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# A model of Social Security Disability Insurance using matched SIPP/Administrative data

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ABSTRACT

We study Disability Insurance (DI) application behavior in the US using matched SIPP and administrative data over 1989–1995. Certain state-contingent earnings projections and eligibility probabilities are central to the analysis. We find evidence for a small work disincentive effect of DI that seems to be restricted to a subset of the DI beneficiaries, including low earning groups such as blue collar workers and those subject to economic dislocation. Processing time, Medicare value, unemployment, private health insurance, and health shocks are some of the major factors that affect application propensity. The behavioral response of female workers to various parameters of the DI program is found to be quite different from that of males.



**Executive summary**

We estimate an econometric model of Social Security Disability Insurance (DI) application behavior, using the 1990, 1991, and 1992 panels of the Survey of Income and Program Participation (SIPP) matched to Social Security Administration data for 1989–1995. The resulting matched file captures a rich set of individual-specific antecedents of the application decision, including: demographics, self-reported health and activity limitations, household composition and family finances, earnings histories, program eligibility status, occupational characteristics, disease-specific Medicare expenditures, and hypothetical DI benefits. Exploiting these data, we focus less on population-wide effects than on subgroup effects with direct policy implications. State-contingent earnings projections and eligibility probabilities as well as individual-specific benefit calculations are all central to the analysis. The main findings are:

- No more than 37% of DI beneficiaries would return to sustained work if they did not receive DI benefits. Using the labor force participation rate of rejected disability applications as a benchmark, Bound (1990) estimated that less than 50% of the DI beneficiaries would have returned to sustained work were they not receiving DI benefits. When pre-application differences in the labor market attachment of allowed and denied applicants are considered along with the observed work efforts by beneficiaries, the estimated work disincentives associated with DI benefits are notably smaller.
- Our estimated elasticity of applications with respect to benefit size is significant only for males (0.496). The overall elasticity is small compared to previous estimates based on cross-sectional data, explaining little of the extraordinary DI enrolment growth over the period.
- We find significant differences in the effect of DI benefits on applications not only by gender, but by pre-application earnings level. The effect is greatest for low earners. Our findings suggest that the moral hazard problem associated with DI is mainly restricted to males and, among males, it is mainly restricted to low earners, such as blue collar workers and those more subject to economic dislocation or stagnant real wages. Hence, the work disincentive associated with the DI benefit may contribute to recent growth in allowances via the vocational grid, which is often an eligibility path for low earners with blue collar jobs. We infer that such subgroups may be good candidates for vocational rehabilitation and return-to-work incentives.
- Individual medical eligibility probabilities have a substantial direct effect on the propensity to apply. Our estimate of the elasticity is 1.54 — much larger than earlier studies. The findings underscore the fundamental role of medical factors in the application decision, notwithstanding the role of vocational and economic elements for key applicant subgroups. We do not find state level variation in allowance rates to be significant in explaining application behavior at the individual level.
- The Medicare variable has a large, statistically significant effect on the decision to apply for DI benefits, with an elasticity of 0.24. Our analysis dispels any presumption that all DI applicants have

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uniformly high health costs. For example, the costs of persons with cancer or AIDS are several times higher than those of persons with mental problems or a stroke and ten times higher than those of persons with hypertension or deafness. Based on diagnosis-specific cost information, in our sample the average expected value of Medicare for applicants is more than 50% higher than that of non-applicants. The availability of Medicare benefits boosts the average probability of application by nearly 12%. Ours is the first study to capture the effect of the expected value of medical insurance on application behavior.
– Local area unemployment rates significantly affect applications. The elasticity is 0.30 for males and females combined; however, the effect is higher for males (0.42). Our unemployment variable explains a large part of the growth in disability applications in the early 1990s. This finding suggests the need for a policy focus on rehabilitation, return to work (including the Ticket to Work effort), and the vocational grid.
– We find a significant effect for variations in processing time across states and over time on applications. The elasticity is significant for males (0.40), but not for females.
– Overall, the disability application equation for females is quite different from that for males. Although medical eligibility probability has a significant impact on both females and males, key policy variables like the DI benefits and processing time do not seem to affect female application behavior. This is consistent with the fact that whereas the male labor force participation rate has decreased during last few decades, the opposite is true for women. The singular behavioral response of female workers to parameters of the DI program is intriguing and warrants further research.

## 1. Introduction

Disability Insurance (DI) and Supplemental Security Income (SSI) are the two largest federal programs providing cash benefits to people with disabilities. Both are administered by the Social Security Administration. Established in 1954, DI provides cash assistance to people with disabilities (and their dependents or survivors) under the age of 65 who have enough work experience to qualify. Created in 1972, SSI is a means-tested income assistance program that provides monthly payments to adults or children who have disabilities and whose income and assets fall below statutory levels. During 1982–2002, the number of disabled workers receiving benefits under DI doubled (increasing from 2.6 million to 5.5 million), while annual payments quadrupled (increasing from about \$13.8 billion to \$55.5 billion). By 2002, another 2.8 million working-age individuals with disabilities were receiving \$18.5 billion in annual SSI federal benefits. The associated medical costs under Medicare and Medicaid programs for the disabled amounted to an additional \$132 billion. Entitlement spending on this scale, growing unabated in more recent years, argues not only for more analysis of economic incentives underlying applications decisions, but also for an expanded focus on the complex procedure for determining eligibility. Not surprisingly, researchers both within the Social Security Administration (SSA) and in academia have been trying to understand the causes of program growth so that policy makers can respond.[1]

The growth of the disability programs is the consequence of both decreasing terminations and increasing applications and awards. The declining death rates of beneficiaries and the lower average age of new awardees are generally considered to be the main reasons for the falling terminations. On the other hand, changes in eligibility rules, the adjudicative climate, and business cycle effects are considered to be the predominant reasons for increasing applications, see Rupp and Stapleton (1995). The DI Program, like all insurance programs, is susceptible to an unintended consequence—the so-called moral hazard problem. With the male labor force participation rate falling during the last three decades, economists have sought to explain this phenomenon by the availability and increasing generosity of the DI program, cf. Parsons (1980). Recent economic research on disability has attempted to measure the impact of a few key policy parameters on application behavior, e.g., the disability benefit level, the individual-specific eligibility probability, and the average processing time for disability applications. Here we focus on these factors and many others, but we do so in a way that tests for differential behavior for subgroups within the pool of potential DI applicants. This approach acknowledges and accommodates the heterogeneity of DI applicants.

Historically, researchers have faced a daunting data problem in studying the growth in disability programs. On the one hand, administrative data, tied to day-to-day operations, have no information at all on non-applicants and, for applicants, little socioeconomic information needed to understand application behavior. On the other hand, household surveys provide information on non-applicants and on a range of socioeconomic details; however, it has been difficult to determine the pool of prospective DI eligibles based on self-reported survey responses. In this paper we study DI application behavior using matched Survey of Income and Program Participation (SIPP) and SSA administrative data files representing 1989–1995.

