accepted}|\psi, \alpha_\kappa) = \text{Prob}(\psi > \kappa|\alpha_\kappa) = P(\psi, \alpha_\kappa) \tag{9}$$

where α_κ is the vector of distributional parameters for κ. We can now write the following decision rules. First, notice that equations (6) and (8) imply that the work/non-work decision is the same for non-applicants and rejected applicants, i.e.,

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[4] C_b might be thought of as the combination of alternative sources of income for those rejected by SSA and remaining out of the labor force. These might include veterans' benefits, general assistance, etc.

$$U_w^{na} \equiv v(C_a) - \theta > v(C_b) \equiv U_{nw}^{na} \quad \Rightarrow \quad U_w^{rej} \equiv v(C_a) - \theta - \xi > v(C_b) - \xi \equiv U_{nw}^{rej}.$$

Thus, a person can be classified as a "worker" iff

$$v(C_a) - \theta \geq v(C_b), \quad \text{or}$$

$$\psi \leq \ln(v(C_a) - v(C_b)) - \epsilon \equiv \psi^*(\epsilon). \tag{10}$$

To model the application decision it will be useful to define the expected utility of applicants as

$$EU^a \equiv \begin{cases} P(\psi, \alpha_\kappa)U^{di} + (1 - P(\psi, \alpha_\kappa))U_w^{rej} & \text{if } \psi \leq \psi^*(\epsilon), \\ P(\psi, \alpha_\kappa)U^{di} + (1 - P(\psi, \alpha_\kappa))U_{nw}^{rej} & \text{if } \psi > \psi^*(\epsilon). \end{cases} \tag{11}$$

Similarly, we can define

$$U^{na} \equiv \begin{cases} U_w^{na} & \text{if } \psi \leq \psi^*(\epsilon), \\ U_{nw}^{na} & \text{if } \psi > \psi^*(\epsilon). \end{cases} \tag{12}$$

Then, an individual will apply for DI iff $EU^a > U^{na}$. For "workers," this condition is (assuming $\xi > 0$)

$$\xi < P(\psi, \alpha_\kappa) \left[v(C_d) - v(C_a) + \exp\{\psi + \epsilon\} \right] \equiv \xi_w, \tag{13}$$

and for non-workers, this condition is

$$\xi < P(\psi, \alpha_\kappa) \left[v(C_d) - v(C_b) \right] \equiv \xi_{nw}. \tag{14}$$

Equations (10), (13) and (14) thus define the decision rules for every individual in the population.

The Government's Problem

There are several possible characterizations of the government's choice of the optimal program. One approach is to maximize the expected utility of an individual who knows only the distributions of the random variables described above, and behaves according to the model above. When working the individual pays the taxes that fund the program and when not working, he receives benefits according to the government's perception of his health. This approach has intuitive appeal because it approximates the choice of an insurance policy that this hypothetical individual makes subject to the constraint that the expected value of his or her output equal the expected payments made by the insurance policy. This concept of the optimal program is problematic, however, when we consider the nature of ϵ and ψ. To the individual these two quantities are equivalent, and the optimal insurance policy (from the perspective of the individual) should protect consumption equally from high values of either. To the extent that ϵ represents non-health disutility, political constraints, among other things, might lead policy-makers to treat variation in this variable differently from variation in disutility that can be clearly classified as health-related.

Given that the policy maker desires to distinguish between health-related and non-health disutility, a medical screen is a natural way to make that distinction. The presence of a screening process induces individuals to treat the two forms of disutility differently in the application decision, since high values of ϵ will not increase the probability of acceptance as will high values of ψ. The policy maker then has two potential instruments to use in designing the optimal set of program, the stringency of the screen and the generosity of disability benefits relative to non-disability benefits. The optimality of having a screen in the presence of imperfect health information and a costly application process, as we will see, depends on the quality of the screening mechanism. For the "representative" individual, a more stringent screening mechanism benefits the working state while a less stringent screen benefits the non-working states. The policy maker's task is to find the appropriate balance between these possible states, and determine levels of income in the non-working states that provide adequate insurance against lost earnings.

