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An empirical analysis of the social security disability application, appeal, and award process

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Abstract

We provide an empirical analysis of the Social Security disability application, award, and appeal process using the Health and Retirement Survey (HRS). We show that the appeal option increases the award probability from 46% to 73%. However, this comes at the cost of significant delays: the duration between application and award is over three times longer for those who are awarded benefits after one or more stages of appeal. Our results reveal the importance of self-selection in application and appeal decisions. In particular, an individual's self-assessed disability status emerges as one of the most powerful predictors of application, appeal, and award decisions. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

This paper provides an exploratory empirical analysis of the Social Security Administration's (SSA) disability application, appeal, and award process using a sample of 13,142 men and women from the first three waves of the Health and Retirement Survey (HRS). We estimate separate binary choice models of the individual's decision to apply for benefits and the government's decision to award benefits. Conceptually, this is a dynamic game since rejected applicants have the right to appeal within 60 days of a denial and may submit any number of new applications. Our results suggest that there may be strong incentives to appeal an initial rejection. The 'first stage award rate' for new applications submitted to one of the 54 state-based Social Security Disability Determination Services (DDS) is only 45.9%, whereas the 'ultimate award rate' increases to 72.5% when we allow for the option to appeal or re-apply. However, over 30% of rejected applicants do not exercise this option, perhaps due to significant delay costs. The mean duration between application and award for first stage awardees is 5 months as compared to 15 months for those who received benefits after one or more stages of appeal. These findings suggest the importance of modelling dynamics and uncertainty in order to obtain an accurate understanding of the disability insurance (DI) award process. [1]

Due to the limitations of the reduced-form models employed in this paper, we are unable to generate predictions of behavioral responses to changes in DI program parameters or identify the relative importance of policy and 'macro' level causes of the recent rapid growth in the DI rolls. Nevertheless, our analysis does shed considerable light on the 'micro' determinants of application and award decisions under the current regime. We use flexibly specified binary logit models to uncover the most important predictors of application, appeal, and award decisions. Our results can be viewed as providing approximations to the decision rules used by individuals and the government in terms of serially independent

[1] To our knowledge, the only other attempt to explicitly model the complete disability application, appeal, and award process was made by Riphahn and Kreider (1997). They used retrospective information from the first wave of the HRS to model the individuals' decisions to apply for DI benefits over the period of 1986 to 1991. However, since the main goal of the study was to approximate the full returns to applying for DI benefits, the various stages of the process were not modeled. Consequently, similar to previous models of the DI application decision by Halpern and Hausman (1986), there is no explicit consideration of the substantial delays involved in appealing an initial rejection and the type of self-selection that these delays might induce. The analyses of Lahiri et al. (1995) and Hu et al. (1997) provide more insight into the initial ('first stage') acceptance decision made by the DDS, but ignore the possibility of appeal. Parsons (1991) employed aggregate data on the mean delays and success rates at various appeal stages in his critique of the analysis of the health and earnings of rejected DI applicants by Bound (1989). The debate between Parsons and Bound about how many of rejected DI applicants would actually return to work illustrates the importance of having a clearer understanding of the incentive effects of the DI appeals process.

unobserved, or latent, state variables and a large number of serially correlated observed state variables from the HRS.

Our results are based entirely on self-reported data on health status, employment status, income, and dates of application, appeal, and award of DI benefits. It is important to interpret our results with caution when it comes to making causal inferences about the impact of health on the propensity to apply for disability since the self-reported health and disability status variables used in our analysis may be subject to measurement error and endogeneity problems. Measurement error can arise from the usual sorts of survey recording errors, misreporting due to memory or other cognitive limitations of respondents, and from a variety of other problems associated with using respondents' subjective self-assessments of health and disability as measures of 'true' health or disability status. There is also significant disagreement in the literature about the endogeneity of self-reported health and disability measures due to various types of intentional or unintentional misreporting on the part of respondents such as 'rationalization bias', where respondents use health problems as a convenient excuse to explain their non-participation. Since we do not attempt to deal with potential measurement error and deal with endogeneity problems only via inclusion of a comprehensive list of 'exogenous' covariates, we acknowledge that some of the relationships we discover could be subject to complicated biases. However, we do not believe that our principal finding—the importance of self-reported disability as a predictor of application and award decisions—is simply a reflection of 'spurious causality'. We have no evidence of systematic misrepresentation of responses on the part of HRS respondents, and believe that to a first approximation, self-reported disability status can be treated as a truthful report of the individual's private information about their 'true' disability status. Space constraints prevent us from presenting this evidence here: we defer a more formal analysis of the magnitude of endogeneity and measurement error biases resulting from self-reported disability status to a subsequent paper. [2]

The rest of the paper is organized as follows. Section 2 provides a brief background on the U.S. Social Security Disability Insurance program (SSDI) and the Supplemental Security Income Disability Insurance program (SSI). Section 3 describes the HRS dataset and some of the compromises imposed by data limitations. Section 4 presents the empirical results from nonparametric estimation of the distributions of delays at various stages of the application process and

[2] The biases resulting from measurement error and endogeneity probably have offsetting effects, with measurement error leading to downward bias and endogeneity leading to an upward bias in the coefficients of self-reported health variables. The literature on this subject has conflicting findings. For example, recent papers by Dwyer and Mitchell (1999) and Bound et al. (1995) do not find significant evidence of bias in self-reported health measures in the HRS, whereas Kreider (1997) finds evidence of significant endogeneity bias.

estimation results for our four-stage model of DI process. Section 5 offers a summary and conclusions.

2. Background on the Social Security disability program

There are two separate Federal disability programs in the U.S.: SSDI and SSI. SSDI is a Social Insurance program enacted in 1956 to insure covered workers, their spouses and dependents against loss of earnings due to disability. [3] Disability is defined as: ''The inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment which can be expected to result in death or which has lasted, or can be expected to last, for a continuous period of at least 12 months'' (see U.S. Department of Health and Human Services (1988), Section 507).

A person's application for SSDI benefits is sent to one of the 54 DDS centers, usually in the state where the claimant resides. The DDS makes initial, or 'first stage', accept/reject decisions according to a sequential five-stage screening procedure illustrated in (Lahiri et al., 1995) and reproduced in Fig. 1. [4] This five-stage procedure is designed to weed out inappropriate cases quickly so that resources can be focused on judging difficult cases where the determination of medical or psychological problems is less clear-cut.

The first stage is to determine whether or not the person has engaged in substantial gainful activity (SGA) subsequent to the claimed onset of disability. Any applicant who is found to earn in excess of the SGA threshold (currently $US500/month) has demonstrated an ability to engage in SGA and is denied benefits at this stage. The second stage is to determine the severity of a medical or psychological problem. Applicants are denied if the impairment is not judged to be sufficiently severe, or if it is not expected to last longer than 12 months or end in death. The third stage consists of a determination of whether the applicant's impairment meets the criteria of one of over 100 standardized impairment classifications known as *Listing Impairments*. If the applicant's impairment is judged to fall into one of these categories of demonstrably severely disabling conditions, then the applicant is automatically granted a *Medical Allowance*. Applicants who are denied a Medical Allowance are then referred to the fourth stage, where the DDS evaluates the applicant's residual functional capacity to determine whether the disability prevents them from doing their previous work. Applicants who are deemed capable of doing their past work are denied benefits, otherwise, the

[3] Workers over age 31 are disability-insured if they had 20 quarters of coverage during the last 40 quarters and are fully insured. They are fully insured if they have at least one quarter of coverage for each year elapsed after 1950 (or age 21, if later) and before the year in which he or she attains age 62 or becomes disabled.

[4] This procedure is also described in the Social Security disability redesign web site.

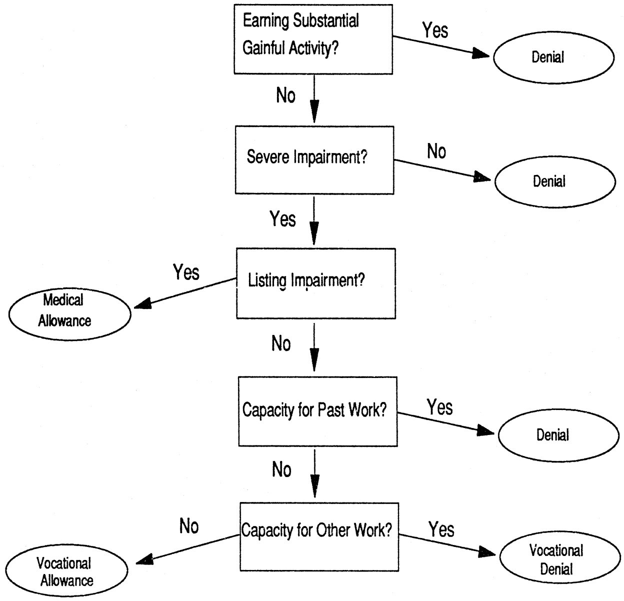

Fig. 1. Stages in Social Security's sequential disability determination process.

application goes to the fifth and final stage where the DDS evaluates whether the applicant is capable of any other type of work. An applicant is awarded benefits only if the DDS determines that the applicant is incapable of engaging in any other type of SGA. Otherwise, the applicant is given a *Vocational Denial*.