Our study offers several advantages over previous studies: (1) Most previous studies have used data from the 1960s and 1970s, even though the nature of DI enrollment has dramatically changed since 1984. (2) We match SIPP data with SSA disability determination records in such a way that the majority of our sample members are observed in the survey before the time of application. One endemic problem with almost all studies mentioned above is that application decisions were observed many years before socioeconomic and health information were collected from the survey respondents. For instance, in Kreider (1999) and Kreider and Riphahn (2000), the disability application dates are 2–7 years before the survey window. (3) The value of Medicare coverage for Social Security Disability Insurance beneficiaries is almost 50% of the average DI benefit level. We have estimated the expected value of medical care under Medicare for each individual by using recent research on disease-specific capitation rates (cf. Ash et al. (2000)) and used it successfully in the application equation. (4) We pay special attention to pre-application health shocks in the earnings equations such that they are not subsumed as part of unobserved heterogeneity and self-selection. There is a great deal of variation in earnings streams prior to application, and in recovery rates based on the earnings of denied applicants. Moreover, these earnings profiles are not based on self-reports, but are obtained from SSA's Summary Earnings Records (SER) data. (5) Three counterfactual earnings projections are central to the analysis: projected earnings if not applying, if allowed, and if denied. The projection of earnings if not applying used in this paper is based on non-applicants after correcting for application self-selection. Unlike the aforementioned studies we generate the hypothetical benefits if allowed from an SSA benefit calculator, rather than estimating it by regression methods using self-reported data. Typically researchers have generated potential disability benefits for all sample members from the self-reported disability receipts of the beneficiaries. (6) Our sample covers both

[1] See, for example, Halpern and Hausman (1986), Leonard (1986), Haveman et al. (1991), Arts and de Jong (1992), Lahiri et al. (1995), Kreider (1999), Gruber and Kubik (2002), Benítez-Silva et al. (1999), Hu et al. (2001), and Autor and Duggan (2006). Further references are available in recent survey articles by Bound and Burkhauser (1999) and Haveman and Wolfe (2000).

men and women over the ages 18–64. Most previous studies are restricted on gender/age dimensions due to limitations in sample design, cf. Gruber (2000). (7) Building on our previous research (see Lahiri et al. (1995) and Hu et al. (2001)) we pay special attention to the disability determination process in generating the eligibility probabilities. The resulting probabilities are critical in obtaining the correct estimates of other behavioral parameters, especially the medical and vocational factors inherent in the medical determination. After all, as Gruber and Kubik (1997) point out, if the SSA's eligibility determination process were foolproof, there would be no moral hazard problem. (8) Because our final analytical sample is obtained after matching a number of different data sources, we utilize a much larger number of meaningful explanatory variables in all structural equations compared to other studies. For example, we consider variables such as blue collar occupation and occupations with a strength requirement.

The results of this study indicate that the estimated elasticity of applications for men with respect to benefit size is approximately 0.5 which is much smaller than the estimates reported in Kreider (1999), but similar to those based on time series data, see Bound and Burkhauser (1999). We find this value to be quite robust to a wide variety of alternative specifications. Furthermore, magnitudes of the effect vary over different groups of individuals classified by gender and by their pre-disability earnings. Our results suggest that the moral hazard problem associated with the Social Security Disability Insurance program is restricted to those with lower earnings during the pre-disability period. Perhaps some low earners may have less attachment to the labor force than those with high earnings, and, of that group, some may be prone to 'shirking'.

Furthermore, estimates from our endogenous switching Tobit earnings model indicate that effects of selection are important in modeling earnings for the denied. The results imply that unobserved factors (e.g., taste for work, motivation, skill) affect application and eligibility decisions as well as earnings of the denied. Ignoring these effects would underestimate the true earnings projections of the denied. The direction of these effects and the differential pre-application labor market attachment of the denied and the beneficiaries suggest that the labor supply disincentive effect of DI in Bound (1989) may be overestimated.

## 2. Data sources

In this study, we use three major sources of data: the Survey of Income and Program Participation (SIPP), the Master Beneficiary Record (MBR), and the Summary Earnings record (SER). The SIPP is a recurring national survey designed as a continuous series of national panels, with sample sizes ranging from approximately 14,000–36,700 interviewed households. Both the MBR and SER are SSA administrative data files. The MBR contains the information needed to generate Social Security benefit checks under the Old Age, Survivors, and Disability Insurance (OASDI) program. The MBR has one record for each Social Security claim number. An MBR record is created whenever an individual first applies for OASDI benefits and the initial decision is made. Hence the record indicates the final decision regarding the initial claim, including denials, based on information from the 831 data on medical determinations generated by state Disability Determination Service agencies. The SER contains annual summaries of Federal Insurance Contributions Act (FICA) earnings received by individuals. A record is created when a new social security number (SSN) is issued.

The sample used in the core of this study is selected from the 1990, 1991, and 1992 SIPP panels. The 1990 and 1991 panels consist of eight waves covering thirty-two months from late 1989 through early 1992 and from late 1990 through early 1993. The 1992 panel consists of ten waves covering forty months from late 1991 through early 1995. The sample from each panel is drawn from the longitudinal file and from topical modules 1, 2, 3, 4, 6, and 7. Various health-related questions including functional limitations, activities of daily living, medical care utilization, and work disability appear in topical modules 3 and 6 for the 1990 panel, topical module 3 for the 1991 panel, and topical module 6 for the 1992 panel. Topical module 1 or 2 includes employment history questions. The longitudinal and core files are used to obtain demographic, economic, program-participation, and labor force variables. The total number of individuals interviewed in all of the waves (number of records in longitudinal files) is 176,217 (69,432, 44,373, and 62,412 observations in the 1990, 1991, and 1992 panels respectively).

**Table 1**
Derivation of analytical sample

| '90 Panel | '91 Panel | '92 Panel | Total |
|---|---|---|---|
| At risk (individuals with health problems) | | | |
| 6383 | 3445 | 4138 | 13,966 |
| Drop SS beneficiaries; drop age $< 18$ as of 1st of month or ages $> 64$ (last month of survey) | | | |
| 4883 | 2681 | 3428 | 10,992 |
| Drop pure SSI; drop not insured non-applicants; drop those who filed before age 18 or after age 65 | | | |
| 3723 | 2087 | 2663 | 8,473 |

We matched these SIPP samples with the MBR in order to obtain disability application and adjudication status, and with the SER to obtain historical earnings records for members of the SIPP sample. Applicants are selected based on the first observable application from the 831 file. The 831 file includes information on application (initial and reconsideration) dates from the late 1970s to the present. Since the paper focuses on applications filed in the 1990s, our application date can be considered to be the very first one. We include both pure DI and concurrent applicants. Concurrent beneficiaries receive SSI as well as DI benefits, reflecting their low income and assets. In order to match SIPP information (health, earnings, employment, etc.) dated prior to application, and also maintain a reasonable sample size, we included DI applicants who were interviewed in SIPP any time during a 32-month window prior to the date of application. Information on the latest allowance status of the initial applications was obtained from the MBR which contains the latest official payment information. The matched MBR files used in the study were extracted in 2002.

