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ABSTRACT

Option Value and Dynamic Programming Model Estimates of Social Security Disability Insurance Application Timing*

This paper develops dynamic structural models - an option value model and 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. Based on tests of both in-sample and out-of-sample predictive accuracy, our option value model performs better than both our dynamic programming model and our reduced form hazard model.

JEL Classification: H31, H55

Keywords: Social Security Disability Insurance, Health and Retirement Survey, option value, dynamic programming

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Introduction

Rapid growth in the number of Social Security Disability Insurance (SSDI) beneficiaries in the early 1990s together with a parallel decline in male labor force participation rates produced extensive research on the behavioral 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 labor force and apply for benefits. While such models are useful approximations of the relationship between past SSDI policies and past application behavior, future policy changes may not yield the same reduced form responses. A better theoretical approach to specify how changes in SSDI policy will change future behavior is to incorporate explicitly SSDI incentives within a structural model.

In this paper, we develop and test dynamic structural models 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. 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. Following the seminal work by Stock and Wise (1990) and Lumsdaine, Stock, and Wise (1992) [LSW, hereafter], we investigate this dynamic decision using both option value and dynamic programming models in addition to a conventional reduced form hazard model. The option value approach was first formalized by LSW to model retirement decisions. The option value model is similar in spirit and structure to the dynamic programming model. However, it has some analytical differences and is computationally less intensive. Option value and dynamic programming models are theoretically more powerful approximations of individual behavior than are reduced form specifications. Reduced form models are most appropriate for studying the implications of policy changes when the underlying behavioral structure remains unchanged (Lucas, 1976). In contrast, structural models are best when the proposed policy change is large enough to significantly alter incentives and individual behavior. By structural models, we mean that the estimation of underlying behavioral elasticities is based on a formal economic model. A priori, we do not differentiate between the two structural models we use in this paper, rather we estimate both and compare them using tests of predictive performance.

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 labor 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 labor force participation rates. They find that labor force participation rates are negatively related to SSDI acceptance rates. Halpern and Hausman (1986) employ a structural estimation approach to analyze both these policy 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) analyzes 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 labor market risks. Kreider (1999) uses a structural model of SSDI applications, awards, and income to analyze the effect of this program on male labor force participation within a lifetime framework. He finds that increases in the level of SSDI benefits modestly reduce male labor 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 labor earnings, and benefit eligibility affect application behavior. They also find that men and women have significant differences in their responsiveness to policy changes. Both Kreider (1999) and Kreider and Riphahn (2000) studies recognize the importance of modeling the timing of applications but did not do so. These studies measured application elasticity over an eight-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, Buchinsky, and Benitez-Silva (2003) proposed to develop and estimate a dynamic programming model of SSDI program together with the Old Age and Survivors Insurance (OASI), and Supplemental Security Income (SSI).

In this paper, we develop dynamic structural models of the SSDI application decision that are adaptations of dynamic structural models used to study retirement. Rust (1989), Berkovec and Stern (1991), Rust and Phelan (1997), and Heyma (forthcoming) have all used dynamic programming models to analyze retirement decisions. Stock and Wise (1990b), based on Stock and Wise (1990a), developed an option value retirement model that they argue is close in spirit to the dynamic programming rule but more convenient to estimate. The difference between the two approaches is that the option value model evaluates the future as the maximum of the expected values of utility, whereas the dynamic programming model uses, theoretically preferred, the expected value of the maximum, which is necessarily larger. Their option value model predicts the age of retirement but underestimates retirement at age 65. They and others then provide evidence of the advantages of option value retirement models in a series of papers.

LSW finds that option value and dynamic programming models work equally well in predicting the effects of a window plan, which is a temporary retirement incentive offered by firms to its employees. But they note that the option value model is easier to estimate. A probit specification is also estimated for comparison purposes, and they find that both structural models outperform probit models.