Individuals whose applications are accepted cannot begin receiving DI benefits until a 5-month waiting period is satisfied. [5] According to program statistics, the mean time required for a DDS to make its initial accept/reject decision is 5 months. Covered individuals who wait this long automatically satisfy the 5-month waiting period and begin receiving DI benefits in the month following notification of the award. SSDI beneficiaries are also entitled to Medicare coverage 2 years after the date of successful application, even if they are younger than 65, the normal age of eligibility for Medicare coverage. The current average disability benefit is $US750/month. [6]

[5] The waiting period start date is the later of: (a) the date of disability onset; and (b) the date the applicant first attained disability insured status (see [3]). This waiting period is exempted if the applicant had a previous period of disability that ended within 5 years of the latest date of disability onset.

[6] Once accepted, a SSDI beneficiary receives a benefit based on their computed Primary Insurance Amount, a concave piecewise linear function of their Average Indexed Monthly Earnings (AIME). There is no actuarial reduction in the primary insurance amount: SSDI benefits are the same as the Social Security old-age benefits of someone who retires at age 65 with comparable AIME.

Following an initial rejection, a rejected applicant has the option to appeal. There are four different appeal stages, as illustrated in Fig. 2. The first level of appeal is known as a *Reconsideration* and is performed by the same DDS that made the initial determination. An application for reconsideration must be filed within 60 days of notification of the initial denial. According to Social Security, in 1993, 48% of denied claimants requested a reconsideration and the mean time required by DDS to come to a decision on a reconsideration was 2 months. The acceptance rate at the reconsideration stage was 50%, higher than the 40% average acceptance rate for the first stage determination. If an applicant is denied benefits at the reconsideration stage, they have 60 days to exercise the option to have their case considered by an ALJ. According to Social Security, in 1993, claimants requested for an ALJ in about 75% of all reconsideration denials. By this time, the claimant has typically retained an attorney for assistance in the appeal process. The mean time to a decision at the ALJ stage is over 9 months and the acceptance rate at this stage increases to 75%. If the applicant is denied benefits by the ALJ, they have 60 days to file a request for consideration at the central Appeals Board in Washington. According to Social Security, the Appeals Board considers about 18% of all ALJ dispositions, including cases it reviews on its own initiative. The mean duration for a decision from the Appeals Board is 3 months and the acceptance rate is 30%. If a claimant is rejected at this stage, their only remaining option is to appeal the case in Federal Court. We have no data on the delays or success rates of Federal Court appeals.

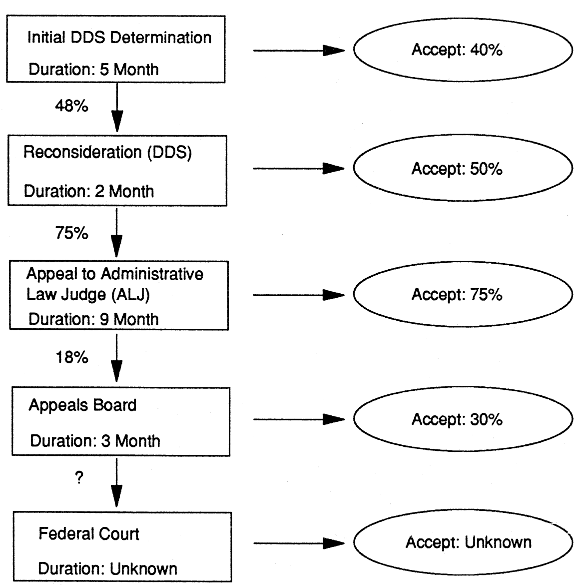

Fig. 2. Summary of the disability application and appeal process.

The other Federal program providing disability benefits is SSI, which is a means-tested cash assistance program enacted in 1974. The purpose of SSI is to assure a minimum level of income for people who are aged, blind, or disabled, and have limited income and assets. In order to qualify for SSI benefits, a person must satisfy the SSDI definition of disability and the person's income cannot exceed the current Federal benefit rate. Furthermore, the person cannot have more than a small threshold value of net worth. The current earnings and asset thresholds for a single individual are $US494/month and $US2,000, respectively. [7] In contrast to the SSDI, if eligible, a person can begin receiving benefits without being subject to the 5-month waiting period. Furthermore, SSI recipients are also immediately eligible for Medicaid benefits. However, monthly SSI benefits are lower than SSDI: in 1996, the average monthly SSI benefit was only $US402/month. The SSI applications are also processed by the 54 states DDSs using the same five-stage sequential procedure as for SSDI applications. Stapleton et al. (1994) show that since the late 1980s, the trends in applications, awards, and acceptance rates for the SSI and SSDI programs were very similar, which is fortunate since the HRS does not distinguish the two programs.

3. Measurement and data issues

The data for our study come from the first three interviews, or 'waves', of the HRS, a nationally representative longitudinal survey of 7,700 households whose heads were between the ages of 51 and 61 at the time of the first interview in 1992 and 1993. Each adult member of the household was interviewed separately, yielding a total of 12,652 individual records. Waves 2 and 3 were phone interviews conducted in 1994/1995 and 1996/1997, respectively, using computer-assisted telephone interviewing (CATI), which enabled interviewers to condition their questions on information provided in previous interviews. Deaths and sample attrition reduced the sample to 11,596 individuals in wave 2 of the survey and 10,970 individuals in wave 3. [8]

The HRS has several advantages over the alternative sources of data previously used to analyze the DI award process, such as the SIPP data (e.g., Lahiri et al., 1995; Hu et al., 1997). The HRS is a long panel focusing on older individuals nearing retirement age, with separate survey sections devoted to health, disability,

[7] The income and asset thresholds for couples are $US794/month and $US3,000, respectively. The asset threshold excludes home, auto, household items, burial plots, and life insurance policies of face values under $US1,500.

[8] Additional households and individuals who were not contacted during the wave 1 interview were added in waves 2 and 3. We include these respondents in our analysis, yielding a total of 13,142 individual records.

and employment that contain numerous questions on objective and subjective indicators of health status, questions about disabilities, beginning and ending dates of employment spells, questions about employer accommodations to disability, and questions about applications and appeals for DI benefits. In wave 1, respondents were asked about the date they first applied for DI benefits and whether or not they were awarded benefits. A respondent who was awarded benefits was asked the month and year they first started receiving them. If a respondent was not awarded benefits, they were asked whether or not they 'appealed or applied again later'; if the answer was positive, then the respondent was further asked about the month and year of their last application or appeal. In subsequent waves, individuals who reported receiving DI benefits in the previous wave were asked if they were still receiving DI benefits, and if not, the month and year at which they stopped receiving benefits. Those who were not receiving benefits at the time of the interview were asked in subsequent waves whether or not they applied for DI benefits since the previous survey, whether or not they were awarded benefits then, and whether or not they appealed or applied again if they were denied. A respondent was further asked about the month and year of the last application or appeal if they appealed or applied again.

There are several limitations of the HRS data for studying the DI award process. First, unlike the SIPP data, there is no match to the SSA Master Beneficiary Record, so we are unable to verify the individual's self-reported information on dates of application and appeal for SSDI and SSI benefits. Second, the HRS did not distinguish between SSI and SSDI applications, appeals, and awards, since all questions combined the two programs into a single category. Third, due to the limited level of detail in the HRS questions on the DI appeal process and the fact that relatively few cases reached higher levels of appeal, we were unable to distinguish various levels of appeal shown in Fig. 2 and were forced to collapse the multi-stage appeal process into a single stage. Finally, the HRS did not include appropriate follow-up questions that would allow us to determine whether the DI applications or appeals reported in previous surveys were awarded, denied or pending, resulting in potential censoring of information on appeals and re-applications. Fortunately, we were able to rectify some of these censoring problems using other information in the HRS. For example, the income section of wave 2 of the HRS included a question about whether respondents received Social Security income, and if so, the type of Social Security Income (SSI/SSDI benefits, retirement, etc.) and the date at which the respondent began to receive those benefits. We used this information to determine that certain previously pending DI cases resulted in awards. However, in some cases, we could not use other survey information to resolve ambiguities when there was no information on the outcomes of previously reported pending DI applications (i.e., in waves 2 or three). Since only a small fraction of cases are pending for more than 24 months, we classified an ambiguous pending DI application or appeal as a denial if we could determine that it had been pending for more than 24 months.