In addition, we added information on: occupational characteristics from the Dictionary of Occupational Titles (DOT); workload from DDS Staffing and Workload Analysis (SWA) reports; and staffing, workload, processing time, and demographics at the district office level from the Profiling System Data base (PSD) of the SSA Office of Workforce Analysis. See Hu et al. (2001) for further details on the occupational variables. Since all of the information regarding disability application and adjudication were obtained from the 2002 MBR, they can be considered as final—including re-applications and decisions at the reconsideration and administrative law judge (ALJ) levels. An important issue is how one selects the sample of non-applicants. The disability non-applicant sample of 7375 individuals was selected because they are: (1) at-risk of disability application because they report some type of health condition or limitation, (2) disability insured,[2] (3) non-participants in DI or SSI, and (4) working age (18–64). Even though our initial dataset contains a large number of person-wave observations, our final sample consists of one observation each for a total of 8473 individuals—7376 individuals who have not applied for DI benefits, 381 denied DI applicants, and 716 allowed DI applicants, see Table 1.

[2] To be DI insured, a worker over age 30 must have 20 quarters of coverage (based on annual payroll deductions) during the last 40 calendar quarters ending in disability. Special rules apply for younger workers.

**Table 2**
Sample characteristics

| Variables | ALL | | Non-applicants | | Denied applicants | | Allowed applicants | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. D. | Mean | Std. D. | Mean | Std. D. | Mean | Std. D. |
| OBS | 8473 | | 7376 | | 381 | | 716 | |
| PHILADELPHIA | 0.097 | 0.296 | 0.099 | 0.298 | 0.063 | 0.243 | 0.095 | 0.293 |
| ATLANTA | 0.185 | 0.387 | 0.174 | 0.379 | 0.252 | 0.434 | 0.255 | 0.436 |
| CHICAGO | 0.203 | 0.402 | 0.207 | 0.405 | 0.173 | 0.378 | 0.176 | 0.381 |
| KANSAS | 0.065 | 0.246 | 0.065 | 0.247 | 0.063 | 0.243 | 0.058 | 0.235 |
| DALLAS | 0.106 | 0.307 | 0.105 | 0.306 | 0.141 | 0.349 | 0.095 | 0.293 |
| DENVER | 0.037 | 0.188 | 0.037 | 0.190 | 0.028 | 0.167 | 0.030 | 0.172 |
| SANFRANCISCO | 0.129 | 0.334 | 0.130 | 0.336 | 0.126 | 0.332 | 0.113 | 0.317 |
| SEATTLE | 0.045 | 0.207 | 0.046 | 0.211 | 0.034 | 0.181 | 0.029 | 0.168 |
| ACCIDENT | 0.130 | 0.336 | 0.116 | 0.321 | 0.280 | 0.450 | 0.187 | 0.390 |
| AGE_35− | 0.310 | 0.462 | 0.333 | 0.471 | 0.233 | 0.423 | 0.108 | 0.311 |
| AGE_35–44 | 0.274 | 0.445 | 0.280 | 0.449 | 0.249 | 0.433 | 0.216 | 0.412 |
| AGE_45–54 | 0.230 | 0.421 | 0.222 | 0.415 | 0.204 | 0.404 | 0.325 | 0.468 |
| AGE_55+ | 0.186 | 0.389 | 0.163 | 0.370 | 0.312 | 0.464 | 0.349 | 0.477 |
| AGE | 41.960 | 11.732 | 41.169 | 11.624 | 45.440 | 12.504 | 48.296 | 10.042 |
| AIME | 1.428 | 0.921 | 1.461 | 0.931 | 1.010 | 0.778 | 1.301 | 0.813 |
| LENIENCY | 0.391 | 0.068 | 0.390 | 0.067 | 0.381 | 0.066 | 0.395 | 0.069 |
| EARNINGS[a] | 15.831 | 14.342 | 16.602 | 14.520 | 7.712 | 10.337 | 12.203 | 12.293 |
| BED_DAY | 0.162 | 0.368 | 0.139 | 0.346 | 0.254 | 0.4362 | 0.347 | 0.476 |
| BENEFICIARY | 0.085 | 0.278 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 |
| WORK_HAZARD | 0.303 | 0.459 | 0.283 | 0.450 | 0.393 | 0.489 | 0.452 | 0.498 |
| WAIT_TIME | 0.876 | 0.215 | 0.879 | 0.214 | 0.860 | 0.222 | 0.855 | 0.218 |
| DOCTOR_VISITS | 0.749 | 1.186 | 0.674 | 1.049 | 1.071 | 1.503 | 1.345 | 1.910 |
| VOLUNTARY_U | 0.154 | 0.361 | 0.136 | 0.343 | 0.320 | 0.467 | 0.243 | 0.429 |
| EARNINGS_DROP[a] | 1.713 | 11.420 | 0.363 | 10.711 | 7.296 | 11.230 | 12.644 | 11.832 |
| INC_VARIABILITY | 1.773 | 2.347 | 1.687 | 2.289 | 2.497 | 2.549 | 2.260 | 2.677 |
| FAMILY_SIZE | 2.985 | 1.488 | 3.005 | 1.470 | 2.818 | 1.578 | 2.865 | 1.601 |
| FAMILY_INC | 22.122 | 21.968 | 22.597 | 22.322 | 17.559 | 16.455 | 19.652 | 20.368 |
| HEALTH_INS | 0.787 | 0.409 | 0.805 | 0.395 | 0.627 | 0.484 | 0.676 | 0.468 |
| IADL | 0.063 | 0.242 | 0.038 | 0.192 | 0.147 | 0.354 | 0.266 | 0.442 |
| BLUE_COLLAR | 0.456 | 0.498 | 0.435 | 0.495 | 0.538 | 0.499 | 0.614 | 0.487 |
| WHITE_COLLAR | 0.218 | 0.412 | 0.228 | 0.420 | 0.149 | 0.357 | 0.139 | 0.346 |
| PHYSICAL_JOB | 0.151 | 0.357 | 0.152 | 0.359 | 0.139 | 0.346 | 0.134 | 0.341 |
| LIFE_INS | 0.658 | 0.47 | 0.675 | 0.468 | 0.469 | 0.499 | 0.581 | 0.493 |
| LIFTING | 0.153 | 0.359 | 0.114 | 0.318 | 0.370 | 0.483 | 0.434 | 0.496 |
| MALE | 0.470 | 0.499 | 0.457 | 0.498 | 0.506 | 0.500 | 0.581 | 0.493 |
| MARRIED | 0.658 | 0.474 | 0.663 | 0.472 | 0.611 | 0.488 | 0.629 | 0.483 |
| MEDICAID[a] | 2.947 | 2.487 | 2.682 | 2.217 | 4.324 | 3.147 | 4.934 | 3.409 |
| MEDICARE[a] | 2.322 | 1.789 | 2.131 | 1.613 | 3.453 | 2.232 | 3.681 | 2.348 |
| CHRONIC | 0.175 | 0.380 | 0.138 | 0.345 | 0.385 | 0.487 | 0.439 | 0.496 |
| CONGENITAL | 0.024 | 0.152 | 0.017 | 0.130 | 0.065 | 0.247 | 0.071 | 0.257 |
| ACUTE | 0.217 | 0.412 | 0.196 | 0.397 | 0.280 | 0.450 | 0.392 | 0.488 |
| MENTAL | 0.079 | 0.270 | 0.075 | 0.264 | 0.057 | 0.233 | 0.128 | 0.334 |
| METRO | 0.719 | 0.449 | 0.729 | 0.444 | 0.666 | 0.472 | 0.638 | 0.480 |
| NETASSET[a] | 82.310 | 150.290 | 84.928 | 152.290 | 55.200 | 123.430 | 69.720 | 140.240 |
| NEVER_MARID | 0.174 | 0.379 | 0.180 | 0.384 | 0.147 | 0.354 | 0.124 | 0.330 |
| LABOR_ATTACH | 7.315 | 2.866 | 7.402 | 2.785 | 5.992 | 3.532 | 7.110 | 3.098 |
| POOR_HEALTH | 0.068 | 0.251 | 0.036 | 0.187 | 0.189 | 0.392 | 0.328 | 0.469 |
| BENEFIT_SIZE[a] | 7.918 | 3.426 | 8.049 | 3.443 | 6.251 | 3.123 | 7.452 | 3.117 |
| POVERTY_RATE | 0.205 | 0.066 | 0.202 | 0.066 | 0.219 | 0.069 | 0.218 | 0.069 |
| SCHOOL_YRS | 12.930 | 2.597 | 13.095 | 2.542 | 11.801 | 2.802 | 11.824 | 2.626 |
| STRENGTH | 0.384 | 0.486 | 0.364 | 0.481 | 0.512 | 0.500 | 0.523 | 0.499 |
| UNEMPLOYMENT | 0.054 | 0.019 | 0.053 | 0.019 | 0.055 | 0.018 | 0.058 | 0.021 |
| USE_AIDS | 0.022 | 0.146 | 0.012 | 0.108 | 0.042 | 0.200 | 0.115 | 0.320 |
| WALKING | 0.142 | 0.356 | 0.104 | 0.306 | 0.372 | 0.484 | 0.487 | 0.500 |
| NON_HAZARD | 0.067 | 0.250 | 0.066 | 0.248 | 0.107 | 0.310 | 0.060 | 0.237 |