Hence, assume that the government, knowing the joint distribution of the three random variables that characterize each individual, seeks to set benefit levels in both the health-screened program and the non-screened program and the mean standard for health-screening to maximize the expected utility of this "representative" individual who knows nothing but these distributions. The government is subject to a resource constraint such that the total consumption of the population equals the output produced by those who work. For simplicity assume that each person who works is equally productive and produces one unit of output. The government's problem is, therefore,

$$\begin{aligned}\max_{\Omega,\lambda} &\iiint_A U(\epsilon,\psi,\xi,\Omega)f(\epsilon,\psi,\xi)d\xi d\psi d\epsilon \\ -\lambda &\iiint_A \left(C(\epsilon,\psi,\xi,\Omega) - Y(\epsilon,\psi,\xi,\Omega)\right) f(\epsilon,\psi,\xi)d\xi d\psi d\epsilon\end{aligned} \tag{15}$$

where $\Omega \equiv (C_a, C_b, C_d, \bar{\kappa})$ is the vector of program parameters, $C(\cdot)$and$Y(\cdot)$ are the levels of consumption and output, respectively, determined by program parameters and realizations of ϵ, ψ andξ. Then if we define the domains of the variables as

$$\epsilon,\, \psi \in (-\infty,\infty) \quad \text{and} \quad \xi \in (0,\infty),$$

the maximization can be written

$$
\begin{aligned}
\max_{\Omega,\lambda} & \int_{-\infty}^{\infty}\int_{-\infty}^{\psi^*(\epsilon,\Omega)} \left[v(C_a) - e^{(\psi+\epsilon)}\right] f(\epsilon,\psi) d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{-\infty}^{\psi^*(\epsilon,\Omega)} \int_{0}^{\xi_w(\epsilon,\psi,\Omega)} \left\{P(\psi,\alpha_\kappa)\left[v(C_d) - v(C_a) + e^{(\psi+\epsilon)}\right] - \xi\right\} f(\epsilon,\psi,\xi) d\xi d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{\psi^*(\epsilon,\Omega)}^{\infty} v(C_b) f(\epsilon,\psi) d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{\psi^*(\epsilon,\Omega)}^{\infty} \int_{0}^{\xi_n(\epsilon,\psi,\Omega)} \left\{P(\psi,\alpha_\kappa)\left[v(C_d) - v(C_b)\right] - \xi\right\} f(\epsilon,\psi,\xi) d\xi d\psi d\epsilon \\
-\lambda \Bigg[& \int_{-\infty}^{\infty}\int_{-\infty}^{\psi^*(\epsilon,\Omega)} (C_a - 1) f(\epsilon,\psi) d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{-\infty}^{\psi^*(\epsilon,\Omega)} \int_{0}^{\xi_w(\epsilon,\psi,\Omega)} P(\psi,\alpha_\kappa)(C_d - C_a + 1) f(\epsilon,\psi,\xi) d\xi d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{\psi^*(\epsilon,\Omega)}^{\infty} C_b f(\epsilon,\psi) d\psi d\epsilon \\
& + \int_{-\infty}^{\infty}\int_{\psi^*(\epsilon,\Omega)}^{\infty} \int_{0}^{\xi_n(\epsilon,\psi,\Omega)} P(\psi,\alpha_\kappa)(C_d - C_b) f(\epsilon,\psi,\xi) d\xi d\psi d\epsilon \Bigg].
\end{aligned}
\tag{16}
$$

We claim that introducing costs of application produces a similar result to the introduction of costs of screening. It can be shown (see Appendix) that in a model where health is not perfectly observable, a system that screens applicants on observable health and pays them higher benefits is optimal when costs of screening are zero; however, the introduction of costs of screening make this optimality ambiguous. In this case, we assert that the ambiguity also arises if the applicant bears the costs instead of the government. Intuitively, when the applicant bears the cost of screening, the government must increase the benefit paid to keep marginal utilities equal across contingencies; therefore the government bears a cost and the same results hold. Once we have this result, the optimality of disability insurance becomes an empirical question. If some level of cost is low enough that a separate program is still beneficial, does the population have a cost of application that lies below that critical level? More precisely, if we assume that there is a continuum of costs in the population, do the existence of low costs for some justify the existence of a separate program? In what follows we propose a method using knowledge of aggregate behavior to calibrate the model of individual behavior described above and determine distributional parameters for the population. These values can then be substituted into the set of first-order necessary conditions for an interior optimum to determine the parameters, Ω^*, of the optimal program.