Despite the problems in the HRS questionnaire design, we found that by imposing reasonable strategies for resolving ambiguous cases and imputing missing dates of application, appeals, and awards (described in more detail in Appendix A), we could make reliable inferences about many aspects of the disability application, appeal, and award process. To the extent that we were able to verify, our estimates of the mean durations between various events such as application and appeal, and appeal and first receipt of benefits, lined up fairly closely with independent information from SSA on the delays at various stages in the DI process (some of which are included in Fig. 2). [9]

We also had to address issues of time aggregation in modeling the DI award process. Although individual decisions about when to apply for disability are made in continuous time, we only observe individuals at successive surveys which are approximately 2 years apart. Obviously, the wider the window of time over which we observe any given person, the higher the likelihood that they will submit an application or appeal. For this reason, it is inappropriate to model the DI application decision in a static context, treating each individual as constituting a single observation as has been done in most of the previous literature. Instead, we want to exploit the panel nature of the HRS, where a single individual can yield many observations on decisions of whether or not to apply. The number of 'application' or 'no application' observations that one can obtain from a single individual is in some respects arbitrary since it depends on how finely we discretize time. However, the finer we discretize time, the more information we need on other covariates which affect application and appeal decisions like health status. In the HRS, we only observe an individual's health status at points in time that are roughly 2 years apart. We decided that a reasonable compromise would be to estimate a model that discretized time into 2-year intervals. This yields a maximum of three 'person-period' observations for an individual who responded to each of the three waves of the HRS, provided the outcome of a previous

[9] The other important variables for our analysis are monthly and annual indicators summarizing the respondent's employment history. These variables are potentially important predictors of DI award decisions since they provide evidence of an applicant's ability to engage in substantial gainful activity. In particular, any evidence of employment subsequent to the reported date of disability onset or the filing of an application for DI benefits could be grounds for immediate rejection at the first stage 'SGA screen' in Fig. 1. We constructed employment histories using information on beginning and ending dates of employment spells in the employment section of the HRS. In particular, we calculated, for each individual in every year between 1991 and 1996, annual hours worked and annual earnings. Monthly employment indicators for each month between January, 1989 and December, 1996 were also calculated. We employed a battery of consistency checks to validate the extensive number of calculations necessary to translate reported dates of beginning and leaving previously held jobs and 'intermediate jobs' held between successive survey waves to determine the time path of employment down to the finest possible time period allowed by the survey questions (i.e., monthly). In addition to the work history data, we also constructed a number of wealth variables, the most important being net worth, housing wealth, and non-housing assets.

application or appeal was not still pending. Since application, appeal, and award decisions do not coincide with the interview dates, we used data from the survey wave *closest* to the date of the application, appeal, or award as representing the state of the individual at that time. However, if the closest wave was previous to the date of application, appeal, or award, and if the person did not report being disabled at that wave, then we used the information from the subsequent wave.

Finally, whether or not an individual is legally eligible to receive disability benefits is obviously an important determinant of application and award decisions. We constructed a dummy variable specifying whether or not an individual was eligible to receive SSI and SSDI disability benefits using the rules of the programs' eligibility criteria described in [3,7]. To implement this, we used matching Social Security earnings records, our monthly labor force participation dummies, and data on earnings and wealth. Appendix A provides further details on the methods we used to construct this variable.

4. Empirical findings

This section describes the estimation results for our empirical model of the SSI and SSDI application and award process. Fig. 3 summarizes the 'game tree' estimated here. The branches below each decision node indicate the possible

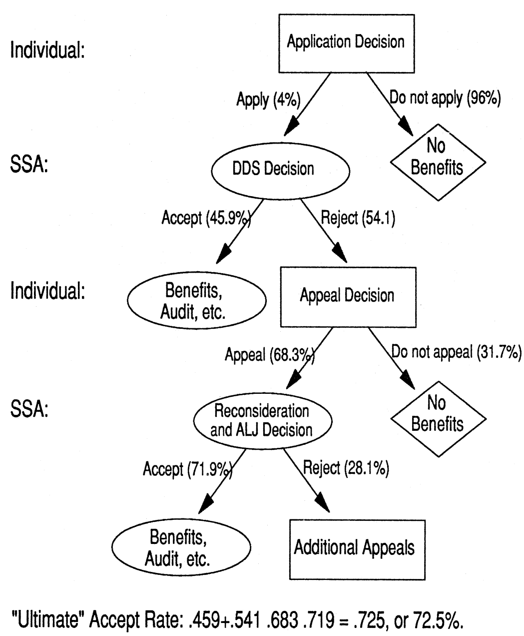

Fig. 3. Estimated 'game tree' for the disability award process.

outcomes at each stage and include the marginal probabilities computed from our sample. Thus, 4% of the ‘person-period’ observations in our sample submitted an application, and of the 4% who submitted applications, 72.5% were ultimately accepted—45.9% were accepted at the first stage by the DDS, while an additional 26.6% were accepted after one or more stages of appeal.

4.1. Delays between disability onset, applications, appeals, and awards

We begin with Fig. 4 which presents nonparametric estimates of the ‘delay distribution’ at various stages of the DI application and appeal process. Fig. 4a presents the distribution of time between the reported onset of disability and the date of application for benefits. Interestingly, most individuals do not apply for DI

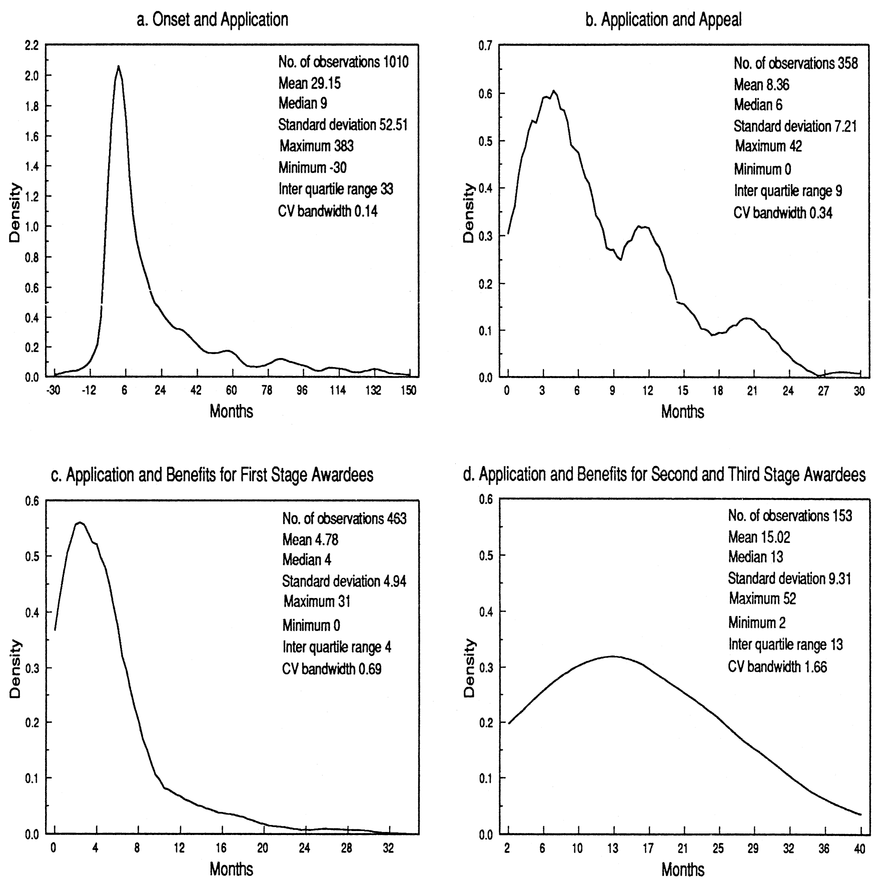

Fig. 4. Duration densities for SSI/SSDI application process (all episodes).

benefits immediately after the reported onset date, perhaps due to the fact that they initially expect to recover. The median duration of 9 months between disability onset and application means that the majority of applicants who attained disability-insured status already satisfied the 5-month waiting period at the time of application. The very long tail of the duration distribution indicates that a significant fraction of individuals wait for more than 2 years prior to filing. Indeed, some disabled individuals may never apply for DI benefits: we found that 20% of individuals who reported having a health limitation that prevents them from working in waves 1, 2, or 3 never applied for DI over the period 1990–1996. While some of these are undoubtedly censored observations on individuals who may ultimately submit applications for benefits, we found that 58% of this group of ‘disabled non-applicants’ were ineligible to receive benefits.

A puzzling finding is the significant number of applicants whose reported date of onset of a disability follows the reported date of application. There are several possible explanations for negative durations including: (a) measurement or recall errors in the dates of onset and application; (b) fraudulent DI applications; or (c) cases where an individual has a steadily deteriorating health condition, expects to become disabled, and files a DI application in anticipation of the delays in the award process.

Fig. 4b depicts the density of the elapsed time between the reported application date and the date of appeal for individuals who were denied benefits at the application stage. [10] The mean delay of 8.4 months reflects the total time elapsed between application and appeal, which we presume is mostly due to the ALJ stage. This matches the administrative data in Fig. 2 quite closely. Note that the mean durations for initial DDS determination and reconsideration are 5 and 2 months respectively, and if an individual’s appeal is received after 30 days (midway through the 60-day limit), then the length of time between initial application and ALJ appeal is 8 months.