Variable definitions are given in the Data Appendix.
[a] In \$1000.

Selected descriptive statistics for our analytical sample, categorized as non-applicants, denied applicants and beneficiaries, are presented in Table 2. Compared to non-applicants, the disability applicants tend to be older, poorer, sicker (both mentally and physically), and less educated. It is noteworthy that the number of doctor visits and bed days immediately prior to the disability application is nearly double the average number for non-applicants. In terms of occupation, significantly more applicants come from occupations classified as hazardous, blue collar or having a strength requirement. Also, more non-applicants have some form of health insurance and more family income. Applicants tend to come from high unemployment areas. The socioeconomic status of the applicants on the average is consistently lower than that of the non-applicants. Sharp differences between the denied and allowed applicants (beneficiaries) are also noticeable most of the time. Allowed applicants are sicker than the denied across every measure of health and disability. The net asset position of the denied applicants (\$55,201) before application is substantially less than that of the allowed applicants (\$69,723), which in turn is less than that of non-applicants (\$84,928).[3] All the statistics are consistent with

[3] Interestingly, Golosov and Tsyvinski (2006) have suggested an optimal disability insurance system where an applicant is granted a benefit only if his/her assets fall below a specified maximum. Our evidence, however, indicates that more severely disabled applicants have higher pre-application assets.

our expectations and suggest that disability application behavior is more than a medical phenomenon—it also has social and economic dimensions. However, as we see later, these dimensions do not manifest themselves uniformly for all subgroups within the applicant pool.

## 3. Structure of the disability application model

To guide our empirical exploration, a structural econometric model similar to that of Kreider (1999) or a fully dynamic life-cycle model (Rust et al., 2003) is needed to understand the tradeoffs involved in the decision to apply for DI and the role of different explanatory variables that should enter specific equations of the model. Given the latest health status, a DI insured worker is assumed to make a rational decision whether to apply for DI benefits based on a comparison of expected discounted lifetime utility when applying and when not applying. These lifetime utilities in turn depend on expected total income when applying and not applying, at the time of the decision. The expected future income when applying involves not only the expected probability of eligibility, expected DI and medical benefits when eligible and expected subsequent earnings when denied, but also the foregone earnings during the application process. The major components of the application model are: the medical determination (eligibility probability), disability benefit amount, earnings projections, Medicare value, and other exogenous factors. In our model, individual health, socioeconomic incentives and family conditions induce individuals to apply for disability benefits. We include individual health conditions directly from the survey (SIPP) to control for health factors. We also use the following four components to capture the financial incentive for disability application: subjective probability of being allowed, Primary Insurance Amount (PIA), expected future earnings if not applying and expected future earnings if denied

In developing these components, we exploited SSA administrative data to obtain our estimates in several ways. The allowance probabilities were estimated using a disability determination model that we developed in Lahiri et al. (1995). Whereas other authors have used survey self-reports without demonstrating how their disability screen relates to SSA's definition of disability, we used wide-ranging information on health and disability from separate waves and modules of SIPP to learn how these subjective and objective self-reports can be used to predict the SSA disability determinations, see Lahiri et al. (1995). To estimate benefits we used a benefit calculator—a modified version of the calculator used by SSA. We then validated the calculator using SSA administrative data. In predicting future earnings we used SSA data, first, to distinguish applicants/non-applicants and allowed applicants/denied applicants and, second, to project earnings based on individual specific earnings histories.

A variable often used to capture the net economic benefit of applying for disability benefits is the so-called 'replacement ratio'. In the DI context, the replacement ratio is typically defined as the ratio of (expected) disability benefits to historical earnings, i.e., Primary Insurance Amount divided by the Average Indexed Monthly Earnings (*AIME*). The *PIA* and *AIME* represent the disability benefit and level of past covered earnings, respectively. The *PIA* is the monthly benefit amount payable to a worker upon retirement at the normal retirement age or upon entitlement to DI benefits. The *PIA* is derived from the worker's *AIME* and is designed to provide a higher replacement ratio to workers with a lower *AIME*. This replacement ratio seems inappropriate in capturing the effect of the net economic benefit in applying for disability benefits because the *AIME* does not necessarily reflect future expected earnings after the onset of disability and health shocks.

A more appropriate measure of replacement ratio in the context of disability application is the expected payoff if applying to expected lifetime earnings that one can earn if not applying, see Kreider (1999). This latter variable is defined as the weighted average of PIA and expected discounted future earnings if denied with expected eligibility probability as the weight. One would hypothesize that the higher the expected payoff, the higher will be the incentive to apply, and the higher the expected earnings if not applying, the lower will be the incentive of application, holding other factors constant. Hence this payoff variable includes not only potential disability benefits and potential earnings if denied; it also incorporates individual specific allowance probability. Unlike the conventional definition of replacement ratio that measures the percentage of long-term historical earnings replaced by disability benefits, this replacement ratio measures the percentage of expected future earnings replaced by disability benefit in a prospective sense. Needless to say, because future earnings for a disabled person are conditioned very seriously by current and past health shocks, projected earnings capacity conditional on current health is more relevant than past earnings in predicting a disability application decision.

In order to construct the replacement ratio variable, we need to predict (1) eligibility probabilities for all sample members including non-applicants, (2) expected labor earnings if not applying, (3) expected labor earnings if denied, and (4) expected disability benefit if allowed. The subjective allowance probability – the probability that an individual will be found medically eligible – is obtained from the disability determination model. This model predicts probabilities based on a sub-sample of disability applicants. Caution is necessary because allowance and application probabilities are expected to be jointly distributed. That is, those who are more likely to be allowed tend to have a higher probability of applying for disability benefits—even after we control for observed characteristics. Unlike Kreider (1999) and Kreider and Riphahn (2000), we find no such correlation in unobserved heterogeneity in the application and eligibility equations. We offer a justification for this finding in terms of the sequential nature of the disability determination process. Halpern and Hausman (1986) did not allow for this effect in their model.