Besides allowing us to characterize the optimal program, knowing the structural parameters of the model allows us to examine some comparative statics results implied by the model. These results serve as both answers to substantive questions and checks on the validity of the model in describing behavior. For example, how would the proportion of the population participating in the labor force change with a balanced-budget change in C_d? $\bar{\kappa}$? Or, what proportion of those on DI would be working if the program did not exist? It should also be interesting to see how the functional form $v(\cdot)$ affects the parameter values, optimal program parameters and the above comparative statics results. How does more risk aversion in the utility function affect the generosity of programs?

Calibration of the Model

To actually obtain values for the distributional parameters, we must impose more structure on the model. In particular, we must specify a functional form for the utility function $v(\cdot)$, the density functions for $\psi, \epsilon, \xi,$ and κ, and the function $P(\cdot)$. To begin, we make the following assumptions:

$$v(z) = \frac{z^{1-\gamma}}{1-\gamma} \tag{17}$$

$$\epsilon \sim N(\bar{\epsilon}, \sigma_\epsilon^2) \tag{18}$$

$$\psi \sim N(0, \sigma_\psi^2) \tag{19}$$

$$\ln \xi \sim N(\bar{\eta}_\xi, \sigma_{\eta_\xi}^2) \tag{20}$$

$$\kappa \sim N(\bar{\kappa}, \sigma_\kappa^2) \tag{21}$$

Note that (13) –(21) imply first that

$$P(\psi, \alpha_\kappa) = \Phi\left(\frac{\psi - \bar{\kappa}}{\sigma_\kappa}\right) \qquad \text{and} \qquad \frac{\partial P(\cdot)}{\partial \bar{\kappa}} = \phi\left(\frac{\psi - \bar{\kappa}}{\sigma_\kappa}\right)\left(-\frac{1}{\sigma_\kappa}\right) \tag{22}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative standard normal distribution and the standard normal density functions, respectively, and second that any joint density function involving two or three variables can be written as the product of marginal density functions.

To get an idea of what these distributional parameters look like we make use of the following observations. We assume that replacement ratios for DI recipients are 60%[5] and for non-recipients are 40%.[6] That is,

$$C_d = .6C_a \qquad \text{and} \qquad C_b = .4C_a \tag{23}$$

These ratios, and the rest of our assumptions, can be varied to test the sensitivity of the structural parameters to those assumptions.

For the purposes of calibration, we begin by assuming that

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[5] See Lando, et. al.(1982). This ratio corresponds to the ratio of average income under DI to average income for an individual in the labor market in 1975.

[6] Based on our tabulations from the 1972 Survey of the Disabled. Comparing income received by disabled non-workers who did not receive DI with income received by DI recipients, we find a ratio of $\frac{2}{3}$. Thus, $\frac{C_b}{C_a} = 0.4$.

$$\frac{\sigma_\psi^2}{\sigma_\psi^2+\sigma_\epsilon^2}=\frac{1}{3} \qquad \text{and} \qquad \frac{\sigma_\kappa^2}{\sigma_\psi^2}=\frac{1}{5} \tag{24}$$

and will vary these assumptions over a range consistent with the estimates derived above. These assumptions leave us with six unknowns: $\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa},$ and C_a. The results of past empirical work can be used to help determine these numbers. We wish to find values of the unknowns which are consistent, given our model, with these empirical observations of the Disability Insurance program. First assume that the proportion of the population that works (of men 45-64) is 0.876.[7]. Assume that the proportion of this age group that applies for DI is 0.136[8] and that the probability of acceptance conditional on application is 0.50[9]. The elasticity of applications with respect to generosity of benefits has been estimated at 0.50[10], and the elasticity of applications with respect to the conditional (on application) probability of acceptance has been estimated at 0.80.[11] Finally, we assume that the internal budget of the combined disability/welfare program balances for the age group in question. Then we can get a system of six equations in the six unknowns. These equations will set the hypothesized numbers above equal to the analytical expressions for the corresponding numbers in the model and as such will be of the form

$$\text{Proportion working} = 0.876 = \pi_w((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \tag{25}$$

$$\text{Proportion applying} = 0.136 = \pi_{app}((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \tag{26}$$

$$\text{Conditional acceptance probability} = 0.50 = \pi_{acc|app}((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \tag{27}$$