Fig. 4c depicts the density of duration until the eventual receipt of benefits for those who were awarded benefits at the first stage, i.e., without having to appeal. The median delay is only 4 months, which suggests that most of these ‘first stage awardees’ have relatively severe conditions. However, we can see from Fig. 4d that it is quite a different story for individuals who obtained benefits only after one or more stages of appeal. The median duration between application and receipt of benefits for these individuals is 13 months. This long delay is likely to deter applicants who are not truly disabled and who were denied at the first stage from appealing. At the same time, it imposes a very large cost on truly disabled individuals who have no other alternative than to appeal an initial denial.

[10] When a respondent reported being denied benefits after initial application and having appealed, the respondent was asked for the date of the last appeal. This date could correspond to a reconsideration or a further stage in the appeal process.

4.2. The application and appeal decisions

Table 1 presents results for a binary logit model of the DI application decision. All but one of the coefficients have intuitively plausible signs, although socio-economic variables such as race, sex, income, and wealth play a much less important role as predictors of the DI application decision once we condition on the health

Table 1
Estimation results for the application decision

Number	Variable	Estimate	Standard error	Marginal effect
1	Constant	−3.915	0.467	–
2	Married	0.205	0.158	0.003
3	Male	0.329	0.112	0.005
4	White	0.002	0.112	0.00003
5	No high school diploma	0.152	0.110	0.003
6	Vocational training	0.079	0.116	0.001
7	Applying at 62 or older	−3.160	0.434	−0.041
8	Applying between 55 and 61	−1.526	0.402	−0.030
9	Applying between 50 and 54	−1.167	0.404	−0.018
10	Applying in your 40’s	−1.191	0.427	−0.016
11	Non-eligible for SSI/SSDI	−1.017	0.132	−0.016
12	Respondent’s earnings (in US$1000) in preceding year	−0.027	0.005	−0.0006
13	Spouse’s earnings (in US$1000) in preceding year	−0.011	0.003	−0.0002
14	Net worth (in US$100,000) in preceding year	−0.037	0.022	−0.0007
15	Previously applied for DI	0.179	0.188	0.003
16	Previous cancer	0.174	0.237	0.003
17	Previous stroke	0.574	0.235	0.012
18	Nursing home stay in past 12 months	0.904	0.410	0.020
19	Back problems	−0.072	0.108	−0.0013
20	Feet problems	0.276	0.113	0.005
21	Had fracture	0.584	0.163	0.012
22	Had diabetes	0.260	0.144	0.005
23	Have arthritis	0.373	0.105	0.007
24	Had lung disease	0.239	0.146	0.004
25	Had angioplasty	0.500	0.184	0.010
26	Difficulty using the stairs	0.317	0.125	0.006
27	Difficulty stooping or crouching	0.431	0.118	0.008
28	Number of hospitalizations in the last year	0.029	0.025	0.0005
29	Doctor visits in the last year	0.016	0.004	0.0002
30	Health limitation prevents work	2.570	0.146	0.088
31	Health got worse in the last year	0.300	0.061	0.003
32	Excellent health	−1.437	0.331	−0.018
33	Very good health	−0.750	0.186	−0.012
34	Fair health	0.331	0.131	0.006
35	Poor health	0.481	0.169	0.009
	Average log L/number of observations/probability	−0.0689	25,596	0.027

status measures. This result corroborates similar findings by Bound et al. (1995). One way to interpret this finding is that the health status variables are acting as approximate ‘sufficient statistics’ in the sense that socio-economic differences in the propensity to apply for DI benefits manifest themselves primarily through the health status variables. A comparison of the characteristics of applicants and non-applicants (not reported here due to space constraints), reveals clear differences in health and socio-economic status. DI applicants are significantly less healthy than non-applicants in terms of both self-assessed health and disability, as well as in terms of objective measures of health status and functional capacity. DI applicants are significantly economically disadvantaged relative to non-applicants in terms of education, income, and assets.

Of the health status variables, the single most important variable is HLIMPW, a dummy variable that equals one if the individual reports having a health problem that prevents them from working altogether, and zero otherwise. This variable has the largest coefficient and the largest marginal effect on the application probability. [11] We interpret this as evidence of the importance of the individual’s private information about their ‘true disability status’ in the application decision. Although we find that truly disabled individuals (i.e., those with {HLIMPW = 1}) are substantially more likely to apply for DI benefits than non-disabled individuals, self-selection is still relatively far from generating a perfect ‘separating equilibrium’ since over 30% of DI applicants in our sample do not consider themselves disabled.

We also included variable 11, a dummy variable which takes the value 1 for individuals who are ineligible for SSDI and SSI disability benefits, and zero otherwise. Not surprisingly, the coefficient for this variable is negative: it is also highly significant, indicating that individuals who are ineligible are more than 50% less likely to apply for benefits. We interpret this as evidence that individuals are familiar with the rules of the DI program.

Other variables that have significant effects on the application decision are age, the applicant’s income in the previous year, and the applicant’s net worth. The dummy variable for applying at age 62 or older shows that individuals over age 62 are significantly less likely to apply for DI. This seemingly counterintuitive result can be easily explained by the fact that 62 is the age of first eligibility for early retirement benefits. Even though DI benefits are more than 20% higher than the early retirement benefits and DI beneficiaries qualify for Medicare benefits sooner than early retirees, the delays and uncertainties involved in the DI application process constitute a sufficiently great ‘hassle cost’ to deter virtually all individuals

[11] The marginal effect for continuous variables is computed as the average derivative of the estimated choice probability with respect to the variable in question. For binary variables, the marginal effect is the average of the difference between the probability with the binary variable set to 1 and the probability with the binary variable set to 0.

over 62 from applying. [12] We interpret this finding as clear evidence of opportunistic behavior in the DI application decision.

Our estimation results also reveal that relatively younger individuals with low income and wealth levels are significantly more likely to apply for DI benefits. As we have shown in Section 4.1, an application for DI benefits involves significant delay costs and presumably other ‘hassle costs’ as well. Therefore, the individuals who stand to gain the most from incurring these costs are those who can expect relatively high replacement rates as well as those who are able to ‘amortize’ the application costs over a relatively long time span. Given the progressive structure of the Social Security benefit formula described in Section 2, DI benefits can provide after-tax replacement rates in excess of 100% for those with the lowest earnings histories declining monotonically towards 0% replacement rates for those in the highest end of the income distribution. While low-income individuals are also more likely to have physically demanding jobs and poor health, the fact that the income effect remains highly significant even after controlling for self-assessed disability is suggestive of problems of incentive compatibility in the DI benefit structure. The majority of the 30% of DI applicants in our dataset who report not being disabled are in the lowest income decile: for this group, the temptation to apply for DI benefits can be quite high.

Most of the other ‘objective’ health and functional status indicators and socio-demographic variables have the expected signs, although relatively few are highly significant. In particular, we find that males and less-educated individuals (i.e., individuals with no high school diploma or only vocational training) are more likely to apply for DI benefits. The model predicts that married and white individuals are marginally more likely to apply for benefits, but the coefficient estimates are not significant. As discussed above, the reason for this is that most of the effects of race and marital status seem to be captured via the HLIMPW indicator. In addition to the HLIMPW indicator, we also found self-rated health status indicators (variables 31–35) to be important predictors of DI application. A person who reports being non-disabled, but in poor health, is four times more likely to apply for DI benefits than someone who reports being in excellent health.

Table 2 presents estimation results for the decision to appeal a denial. The table contains most of the variables included in our model of the application decision except for the age dummies that were eliminated because they were insignificant or co-linear predictors of the appeal decision. It was more difficult to find significant predictors of the appeal decision because of the smaller sample size and the self-selected nature of the subsample of individuals who chose to appeal. Many

[12] Peter Diamond has noted an interesting puzzle: why do more people not simultaneously apply for early retirement and DI benefits? Apparently, the hassle or ‘stigma cost’ of submitting an application for DI benefits exceeds the expected utility of the extra 20% benefit margin and the ability to qualify for Medicare up to 1 year earlier than otherwise.

Table 2
Estimation results for the appeal decision

		Estimate	Standard error	Marginal effect
1	Constant	0.397	0.804	–
2	Married	−0.794	0.429	−0.134
3	Male	0.454	0.276	0.082
4	White	0.312	0.288	0.057
5	No high school diploma	0.044	0.303	0.008
6	Vocational training	0.152	0.300	0.027
7	Respondent's earnings (in US$1000) in preceding year	0.018	0.012	0.003
8	Spouse's earnings (in US$1000) in preceding year	−0.003	0.008	−0.0006
9	Net worth (in US$100,000)	0.001	0.088	0.0003
10	Number of hospitalizations in the last year	0.128	0.162	0.023
11	Doctor visits in the last year	0.005	0.010	0.001
12	Difficulty walking one block	0.752	0.341	0.133
13	Difficulty using the stairs	−0.320	0.303	−0.060
14	Difficulty stooping/crouching	−0.109	0.313	−0.019
15	Difficulty reading a map	0.199	0.309	0.036
16	Had angioplasty	−0.622	0.381	−0.119
17	Had high blood pressure	−0.120	0.289	−0.022
18	Had back problems	0.402	0.288	0.075
19	Had a fracture or broken bone	−0.723	0.353	−0.143
20	Had lung disease	−0.189	0.379	−0.035
20	Had arthritis	−0.464	0.264	−0.087
21	Health got worse in the last year	−0.050	0.150	−0.008
22	Health limitation prevents work	0.985	0.293	0.197
23	Psychological problems in the last year	0.174	0.302	0.031
25	Fair health	0.551	0.338	0.099
26	Poor health	0.323	0.388	0.059
27	Probability of living to 75	−0.481	0.395	−0.088
	Average log L/number of observations/probability	−0.547	380	0.681

applicants with the most disabling conditions (such as those who have 'listed impairments' in the SSA *Blue Book*) were already awarded benefits in the first stage. Those who were rejected at the first stage are more likely to have less clear-cut health impairments that may not necessarily prevent them from working.

