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DYNAMIC PROGRAMMING MODEL ESTIMATES OF SOCIAL SECURITY DISABILITY INSURANCE APPLICATION TIMING

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SUMMARY

This paper develops a dynamic programming model of the Social Security Disability Insurance (SSDI) application timing decision. We estimate the time to application from the point at which a health condition first begins to affect the kind or amount of work that a currently employed person can do. We use Health and Retirement Study (HRS) and restricted access Social Security earnings data for estimation. Our results show that the type of work-limiting health condition, presence of employer accommodation, and the relative value of income in the application state to income in the work state significantly affect the timing of SSDI application. Copyright © 2004 John Wiley & Sons, Ltd.

1. INTRODUCTION

Rapid growth in the number of Social Security Disability Insurance (SSDI) beneficiaries in the early 1990s, together with a parallel decline in male labour force participation rates, produced extensive research on the behavioural effects of policy variables on SSDI applications.[1] This empirically based research has primarily used reduced form models to test the importance of the effects of size and availability of SSDI benefits on workers' decisions to leave the labour force and apply for benefits. While such models are useful approximations of the relationship between past SSDI policies and past application behaviour, future policy changes may not yield the same reduced form responses. A better theoretical approach to predict how changes in SSDI policy change future behaviour is to incorporate SSDI incentives within a structural model.

Workers' decisions to apply for SSDI can be made at the onset of a work limitation or can be postponed. Hence, SSDI application decisions are intrinsically dynamic and stochastic. In this paper, we develop and test a dynamic programming model of the timing to SSDI application, once a health condition begins to affect the kind or amount of paid work a currently employed worker can do.

Section 2 reviews the literature, Section 3 presents the dynamic programming model, Section 4 briefly describes how the SSDI programme works, Section 5 describes the data, Section 6 presents the econometric results, and Section 7 concludes.

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[1] See Bound and Burkhauser (1999) for a review of this literature. See Stapleton and Burkhauser (2003) for a more recent discussion of the employment rates of working age people with disabilities.

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2. PREVIOUS RESEARCH

Previous studies have focused on the responsiveness of labor supply to SSDI benefit levels or to replacement rates using reduced form models, e.g. Parsons (1980), Haveman and Wolfe (1984), Slade (1984), and Bound (1989). These studies show that labour force participation is negatively related to SSDI benefit levels, but the magnitude of this relationship remains unresolved. Other researchers (Parsons, 1991; Bound and Waidmann, 1992; Gruber and Kubik, 1997) have studied the effects of SSDI acceptance rates on the decline in male labour force participation rates. They find that labour force participation rates are negatively related to SSDI acceptance rates. Halpern and Hausman (1986) employ a structural estimation approach to analyse both of these variables. Using a two-period model they find that SSDI applications are more responsive to changes in the benefit levels than to changes in acceptance rates. Kreider (1998) analyses the effect of wage and eligibility uncertainty on SSDI application decisions. He argues that uncertainty about future earnings increases application probabilities as individuals may apply for benefits in order to avoid labour market risks. Kreider (1999) uses a structural model of SSDI applications, awards and income to analyse the effect of this programme on male labour force participation within a lifetime framework. He finds that increases in the level of SSDI benefits modestly reduce male labour force participation rates. Kreider and Riphahn (2000) study the determinants of SSDI applications using a semi-parametric discrete factor procedure. They use this method to approximate a dynamic optimization model and find that factors such as benefit levels, past labour earnings and benefit eligibility affect application behaviour. They also find that men and women have significant differences in their responsiveness to policy changes.

Both Kreider (1999) and Kreider and Riphahn (2000) recognize the importance of modelling the timing of applications, but did not take this step. These studies measured application elasticity over an 8-year period for a group of health-limited workers at risk. We argue that this is a useful approximation of one part of the impact of policy changes on caseload, but one must model the timing of application over the entire lifetime. Rust *et al.* (2003) propose to develop and estimate a dynamic programming model of SSDI along with Old Age and Survivors Insurance (OASI) and Supplemental Security Income (SSI).

In this paper, we develop a dynamic programming model of the SSDI application decision that is an adaptation of dynamic programming models used to study retirement. Rust (1989), Berkovec and Stern (1991), Rust and Phelan (1997) and Heyma (2004) have all used dynamic programming models to analyse retirement decisions. Related to this, Daula and Moffitt (1995) develop a dynamic programming model of army re-enlistment with two periods. They add a vector of observable variables into their model in order to allow such variables to reflect valuations of non-monetary characteristics of application and work states. Dynamic programming produces more plausible predictions out-of-sample than alternative structural models. Below, we adapt Daula and Moffitt (1995) in the utility function.