Unlike other studies, we calculate PIA based on individual past earnings reported in the matched SER file using a benefit calculator modeled on how SSA actually computes benefits. The benefit calculation method actually used by SSA to derive a disability benefit is described in Myers (1993) and the SSA Annual Statistical Supplement (various issues). The first step in calculating the *AIME* and *PIA* is determining the number of computation years. The number of computation years for disability applicants equals the number of years that have elapsed since 1950 (or, if later, the year of attainment of age 21) and before the year in which the worker attained age 62 (or earlier if the person dies or becomes disabled) minus the drop-out years. The drop-out years can be between zero and five depending on age at disability (Myers, 1993, pp. 68–71). The next step is calculating the *AIME* using the number of years with highest indexed earnings regardless of the beneficiary's age. The indexing year is the second year prior to the year in which the individual attains age 62 (or earlier in cases of death or disability). The average wage for the indexing year is divided by the national average wage in each year to get the factor for that year. Then the factors are multiplied by the actual covered earnings to obtain the indexed earnings. After the indexing, the highest indexed earnings corresponding to the number of computation years are selected and totaled. Then the total is divided by the number of calculating months to obtain the *AIME*. The last step in calculating the *PIA* is to put the *AIME* into a piece-wise linear concave benefit formula involving bend points, which are different based on the calendar year of disability. Then the *PIA* is rounded to the next lower ten cents.

In calculating the *PIA*, we assign the disability-onset year by choosing one year after the most recent non-zero earnings in the SER file for those who show recent years of no earning activities. For others who show consistent earnings activity, the year prior to the application is assigned as the disability-onset year. The application years for non-applicants were assigned randomly based on the distribution of applicants over sample years, see Kreider (1999).

The remaining two variables required to impute the replacement ratio are post-application earnings capacity if not applying and if denied. The strict sequential process of application and adjudication separate the sample into three distinctive groups—non-applicants, allowed applicants, and denied applicants. We allow for the possibility of joint determination of the application decision and earnings. The observed earnings could be endogenous and they are also observed conditional on the labor force participation status of individuals. Hence, we use an endogenous switching Tobit model in obtaining predicted earnings for applicants as well as non-applicants. The Tobit model is used because for many individuals, particularly women, the recorded earnings are zero in many years.

Our model consists of four equations—application, eligibility, earnings of non-applicants, and earnings of denials:

1. Application (1: apply, 0: else)

$$\begin{aligned} I_{iA}^* &= X_{iA}\beta_A + F(eligibility,\ benefit,\ earnings) + e_{iA} \\ &= \Delta_{iA} + e_{iA} \\ I_{iA} &= 1, \quad \text{if } I_{iA}^* \geq 0; \qquad I_{iA} = 0, \quad \text{otherwise.} \end{aligned}$$

2. Medical determination model (1: eligible, 0: else)

$$\begin{aligned} I_{iE}^* &= X_{iE}\beta_E + e_{iE} (\text{if application} = 1) \\ &= \Delta_{iE} + e_{iE} \\ I_{iE} &= 1, \quad \text{if } I_{iE}^* \geq 0; \qquad I_{iE} = 0, \quad \text{otherwise.} \end{aligned}$$

3. Earnings model:

$$\text{Non-applicants:} \quad \begin{aligned} Y_{in}^* &= X_{in}\beta_n + e_{in} = \Delta_{in} + e_{in} \\ Y_{in} &= \max(0, Y_{in}^*). \end{aligned}$$

4. Earnings model:

$$\text{Denied applicants:} \quad \begin{aligned} Y_{id}^* &= X_{id}\beta_d + e_{id} = \Delta_{id} + e_{id} \\ Y_{id} &= \max(0, Y_{id}^*). \end{aligned}$$

Since the benefit projections will be done using the actual SSA benefit calculator, we will not estimate the earnings equation for the beneficiaries. Due to sample selection problems, error terms in the eligibility (medical determination) and remaining two earnings equations will be jointly distributed, and are censored. As a result our model contains two Probit, and two Tobit equations. We did not require a two-limit Tobit model because the number of individuals reaching the maximum taxable income was negligible.

Based on the non-linearity in the functional forms implied by von Neumann–Morgenstern expected utility theory, Kreider (1999) has shown that all of the coefficients of this model are technically identified (up to scale for the binary application and eligibility equations) without any arbitrary exclusion restrictions. Since we found that the estimated eligibility probabilities are highly variable across individuals, the application and the earnings equations are identified. Additionally the identifiability of the earning equations can be justified by the joint normal distributional assumption or the non-linearity of the selection equations. Due to the rich and diverse data sources used in this study, assumed non-linearity in the functional from and normality in errors assure identification of all model parameters.

## 4. Estimation method

Our model essentially represents a recursive system of multiple equations with correlated errors. The strategy here is to estimate the four endogenous Tobit equations together by full-fledged FIML. The likelihood function of the model is:

$$\begin{aligned} \ln L = &\sum_{\text{non-applicants},\ y=0} \ln\left[\int_{X_A\beta_A}^{\infty}\int_{X_n\beta_n}^{\infty}\phi_2(e_n, e_A)\mathrm{d}e_n\mathrm{d}e_A\right] \\ &+ \sum_{\text{non-applicants},\ y>0} \ln\left[\int_{X_A\beta_A}^{\infty}\phi_2(Y_n-\Delta_n, e_A)\mathrm{d}e_A\right] \\ &+ \sum_{\text{applicants-allowed},\ y=0} \ln\left[\int_{-\infty}^{X_A\beta_A}\int_{-\infty}^{X_E\beta_E}\int_{X_a\beta_a}^{\infty}\phi_3(e_a, e_E, e_A)\mathrm{d}e_a\mathrm{d}e_E\mathrm{d}e_A\right] \\ &+ \sum_{\text{applicants-allowed},\ y>0} \ln\left[\int_{-\infty}^{X_A\beta_A}\int_{-\infty}^{X_E\beta_E}\phi_3(Y_a-\Delta_a, e_E, e_A)\mathrm{d}e_E\mathrm{d}e_A\right] \\ &+ \sum_{\text{applicants-denied},\ y=0} \ln\left[\int_{-\infty}^{X_A\beta_A}\int_{X_E\beta_E}^{\infty}\int_{X_d\beta_d}^{\infty}\phi_3(e_d, e_E, e_A)\mathrm{d}e_d\mathrm{d}e_E\mathrm{d}e_A\right] \\ &+ \sum_{\text{applicants-denied},\ y>0} \ln\left[\int_{-\infty}^{X_A\beta_A}\int_{X_E\beta_E}^{\infty}\phi_3(Y_d-\Delta_d, e_E, e_A)\mathrm{d}e_E\mathrm{d}e_A\right] \end{aligned}$$