The four most important predictors of the appeal decision are three objective health status indicators (having had a fracture or broken bone, having had an angioplasty and the indicator for having a difficulty walking one block), and one subjective measure (the HLIMPW indicator). Having a health limitation that prevents work has the largest coefficient and raises the probability of an appeal by almost 20 percentage points. Having a difficulty walking one block increases the probability of appeal by more than 13%. Several objective health indicators have counterintuitive coefficient estimates. For example, having had an angioplasty or a fracture in the last year decreases the probability of appeal by 11% and 14%, respectively. Also, treatable conditions, such as high blood pressure or arthritis, have a negative effect on the appeal probability.

Most of the other objective health and functional indicators are statistically insignificant predictors of the appeal decision. We interpret the strong impacts of the subjective health status variables as evidence of the importance of self-selection in the appeal process. In particular, individuals who believe they are truly disabled are significantly more likely to appeal an initial denial. For example, while 68.8% of the individuals submitting an initial application for DI benefits reported having a health limitation that prevents them from working, 76.8% of those who were denied and chose to appeal reported {HLIMPW = 1}. Nevertheless, it appears that a fair number of truly disabled individuals are discouraged from appealing their first stage rejections; of the 35% of rejected applicants who chose not to appeal, 52.2% had {HLIMPW = 1}.

4.3. Social Security Administration (SSA) decisions

We estimated two alternative models of the government's first stage acceptance decision, i.e., the first government decision node in Fig. 3: (a) a binary logit model, and (b) a 'marginal probability' model. [13] The marginal probability model is similar to models estimated in (Lahiri et al., 1995; Hu et al., 1997) which compute the probability of being accepted or denied benefits at each stage of the five-stage sequential DDS process outlined in Fig. 1. Unlike these previous papers, we do not have access to administrative data that would allow us to observe the stage of this process at which an applicant was accepted or denied. Hence, we compute the marginal probability of acceptance or denial for all stages simultaneously. Due to the similarity of the last two stages of Fig. 1, we combined them into stage 4 of the estimated model below.

Let $\{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \boldsymbol{x}_4\}$ be vectors representing information used to determine whether an application is accepted or denied at stages {1,2,3,4} of the sequential process, respectively, and let $\{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \boldsymbol{\theta}_3, \boldsymbol{\theta}_4\}$ be conformable parameter vectors. Let $1 - p_1(\boldsymbol{x}_1; \boldsymbol{\theta}_1)$ be the conditional probability of being denied at the first stage, i.e., as having evidence of ability to engage in SGA. Let $p_2(\boldsymbol{x}_2; \boldsymbol{\theta}_2)$ be the conditional probability of being 'passed on' to the third stage, i.e., as having a severe impairment. Let $p_3(\boldsymbol{x}_3; \boldsymbol{\theta}_3)$ be the probability of being accepted at the third stage, i.e., having a listed impairment. As explained above, in the fourth and last stage, $p_4(\boldsymbol{x}_4; \boldsymbol{\theta}_4)$ denotes the probability of being determined as incapable of performing

[13] See Appendix B for detailed description of the marginal probability model.

past or other work. Thus, the marginal probability of being awarded benefits is given by: [14]

$$\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta}) = p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)\,p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)\big[\,p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3) + p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4) - p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)\,p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)\big].$$

The maximum likelihood estimates for the two models are given in Table 3. Note that in the marginal probability model, no variable appears in more than one step. The allocation of the variables across the four steps was done according to the SSA classification of the variables which are used in their eligibility determination. This is also in line with the classification used by Lahiri et al. (1995). [15] Evidently, some of the most obvious variables do not seem to be good predictors of the approval probability under either model. In the set of variables listed under the first step, most variables are insignificant, although, in general, have the expected sign. Among all variables, the average number of hours worked per week in the 4 months following the application for benefits seems to be quite important. The earnings and wealth variables, which are the key ingredients in determining one's ability to engage in SGA, and meeting the income and asset eligibility thresholds for SSI, seem to be very poor predictors of the approval probability. This may reflect self-selection on the part of individuals since very few people apply for SSI if they know they exceed the income and asset thresholds or earn in excess of the SGA limit. The set of variables listed under the second step seems to contain more information about one's chances of getting benefits. In particular, the self-reported health (variable 7) has strong effects on the award probability, with robust positive coefficients in all the alternative specifications we tried.

The other variables included seem to have low predictive power, or even have the 'wrong' sign, such as functional limitation indicators 9 through 12. The results indicate that only the more serious problems increase one's award probability. The same results also apply for the group of variables listed under the third step. Some of the variables, such as having back problems, have counterintuitive signs and are statistically significant. One possible explanation might be that SSA may have found that many applicants use false excuses such as 'back problems', so this variable might actually be a signal that a given applicant is an impostor. Reassuringly, we find that the more serious health problems such as cancer or stroke significantly increase the probability of being awarded benefits.

There are a number of variables that seem to be good predictors of the fourth stage of the DDS's determination procedure, which evaluates a candidate's capability to engage in past work or other work. The age at application variables

[14] Each of the stage-specific probabilities $\{p_1, p_2, p_3, p_4\}$ was specified as binary logits. See Appendix B for more details.

[15] We also estimated the marginal probability model with constants entering at each of the four steps. However, this model yields almost identical results to the results presented in Table 3, with the constants in the last three steps being statistically and economically insignificant.

(23 and 24) significantly increases the odds of acceptance, reflecting the fact that disabled older individuals have fewer alternative job opportunities and capacity to engage in their past work. On the other hand, vocational training and a college degree have negative, although statistically insignificant, effects on the approval probability. The negative coefficient can be interpreted as an indication that the DDS regards more highly educated individuals as having higher levels of human capital and higher capacity to do alternative kinds of work than those with lower education levels. Being married or divorced reduces the probability of acceptance relative to those who were never married, possibly reflecting the fact that the SSA regards these people as likely to have other means of support within their extended family units.

The year dummies in Table 3 were included to capture changes in SSA's disability award policy over the period of our sample. Note that there is tremendous variation in the magnitude and significance of these dummy variables under both specifications. Since the SSA procedures and rules have not changed dramatically during the period from 1990 to 1995, the variation in these coefficients may be spurious, capturing chance variation in acceptance rates for cohorts of applicants in various years. For example, a relatively small number of individuals were observed to apply in 1995 and by chance, a large fraction of these applications happened to be accepted. This seems to be a plausible explanation for the positive, although statistically insignificant, estimate of variable 36 since we have no independent evidence of a sudden increase in DDS leniency in awarding benefits in 1995, relative to 1989.

The log-likelihood values indicate that the binary logit specification fits the data slightly better than the supposedly 'correctly specified' marginal probability model. Note that since both models have the same number of parameters, any model selection criterion (such as the Bayesian Information criterion or the Akaike Information criterion) reduces to comparison of the likelihood values for the two models. On that basis the logit model should be chosen over the marginal likelihood model. However, the non-nested hypothesis test of Cox (1961, 1962) rejects the null hypothesis that the marginal likelihood is the true model in favor of the logit alternative only at the 5% significance level.