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7 We will calibrate the model with assumptions based on 1975 observations. For this number see Bureau of Labor Statistics(1986).

8 Social Security Administration(1987).

9 Lando, et. al.(1982) give this number for applicants of all ages.

10 Halpern(1979) based on time-series regressions of applications on benefit levels.

11 Marvel(1982) using pooled cross section time series state data where some states tightened requirements under federal pressure over the period studied. Estimates are based on within-state first-differences.

$$\text{Benefit elasticity of applications} = 0.50 = \rho_{\pi_{app},C_d}((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \quad (28)$$

$$\text{Probability elasticity of applications} = 0.80 = \rho_{\pi_{app},\pi_{acc|app}}((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \quad (29)$$

$$\text{Program Budget Deficit} = 0 = D((\bar{\epsilon}, \sigma_\epsilon, \bar{\eta}_\xi, \sigma_{\eta_\xi}, \bar{\kappa}, C_a)) \quad (30)$$

The six equation system can be reduced to a five equation system by substituting through the budget constraint which, at the solution, satisfies

$$\pi_w(C_a - 1) + \pi_{acc|app}\pi_{app}(.6C_a) + (1 - \pi_w - \pi_{acc|app}\pi_{app})(.4C_a) = 0. \quad (31)$$

The six constants used here imply $C_a = 0.93$ regardless of the values of γ and $\frac{\sigma_\psi^2}{\sigma_\psi^2+\sigma_\epsilon^2}$.

While there is no guarantee that a system of non-linear equations with as many equations as unknowns will have a unique solution (if it has any), if we believe that this model is correct then the existence of a solution in the real-world should give us faith that one exists in the model. This concern may be moot, however, because it turns out that the model does have a solution which seems reasonable given its structure.[12] Table 1 gives parameter estimates for several values of the utility function parameter, γ, several levels of screening validity, $\frac{\sigma_\psi^2}{\sigma_\psi^2+\sigma_\epsilon^2}$, and several values of the screening reliability parameter, $\frac{\sigma_\kappa^2}{\sigma_\psi^2+\sigma_\kappa^2}$. The direction of change in the parameter values with different levels of risk-aversion and screening validity and reliability seem to make sense.

`[Table 1 here]`

As the assumed level of risk aversion goes up, in order for the observed level of labor force participation and DI application to remain the same, we would expect to have lower levels of unobserved disability, higher levels of application costs, and lower expectations of acceptance for DI applicants since higher levels of risk aversion lead to lower thresholds for DI application, other things equal. All of these expectations are borne out in the calibrations reported in table 1.

[12] The system is solved numerically using Broyden's secant method for non-linear equations.

When we vary the parameter representing screening reliability, the structural parameters behave as expected. With higher assumed levels of screening reliability (lower relative variance in the disability threshold), those with marginal levels of observed disability will be less likely to apply. To keep participation and application rates constant, we would expect either a lower average threshold in the disability determination process, a lower average level of application costs, or higher levels of unobserved disability. Each of these is seen when we vary the assumed reliability of the screening process.

When we vary the parameter representing screening validity (by changing the variance of observed disability relative to the variance of total disability), we get a different story. We would expect that several forces are operative in the calibration results. First, an increase in the variance of observed disability (while the mean of observed disability is assumed to be constant) will mean an increase in the numbers of individuals qualifying to be disabled. In order for participation, application and acceptance rates to remain constant, there might be a decrease in unobserved disability, a higher threshold level of disability in the disability determination process, or a higher mean level of application costs. However, a higher variance in observed disability also implies a lower level of sensitivity in the application process to benefit levels and acceptance probabilities. If application elasticities are to remain constant, we might expect higher levels of unobserved disability or lower threshold levels of disability in the determination process. As we see when we vary the validity parameter in the range from 0.33 to 0.50, the structural parameters move in both directions.