which can be rewritten as

$$\begin{aligned} \ln L = &\sum_{\text{non-applicants},\ y=0} \ln\left[\Phi_2(-\Delta_{iA}, -\Delta_{in}; \rho_{An})\right] \\ &+ \sum_{\text{non-applicants},\ y>0} \ln\left[\frac{1}{\sigma_n}\phi\left(\frac{Y_{in}-\Delta_{in}}{\sigma_n}\right) \times \Phi_1\left(\frac{\Delta_{iA}+\frac{\rho_{An}}{\sigma_n}(Y_{in}-\Delta_{in})}{\sqrt{1-\rho_{An}^2}}\right)\right] \\ &+ \sum_{\text{applicants-allowed},\ y=0} \ln\left[\Phi_3(\Delta_{iA}, \Delta_{iE}, -\Delta_{ia}; \rho_{AE}, -\rho_{Ea}, -\rho_{Aa})\right] \\ &+ \sum_{\text{applicants-allowed},\ y>0} \ln\left[\frac{1}{\sigma_a}\phi\left(\frac{Y_{ia}-\Delta_{ia}}{\sigma_a}\right) \times \Phi_2\left(\frac{\Delta_{iA}+\rho_{Aa}\frac{Y_{ia}-\Delta_{ia}}{\sigma_a}}{\sqrt{1-\rho_{Aa}^2}}, \frac{\Delta_{iE}+\rho_{Ea}\frac{Y_{ia}-\Delta_{ia}}{\sigma_a}}{\sqrt{1-\rho_{Ea}^2}}; \frac{\rho_{AE}-\rho_{Aa}\rho_{Ea}}{\sqrt{(1-\rho_{Aa}^2)(1-\rho_{Ea}^2)}}\right)\right] \\ &\times \sum_{\text{applicants-denied},\ y=0} \ln\left[\Phi_3(\Delta_{iA}, -\Delta_{iE}, -\Delta_{id}; -\rho_{AE}, \rho_{Ed}, -\rho_{Ad})\right] \\ &+ \sum_{\text{applicants-denied},\ y>0} \ln\left[\frac{1}{\sigma_d}\phi\left(-\frac{Y_{id}-\Delta_{id}}{\sigma_d}\right) \times \Phi_2\left(\frac{\Delta_{iA}+\rho_{Ad}\frac{Y_{id}-\Delta_{id}}{\sigma_d}}{\sqrt{1-\rho_d^2}}, -\frac{\Delta_{iE}+\rho_{Ed}\frac{Y_{id}-\Delta_{id}}{\sigma_d}}{\sqrt{1-\rho_{Ed}^2}}; -\frac{\rho_{AE}-\rho_{Aa}\rho_{Ed}}{\sqrt{(1-\rho_{Ad}^2)(1-\rho_{Ed}^2)}}\right)\right]. \end{aligned}$$

Given the complexity of the likelihood function, a good set of starting values is important for smooth convergence without interruptions. Thus we first estimate the model by the two-stage method. Then we use two-stage estimates as starting values for FIML. To implement the two-stage method, we rewrite the equations as follows:

$$I_{iA}^{*} = X_{iA}\beta_A + e_{iA} \text{ (application)}$$

$$I_{iE}^{*} = X_{iE}\beta + \sigma_{AE}\frac{\phi(X_{iA}\beta)}{\Phi(X_{iA}\beta)} + \varepsilon_{iE} \text{ (eligibility)}$$

$$Y_{id}^{*} = X_{id}\beta + \sigma_{Ad}\frac{\phi(X_{iA}\beta)}{\Phi(X_{iA}\beta)} + \sigma_{Ed}\frac{-\phi(X_{iE}\beta)}{1-\Phi(X_{iE}\beta)} + \varepsilon_{id} \text{ (earnings of the denied)}$$

$$Y_{in}^{*} = X_{in}\beta + \sigma_{An}\frac{-\phi(X_{iA}\beta)}{1-\Phi(X_{iA}\beta)} + \varepsilon_{in} \text{ (earnings of non-applicants)}$$

where $\phi(.)$ and $\Phi(.)$ are standard normal density and distribution functions; $\sigma_{AE}, \sigma_{An}, \sigma_{A\alpha}, \sigma_{Ad}, \sigma_{E\alpha}$, and $\sigma_{Ed}$ are error covariance terms of application and eligibility, application and non-applicants earnings, application and allowed applicants earnings, application and denied applicants earnings, eligibility and allowed applicants earnings, and eligibility and denied applicants earnings, respectively. Note that for convenience (and only in the two-stage estimation of the model), we have assumed $\sigma_{AE} = 0$ in the third equation above, cf. Maddala (1983, p. 282). Also, the Heckman-corrected Probit regression above is inconsistent, but the two-step estimates are used as convenient starting values for FIML which is consistent and asymptotically efficient.

Two-stage estimates can be obtained by the following sequential steps. First, we estimated the reduced form application equation over the whole sample and obtain two inverse Mills ratio terms ($\frac{\phi(X_{iA}\beta)}{\Phi(X_{iA}\beta)}$ and $\frac{\phi(X_{iA}\beta)}{1-\Phi(X_{iA}\beta)}$). Second, the eligibility equation is estimated over the applicant sub-sample including an inverse Mills ratio from the estimated application equation ($\frac{\phi(X_{iA}\beta)}{\Phi(X_{iA}\beta)}$), and obtained two additional inverse Mills ratios ($\frac{\phi(X_{iE}\beta)}{\Phi(X_{iE}\beta)}$ and $\frac{\phi(X_{iE}\beta)}{1-\Phi(X_{iE}\beta)}$). Third, two separate Tobit earning regressions – one for non-applicants and the other for denied applicants – are estimated. For the non-applicant earnings regressions, an inverse Mills ratio from the application equation is added: ($\frac{\phi(X_{iA}\beta)}{1-\Phi(X_{iA}\beta)}$). For the denied applicant earnings regression, two inverse Mills ratios – one from the application and the other from the eligibility equation – are added as additional regressors: ($\frac{\phi(X_{iA}\beta)}{\Phi(X_{iA}\beta)}$ and $\frac{\phi(X_{iE}\beta)}{1-\Phi(X_{iE}\beta)}$).

Since the structural application equation allows for direct feedback from the eligibility and the earnings equations, as step 1 we estimate the above system using a reduced form application equation. In step 2, we generate earnings projections based on the step 1 estimation after correction for multiple selectivity. In step 3, we re-estimate the whole system after re-specifying the application equation with the estimated eligibility probability and income projections as explanatory variables. The starting values were obtained from a two-step sample selection procedure. Finally, using these estimates as starting values we maximized the likelihood function directly without using the estimated eligibility probabilities and the projected earnings on the right hand side of the application equation. This way, parameter estimates and their standard errors will be consistent.