In order to compare the predicted acceptance probabilities under the two specifications, Fig. 5 plots the estimated acceptance probabilities for each observation, sorted from low to high. We note that for most of the observations, the predicted probabilities of the logit and the marginal probability model are reasonably close. The marginal probability model predicts slightly higher probabilities of acceptance for slightly over 50% of the observations with the lowest probabilities of acceptance. However, the marginal probability model predicts much lower probabilities of acceptance for the remaining. We do not have a clear idea which model provides a better approximation to the 'truth' in this case. It is interesting to note that both specifications predict a very wide range of predicted acceptance probabilities, ranging from 10% to nearly 100% over our sample. Approximately

Table 3
First stage decision by the disability determination services

Number	Variable	Binary logit			Marginal likelihood		
		Estimate	Standard error	Marginal effect	Estimate	Standard error	Marginal effect
First step: SGA							
1	Constant	−0.713	1.400	–	3.506	2.849	–
2	Net wealth (in US$100,000)	0.115	0.070	0.041	0.033	0.592	0.001
3	Total hours worked (in 1,000)	0.249	0.196	0.088	0.331	1.071	0.005
4	4-month average hours/week after application	−0.022	0.010	−0.008	−0.051	0.053	−0.001
5	Previously applied	0.664	0.215	0.127	0.494	4.111	0.007
6	Earnings in preceding year (in US$1,000)	0.009	0.010	0.003	0.009	0.129	0.000
Second step: severe impairment							
7	Health limitation prevents work	0.500	0.188	0.098	1.395	0.581	0.138
8	Number of hospitalizations	0.089	0.054	0.032	0.248	0.226	0.021
9	Difficulty jogging	−0.034	0.311	−0.007	0.520	0.370	0.047
10	Difficulty sitting	−0.178	0.172	−0.035	−0.159	0.369	−0.013
11	Difficulty picking a dime	−0.283	0.235	−0.055	0.211	0.588	0.017
12	Difficulty reaching over shoulders	−0.582	0.188	−0.114	−0.305	0.417	−0.026
13	Difficulty walking one block	0.227	0.203	0.044	0.168	0.492	0.014
14	Difficulty walking around room	0.308	0.274	0.060	0.436	0.775	0.033
15	Difficulty reading map	0.142	0.182	0.028	0.356	0.432	0.028

Third step: listing impairment							
16	Had cancer	0.583	0.326	0.112	1.608	0.666	0.152
17	Had stroke	0.725	0.307	0.138	1.513	0.600	0.144
18	Nursing home stay in last 12 months	0.041	0.429	0.008	0.012	0.705	0.001
19	Back problems	−0.593	0.181	−0.118	−1.398	0.464	−0.139
20	Psychological problems	0.236	0.195	0.046	0.081	0.352	0.007
21	Have arthritis	0.125	0.182	0.024	0.282	0.354	0.026
22	Weight in pounds	−0.004	0.020	−0.001	0.000	0.023	0.000
Fourth step: ability to perform past or other work							
23	Age at application for SSDI	0.060	0.020	0.021	0.068	0.038	0.005
24	Age at application for SSDI × age 62+	0.004	0.007	0.001	0.020	0.019	0.002
25	Vocational training	−0.311	0.186	−0.061	−0.709	0.512	−0.054
26	College degree	−0.350	0.331	−0.068	0.001	0.772	0.000
27	Married	−0.766	0.398	−0.145	−1.894	1.178	−0.136
28	Divorced	−0.701	0.409	−0.134	−2.160	1.246	−0.149
29	Male	0.175	0.182	0.034	0.466	0.434	0.036
30	White	0.235	0.172	0.046	0.576	0.448	0.044
31	Dummy variable for 1990	−1.584	0.707	−0.274	−1.647	1.629	−0.104
32	Dummy variable for 1991	−2.420	0.703	−0.399	−3.205	1.886	−0.201
33	Dummy variable for 1992	−2.840	0.700	−0.464	−4.163	2.195	−0.251
34	Dummy variable for 1993	−2.157	0.712	−0.354	−2.791	1.839	−0.169
35	Dummy variable for 1994	−1.384	0.701	−0.242	−1.118	1.669	−0.074
36	Dummy variable for 1995	0.626	0.985	0.119	0.128	2.221	0.010
	Average log L/number of observations/probability	−0.569	828	0.550	−0.599	828	0.534

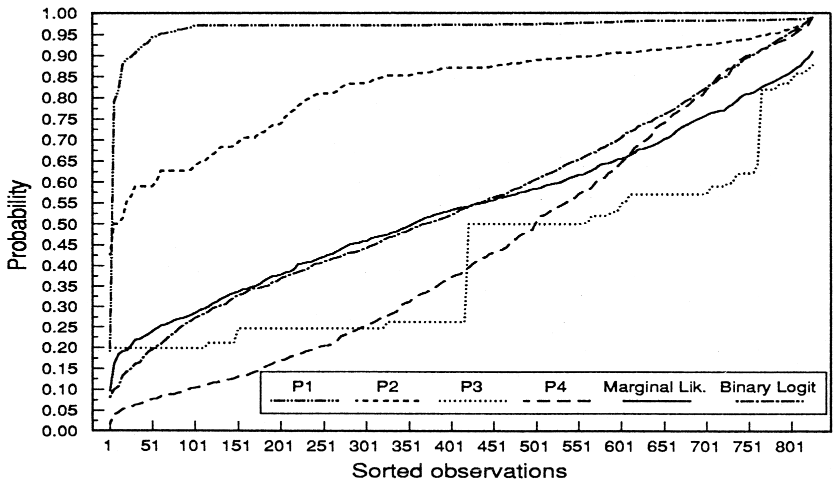

Fig. 5. Estimated first stage acceptance probabilities.

50% of the observations have a predicted acceptance probability of less than 50%, and the average acceptance probability are 55.0% and 53.4% for the binary logit and marginal likelihood models, respectively.

The remaining four curves in Fig. 5 plot the estimated probabilities $\{p_1, p_2, p_3, p_4\}$ of the four stages in the DDS's sequential disability determination process. Among these probabilities, p_1, the probability of satisfying the SGA test, is the highest, indicating that few applicants are rejected at this stage. It is probably an indication that most DI applicants are sufficiently familiar with the DDS screening procedure that very few make the mistake of engaging in SGA subsequent to their claimed date of disability onset. Our estimate of p_2, the probability of being judged to have a severe impairment, is significantly less than p_1 for most observations, indicating that many more applications are denied at this stage. Nevertheless, most of the observations are predicted to have a stage 2 acceptance probability of at least 50%. The estimate of p_3, the probability of having a listing impairment, is, in general, the lowest. Even if an individual is determined to have severe impairment, there is still quite a high probability that the individual will not be awarded benefits. This is due to the fact that it may not be a sufficiently severe disability to be included as one of the listed impairments in the SSA's 'Blue Book'. The final probability p_4, capacity for past/other work, lies mostly between p_2 and p_3. This curve indicates that over 50% of the applicants who are determined not to have a listing impairment are judged to have a capacity to do either their past work or some other type of work, with probability of at least 40%. Overall, the estimated probabilities are intuitively plausible, reflecting SSA's stated goal of designing the DDS screening process in stages so as to weed out the 'easy' cases first so that scarce administrative resources can be focused on judging the more difficult or ambiguous cases that reach the last stage of the sequential decision process.

The predicted probabilities from our marginal likelihood model are comparable to those obtained by Lahiri et al. (1995). They report that the approval rate at the very first step was very close to 100% (which is the reason they estimated only the last four stages). The average approval rate estimated by our model is 96.8%. For the second stage, the average approval rate based on our model is 82.7%, while that obtained by Lahiri et al. is 81.9%. The approval rates for the third stage are 41.0% and 35.7%, respectively. The average approval rates for the last two stages (aggregated in our model) are estimated to be 43.9% and 32.9%, respectively. The average acceptance probability for the full DDS determination process was estimated to be 46.5% in the Lahiri et al. study, as compared to our estimate of

Table 4
Government decision at the second stage a binary logit model

Number	Variable	Logit estimates		
		Estimate	Standard error	Marginal effect
1	Constant	−0.108	2.619	–
2	Net wealth (in US$100,000)	−0.044	0.177	−0.025
3	Total hours worked in application year (in 1000)	−1.138	0.486	−0.650
4	Previously applied	−0.275	0.468	−0.040
5	Earnings in preceding year (in US$1000)	0.085	0.029	0.049
6	Health limitation that prevents work	1.190	0.402	0.186
7	Difficulty jogging	−0.729	0.708	−0.096
8	Difficulty sitting	0.798	0.358	0.119
9	Difficulty walking around room	1.023	0.594	0.132
10	Difficulty reading map	0.822	0.376	0.114
11	Back problems	0.621	0.370	0.093
12	Any psychological problems?	−0.390	0.368	−0.057
13	Have arthritis	−0.438	0.364	−0.063
14	Weight in pounds	0.006	0.005	0.004
15	Age at application for SSDI	0.057	0.038	0.033
16	Age at application for SSDI × age 62+	0.009	0.017	0.005
17	Vocational training	1.665	0.417	0.220
18	College degree	0.409	0.668	0.056
19	Married	−1.850	1.037	−0.227
20	Divorced	−2.117	1.061	−0.301
21	Male	−0.844	0.376	−0.122
22	White?	−0.235	0.341	−0.034
23	Dummy variable for 1991	−1.068	1.203	−0.161
24	Dummy variable for 1992	−3.088	1.119	−0.427
25	Dummy variable for 1993	−1.430	1.160	−0.207
26	Dummy variable for 1994	−3.326	1.164	−0.454
	Average log L/number of observations/probability	−0.440	295	0.715

53.4%. Given that the sample used here is quite different from that used by Lahiri et al., and given the sample variability in the approval rate estimates, the two sets of estimates are fairly close. This is very encouraging, and indicates that even without administrative data on the exact stage at which an applicant was qualified or disqualified, we can still accurately estimate the overall acceptance probability, contrary to the claims of Lahiri et al. (1995).