Our paper develops a structural model of the decision to apply for SSDI. The present work focuses on explicit modelling of the time to application. Once people get on the SSDI rolls, they tend to stay, so the timing of application is an important factor in determining the SSDI caseload and programme cost. We show that an important policy variable, namely, employer accommodation, the increase in which is a goal of the Americans with Disabilities Act of 1990, has a statistically significant effect on the transition onto the SSDI rolls following the onset of a work-limiting condition. Our structural model could in addition be used to assess the effect of benefit levels, replacement rates, acceptance rates, and so forth. This is a potentially fruitful avenue of research, since the reduced form models from the existing literature can be criticized for being unable to capture the consequences of a changing structure (Lucas, 1976). We leave this for future research.

3. HOW SSDI WORKS

SSDI is a social insurance programme that provides benefits based on previous Social Security covered employment. The programme is financed by the Social Security payroll taxes. In 2002, SSDI paid 5.3 million disabled workers an average monthly benefit of \$814 (US Social Security Administration, 2002). Here we provide a brief overview of SSDI programme rules. A full description can be found in the *Annual Statistical Supplement to the Social Security Bulletin.*

To be eligible for SSDI benefits, workers must first be insured, which varies with age but generally means being in Social Security covered employment for one-half of the quarters over the previous 10 years. Applicants must have a medically determinable physical or mental condition that lasts at least 12 months or results in death, and that prevents them from earning more than a certain amount, \$780 per month in 2002 (the amount is indexed by average wages), called substantial gainful activity (SGA).

Successful applicants start to receive their monthly benefits (Primary Insurance Amount, PIA) following at least 5 months almost completely withdrawn from the labour market after onset of the medical condition. Benítez-Silva *et al.* (1999) report that the process takes about the same amount of time on average whether the application is accepted or rejected. PIAs are based on workers' covered earnings history (Average Indexed Monthly Earnings, AIME). Workers can apply for SSDI at any age prior to normal retirement age. Workers with a sufficient work history become eligible for actuarially reduced retirement (the Social Security Old Age and Survivors Insurance, OASI) benefits at age 62 and full OASI benefits at the normal retirement age of 65. We consider a sample of individuals with work-limiting health conditions and assume that everyone in this sample who chooses not to apply for SSDI prior to age 62 applies for OASI benefits at age 62.[2]

Application to SSDI can be the beginning of a multiple step eligibility process and a protracted appeals process whose final outcome is uncertain. Thus, while a probability of acceptance is not required in retirement models, models of SSDI application must include it because applicants may be either accepted or rejected. The probability that an application for SSDI is approved has varied dramatically over time and state (see Burkhauser *et al.*, 2002). In our model, we use the rates of approval (called α) by state and year, which varied from 25% to 75% between 1974 and 1993. We do not consider the probability of returning to work or recovering sufficient health to leave the SSDI programme.

Applicants who are initially rejected for benefits can file appeals at various levels. The main focus of this paper is modelling the timing of first application for SSDI. We abstract from appeals and from returning to work whatever the outcome of application. SSDI benefits may be terminated because the beneficiary returns to work or the condition improves. However, beneficiaries rarely return to work. Bound and Burkhauser (1999) reported Social Security Administration estimates

[2] This paper focuses on the decision to apply for SSDI by workers who experience a work-limiting health condition at ages well below normal retirement age. We abstract from the decision to apply for OASI or SSDI at age 62 and assume that workers who have not applied for SSDI benefits by age 62 apply for OASI benefits at 62. This is a simplified model of a labour market exit behaviour that ignores the periods after age 62. A fuller model would integrate OASI and SSDI into a model of labour market exit.

(Hennessy and Dykacz, 1989) of 11% of SSDI beneficiaries eventually returning to work, estimated using data through 1981, but the rate of termination for this reason (as opposed to retirement or death) was much lower in subsequent years, and especially in the 1990s. Even in 1981, the estimated rate of recovery was only 4% for beneficiaries over the age of 50. Also see Bound (1989) and Bound *et al.* (2003) for evidence concerning terminated beneficiaries. We assume that once workers get SSDI, they stay on the rolls, not returning to work, until they are automatically moved to the OASI programme at normal retirement age.

4. OPTIMAL TIMING OF SSDI APPLICATION: THE DYNAMIC PROGRAMMING MODEL

At period t, W_t is pre-application work income and D_t is expected value of income from applying for SSDI, a weighted average of SSDI income if approved or alternative sources of income if denied. The probability of being approved is α, based on state and year but not medical condition. If income when one is accepted is A_t and when one is rejected is R_t, then $D_t = \alpha A_t + (1-\alpha)R_t$. We do not model risk aversion relative to this expectation. Several extensions of the model would be possible relative to the probability of approval: dependence on personal characteristics could be modelled, stages of appeals could be considered, α could be analysed with an equation, and risk aversion relative to approval could be introduced to the model.