Daula and Moffitt (1995) develop a dynamic programming model of army reenlistment 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. They also use two simpler-to-compute structural models, an option value model and an annualized cost of leaving model, and compare their predictions with their dynamic programming model. They conclude that all models produce similar predictions in-sample, but dynamic programming produces more plausible predictions out-of-sample.

Our paper which develops a structural model of the decision to apply for SSDI contributes to the literature in several ways. The present work focuses on explicit modeling of 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 program cost. Using structural modeling, we show that the policy variables are important for the transition onto the SSDI rolls following the onset of a work-limiting condition. Most of the literature using option value and dynamic programming models focuses on retirement decisions. We estimate and compare option value and dynamic programming models of SSDI application. As a technical improvement, we add to the literature by estimating structural models of SSDI for up to 16 periods (LSW include at most a three-period analysis). Finally, following Daula and Moffitt (1995), we also include fixed utility differences as discussed below.

Dynamic programming and its alternatives

It can be argued that option value models more closely reflect how individuals actually behave. If people intuitively make decisions by comparing the consequences of an application this year with an application made in one, two, or five years, then option value models mimic that process. Further, option value models are close to dynamic programming models when the relevant choice set as opposed to the complete choice set is circumscribed. It is, at the very least, an open question as to how well option value models perform in such cases. This is one of the issues we explore in this paper. But the main reason to investigate both option value and dynamic programming models is that little is known about the success of the two types of models in decisions other than retirement. The fact that option value models are more convenient to estimate, and thus might simplify more complex models of government programs and the simulation of policy changes, is an additional reason to consider that question. However, one should note that the results of the comparison we carry out critically depend on the modeling assumptions we make. In this paper, our focus is to model the decision whether and when to apply for SSDI by workers who experience a work limiting health condition. Therefore, we chose to abstract from modeling decisions about returning to work, applying for retirement or other programs (such as SSI), SSDI appeals, saving and labor supply choices. Thus, a more formal model which incorporates all these aspects could provide different results of comparison between the two models.

Of course similar arguments regarding convenience can be made with respect to the value of reduced form models, such as hazard models, which are even less difficult to estimate, primarily because they are available in standard computer packages. These reduced form models can be criticized for being unable to capture the consequences of a changing structure, but they offer such convenience in practice that they should also be considered. The only way to know how reduced form models compete with structural models in their ability to predict the behavioral consequences of policy changes is to estimate both reduced form and structural models of real and complex problems. This is another issue we explore in this paper, by comparing the predictive power of reduced form hazard models to our structural models.

How SSDI Works

SSDI is a social insurance program that provides benefits based on previous Social Security covered employment. The program is financed by the Social Security payroll taxes. In December 2000, SSDI paid 5,042,334 disabled workers an average monthly benefit of $786 (U.S. Social Security Administration, 2001). Here we provide a brief overview of SSDI program rules. A much fuller description can be found in the *Annual Statistical Supplement to the Social Security Bulletin*.

To be eligible for SSDI benefits workers must be judged to have a medically determinable physical or mental condition that has lasted or is expected to last at least 12 months or result in death, and that prevents them from performing any substantial gainful activity (SGA). In 2001, earnings of more than $740 a month ordinarily demonstrated that an individual is engaged in SGA (The SGA level is automatically adjusted annually based on increases in the national average wage index.). They must also be in insured status. Fully insured status depends on age at the time of onset and time in Social Security covered employment. They must also meet a substantial recent work activity test. In general, this test requires being in Social Security covered employment for one-half of the quarters over the previous 10 years.

Successful applicants start to receive their monthly benefits (Primary Insurance Amount, PIA) following a five month non-work period. This is the statutory waiting period before benefits can be received following the onset of disability and during this period applicants need to be almost completely withdrawn from the labor market. Benitez-Silva, Buchinsky, Chan, Rust, and Sheidvasser (1999) report that the rejection or award process on average takes about the same amount of time. PIAs are based on workers' covered earnings history (Average Indexed Monthly Earnings, AIME). Workers can apply for SSDI at any age prior to age 65. Workers with a sufficient work history will become eligible for actuarially reduced retirement (Old-Age and Survivors Insurance, OASI) benefits at age 62 and full OASI benefits at age 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].