Table 4 presents the results for the government's appeal decision. In principle, the same variables affecting the initial decision are those on the basis of which the appeal decision is being made. There can be additional information that may be provided, though, by the individual during the appeal process. However, given the relatively smaller number of observations on appeals, the number of variables included in the estimation of the second stage decision is somewhat smaller than the number of variables included in the first stage. In particular, there are some variables for which there is not enough variation in the data to be able to get any useful results. Furthermore, in the later stages of the process, the SSA simply decides whether or not to accept the appeal, but does not have to go through the multi-step procedure as in the first stage decision. Therefore, for this stage, we only estimate a binary logit model.

As can be seen from Table 4, the variables which are the most important for predicting the initial DDS decision are also important for predicting the appeal decision with the exception that the vocational training dummy emerges as the strongest predictor (next to the time dummies) and has a counterintuitive positive sign. Among the health variables, the most important predictor is HLIMPW (variable 6). Difficulty in walking around the room, sitting, and reading a map also have strong prediction power. Other variables, such as the age at application and the variables providing information on recent employment history, seem to have more, yet limited, power in explaining the probability of acceptance than in the first stage decision by the SSA. As previously noted, the wide variation in the year dummies is probably a reflection of overfitting with a small number of observations rather than an indication of substantial year to year variations in SSA's stringency in judging appeals.

5. Summary and conclusions

This paper analyzed the Social Security disability application, appeal, and award process using self-reported data from 13,142 individuals interviewed in one or more of the first three waves of the HRS. Our analysis of the disability award process using the HRS data has shown that the conditional probability of being awarded benefits is more than 50% higher at the appeal stage than at the initial application stage. In future work, we will assess whether the higher award rate for appealed case is a result of a combination of large backlogs and excessive leniency at the ALJ stage as suggested in a 1997 GAO report (U.S. General Accounting

Office, 1997), or is a result of valid reversals due to excessive stringency and poor documentation of reasons for denials at the DDS stage. Our results suggest that the relatively large chances of waging a successful appeal could explain why over two thirds of rejected applicants choose to appeal. This has the effect of increasing the initial award rate at the DDS level from 46%, to an 'ultimate award rate' of 73% when we account for the possibility of appeal and reapplication. However, we have also shown that there is a substantial cost to appealing an initial rejection: the mean delay between application and receipt of benefits for 'first stage awardees' is 5 months as compared to 15 months for individuals who received benefits after one or more stages of appeal. The uncertainties and opportunity costs of these delays could explain why 32% of rejectees (55% of whom report a health limitation that prevents them from working) do not appeal an initial denial.

Among the long list of health and disability status indicators used as covariates in our models, we found that the applicant's self-assessed disability status consistently emerged as one of the most robust and powerful predictors of whether an individual will apply for DI benefits or appeal a rejection. We have focused on a simple indicator variable HLIMPW (equal to 1 if the respondent reports having a health limitation that prevents them from working) which we argue can be interpreted as a measure of the applicant's private information about their 'true disability status'. We have shown that this indicator constitutes an approximate 'sufficient statistic' for predicting application, appeal, and award decisions in the sense that relatively few other socio-economic variables or 'objective' health status measures emerge as significant predictors of these decisions once we condition on the HLIMPW variable.

Our finding that HLIMPW is an approximate 'sufficient statistic' for predicting disability application and appeal decisions is especially important for future work on estimation of structural dynamic programming (DP) models of individuals' disability application and appeal decisions. [16] In spite of recent improvements in hardware and solution methods, the computational burden involved in estimating DP models still grows quite quickly as the number of variables increases, so the feasibility of this approach depends on our ability to discover relatively low-dimensional vectors of state variables that adequately capture the main factors influencing individuals' decisions. [17]

[16] We are currently working on extending the DP model of retirement behavior of Rust and Phelan (1997) to include disability as an exit route from the labor force.

[17] New solution algorithms such as the 'random multigrid algorithm' of Rust (1997) have been proven to break the curse of dimensionality in the sense that the computational complexity of these alternative randomized methods increases polynomially rather than exponentially fast in the number of state variables. But the polynomial growth rates are still sufficiently fast that there is a substantial premium on finding parsimonious specifications of the state and control variables entering the DP model.

Despite the fact that our results are based on self-reported data, we believe that we have been able to construct a fairly accurate model of SSA's disability award process. In particular, our estimates of award rates and delays at various stages of the application and appeal process are fairly close to estimates from administrative records, and our estimates of the success probabilities at each of the stages in the DDS' sequential disability evaluation procedure are quite close to previous estimates by Hu et al. (1997) and Lahiri et al. (1995) using SIPP data with matching Social Security administrative data. However, to the extent that individuals are only interested in the 'bottom line' of whether their application is accepted or rejected, our results suggest that a binomial logit model that does not attempt to 'integrate out' the unobserved basis for award or denial turns out to be a slightly more accurate predictor than a 'marginal probability model' that captures the details of the sequential disability evaluation process currently used by the DDS.

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Appendix A. Data appendix

We first explain the construction of the 32,869 observations for the individuals' application decision presented in Table 1. We assume that each individual makes a decision whether or not to apply once in each wave. If an individual did not apply, he is assumed to make his decision at the interview date. If on the other hand, an individual did apply, then the decision date is assumed to be the first application date. An individual was assumed to make a decision only if he was not already receiving SSDI or SSI benefits and did not have a pending application. As a result, each individual has a maximum of three, and a minimum of zero application decisions. At each decision date, we assigned the appropriate set of income, health and demographic variables to the individual. In this assignment, we matched each decision with the variables' values obtained from closest interview information. The only exception is for people who applied right after an interview but reported not being disabled at that interview. In this case, we assigned the individual with the variables' values of the subsequent interview, even if it was long after the application.

The 663 observations used in the appeal estimation were constructed in a similar fashion. It is important to note that in this estimation, we combined all observations for first, second, and even third, appeals. We did that because the number of individuals for whom we observed second and third appeals is rather small, making it impossible to estimate models for individuals' decisions for these appeals.

A.1. Constructed variables [18]

An important issue for the construction of the income and wealth variables is the fact that questions on these variables were only answered by the primary respondent of the household, usually the financially knowledgeable person of the family. Therefore, we had to merge this information in order to obtain the relevant values of these variables for the spouses, and to compute total family income for each respondent.

The definitions of the income and wealth variables are as follows:

1. Family income—the sum of the respondent's earnings, spouse's earnings (if applicable), and income from pensions, welfare, Social Security and capital gains;
2. Home equity—net worth of the family's first home;
3. Net worth—net worth of all housing and non-housing assets (including vehicles, stocks, bonds, private businesses, bank accounts, etc.).

The definition of the employment history variables:

1. Total hours worked in a given year—the sum of the respondent's hours worked in that year on the current job, previous job, and any intermediate job (when applicable);

[18] A more detailed explanation of the calculation algorithms is available from the authors upon request.

2. Earnings in a given year—data from the income section, in some cases corrected using our calculations of employment income as a sum of the respondent's income earned in that year on the current job, previous job, and any intermediate job (when applicable).

Using the SSA matching earnings records, our monthly labor force participation dummies and our earnings and wealth calculations, we have constructed an indicator of non-eligibility for SSI/SSDI. This indicator is one if a respondent was not eligible for either program at the time of the application decision. A person is not eligible for SSI if he does not meet the income and wealth test (see Section 2; [7]); we have used our own calculations of these variables to screen out the ineligible respondents. To decide whether a person was eligible for SSDI, we had to use the SSA matching earnings records that gave us the quarters of coverage for each respondent that gave permission to release such information. Only 70% of respondents gave this permission, for the rest, we had to predict their quarters of coverage given their information as of wave one, using the parameter estimates of those that released the information. The SSA only had information up to 1991, and since we needed information up to 1996, we had to use our monthly labor force participation dummies to construct quarters of coverage for the remaining years. Then for each respondent, we calculated the coverage status at the moment of the application decision.

A.2. Imputations

It is worthwhile to briefly summarize some of the imputations used in constructing the data extract, which was carried out in an attempt to minimize the number of observations which were eliminated from the estimations. Imputations were carried out only for dates of different events connected to the application and appeal process. It was common to find missing months of application, appeal, onset of disability, or the starting month of disability benefits reception. In some cases, even the year of the event was missing. In some other instances, the dates were not consistent with other information provided in the survey. Our imputations were aimed at avoiding any systematic biases. When other available dates could not provide bounds for our imputations, we simply assigned the number '6' for the missing month. When the year was missing, we dropped that observation, unless we could unambiguously restore it given the other available information. Although for those that ever applied or were awarded benefits 52% of the observations had some imputations, a number of internal consistency checks using independent information from the employment, disability and income sections of the HRS survey have shown that reported date of disability onset, exit from the labor force, and receipt of DI benefits match up in predictable fashion. These results (omitted due to space limitations) have been highly encouraging and reinforce our confidence in the quality of the HRS data, the quality of our imputations and the truthfulness of the respondents.