Pre-application and post-application utilities are subject to shocks ω_t and ξ_t assumed to be independent over people and time, and distributed normal with constant variance. Only the variance of the difference of the shocks can be identified by observing choices to apply or not to apply.

Assuming a constant coefficient of relative risk aversion of $1-\gamma$, the utility of income W_t is W_t^γ. The utility of post-application income is different by the factor κ—1 dollar post-application is worth κ dollars pre-application—which is greater than 1 if income from SSDI entails less difficult effort given work-limiting health.

Following Daula and Moffitt (1995), we add an observable variable vector $\mathbf{x}_t$ to the utility of income from work. The effects of this vector are Daula–Moffitt parameters $\boldsymbol{\delta}$. The $\mathbf{x}_t$ vector controls for a preference independent of income towards application (including discrimination) and includes years of education, dummies for race, marital status, employer accommodation, health conditions and for being a white collar worker. Positive Daula–Moffitt parameters discourage application and negative ones encourage application. Assigning this vector to non-application is arbitrary, as it shows the difference between application and non-application.

Incorporating all of these components, pre-application utility is

$$U_W(W_t) + \omega_t = W_t^\gamma + \mathbf{x}_t'\boldsymbol{\delta} + \omega_t \tag{1}$$

and post-application utility is

$$U_D(D_t) + \xi_t = (\kappa D_t)^\gamma + \xi_t \tag{2}$$

The conditional probability of survival at time $\tau \geq t$ given survival until current time t is $\pi(\tau|t)$. Let the optimal time to apply be r, so the value function at time t of choosing r is $V_t(r)$, which is the current utility of income from work plus the value of acting optimally from $t+1$ on. If $r = t$ (it is optimal to apply now), then this is the value of applying now and not working any more. If $r > t$ (it is optimal to apply later), then $V_{t+1}(r)$ is the value next period $(t+1)$ of choosing r then, i.e., the utility of acting optimally next period. The future is discounted β per time period.

The value function at time t is the maximum of the value of applying now or of choosing again next period:

$$V_t(r) = \max\left\{E_t[U_W(W_t) + \omega_t + \beta\pi(t+1|t)V_{t+1}(r)],\ E_t\left(\sum_{\tau=t}^{d}\beta^{\tau-t}\pi(\tau|t)[U_D(D_\tau) + \xi_t]\right)\right\} \tag{3}$$

Defining the utility apart from shocks of deferring the decision one period or applying now to be

$$\overline{V}_{1t}(r) = U_W(W_t) + \beta\pi(t+1|t)E_t V_{t+1}(r) \tag{4}$$

$$\overline{V}_{2t}(t) = E_t\left[\sum_{\tau=t}^{d}\beta^{\tau-t}\pi(\tau|t)U_D(D_\tau)\right] \tag{5}$$

then

$$V_t(r) = \max\{\overline{V}_{1t}(r) + \omega_t, \overline{V}_{2t}(t) + \xi_t\} \tag{6}$$

The application rule here is: if $\overline{V}_{1t}(r) + \omega_t < \overline{V}_{2t}(t) + \xi_t$, then the individual applies for SSDI in period t, otherwise he or she continues working. Therefore, the probability of SSDI application at time t (conditional on not applying before t) is $\Pr(\overline{V}_{1t}(r) - \overline{V}_{2t}(t) < \xi_t - \omega_t)$. The decision varies given observable characteristics because of the difference of the shocks $\xi_t - \omega_t$.

The calculations in the dynamic programming model involve the expected maxima of utility over all possible future SSDI application times. We use backward recursion to estimate the dynamic programming model. First we write the expected utility of permanent labour market exit at the terminal period d, age 62, which we assume to be the last possible exit date, since our sample consists of individuals with a work-limiting health condition. We then write the expected maximum utility of applying for SSDI at period $d-1$, continuing back to the onset of the work-limiting health condition.

The parameters of the dynamic programming model are: κ (the relative value of income in the non-application state to income in the application state), γ (a utility function parameter representing risk aversion with respect to income variability where the coefficient of relative risk aversion $= 1 - \gamma$), $\boldsymbol{\beta}$ (discount factor) and δ (Daula–Moffitt parameter defined to enter the utility of non-application). The mean of the difference of random utility shocks, if it is not zero, is absorbed in a Daula–Moffitt constant term, and there is nothing to identify the scale of the shocks because no value is ever observed for utility, so the variance of the difference of the shocks is normalized to 1.0 as in a probit model. The estimates of the dynamic programming model are obtained by assuming a normal distribution for the difference of the random utility shocks and perfect predictability of future potential incomes D_t and W_t in the application and non-application states. The predictions are required for the calculation of the likelihood function and are obtained from regressions over observed states (see Section 5).