## 5. Imputed value of Medicare coverage

Enrollment in the DI program entitles the disabled worker to Medicare coverage after a two-year waiting period. Under the conventional assumption that a disabled person is expected to have significantly higher health care costs than the non-disabled, the implied insurance value of the Medicare coverage under DI should be an important factor in explaining application behavior.[4] Yelowitz (1998) has attempted to incorporate the incentive effects of Medicaid on SSI participation probabilities by using the average state Medicaid expenditure as a proxy for the value of Medicaid for the SSI recipient. As Bound and Burkhauser (1999) note, since Medicare is a nationally-run program with little variation in per capita expenditure across states, finding a simple relationship between Medicare benefits and application propensity has proven to be difficult. In addition, since the health conditions amongst the disabled can be widely different, the state averages may not accurately proxy the valuation of the health insurance by a specific individual. The value of Medicare for the sick is not just the dollar value of benefits, but also the insurance value. The cost of being uninsured is the possibility of having to pay large medical bills. The individuals having full knowledge of their diseases will be the best judge of such insurance value of the medical coverage, and thus the insurance value will be an important determinant of application propensity, cf. Bound et al. (2005). By linking 1984-86 SIPP and 1980 NMCUES data, Moffitt and Wolfe (1992) constructed a family specific "heterogeneity" index for Medicaid's value based on individual health status, expected utilization, cost of medical care and other characteristics, and found that it had significant effect on AFDC participation. In this study we estimate the expected cost of medical care for each member in our sample using a different approach.

Since 1985 the Health Care Financing Administration (HCFA), now the Center for Medicare and Medicaid Services (CMS), has sponsored much research to develop Diagnostic Cost Group (DCG) models that make risk-adjusted capitated payments to HMOs that enroll Medicare beneficiaries. DCG models use age, sex, and clinical diagnoses generated from patient encounters with the medical delivery system to predict health-based "expected cost" of medical care for an individual due to the presence of a disease. We utilize the DCG/HCC (Diagnostic Cost Group/Hierarchical Condition Category) model of Ash et al. (2000) which incorporates multiple diagnoses in computing the expected health care cost of an individual.[5] The strong predictive relationship between diagnoses and future medical costs for the disabled makes this approach particularly useful in our context, Kronick et al. (2000).

The DCG/HCC model maps over 1500 diagnostic codes from ICD-9-CM to 118 condition categories (CC) that are medically related, and have similar expected costs. We use the cost estimates for the Medicare beneficiaries under age 65 (Ash et al., 2000, Table 2). The cost associated with each condition category is an incremental cost associated with that particular health problem. These are estimated based on regression methods using Medicare's 5% research sample from 1991 and 1992, with over 1.3 million records. The model allows for the presence of multiple conditions and age/sex groups.

The health and disability module of SIPP provides many details on functional limitations, activities of daily living, and instrumental activities of daily living, and diagnostic medical conditions associated with respondent work limitations. Corresponding to each reported limitation, the respondent has the option of choosing up to three of the 30 health conditions (e.g., paralysis, stroke, kidney) that caused it. We mapped these 30 health conditions to one of 118 condition categories of Ash et al. (2000). In Table 3 we

[4] For instance, during 1998, the total Medicare amount spent on Hospital Insurance and Supplemental Medical Insurance was $23,855 million, and the total DI benefits paid to disabled workers, spouses and children was $48,173 million. Thus the ratio of Medicare benefits to total DI benefits was 0.495. In 1990 the ratio was 0.475. (See *Social Security Bulletin*, Annual Statistical Supplement, 2000).

[5] Apart from 112 health condition categories (CC), the model includes 30 age/sex dummies and a number of Age/CC interaction dummies.

**Table 3**
Mapping of diagnostic medical categories from DCG/HCC to SIPP

| SIPP | | DCG/HCC |
|---|---|---|
| Code | Category[a] | Category |
| 01 | Alcohol or drug problem or disorder ($1,122) | Drug/alcohol dependence/psychoses (CC31) |
| 02 | AIDS or AIDS related Condition (ARC) ($6653) | HIV/AIDS (CC1), Aplastic and acquired hemolytic anemias (CC27), blood immune disorders (CC28) |
| 03 | Arthritis/rheumatism ($1218) | Rheumatoid arthritis and connective tissue disease (CC25) |
| 04 | Back/Spine problems ($2070) | Bone/joint infections/necrosis (CC24) |
| 05 | Blindness or vision problems (difficulty seeing well enough to read a newspaper, even with glasses on) ($242) | Higher cost eye disorders (CC 72) |
| 06 | Broken bone/fracture ($993) | Hip fracture/dislocation (CC94) |
| 07 | Cancer ($3,272.75) | Metastatic cancer (CC 5), High cost cancer (CC 6), moderate cost cancer (CC 7), lower cost cancers/tumors (CC 8) |
| 08 | Cerebral palsy ($1671) | Moderate cost neurological disorders (CC 43), Higher cost congenital/pediatric disorders (CC102) |
| 09 | Deafness or serious trouble hearing ($147) | Higher cost ear, nose, and throat disorders (CC 74) |
| 10 | Diabetes ($2375) | Diabetes with chronic complications (CC13), diabetes with acute complications/nonproliferative (CC 14), diabetes with no or unspecified complications (CC 15) |
| 11 | Epilepsy ($896.5) | Higher cost neurological disorders (CC 42), moderate cost congenital disorder (CC104) |
| 12 | Head or spinal cord injury ($858.5) | Vertebral fractures and spinal cord injuries (93), head injuries (CC 95) |
| 13 | Heart trouble (including heat attack (coronary), hardening of the arteries (arteriosclerosis)) ($3128.6) | Respirator dependence/tracheostomy status (CC45), respiratory arrest (CC46), cardio-respiratory failure and shock (CC 48), congestive heart failure (CC 48), heart arrhythmia (CC 49), acute myocardial infarction (CC 50), other acute ischemic heart disease (CC 51), chronic ischemic heart disease (CC 52), valvular and rheumatic heart disease (CC 53) |
| 14 | Hernia or rupture ($730) | Moderate cost gastrointestinal disorders (CC 22) |
| 15 | High blood pressure (hypertension) ($281.5) | Hypertensive heart disease (CC 54), hypertension (high blood pressure (57)) |
| 16 | Kidney stones or chronic kidney trouble ($4505.75) | Dialysis status (76), kidney transplant status (CC 77), renal failure (78), nephritis (79) |
| 17 | Learning disability ($348) | Lower cost congenital disorder (CC 104) |
| 18 | Lung or respiratory trouble (asthma, bronchitis, emphysema, respiratory allergies, tuberculosis, or other lung trouble) ($1640.66) | Chronic obstructive pulmonary disease (CC 64), higher cost pneumonia (CC 65), moderate cost pneumonia (CC 66), pulmonary fibrosis and other chronic lung disorders (CC 68), pleural effusion/pneumothorax (CC 69) |
| 19 | Mental or emotional problem or trouble ($1181) | Psychosis and other higher cost mental disorders (CC32), depression and other moderate cost mental disorders (CC 33), anxiety disorders (CC 34) |
| 20 | Mental retardation ($2544) | Profound mental retardation (CC 36), severe mental retardation (CC 37), moderate mental retardation (CC 38), mild/unspecified mental retardation (CC 39) |
| 21 | Missing legs, feet, arms, hands, or fingers ($1256) | drug poisoning, internal injury, traumatic amputation, burn (CC 96) |
| 22 | Paralysis of any kind ($5737) | Quadriplegia (CC 40), paraplegia (CC 41) |
| 23 | Senility/dementia/Alzheimer's disease ($1851) | Higher cost neurological disorders (CC 42) |
| 24 | Speech disorder ($348) | Lower cost congenital disorder (CC 104) |
| 25 | Stiffness or deformity of the foot, leg, arm, or hand ($2070) | Bone/joint infections/necrosis (CC 24) |
| 26 | Stomach trouble (including ulcers, gallbladder, or liver conditions) ($3377) | Protein-calorie malnutrition (CC 16), liver disease (CC 19), high cost chronic gastrointestinal disorders (CC 20), high cost acute gastrointestinal disorders (CC 21) |
| 27 | Stroke ($1377) | Higher-cost cerebrovascular disease (CC 58), lower cost cerebrovascular disease (CC 59) |
| 28 | Thyroid trouble or goiter problems ($1348.5) | High cost vascular disease (CC 60), Thromboembolic vascular disease (CC 61) |
| 29 | Tumor, Cyst, or Growth ($2473) | Chronic ulcer of skin (CC 91) |
| 30 | Other ($1783.75) | Moderate cost genital disorders (CC 82), complications of care (CC 98), heart, lung, liver transplant status (CC 110), artificial opening status/attention (CC 112) |