For each of the cases reported in table 1, we then numerically solve the system of first order conditions corresponding to the maximization problem given in (11). The first four rows of each panel give the values of the program parameters with respect to which the optimization is performed. The table indicates that the optimal levels of income replacement are higher for larger values of the risk aversion parameter, as individuals are willing to forego more in taxes collected from the working state to insure against lost consumption in the non-working states. Compared to current levels of income replacement in both the DI system and in alternative transfer systems, the optimal rates of replacement are often considerably larger.

[Table 2 here]

Values of the disability threshold are also presented in this table, but without knowledge of the underlying distribution of disability and the other structural parameters, it is impossible to know what happens to acceptance rates. Thus, in the next section of the table, we present simulated values for the population's DI application rate, the conditional acceptance rate and the labor force participation rate. These indicate that while transfer programs are more generous at the optimum, application rates for disability insurance are not much larger, most probably due to the relatively large increase in the generosity of non-DI transfer income. Hence, application costs must be large enough to discourage many of the non-working non-disabled (as defined by the observed disability level) from applying for DI benefits. At high levels of risk aversion the presence of large application costs apparently begins to drive down application rates. For example, if the disability screen captures half of the variance in work disutility (validity parameter=0.5), the level of the screen (as implied by the observed application rates) is very high. In this scenario, high levels of risk aversion combined with high implied application costs produce an optimal program in which the DI program becomes unimportant. Application costs are too high, and the utility gain in receiving DI benefits is too low to justify any applications to the program. The same trend is evident, though less dramatic, at higher levels of risk aversion under other assumptions about the validity of screening.

Labor force participation rates are in general lower at the optimum than those we observe, but as the next two lines in the tables indicate, a much smaller fraction of the DI recipient population under the optimal program who would be working if they were not receiving DI. The optimal program apparently provides an income alternative for those with high levels of work-disutility but who would fail to qualify for DI benefits. Combined with apparently considerable costs of application, this generous alternative produces an apparently more self-selected group of applicants. Under the assumption, however, that the screening process is less reliable (reliability parameter=0.25), the improved self-selection of the applicant pool disappears. Conversely under the assumption that screening is more reliable, the improvement in self-selection is apparently larger.

Finally, table 2 presents a utility comparison of the current and optimal program under each set of assumptions. In addition to calculating the level of utility under both the optimal and current programs, we also calculate the fraction of income necessary to compensate a person facing the optimal program in order to make him/her indifferent between the optimal program and the current program. We exploit the feature of constrained optimization problems that the value of the Lagrange multiplier at the optimum is equal to the marginal utility of income. Then, we can get a rough idea of the value of the utility difference by dividing the difference in utility by the value of the Lagrange multiplier. These calculations indicate that the current and optimal programs are much farther apart in value to the representative agent if the agent's level of risk aversion is large. At low levels of risk aversion such as g=1.5, having the optimal program is only worth about 1% of a representative individual's income, but at higher levels, the optimal program may be worth up to 15% of that individual's income.

Another set of simulations not reported here can be used to get an idea of the benefits of improving the screening process. For example, in calculating the parameters of the optimal program from the implied values of the structural parameters, we could simulate an improvement in the reliability parameter. Such a simulation indeed produces an expected utility gain for the population, though of a fairly small magnitude. Assuming a risk aversion parameter of 0.3, and a validity parameter of 0.33, a 25% reduction in the relative variance of the disability screen (an increase in the implied rate of agreement between independent disability evaluators from 83% to 87%) produces a utility gain worth less than 0.02% of the average individual's income. Whether this screening improvement is worthwhile depends on whether the cost of achieving a more reliable system is smaller or larger than the benefit summed over the entire population.