Each person has a conditional probability of applying at each relevant, post-onset age given no application before that age. Person j, $1 \le j \le n$, at age a, $a \le 61$, has a conditional probability of application p_{aj} derived above. These conditional probabilities are independent across person and age because the shocks are independent and application and predicted income are predetermined. For person j and all ages before onset or after age 61, $p_{aj} = 0$. The unconditional probability of application for person j and age a is

$$\Pr(j \text{ applies at age } a) = p_{aj} \prod_{i=0}^{a-1} (1 - p_{ij}) = q_{aj} \tag{7}$$

In the application, one would not consider ages before onset, but they are entered correctly in (7); the probability of application is 0, and 1 minus that is 1.

Maximum likelihood estimation follows based on the log-likelihood function, which is $L^* = \Sigma_{j=1}^{n} \ln(q_{aj})$.

5. DATA

In this section, we briefly describe the data sets we use and define the variables in our analysis.[3] Our data come from the first three waves of the Health and Retirement Study (HRS).[4] The HRS is a longitudinal study of the health, wealth, income and employment of primary respondents aged 51–61 in 1992 and secondary respondents (spouses or partners of these primary respondents) who were interviewed regardless of their age. Respondents born between 1931 and 1941 are 'age eligible'. Individuals were interviewed biennially, and five waves of data are currently available, three in final form. HRS data can be linked to restricted access SSA administrative data.[5] Three restricted access files are used in this study: the HRS Covered Earnings File, the Summary of Earnings and Projected Benefits (SEPB) File, and the Wage and Self-Employment Income in Covered and Non-Covered Jobs File.

The HRS is an excellent source of data for analysing policy issues related to SSDI. It includes a module on disability with detailed retrospective questions about SSDI applications and awards. Data on individuals' demographic characteristics, labour force participation, employment and health status are also available in separately designed sections. The income section provides data on benefits, income and wealth holdings.

We also use additional sources of data. The Lewin Group created a Public Use File which includes state level data on SSDI and SSI programmes as well as state level descriptive variables for the years 1974 through 1993. The data contain initial SSDI allowance rates for each state, computed as the number of people awarded SSDI benefits at the initial state level screening process divided by the total number of initial SSDI applications in that state. These data are used to form the probabilities of acceptance for SSDI application.[6] The restricted HRS data set Wave 1 Geographic Indicators Version 1.0 File provides state geographic identifier variables from HRS Wave 1, including information on Wave 1 state of residence and state or country of birth. These variables are masked in the public HRS files. We obtained special permission from the HRS staff at the ISR at the University of Michigan to be able to merge the geographic state identifier variables

[3] A data appendix that includes detailed information on the data sets used and a discussion of the construction of the variables used in the analysis is available from the authors upon request. It is also contained in Gumus (2002).

[4] We draw our samples from the first two waves and use only earnings data from the third wave.

[5] These restricted access records can be obtained under certain conditions from the HRS staff at the Institute for Social Research (ISR) at the University of Michigan. See http://www.umich.edu/~hrswww/for more information.

[6] One would, of course, ideally use allowance rates which depend also on some individual characteristics, in particular on the type and severity of the health condition. However, such data are not available to the best of our knowledge.

with the Lewin Group Public Use File on allowance rates.[7] In our study we need data on the probabilities of death for individuals with work-limiting health conditions, and for this purpose we use life table data provided in Zayatz (1999).

We draw our sample from both age eligible and age ineligible persons who reported a work-limiting health problem in Wave 1 (1992) or Wave 2 (1994) of the HRS as defined by a positive response to the question 'Do you have an impairment or health problem that limits the kind or amount of paid work you can do?' Benítez-Silva *et al.* (2004) argue that the self-reported disability measure in HRS is a valid indicator of the true disability status. In the first wave, 2717 persons (1324 men and 1393 women) reported that they had such an impairment or health problem. To this population we added 340 persons (140 men and 200 women) who first reported having a work-limiting health condition in Wave 2. Of these 3057, we kept those with permanent conditions (impairments expected to last for more than 3 months) who were working for someone else (not self-employed) at the onset of their work-limiting health condition. This initial screening yielded a sample of 1653 individuals (924 men and 729 women). We include both primary and secondary respondents to the HRS. Secondary respondents are not representative of their age cohort; they were sampled because they were married to an age eligible primary respondent. Since husbands tend to be older than their wives, there are many more men aged 62 and over than there are women. The sample is not representative of the population but sampling is not based on application for SSDI, so sampling weights are not needed for our purposes.

Individuals were asked when their condition first began to bother them, and this date is used as the onset of the health problem. For those who applied for SSDI, their spell ends at the year of application. SSDI benefit award status can be obtained using the income section of the survey. We excluded individuals with a missing onset or SSDI application date, or with missing SSDI application or award status information. We kept those with an onset date after 1950 and before 1993 (to observe applications for SSDI in the data set) and before age 61. The final sample includes only those who were fully insured for SSDI benefits in at least one period following onset. This guarantees that the individuals in our sample whose application is rejected are denied SSDI benefits due to medical screening results. Applying these criteria, our final sample consisted of 1085 individuals (592 men and 493 women). Table I provides descriptive statistics for the variables used in our analysis.