[a] Dollar values in the parentheses are the incremental costs (excluding the intercept and age/sex dummies) associated with each particular health condition for disabled Medicare beneficiaries.

present the categories with the incremental costs associated with each SIPP condition. Since Ash et al. (2000) provide cost estimates at much finer categories of conditions, whenever necessary, we took a simple average of the finer category costs to assign to the broader SIPP category. For instance, the SIPP health condition # 07 (cancer) corresponds to four neoplasm categories (from metastatic to lower cost cancers) in Ash et al. (2000). In our sample, the average predicted value of Medicare coverage is $2322. It is $2132 for non-applicants, $3454 for the denied applicants and $3682 for the DI beneficiaries. This latter estimate compares favorably with Ash et al. (2000) where the predicted mean cost for the sample Medicare beneficiaries was $3778.[6]

This approach challenges the conventional belief that the disabled uniformly have high health care costs. As expected, the CMS data show that costs for certain conditions are prodigious ($6,653 for AIDS, $3128 for heart trouble, and $3273 for cancer). However, the costs reported for some conditions – often congenital conditions – suggest that few treatments are available ($242 for blindness; $896 for epilepsy). For other conditions initial trauma-related costs may be substantial, but most bear the much lower costs of ongoing maintenance ($993 for broken bones; $858 for head or spinal cord injuries). Our approach reflects this heterogeneity in expected medical costs across diagnostic subgroups.

## 6. Estimation results

### 6.1. Reexamining the disincentive effects of DI

Before modeling the earnings equations for the purpose of projections, we looked at the dynamics of annual earnings of denied and allowed DI applicants 7 years before and after their applications. As noted earlier, we utilized 2002 MBR records to reflect the final decisions on initial claims, including denials, reconsiderations and ALJ adjudications. Hence our earnings estimates will not suffer from an important limitation noted by Parsons (1991) of Bound (1989) that many of the denials could have been in the process of reapplication and appeals. We use SSA 831 files to identify the initial DI applicants that were 35–60 years old at

[6] Utilizing the work of Kronick et al. (2000, Table 6) we also created another health-care heterogeneity index based on estimated cost of illness for Medicaid beneficiaries. Like the Medicare variable, this variable was also highly significant with expected sign in the application equation with all other covariates maintaining their values and significance. This result is not entirely unexpected in view of the finding in Ash et al. (2000) that the incremental cost estimates for different condition categories based on Medicaid and Medicare data are very similar.

**Fig. 1.** Average earnings of SSDI applicants during pre- and post-application years.

the time of application.[7] Since the applications are scattered over the 1980's and the 1990's, the annual earnings were deflated to 1990 values using national average-wage levels.

The 15-year earnings profiles with the application year at the center for both denied and allowed DI applicants are depicted in Fig. 1. The so-called "Ashenfelter dip" at $t = 0$ can be explained by the fact that to be eligible to apply for disability the monthly earnings during the five months before application should be below the substantial gainful activity amount (SGA—during 1997 it was \$500 per month for the non-blind).[8] Fig. 1 also displays a remarkable difference in the average earnings between the denied and the allowed in the pre-application years. During the 5–7 years before application, whereas the average annual earnings of the allowed was \$17,490, it was only \$12,939 for the denied—a difference of about \$4550. Even though the drop in earnings for the denied applicants begins earlier than that of the allowed, the earnings drop for the latter group is much more dramatic during the last two years before application because of its higher pre-application earnings.[9] The denied applicants partly recover their pre-application earnings within 2–3 years, but the recovered level is, on average, almost half the pre-application level. Interestingly, cross tabulations revealed that a vast majority of the denied applicants with low pre- and post-application earnings are women.

In Fig. 2 we also present the percentage distributions of individuals in specific earnings ranges: \$0, \$1–\$6000, \$6001–\$12,000, \$12,001–\$24,000, and above \$24,000 for the allowed and the denied group separately. The remarkable difference between the two groups in every earnings range is noteworthy. During the 5th year prior to application, 6.15% of the allowed applicants had no labor earnings, and 21.38% earned less than \$6000 per year (SGA amount for 1990). By contrast, 17.18% of the denied had no earnings and 38.93% earned less than the SGA amount. Fig. 2 also shows that 50.24% of the denied applicants had no earnings even seven years after the decision and 65.46% had earnings less than \$6000 per year. These numbers are somewhat worse than those reported in Bound (1989). The latter percentage suggests that close to 34.54% of the denied applicants do some amount of gainful labor market activity after their denials. Since the reported health status of the allowed is considerably inferior to that of the denied across all dimensions (see Table 2), one can infer that an upper bound estimate of the labor force non-participation effect of the DI program is 34.54% of the allowed if the labor-force participation is defined as earning at least the SGA amount. This is Bound's (1989) methodology where he found using data from the 1970's that fewer than 50% of the rejected applicants work.

However, the differential pre-application labor market activity between the allowed and the denied as presented in Fig. 2 clearly suggests that this 34.54% upper bound estimate can be an underestimate. Table 2 shows that the lower level of labor market activity of the denied in the pre-applications years cannot possibly be all explained by worse health including the incidence of chronic, congenital, acute or mental conditions. Given the residual functional capacity, the occupational demands (e.g., *WORK_HAZRD, BLUE_COLLAR, PHYSICAL_JOB, and STRENGTH*) of the denied applicants cannot explain the discrepancy either because these characteristics are seen to be, in fact, less demanding for the denied group. Thus, there must be other unobservable factors (taste, motivation, etc.) that contribute towards the lower labor market attachment of the denied applicants. Since historically the allowed applicants are seen to be more attached to the labor market, it may be reasonable to expect that the labor market activity of these workers would have continued to be more than that of the denied in the absence of the DI program.[10]

**Fig. 2.** Earnings distribution of DI applicants during pre- and post-application years.

[7] Unlike in Bound (1989), since our sample is restricted to DI insured workers, some of the zero earnings cannot be attributed to "uncovered" workers, see Parsons (1991). Also, the age restriction 35–60 avoids the problem of having zero earnings that occur before the first year of working or retirement.

[8] Note that the lowest earnings level for the allowed is slightly to the right of the same for the denied because the allowed–denied status is based on the latest MBR records where the earnings were recorded in real time.

[9] Using monthly SIPP earnings data during the 12 months before the application, Bound et al. (2003) found that earnings fell by more than 30% for males, while for females the drop was a little less.

[10] In view of the fact that prior to application, the labor market attachment of the applicants was not very strong, the 5-month waiting period cannot possibly