Discussion

Some Preliminary Conclusions

Given the model of disability insurance formulated above, and results of past empirical work on DI, we have shown that it is optimal, under plausible conditions, to have a program like DI that targets a segment of the population considered to have special need and smaller-than-average elasticities of labor supply, and gives them higher-than-average transfer payments. The group is tagged using observable health as an imperfect measure of ability to work. Even if the process involves costs to both beneficiaries and non-beneficiaries, it is still optimal to use this process to categorize the population. However, the structure of the optimal program varies considerably with the assumptions we make about information quality. While this variability makes concrete policy recommendations on stringency difficult, it is fairly clear that the consumption advantage experienced by applicants who pass the health screen over those who do not is larger than optimal regardless of the quality of information. If the levels of risk aversion used in determining the optimal program approximate the risk aversion in the population, rejected DI applicants and other non-workers suffer inefficiently large losses in income under the current benefit structure.

A central point of this paper is to understand the welfare implications of imperfect screening. These results allow us to make several preliminary conclusions. First, with the implied levels of application costs, the observed levels of imperfection in the screening process are not large enough to eliminate the utility gain from having a two-tiered transfer system. However, they do imply that the current system probably relies too **heavily** on this medical screening. Second, improvements in the screening process would produce benefits for the population. Whether doing so is desirable obviously depends on the costs of those improvements.

Directions For Ongoing Research

These conclusions are preliminary, as several areas of the research reported here are currently being refined. The results obtained after these modifications are made will serve as a test of the robustness of the preliminary findings. First, the data used here are largely obtained from the 1970s. The SSA has linked data from the Survey of Income and Program Participation with administrative data on SSDI applicants. These can be used to obtain more recent estimates of the fraction of the population applying for benefits, the fraction allowed, and the fraction of non-applicants and denied applicants who participate in the labor force. These changes will largely require recalibrating the model and re-estimating optimal program parameters.

Second, the model described above is a static model, in that the award decision and benefit receipt is assumed to be instantaneous. The SSDI program has a built-in waiting period for recieving benefits after the determination is made that an individual is disabled. During the waiting period, the successful applicant will not have been working. Thus, we are incorporating a waiting period into the model, during which applicants will only be able to consume what non-working persons who aren't receiving DI benefits can consume (C_b). In addition, the random application costs, ξ, like the monetary cost of reduced income, are assumed to be limited in time to the waiting period. This change necessitates the introduction of discounting for both cash flows and future utility.

Third, the government problem we present here seeks the parameters of the DI and non-DI transfer system that balance the budget and maximize the welfare of the entire population. It is perhaps more appropriate to think of the goal of the programs to maximize the value of the program to the population with some limitation on their ability to work. Thus, in calculating our benchmarks and in maximizing social welfare, we will confine ourselves to the 15 to 20 percent of the working age population who have some limitation.

Finally, we will add to the simulation exercise a calculation of the optimal program parameters under two extreme cases. The first of these is the case of perfect information. Here, individuals know with certainty whether or not they will be awarded benefits, so only those who qualify will bother to apply. The optimal policy will provide two levels of benefits. In fact, the optimal disability benefit should completely replace lost income from work, as well as reimburse individuals for any costs in application. The other extreme case is one in which there is no information contained in the SSA screening, i.e., awards are distributed randomly. In this case, the optimal program will presumably not distinguish between persons who pass the screen and persons who do. We can then compare the optimal programs in the extreme cases with the optimal program under the imperfect information case as we observe it. While two levels of benefits emerge in this case, they are presumably closer in magnitude than they would be in the perfect information case. The three-way comparison will give a broad picture of the implication of screening quality on optimal program design.