The time unit in our analysis is a biennial period because the data on SSDI award status and income during the survey period are known over biennial periods. We calculate utility from the stream of labour earnings in different states and the potential SSDI benefits that would result from application for each period of potential application.

Table II describes the distribution of spell length from onset to application by gender for our sample. The first column shows the number of periods since the first period of eligibility after the onset of a work-limiting health condition. The next five columns show the number of men who apply within the period; who are censored within the period (meaning that the date reached 1994 or that the individual dropped out of the survey); their empirical hazard rate; their probability of not applying before the beginning of the period; and the estimated probability mass function. The next five columns show these same values for women. The hazard rate is greatest in the first period both for men and for women.

[7] See Lewin Group (1995) for further details. Burkhauser *et al.* (2002) also use these variables at the state level in a reduced form hazard model of SSDI application.

Table I. Descriptive statistics, by gender

Variables	Men		Women	
	Mean	St. Dev.	Mean	St. Dev.
Spell length	4.035	3.751	3.469	2.905
Age at onset	45.326	9.624	45.201	8.905
SSA records available	0.833	0.373	0.805	0.396
Marital status	0.829	0.376	0.673	0.469
White	0.708	0.455	0.692	0.462
Black	0.194	0.396	0.221	0.415
Other race	0.098	0.298	0.087	0.282
Education	11.059	3.467	11.487	2.580
White collar	0.149	0.356	0.134	0.341
Employer accommodation	0.270	0.444	0.266	0.442
Two conditions	0.289	0.454	0.314	0.465
Three conditions	0.177	0.382	0.191	0.393
Arthritis	0.084	0.278	0.172	0.378
Cardiovascular	0.287	0.453	0.105	0.307
Musculoskeletal	0.395	0.489	0.424	0.495
Other health condition	0.233	0.423	0.298	0.458
SSDI allowance rate[a]				
Period 1	0.375	0.065	0.369	0.063
Period 5	0.378	0.066	0.373	0.063
Period 10	0.371	0.059	0.375	0.063
Period 15	0.368	0.061	0.371	0.049
Expected earnings[a,b]				
No application				
Period 1	4.182	3.381	1.816	1.900
Period 5	3.626	2.908	1.789	1.822
Period 10	3.230	2.578	1.713	1.740
Period 15	2.713	2.175	1.591	1.582
Applied and rejected				
Period 1	2.005	1.515	1.033	1.045
Period 5	1.675	1.236	1.024	0.995
Period 10	1.538	1.128	0.963	0.936
Period 15	1.381	1.037	0.893	0.840
Applied and accepted				
Period 1	0.797	0.852	0.533	0.865
Period 5	0.672	0.719	0.476	0.677
Period 10	0.611	0.708	0.385	0.552
Period 15	0.508	0.634	0.337	0.398
Expected Benefits[a,b]				
Period 1	2.071	0.708	1.154	0.491
Period 5	2.132	0.699	1.198	0.509
Period 10	2.204	0.691	1.309	0.493
Period 15	2.082	0.718	1.221	0.533
Number of observations	592		493	

[a] Number of periods elapsed since the first period of eligibility after the onset of a work-limiting health condition.
[b] All monetary values are in $1000 (1967 dollars).
Source: Authors' calculations using HRS data.

All of the following variables are assumed to be exogenous inputs to the model: labour earnings, SSDI benefits, socio-demographic variables, the type of health condition, accommodation by employers following onset, institutional details of SSDI and OASI, including the probability of acceptance in the SSDI programme, and the probability of death.

Table II. Distribution of spell length

Spell length	Men ($N = 592$)					Women ($N = 493$)				
	Apply	Censor	Hazard rate	Survival rate	Estimated pmf	Apply	Censor	Hazard rate	Survival rate	Estimated pmf
1	159	47	0.280	1.000	0.280	123	46	0.262	1.000	0.262
2	61	34	0.165	0.720	0.119	50	35	0.163	0.738	0.120
3	30	21	0.107	0.601	0.064	22	30	0.098	0.618	0.061
4	24	33	0.107	0.537	0.058	18	29	0.104	0.557	0.058
5	13	15	0.074	0.479	0.036	12	25	0.094	0.499	0.047
6	16	13	0.108	0.444	0.048	11	17	0.116	0.452	0.053
7	11	11	0.091	0.396	0.036	10	15	0.148	0.399	0.059
8	7	11	0.071	0.360	0.026	3	12	0.068	0.340	0.023
9	6	11	0.075	0.334	0.025	8	5	0.246	0.317	0.078
10	6	10	0.094	0.309	0.029	1	5	0.051	0.239	0.012
11	4	10	0.083	0.280	0.023	4	2	0.267	0.227	0.060
12	4	7	0.113	0.257	0.029	0	1	0.000	0.166	0.000
13	1	5	0.039	0.228	0.009	1	3	0.133	0.166	0.022
14	2	9	0.114	0.219	0.025	0	3	0.000	0.144	0.000
15	3	4	0.333	0.194	0.065	0	2	0.000	0.144	0.000
16	0	4	0.000	0.129	0.000	0	0	0.000	0.144	0.000
Total	347	245				263	230			