SSDI benefits may be terminated for several reasons. In some cases, beneficiaries' conditions improve and they return to work. In other cases, they are found capable of SGA. However, beneficiaries rarely return to work, and when they do, their wages are usually lower than they were before (see Bound, 1989 and Bound, Burkhauser, and Nichols, 2003 for evidence). We assume that once workers get SSDI, they stay on the rolls until they are automatically moved to the OASI program at age 65.

The decision to apply for SSDI is far more difficult than is the decision to apply for OASI. Eligibility to both depends on past payroll contributions, however, OASI eligibility is based on age and thus is fairly easy to determine whereas eligibility for SSDI is harder to verify. Application to SSDI is merely the beginning of a multiple step eligibility process and a protracted appeals process which can be long and 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 rejected or accepted. The probability that an application for SSDI is approved has varied dramatically over time and state (see Burkhauser, Butler, and Weathers, 2002). In our model, we use the rates of approval by state and year, which varied from 25 percent to 75 percent between 1974 and 1993.

Applicants who are initially rejected for benefits can file appeals at various levels. In theory, our setup is adaptable for appeals process as well. However, appeals are not a random sample and therefore we choose not to model them in this paper as the estimation would become much more complicated. The main focus of this paper is modeling the timing of first application for SSDI. For the same reason, we also abstract from returns to work either after being accepted or rejected. Bound and Burkhauser (1999) report that accepted individuals rarely return to permanent work. Bound (1989) shows that return to work is not likely for the rejected group since the relative rewards for returning to work are small.

The Optimal Timing of SSDI Application

Our option value and dynamic programming models follow LSW. We first specify the choice and its potential consequences and then describe the utility functions and the distributions of the stochastic elements.

The Option Value Model

Time is discrete and the horizon is finite. The choice in each period is to continue to work or to apply for SSDI as long as one is eligible for these benefits. Thus, an eligible individual can either choose to apply for SSDI, or never apply. The consequence of an application is either rejection or acceptance and receipt of benefits until retirement or death. If rejected, one may either appeal to the decision, or return to work, or not work and live exclusively on non-labor income which are not explicitly modeled here. As discussed above, we assume everyone who does not apply for SSDI by age 62, retires at age 62. We will specifically model the consequences of (1) continued work (no application), (2) application and acceptance, and (3) application and rejection.

Let the current period be t. One can apply for SSDI in period r, $r \geq t$. The end period is called d, 62 years of age in our case. The probability of surviving to period s given survival to period t, $s \geq t$, is $\pi(s \mid t)$. If one applies for SSDI, the probability of being approved is $\alpha(t)$, and $\pi(s \mid t)$ and $\alpha(t)$ are not estimated in the model. Earnings while still working is W_s, and expected income if one applies for SSDI is D_s. Note that, in our model, income in the SSDI acceptance state becomes OASI income at age 62. Income is Y_s if one is turned down for SSDI, and income is B_s if one is accepted. Hereafter, we will not write out all of these terms but use D_s to stand for the weighted average of B_s and Y_s where the weights are $\alpha(t)$ and $1-\alpha(t)$, respectively.

Let U_t denote the utility function and β denote the discount factor. We follow LSW in specifying that utility is a function of labor earnings and income in the SSDI acceptance state. This assumption of forced consumption is clearly restrictive. However, here we focus on the SSDI application decision and therefore we abstract from borrowing, saving and consumption smoothing issues by assuming incomplete markets as in Rust and Phelan (1997). In general, U_t includes a systematic predetermined portion and a stochastic, random portion[3]. As in LSW, we assume that income may produce more or less utility after application for SSDI. Application timing decision depends on several incentives which consist of factors affecting individual preferences for consumption and leisure, labor earnings, SSDI benefits, health condition, socio-demographic characteristics, job characteristics and work conditions such as employer accommodation following onset, and institutional details of the SSDI program. Further discussion on the relevance of these variables for the application timing decision can be found below. In this context, at any given period, postponing application may provide higher current consumption and higher future potential benefits due to continued labor market activity, but may also lead to lower current leisure consumption and higher discomfort from work. Utility in the pre-application state is:

$$U_W(W_s) = (W_s)^\gamma + \omega_s, \tag{1}$$

and utility in the post-application state is:

$$U_D(D_s) = \kappa^\gamma (D_s)^\gamma + \xi_s, \tag{2}$$

where κ is the utility function parameter which represents the relative value of income in the application state to income in the work state. Income in different states may be valued differently as no-work state may also imply higher leisure or stigma from application. We assume that this parameter is the same, regardless of which outcome (approval or rejection) occurs. As a simplification, we chose to approximate the preferences by entering D_s as the argument of the post-application state utility function whereas a more complete formal model would define preferences over lotteries. Therefore, the utility function parameter γ only represents risk aversion with respect to income variability and not the risk aversion with respect to application for the SSDI program. Our simplification can be justified by arguments made by Kreider (1998) who finds that the risk aversion with respect to rejection by the program is weak compared to the risk aversion with respect to labor earnings variability in the context of SSDI applications. Note that, our simplification does not necessarily imply risk neutrality with respect to rejection in our model, as κ can also be thought as representing the relative value of the lottery (i.e. the application state) to the work state. So, if individuals are risk averse with respect to rejection, this would imply a relatively lower κ which would indicate that the non-work income is valued less relative to work income due to its uncertainty. A priori, we do not impose any restrictions on κ and allow its estimate to take any value.

The disturbances are assumed to be independent over people and time. One can calculate the utility of applying for SSDI payments at various periods. The utility value at time t of applying for SSDI at time $r \geq t$ is denoted as $V_t(r)$.

$$V_t(r) = \sum_{s=t}^{r-1} \pi(s \mid t)\beta^{s-t} U_W(W_s) + \sum_{s=r}^{d} \pi(s \mid t)\beta^{s-t} U_D(D_s(r)) \tag{3}$$

The problem is to maximize $E_t[V_t(r)]$ over r. The value of applying for SSDI now (period t) is $E_t(V_t(t)) = \sum_{s=t}^{d} \pi(s \mid t)\beta^{s-t} U_D(D_s(t))$. To define the problem more conveniently, define the expected value of applying for SSDI in year r minus the expected value of doing so now as $G_t(r)$.

$$G_t(r) = E_t(V_t(r)) - E_t(V_t(t)) \tag{4}$$

This is the gain, evaluated at period t, from postponing SSDI application until period r. Substituting in the above formulae leads to:

$$G_t(r) = \sum_{s=t}^{r-1} \pi(s \mid t)\beta^{s-t} E_t(W_s^{\gamma}) + \sum_{s=r}^{d} \pi(s \mid t)\beta^{s-t} \kappa^{\gamma} E_t(D_s^{\gamma}(r)) - \sum_{s=t}^{d} \pi(s \mid t)\beta^{s-t} \kappa^{\gamma} E_t(D_s^{\gamma}(t))$$
$$+ \sum_{s=t}^{r-1} \pi(s \mid t)\beta^{s-t} E_t(\nu_s) \tag{5}$$

where $\nu_s = \omega_s - \xi_s$. Thus, $G_t(r)$ consists of the following two parts:

$$g_t(r) = \sum_{s=t}^{r-1} \pi(s \mid t)\beta^{s-t} E_t(W_s^\gamma) + \sum_{s=r}^{d} \pi(s \mid t)\beta^{s-t}\kappa^\gamma E_t(D_s^\gamma(r)) - \sum_{s=r}^{d} \pi(s \mid t)\beta^{s-t}\kappa^\gamma E_t(D_s^\gamma(t)) \tag{6}$$