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Table 1: Calibration of Disability Insurance Application/Acceptance Model

$\frac{? \, ?^2}{? \, ?^2}$	reliability parameter			0.20					0.20					0.20		
$\frac{? \, ?^2}{? \, ?^2 \; ? \, ? \, ?^2}$	validity parameter			0.33					0.40					0.50		
γ	risk aversion parameter	1.5	2.0	2.5	3.0	3.5	1.5	2.0	2.5	3.0	3.5	1.5	2.0	2.5	3.0	3.5
? ?	mean (unobs. disability)	-5.18	-5.86	-6.65	-7.57	-8.60	-4.90	-5.29	-5.79	-6.40	-7.10		-7.49	-8.23	-8.84	-9.56
? ? ?	mean (app.cost)	-5.84	-5.45	-5.05	-4.66	-4.27	-5.59	-5.18	-4.78	-4.37	-3.97		-5.23	-4.82	-4.40	-3.98
$\bar{?}$	disability screen	3.71	4.38	5.14	6.01	6.97	3.68	4.14	4.70	5.36	6.11		7.11	7.96	8.62	9.41
? ?	s.d. (unobs. disability)	3.68	4.34	5.10	5.95	6.90	3.29	3.73	4.25	4.85	5.52		4.77	5.39	5.93	6.55
? ? ?	s.d. (app.cost)	0.48	0.48	0.48	0.48	0.48	0.53	0.54	0.55	0.55	0.56		0.47	0.49	0.53	0.56

Table 1 (cont): Calibration of Disability Insurance Application/Acceptance Model

$\frac{?_?^2}{?_?^2}$	reliability parameter			0.15					0.25		
$\frac{?_?^2}{?_?^2 ??_?^2}$	validity parameter			0.33					0.33		
γ	risk aversion parameter	1.5	2	2.5	3	3.5	1.5	2	2.5	3	3.5
$?_?$	mean (unobs. disability)	-4.23	-4.69	-5.24	-5.89	-6.65		-6.61	-7.67	-8.92	-10.35
$?_{??}$	mean (app.cost)	-6.15	-5.76	-5.37	-4.98	-4.58		-5.43	-5.05	-4.66	-4.26
$\bar{?}$	disability screen	2.79	3.27	3.81	4.43	5.13		5.38	6.44	7.65	9.04
$?_?$	s.d. (unobs. disability)	2.97	3.48	4.06	4.72	5.47		4.90	5.85	6.93	8.17
$?_{??}$	s.d. (app.cost)	0.59	0.59	0.59	0.58	0.57		0.32	0.32	0.32	0.32

Table 2: Characteristics of the Optimal Disability Insurance Program

Reliability Parameter			0.20					0.20					0.20		
Validity Parameter			0.33					0.40					0.50		
Risk Aversion Parameter	1.5	2	2.5	3	3.5	1.5	2	2.5	3	3.5	1.5	2	2.5	3	3.5
Parameters of Optimal Program															
After-tax consumption rate (cf. 0.93)	0.903	0.887	0.874	0.865	0.859	0.903	0.887	0.874	0.864	0.856		0.884	0.874	0.867	0.860
Welfare replacement rate (cf. 0.4)	0.584	0.625	0.670	0.731	0.761	0.579	0.630	0.674	0.712	0.743		0.659	0.718	0.764	0.788
DI replacement rate (cf. 0.6)	0.643	0.692	0.741	0.784	0.810	0.658	0.710	0.750	0.779	0.803		0.747	0.805	0.805	0.813
Disability Threshhold	2.39	1.24	1.51	3.97	4.24	3.28	3.41	3.73	4.01	4.28		5.02	8.41	21.93	27.80
Simulated population rates under optimal program															
Application Rate (cf. 0.136)	0.108	0.120	0.139	0.137	0.134	0.111	0.122	0.134	0.139	0.138		0.123	0.108	0.001	0.000
DI Acceptance Rate (cf. 0.5)	0.524	0.669	0.686	0.613	0.644	0.473	0.510	0.559	0.608	0.644		0.525	0.440	0.165	0.041
LF Participation Rate (cf. 0.876)	0.850	0.840	0.833	0.829	0.826	0.850	0.839	0.831	0.825	0.821		0.844	0.838	0.832	0.829
Expected Utility															
under current program	-2.25	-1.29	-1.01	-0.93	-0.95	-2.25	-1.29	-1.02	-0.93	-0.95		-1.29	-1.02	-0.95	-0.99
under optimal program	-2.23	-1.25	-0.93	-0.77	-0.68	-2.23	-1.25	-0.94	-0.79	-0.70		-1.23	-0.90	-0.75	-0.67
Willingness to pay for optimal program (as portion of income)	1.2%	2.8%	5.5%	9.3%	13.9%	1.1%	2.7%	5.2%	8.4%	12.7%		4.6%	7.9%	11.8%	17.0%
Fraction of DI recipients who would be working otherwise															
under current program	0.144	0.143	0.141	0.140	0.138	0.120	0.123	0.125	0.126	0.126		0.076	0.079	0.084	0.088
under optimal program	0.066	0.089	0.081	0.038	0.034	0.074	0.076	0.065	0.052	0.045		0.073	0.043	0.001	0.000