Note: The hazard and survival rates correspond to Kaplan–Meier estimates of the time to application for SSDI.
Source: Authors' calculations using HRS data.

Economic variables: the model requires estimated future labour earnings and potential benefit levels. Expected real labour earnings are intended to capture the opportunity cost of applying for benefits. We need to predict labour earnings profiles for each individual for each of three states: (1) no application, (2) applied and rejected, and (3) applied and accepted. The model of predicted labour earnings predictions is not intended to be structural. Expected income is a weighted average of income from SSDI or from alternative sources if the application is rejected, with the probability of approval by SSDI, called α, being based on state and year but not medical condition. If income when one is accepted is A_t and when one is rejected is R_t, then $D_t = \alpha A_t + (1 - \alpha)R_t$. We assume that predicted earnings are known with certainty, i.e., that for this purpose, the utility of the expected value, not the expected utility, is the relevant concept.

Total labour earnings are defined as the sum of covered earnings (covered by OASDI taxes) and non-covered wages, and they are adjusted for inflation. Non-covered wages had to be imputed in some cases (see Gumus, 2002). Covered earnings are censored at the OASDI taxable earnings maximum. To obtain expected values of labour earnings in such cases, we fitted a separate log-normal distribution for each year. Once these issues were addressed, an autoregression was used to construct expected earnings profiles for the three states described above. Following Burkhauser *et al.* (1999), we predicted labour earnings using an autoregression which includes: a constant and four lagged values of labour earnings alone and interacted with a dummy variable that controlled for having a limitation as to the kind or amount of work that one can do; spell length defined as the time lag between each period and the first period of eligibility after the onset year; dummies for 'applied and rejected' or 'applied and accepted'; age, age square, and unemployment rate at each period.

We then consider the probability of having zero labour earnings to control implicitly for selection bias. In a structural selection bias model, there is an equation for having earnings and a correction usually involving inserting the expectation of the earnings disturbance conditional on having earnings (this is Heckman's lambda if joint normality of disturbances is used). The bias in the structural coefficients results from omitted variable bias if that expectation is omitted. We substitute a prediction equation for having earnings and a prediction equation for earnings conditional on having any. This prediction controls for the selection into having earnings without attempting to identify the structure. A probit equation is estimated to obtain the predicted probabilities of having zero earnings. A final prediction of labour earnings is done by incorporating the predicted values of covered wages from the autoregression, the probit and the predicted values of the non-covered wages. Labour earnings estimation for individuals with no administrative records is done in the same way, except that the self-reported labour earnings values from the first three waves of the HRS are used instead of the restricted access earnings histories.

Using actual earnings histories (and predictions of them when histories are not available), we then compute potential PIAs following SSDI programme rules. Details of the PIA computation rules can be found in the *Annual Statistical Supplement to the Social Security Bulletin*. The benefit computation is described in detail in an unpublished data appendix (see Gumus, 2002). We need to project SSDI benefit rules for years after 2000, and for this purpose we assumed that the institutional details of the SSDI programme do not change, except as described by statute in 2000. We assume potential SSDI recipients know and act on this information. Annual SSDI benefits are converted into real 1967 dollars.

Demographic variables: we include several demographic variables such as race, education and marital status. These variables reflect labour market attachment and discrimination, and thus are relevant to the utility function specification.

Health variables: to be included in our sample, a worker must experience the onset of a work-limiting impairment or health problem. But the conditions vary in type and severity. The type of condition is included in the HRS data, as well as comorbidity, the presence of other mental and physical conditions. These are factors affecting wages and thus the decision to apply for SSDI benefits. They are also considered as factors affecting the utility differences between the work and application states.

Policy variables: employer accommodation is based on a question to the individual asking 'if the employer did anything special for the individual at onset so that she or he could remain at work'. Accommodation by employers can increase the length of time during which an employee stays on a job and does not apply for SSDI (Burkhauser *et al.*, 1999, 2002). Accommodation is a policy variable because increasing accommodation is a goal of the Americans with Disabilities Act of 1990.