$$\phi_t(r) = \sum_{s=t}^{r-1} \pi(s \mid t)\beta^{s-t} E_t(\nu_s) . \tag{7}$$

Then $g_t(r)$ is the systematic term, the exogenous portion of utility associated with applying for SSDI in period r, and $\phi_t(r)$ is the stochastic portion of utility. If we define $r^* = \arg\max_r E_t[V_t(r)]$, then the person postpones SSDI application if $G_t(r^*) = E_t(V_t(r^*)) - E_t(V_t(t)) > 0$, i.e. if the option value $G_t(r^*)$ is positive. The application rule can be explained as follows: one applies for SSDI in period $r > t$ if $g_t(s) + \nu_t < 0$ for $r+1 \le s \le d$ and for $\forall t' < r$, $\exists s$ such that $g_{t'}(s) + \nu_{t'} > 0$.

Thus, one must compute $g_i(j)$ for $t \le i < j \le d$. This step is recursive and entails Taylor expansion of $E_t[X_s^\gamma]$ unless the analytical expectation exists. LSW use the following Taylor series expansion:

$$E_t[X_s^\gamma] \cong \left\{1 + \frac{1}{2}\gamma(\gamma-1)E_t\left[\frac{X_s - E_t X_s}{E_t X_s}\right]^2\right\}(E_t X_s)^\gamma \tag{8}$$

Therefore, we have

$$E_t[X_s^\gamma] \cong \left\{1 + \frac{1}{2}\gamma(\gamma-1)(s-t)Var(X_t)\right\}\{E_t X_s\}^\gamma \tag{9}$$

LSW does not expand $(\kappa^\gamma D_s^\gamma)$ in a Taylor series on the assumption that the variance of income is small in the non-work state. We alter the formulae of LSW by expanding $[E_t X_s]^\gamma$

$$[E_t X_s]^\gamma = E_t X_s + (\gamma-1)EX_s \ln(E_t X_s) + \frac{1}{2}(\gamma-1)^2 E_t X_s [\ln(E_t X_s)]^2 \tag{10}$$

and similarly for $(\kappa^{\gamma} D_s^{\gamma})$. This expansion increases the accuracy of the approximations and improves numerical performance. The next step is to find the maximum $g_i(j)$ over j, this is $g_i(j^*)$, where j^* is the period in which application for SSDI occurs. To calculate the likelihood function, we define the following probabilities, which all add to unity:

- Probability of applying for SSDI at period t:

$$\Pr(SSDI = t) = \Pr(g_t(j^*) < -v_t) \tag{11a}$$

- Probability of applying for SSDI at period $j > i$:

$$\Pr(SSDI = j) = \Pr(g_t(i^*) > -v_t, g_t(j^*) < -v_t) \tag{11b}$$

- Probability that the individual does not apply for SSDI before the end period d:

$$\Pr(SSDI > d) = \Pr(g_t(j^*) > -v_t, g_d(j^*) > -v_d) \tag{11c}$$

The Dynamic Programming Model

The dynamic programming version of this model uses most of the above equations, but somewhat different probability computations. The maximization in the option value model is the maximum of the expected values of utility, whereas the maximization in the dynamic programming approach is the expected value of the maximum utility. The latter is necessarily larger and the option value model understates the expected value of waiting. Therefore, dynamic programming is theoretically preferred to option value as it provides a more formal solution to the intertemporal utility maximization problem. These two approaches are the same only if the maximum utility is guaranteed to be in one certain year, whose expected value is then the maximum. Alternatively, imagine a set of nontrivial zero-mean random variables which are not perfectly correlated. The maximum expected value of future disturbances (indeed, every expected value) is zero, but the expected maximum exceeds zero, the more so, the more periods there are to come.