Appendix B. Derivation of the marginal likelihood

In order to be awarded DI benefits at the first stage by the DDS, an application is evaluated according to the five-stage sequential disability determination procedure illustrated in Fig. 1 and described in Section 2. For simplicity and due to data availability, we combined step 4, which evaluates the applicant's capacity to do past work, and step 5, which evaluates the applicants capacity to do any other work, into a single step 4 in our collapsed model.

B.1. Notation and specification

Let $\boldsymbol{x}_1$, $\boldsymbol{x}_2$, $\boldsymbol{x}_3$, and $\boldsymbol{x}_4$ be the relevant regressor vectors at steps 1 through 4, respectively. Let $p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)$ be the probability that a person was determined as not being engaged in any substantial or gainful activity at step 1 (i.e., the person is passed on to step 2 of the sequential process). Similarly, let $p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)$ be the probability that a person was determined to have severe impairment (i.e., the person is passed to step 3). At each of the first two steps, the individual can be flatly denied with probabilities of $1-p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)$ and $1-p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)$, respectively.

Step 3 is slightly different, in that at this step, no individual is being denied disability benefits. The DDS determines whether or not the impairment(s) the individual has is(are) in the list of severe impairments of the SSA. If the impairment(s) is(are) in the SSA listing, then the individual is awarded disability benefits, otherwise, the individual is passed on to the fourth and last step, but is not denied disability benefits. Let $p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)$ denote the probability that the individual is awarded benefits at step 3.

In step 4, the DDS determines whether or not an individual is capable of performing his past job(s) or any alternative job, given the individual's characteristics (i.e., labor market characteristics, age, etc.). At this step, the individual is either awarded or denied disability benefits; let the probability of being awarded benefits be denoted by $p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)$.

Define now the following dummy variables (omitting the ith subscript): $d_{\mathrm{D}}=1$ if an individual is denied benefits at some step along the four-step procedure; and $d_{\mathrm{D}}=0$ otherwise. Let $d_1=1$ if an individual is denied benefits at step 1; and $d_1=0$ otherwise, and let $d_2=1$ if an individual is denied benefits at step 2; and $d_2=0$ otherwise. Let $d_3=1$ if an individual is passed on (to next step) at step 3; and $d_3=0$ otherwise. Finally, let $d_4=1$ if individual is denied benefits at step 4; and $d_4=0$ otherwise.

Our goal is to compute the probability of an individual being denied benefits somewhere in the initial stage, namely, at either step 1, step 2, or step 4, conditional on the observed data $x=(x_1',x_2',x_3',x_4')'$ and the model's parameter vector $\boldsymbol{\theta}=(\boldsymbol{\theta}_1',\boldsymbol{\theta}_2',\boldsymbol{\theta}_3',\boldsymbol{\theta}_4')'$. We denote this probability by $p(d_{\mathrm{D}}=1|\boldsymbol{x};\boldsymbol{\theta})$. Note that $d_{\mathrm{D}}=1$ in one of the following three cases: (i) $d_1=1$; (ii) $d_1=0$ and $d_2=1$;

or (iii) $d_1 = 0$ and $d_2 = 0$ and $d_4 = 1$. The corresponding probabilities for these three cases are given, respectively, by:

$$p(d_1 = 1 | \boldsymbol{x};\boldsymbol{\theta}) = 1 - p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1),$$

$$p(d_1 = 0 \cap d_2 = 1 | \boldsymbol{x};\boldsymbol{\theta}) = p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)(1 - p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)),$$

and

$$p(d_1 = 0 \cap d_2 = 0 \cap d_4 = 1 | \boldsymbol{x};\boldsymbol{\theta}) = p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)(1 - p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3))(1 - p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)).$$

Therefore, we have that:

$$\begin{aligned} p(d_\mathrm{D} = 1 | \boldsymbol{x};\boldsymbol{\theta}) = 1 &- p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3) \\ &- p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4) \\ &+ p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3) p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4) \end{aligned}$$

$$p(d_\mathrm{D} = 1 | \boldsymbol{x};\boldsymbol{\theta}) \equiv 1 - \boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta}),$$

where

$$\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta}) = p(d_\mathrm{A} = 1 | \boldsymbol{x};\boldsymbol{\theta})$$

$$\begin{aligned} \boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta}) = &\ p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3) \\ &+ p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4) \\ &- p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1) p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2) p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3) p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4), \end{aligned}$$

and $d_\mathrm{A} = 1 - d_\mathrm{D}$.

Assuming that the error terms of the underlying utility are distributed according to the extreme value distribution, it follows that for each $p_j(\boldsymbol{x}_j;\boldsymbol{\theta}_j)$, we have $p_j(\boldsymbol{x}_j;\boldsymbol{\theta}_j = (1 + \exp(-\boldsymbol{x}_j'\boldsymbol{\theta}_j)^{-1})$.

B.2. Maximum likelihood estimation

The log likelihood function is straightforward and is given by:

$$l(\boldsymbol{\theta} | \boldsymbol{x},d) = \sum_{i=1}^{n} \left\{ d_{\mathrm{A}i} \log \boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}) + (1 - d_{\mathrm{A}i}) \log(1 - \boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta})) \right\},$$

where $d = (d_{\mathrm{A}1}, \ldots, d_{\mathrm{A}n})$, and $d_{\mathrm{A}i}$ $(i = 1, \ldots, n)$ are the individuals' dummy variables for being awarded disability benefits. The score function is given then by:

$$\frac{\partial l(\boldsymbol{\theta} | \boldsymbol{x},d)}{\partial \boldsymbol{\theta}} = \sum_{i=1}^{n} \frac{d_{\mathrm{A}i} - \boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta})}{\boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta})(1 - \boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}))} \frac{\partial \boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta})}{\partial \theta}.$$

Note that $\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}$ is comprised of four separate parameter vectors, i.e., $\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}=(\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}_1',\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}_2',\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}_3',\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}_4')'$.

Now, for any $p_j(\boldsymbol{x};\boldsymbol{\theta}_j)$ ($j=1,2,3,4$), we have $\partial p_j(\boldsymbol{x};\boldsymbol{\theta}_j)/\partial\boldsymbol{\theta}_j=p_j(\boldsymbol{x}_j;\boldsymbol{\theta}_j)(1-p_j(\boldsymbol{x}_j;\boldsymbol{\theta}_j))\boldsymbol{x}_j$. Hence, for $\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})/\partial\boldsymbol{\theta}_j$ ($j=1,2,3,4$), we have:

$$\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})}{\partial\boldsymbol{\theta}_1}=p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)(p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)+p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)$$
$$-p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4))\boldsymbol{x}_1,$$
$$\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})}{\partial\boldsymbol{\theta}_2}=p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)(1-p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2))(p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)$$
$$+p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)-p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4))\boldsymbol{x}_2,$$
$$\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})}{\partial\boldsymbol{\theta}_3}=p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)(1-p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4))$$
$$\times p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3)(1-p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3))\boldsymbol{x}_3,$$

and

$$\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x};\boldsymbol{\theta})}{\partial\boldsymbol{\theta}_4}=p_1(\boldsymbol{x}_1;\boldsymbol{\theta}_1)p_2(\boldsymbol{x}_2;\boldsymbol{\theta}_2)(1-p_3(\boldsymbol{x}_3;\boldsymbol{\theta}_3))p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4)$$
$$\times(1-p_4(\boldsymbol{x}_4;\boldsymbol{\theta}_4))\boldsymbol{x}_4.$$

By the standard maximum likelihood result, we have that $\sqrt{n}(\hat{\boldsymbol{\theta}}-\boldsymbol{\theta}_0)\xrightarrow{D}N(0,\Lambda_{\boldsymbol{\theta}}^{-1})$, where $\hat{\boldsymbol{\theta}}$ is the maximum likelihood estimator for the population parameter $\boldsymbol{\theta}_0$ and:

$$\Lambda_{\boldsymbol{\theta}}=E\left[\frac{1}{\boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}_0)(1-\boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}_0))}\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}_0)}{\partial\boldsymbol{\theta}}\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x}_i;\boldsymbol{\theta}_0)}{\partial\boldsymbol{\theta}'}\right].$$

An estimate for $\Lambda_{\boldsymbol{\theta}}$ is immediately available by the sample analog of $\Lambda_{\boldsymbol{\theta}}$, i.e.,

$$\hat{\Lambda}_{\boldsymbol{\theta}}=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{\boldsymbol{\varphi}(\boldsymbol{x}_i;\hat{\boldsymbol{\theta}})(1-\boldsymbol{\varphi}(\boldsymbol{x}_i;\hat{\boldsymbol{\theta}}))}\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x}_i;\hat{\boldsymbol{\theta}})}{\partial\boldsymbol{\theta}}\frac{\partial\boldsymbol{\varphi}(\boldsymbol{x}_i;\hat{\boldsymbol{\theta}})}{\partial\boldsymbol{\theta}'}.$$

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