6. DYNAMIC PROGRAMMING ESTIMATION RESULTS

Table III presents the estimation results. The first column of results is for men. The dynamic programming model produces statistically significant estimates of κ and γ, when β is set equal to 0.85. This is the 2-year value used by Lumsdaine *et al.* (1992), and other reasonable values make almost no difference to the fit of the model. Estimated γ is statistically significantly less than 1 (0.4, asymptotic t-test of $\gamma = 1$ generates a test statistic of -8.87) and suggests that people are risk averse with respect to income variations. The Arrow–Pratt coefficient of relative risk aversion (with respect to income variability) is about 0.6. The estimate of κ is statistically significantly greater than 1 (1.431, asymptotic t-test of $\kappa = 1$ generates a test statistic of 2.32), which suggests that every dollar earned without work is worth more than every dollar earned from work. The estimate is around 1.4, which means that the average man in our sample would be indifferent between getting a dollar from work and getting 71 cents under SSDI. The estimates of the Daula–Moffitt parameters are almost always statistically significant. Additional education or accommodation by employers increases the utility of earnings relative to SSDI, discouraging application. Being African-American or being married encourages application. Being a white collar worker at the onset of a work limitation has no statistically significant effect. Some health conditions lead to more rapid application than others. Note that everyone in the sample has a health condition of some kind, so the effects are not compared for persons without a health condition. Musculoskeletal conditions, such as back, neck and spine problems, or arthritis, lead to a relatively longer duration until SSDI application since these conditions tend to be chronic. On the other hand, cardiovascular conditions, such as stroke or heart attack, lead to shorter duration to SSDI application since they tend to be acute. The omitted category is all other health conditions. All results are consistent with the reduced form findings of Burkhauser *et al.* (2002).

The last column in Table III presents the estimation results for women. The estimated γ is statistically significantly less than 1 (0.520, asymptotic t-test of $\gamma = 1$ generates a test statistic of

Table III. Dynamic programming estimation results

Parameter	Men ($N = 592$)	Women ($N = 493$)
κ	1.431	2.123
	(7.706)	(7.334)
β	0.850*	0.850*
γ	0.407	0.520
	(6.093)	(3.211)
Education	0.081	0.068
	(2.443)	(1.739)
Married[a]	−0.125	0.002
	(−4.276)	(0.063)
Black[b]	−0.132	−0.186
	(−4.164)	(−4.642)
Accommodation	0.093	0.074
	(3.711)	(2.618)
White collar	0.008	0.089
	(0.237)	(2.447)
Arthritis[c]	0.075	0.030
	(1.687)	(0.758)
Cardiovascular[c]	−0.119	0.015
	(−3.225)	(0.268)
Musculoskeletal[c]	0.016	0.117
	(0.550)	(3.660)
−Log-likelihood	−1054.871	−848.340

Note: κ is the relative value of income in the non-work state to income in the work state, γ is the risk aversion parameter of the utility function (with respect to income variability) where the coefficient of relative risk aversion $= 1 - \gamma$, and β is the 2-year discount factor (its estimate would not converge numerically).
* Denotes the parameters that are set outside the model. T-values are in parentheses. All monetary values are in \$1000 (1967 dollars).
[a] The reference category is single.
[b] The reference category is all other races including white race.
[c] The reference category is all other health conditions.
Source: Authors' calculations using HRS data.

-2.96), so women are estimated to be risk averse. The estimate of κ (relative value of non-work income) is statistically significantly greater than 1 (2.123, asymptotic t-test of $\kappa = 1$ generates a test statistic of 3.88). Accommodation and being a white collar worker at onset have statistically significant estimated effects discouraging application, and being African-American statistically significantly encourages application, but education and marital status do not have statistically significant effects. The effects of arthritis and cardiovascular conditions are not statistically significant but the effect of musculoskeletal conditions is, leading to relatively longer duration until SSDI application.

Figure 1 compares the predicted in-sample distributions of spell length with the empirically observed distributions for men and women. The model predicts fewer early applicants and fewer non-applicants than the data indicate.

One way to evaluate a complex model is out-of-sample forecasting. We choose random subsamples of the men and women to estimate the dynamic programming model, then use the remaining observations to compare the empirical distribution of times to application and the probability of non-application. Table IV reports the results of this computation. We compare the empirical distribution and the out-of-sample predictions of the model for the men and women not used in fitting the subsample model. Confirming the results from Figure 1, the model underpredicts early application, shifting half of the first period forward to the third period or later. The model also overpredicts non-applicants. This could result from unmeasured severity of medical conditions, specification of the variables in the model, or the assumed functional form of the utility function. Early application can result from unmeasured severity. Omitted variable bias can afflict the dynamic programming model as it does a linear regression. Finally, the functional form of utility has