At period t, the pre-application and post-application utilities are given by $U_W(W_t)+\omega_t$ and $U_D(D_t(s))+\xi_t$, where ω_t and ξ_t are assumed to be independent over people and time. The value function at time t is given by:

$$V_t(r)=\max\left\{E_t\left[U_W(W_t)+\omega_t+\beta\pi(t+1\mid t)V_{t+1}(r)\right], E_t\left(\sum_{\tau=t}^{d}\beta^{\tau-t}\pi(\tau\mid t)[U_D(D_\tau)+\xi_t]\right)\right\} \tag{12}$$

Again we define the probability of survival as $\pi(\tau\mid t)$ and we obtain

$$V_t(r)=\max\left\{\overline{V}_{1t}(r)+\omega_t,\overline{V}_{2t}(t)+\xi_t\right\} \tag{13}$$

where $\overline{V}_{1t}(r)=U_W(W_t)+\beta\pi(t+1\mid t)E_tV_{t+1}(r)$, and $\overline{V}_{2t}(t)=E_t\left[\sum_{\tau=t}^{d}\beta^{\tau-t}\pi(\tau\mid t)U_D(D_\tau)\right]$

The application rule here is: if $\overline{V}_{1t}(r)+\omega_t<\overline{V}_{2t}(t)+\xi_t$, then the individual will apply for SSDI in period t, otherwise he or she will continue working. Therefore, the probability of SSDI application is $\Pr(\overline{V}_{1t}(r)+\omega_t<\overline{V}_{2t}(t)+\xi_t)$. The calculations in the dynamic programming model involve the expected maxima of utility over all possible SSDI application times.

Data

In this section, we will briefly describe the data sets we use and define the variables in our analysis[4]. Our data come from the first three waves of the Health and Retirement Study (HRS)[5]. 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 the years of 1931 and 1941 are considered "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[6]. 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 analyzing 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, labor 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 programs 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[7]. 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 with the Lewin Group Public Use File on allowance rates[8]. 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?” Benitez-Silva, Buchinsky, Chan, Cheidvasser, and Rust (forthcoming) show that the self-reported disability measure in HRS is an unbiased indicator of the true disability status. In the first wave, 2,717 persons (1,324 men and 1,393 women) reported that they had such an impairment or health problem[9]. To this population we added 340 persons (140 men and 200 women) who were not in the sample drawn from Wave 1 but who reported having a work limiting health condition in Wave 2. Of these 3,057, we kept those with permanent conditions (impairments expected to last for more than three 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 1,653 individuals (924 men and 729 women).

Individuals were asked when their condition first began to bother them, and this date is used as the onset of the health problem. They were also asked if they applied for SSDI benefits. For those who applied, 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 age 61. Finally, only those who were eligible for SSDI benefits in terms of being fully insured in at least one period following onset were kept in the final sample. This way, we guarantee that the individuals in our sample whose application is rejected are denied SSDI benefits solely due to medical screening results. Individuals who became eligible after 1993 were also dropped from the analysis since it was not possible to observe them applying for SSDI. Applying these criteria, our final sample consisted of 1,085 individuals (592 men and 493 women). Table 1 provides descriptive statistics for the key variables used in our analysis.

The time unit in our analysis is a biennial period since the date on SSDI award status and income during the survey period are known over biennial periods. We calculate utility from the stream of labor earnings in different states and the potential SSDI benefits which would result from application for each period of potential application. We construct other inputs which are assumed to be exogenous to the model. We include all of these measurements and predictions in our option value and dynamic programming models in order to analyze the decision to apply for SSDI.

Table 2 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; their 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. Nonetheless, only about a quarter of the sample apply for SSDI in the first period (first two years following onset). The vast majority of workers who experience the onset of a work limiting health condition do not apply for SSDI in the first two years but choose to wait to apply. The hazard rate declines after the first period, and the longest observed spell is 16 periods (32 years) for men and 15 periods (30 years) for women. These life tables demonstrate the substantial variation in spell lengths from onset to application but not the reasons for such great variation in outcomes.