Table 2 (cont): Characteristics of the Optimal Disability Insurance Program

Reliability Parameter			0.15					0.25		
Validity Parameter			0.33					0.33		
Risk Aversion Parameter	1.5	2	2.5	3	3.5	1.5	2	2.5	3	3.5
Parameters of Optimal Program										
After-tax consumption rate (cf. 0.93)	0.908	0.890	0.876	0.865	0.857		0.882	0.870	0.861	0.860
Welfare replacement rate (cf. 0.4)	0.564	0.623	0.667	0.704	0.736		0.656	0.690	0.706	0.781
DI replacement rate (cf. 0.6)	0.627	0.678	0.724	0.761	0.789		0.738	0.783	0.816	0.825
Disability Threshhold	2.58	2.54	2.67	2.90	3.11		3.40	3.10	2.33	6.35
Simulated population rates under optimal program										
Application Rate (cf. 0.136)	0.120	0.121	0.126	0.135	0.144		0.108	0.124	0.130	0.117
DI Acceptance Rate (cf. 0.5)	0.523	0.544	0.568	0.604	0.655		0.404	0.491	0.601	0.579
LF Participation Rate (cf. 0.876)	0.852	0.839	0.830	0.824	0.820		0.840	0.835	0.831	0.831
Expected Utility										
under current program	-2.27	-1.31	-1.05	-0.97	-1.01		-1.28	-1.01	-0.92	-0.94
under optimal program	-2.24	-1.26	-0.95	-0.80	-0.71		-1.24	-0.92	-0.77	-0.67
Willingness to pay for optimal program (as portion of income)	2.0%	3.7%	6.4%	10.1%	15.2%		2.9%	5.4%	8.7%	14.8%
Fraction of DI recipients who would be working otherwise										
under current program	0.241	0.242	0.243	0.244	0.244		0.111	0.108	0.106	0.103
under optimal program	0.051	0.058	0.062	0.059	0.049		0.110	0.115	0.134	0.025

Table A.1 Validity of SSDI Screening

Work Capacity[1]	Final Determinations[2] Denied Number	Denied *Percent*	Allowed Number	Allowed *Percent*	Total Number	Total Category Pct
Fit for work under normal conditions	9	*100.0*	0	*0.0*	**9**	***0.4***
Fit for specific jobs, including former job, under normal condtions	142	*86.1*	23	*13.9*	**165**	***6.7***
Fit for specific jobs, excluding former job, under normal condtions	167	*64.0*	94	*36.0*	**261**	***10.6***
Fit for work under special conditions	90	*49.5*	92	*50.5*	**182**	***7.4***
Can work part-time under normal conditions	84	*50.6*	82	*49.4*	**166**	***6.8***
Can work under sheltered conditions	87	*39.4*	134	*60.6*	**221**	***9.0***
Can work at home only	29	*30.5*	66	*69.5*	**95**	***3.9***
Not fit for work	336	*24.8*	1019	*75.2*	**1355**	***55.2***
Total	**944**	***38.5***	**1510**	***61.5***	**2454**	***100.0***

Notes: 1. Clinical Teams' Evaluations of Work Capacity. 2. Final SSDI Determinations.

Source: Reprinted from Nagi (1969), p. 94.

Table A.2 Reliability of SSDI Screening

State	Probability Accepted	Fraction of Screenings with Inconsistent Results
1	0.280	0.091
2	0.341	0.121
3	0.250	0.139
4	0.379	0.131
5	0.398	0.151
6	0.367	0.051
7	0.278	0.168
8	0.305	0.101

Source: Gallichio & Bye, 1980