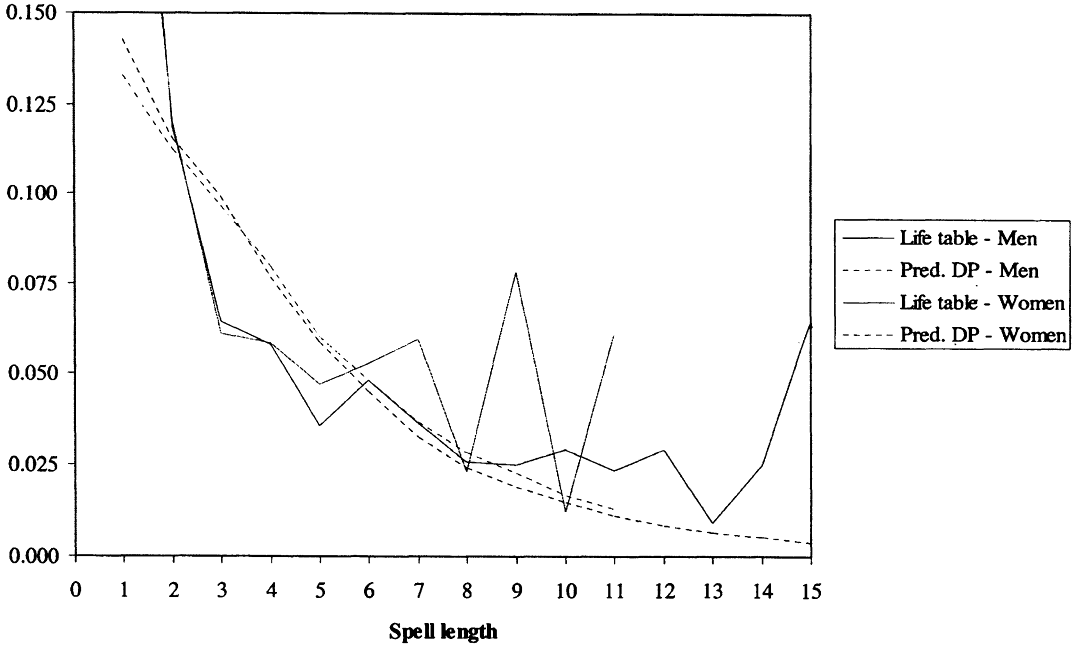

Figure 1. Life table application rates vs. dynamic programming predictions

Table IV. Application rates, out-of-sample prediction

Period	Men			Women		
	Life table	Predicted	Difference	Life table	Predicted	Difference
1	0.266	0.135	0.131	0.267	0.146	0.121
2	0.123	0.109	0.014	0.133	0.120	0.013
3	0.075	0.094	−0.019	0.061	0.100	−0.039
4	0.047	0.070	−0.023	0.053	0.080	−0.027
5	0.037	0.056	−0.019	0.040	0.057	−0.017
6	0.050	0.044	0.006	0.076	0.044	0.032
7	0.030	0.033	−0.003	0.059	0.034	0.025
8	0.034	0.026	0.008	0.021	0.023	−0.002
9	0.025	0.020	0.005	0.078	0.020	0.058
10	0.030	0.016	0.014	0.015	0.016	−0.001
11	0.028	0.011	0.017	0.075	0.012	0.063
12	0.047	0.008	0.039			
Never apply	0.123	0.349	−0.226	0.100	0.323	−0.223
Test statistic[a]		24.140			20.858	

Note: The dynamic programming model is estimated under normality assumption. Two-thirds of the sample is randomly chosen to estimate the model, which is then used to simulate the distribution of probability of application by the remaining one-third of the sample. The life table shown here is that for the one-third subsample used for out-of-sample comparison. Sample sizes for the life table and simulation: men, 197: women, 164.
[a] The test statistics shown are multinomial likelihood ratio statistics for the null hypothesis that the discrete distributions of time to application estimated using life table techniques out-of-sample are equal to the fitted distributions resulting from the dynamic programming models in this table. Critical chi-square values are 21.026 (0.05) and 26.217 (0.01).
Source: Authors' calculations using HRS data.

unpredictable consequences, and maximum likelihood estimation is sensitive to the distributional assumptions made concerning shocks.

7. CONCLUSIONS

In this paper, we model the timing of SSDI applications using a dynamic programming model to estimate how timing to SSDI application is affected by both health conditions and policy variables. Our results show that the type of work-limiting health condition (arthritis, cardiovascular or musculoskeletal versus all others), presence of employer accommodation and relative value of income in the application state to income in the work state significantly affect the timing of SSDI applications. Using a random subsample to estimate out-of-sample performance of the model, we find that the model underpredicts early application, shifting half of the first period forward to the third period or later. The model also overpredicts non-applicants. This could result from unmeasured severity of medical conditions, specification of the variables in the model, the assumed functional form of the utility function, or distributional assumptions.

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