Explanatory Variables

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

Economic Variables. In order to estimate a dynamic programming or option value model, it is necessary to estimate future labor earnings and potential benefit levels. Expected real labor earnings are intended to capture the opportunity cost of applying for benefits. We need to predict labor earnings profiles for each individual for each of the three states we will investigate: (1) no application, (2) applied and rejected, and (3) applied and accepted. Our aim is to get good labor earnings predictions rather than to estimate a structural model of lifetime earnings.

Total labor 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 labor 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, Butler, Kim, and Weathers (1999), we predicted labor earnings using an autoregression which includes: a constant and four lagged values of labor 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 being in the "applied and rejected group" or the "applied and accepted group"; age, age square, and unemployment rate at each period. Once we obtained these three time-varying earnings predictions, we then computed their corresponding standard deviations, which we interpret as the uncertainty of the earnings streams themselves.

We, then consider the probability of having zero labor earnings. A probit equation is estimated to obtain the predicted probabilities of having zero earnings. A final prediction of labor 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. Labor earnings estimation for individuals with no administrative records is done in the same way, except that the self-reported labor 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 program 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 program 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 then converted into real 1967 dollars.

Demographic Variables. We include several demographic variables such as race, education, and marital status. These variables reflect labor market attachment and discrimination, and thus are relevant to the utility function specifications.

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 will also be considered as factors affecting the utility differences between the work and application states.

Policy Variables. We are interested in several 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; Burkhauser *et al*., 2002). We include the initial SSDI allowance rates in our computation of expected income in the application state. In our econometric model, W_s is the labor earnings in the no application state, and D_s is the weighted average of the income for the applied and accepted state (B_s) and the labor earnings for the applied and rejected state (Y_s). The weights are given by the initial allowance rates. These rates are available at the state level. Higher allowance rates are expected to increase the speed at which individuals apply for SSDI benefits.

Option Value and Dynamic Programming Estimation Results

To estimate our option value model we estimate the systematic utility (g) using Taylor expansions of the nonlinear functions, and then estimate the univariate or multivariate normal likelihood functions for the optimal timing of SSDI application. The latter step produces parameters of the utility function and the variances. To estimate our dynamic programming model, we first calculate the expected utility of permanent labor market exit at the terminal period d (age 62). We then calculate the expected maximum utility of applying for SSDI at period $d-1$ which entails a maximum over two independent disturbances. The probability of applying at $d-1$ is the probability that the utility of doing so exceeds the utility of waiting. The utility of exiting at d is $V_d = U_D(D_d)$. That is not a choice at that time since it is the end period. The utility of working at $d-1$ is the value function $U_W(W_{d-1}) + \beta U_D(D_d)$, where β is a discount factor whose estimation is often not successful in these models. We did not estimate β, so this parameter will be set outside the model at a value based on LSW (1992). The utility of applying at $d-1$ is $U_D(D_{d-1}) + \beta U_D(D_d)$ [10].

All of the utilities involve disturbances and we obtain the probabilities in the following way. By assumption, $\Pr(\text{exit at } d \,|\, \text{no application before that}) = 1.0$. Then, we have $\Pr(\text{exit at } d-1 \,|\, \text{no application before that}) = \Pr(U_W(W_{d-1}) + \beta U_D(D_d) < U_D(D_{d-1}) + \beta U_D(D_d))$. Define V_{d-1} as the value function at $d-1$, including both possible paths. We continue this backward recursion one more period. The utility of working at $d-1$ is $U_W(W_{d-2}) + \beta E_{d-2} V_{d-1}$. The utility of applying for SSDI at $d-2$ is $U_D(D_{d-2}) + \beta U_D(D_{d-1}) + \beta^2 U_D(D_d)$. Finally,

$$\Pr(\text{exit at } d-2 \,|\, \text{no application before that}) = \Pr(U_W(W_{d-2}) + \beta V_{d-1} < U_D(D_{d-2}) + \beta U_D(D_{d-1}) + \beta^2 U_D(D_d)).$$

This recursive process continues with ever-growing formulae back to time t, thereby defining the probabilities for maximum likelihood or other methods of estimation. Each time the value function V is defined. Eventually one returns to t, the present, and the first probability in time, but the last in calculation. The probability that working now in t has lower utility is the probability that choosing next period $U_W(W_t) + \beta E_t V_{t+1}$ has lower utility than applying for SSDI now $(U_D(D_t)+\beta U_D(D_{t+1})+...+\beta^{d-t}U_D(D_d))$. The normal distribution, or indeed most distributions, of stochastic utility make this sequential approach difficult, because the maximum of a set of random variables has a distribution that is not known in closed form. Therefore, in all cases we directly integrate the expected maximum utility numerically.

Following Daula-Moffitt (1995), we add an observable variable vector $\underline{x}$ to the original utility functions described in equation (1) and we denote the effects of this vector by $\underline{\delta}$. Thus, the utility function in the work state takes the form $U_W = Y^{\gamma} + \underline{x}'\underline{\delta} + \varepsilon$. Here the idea is to include some fixed utility differences between the pre-application state and post-application state. These are different from the marginal utility differences we imposed originally through κ, but they also reflect the relative valuations of the pre-application state and post-application state. The $\underline{x}$ vector includes years of education, dummies for race, marital status, employer accommodation, health conditions and for being a white collar worker. We call the parameters corresponding to these variables Daula-Moffitt parameters. Note that positive Daula-Moffitt parameters discourage application and negative ones encourage application.

The parameters of the option value and dynamic programming models to be estimated are: κ (the relative value of income in the non-work state to income in the work state), γ (utility function parameter representing risk aversion with respect to income variability where the coefficient of relative risk aversion=$\gamma-1$), β (discount factor), and $\underline{\delta}$ (Daula-Moffitt parameters). The estimates of the dynamic programming model are obtained by assuming a normal distribution for the disturbances. We estimated two versions of the option value model, one assuming a normal and the other a Weibull distribution. Table 3 and Table 4 present estimation results for men and women, respectively.

In Table 3, both our option value and dynamic programming models produce statistically significant estimates of κ and γ, when β is set equal to 0.85. Estimated γ is less than one in each of the three sets of results 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 in the dynamic programming and about 0.55 and 0.4 in the option value models. The estimate of κ is greater than 1 in the dynamic programming model and the normal version of the option value model, which suggests that every dollar earned without work is worth more than every dollar earned from work. The estimate is around 1.4 in the dynamic programming model. This means that the average man in our sample would be indifferent between getting a dollar from work and getting 71 cents under SSDI. Using the Weibull version of the option value model, however, we find that the average man values non-work income less relative to work income since estimated κ is smaller than 1 in this model -- it is around 0.4[11]. This apparently large difference does not however, have much of an effect on the likelihood or other parameters in the model.

The estimates of the Daula-Moffitt parameters are almost always significant and they are similar across models. Additional education or accommodation by employers increases the utility of earnings relative to SSDI, discouraging application. Being African-American or being married encourages application with one exception: the effect of marital status is positive but small in the normal version of the option value model. Being a white collar worker at the onset of a work limitation has no statistically significant effect. There is evidence some health conditions lead to more rapid application than others. 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. Note, however, that estimated effects are not always statistically significant. 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. This effect is always statistically significant. The omitted category is all other health conditions. All these results are consistent with reduced form model findings (see Burkhauser *et al*., 1999; and Burkhauser *et al*., 2002).

Table 4 presents the estimation results for women. The estimated γ takes a wide range of values. It is around 0.5 in the dynamic programming model. It is estimated to be around 1.7 in the normal version of the option value model and about 1 in the Weibull version of the option value model. This wide range of γ again does not affect the general nature of the results when one looks at the certainty equivalents[12]. The estimate of κ is greater than 1 in each model. It is about 2.1 in the dynamic programming model and about 2 and 1.8 in the option value models. The estimates of the Daula-Moffitt parameters are similar to those of men with a few exceptions. Education, marital status, and accommodation are not always significant. Being a white collar worker at the onset discourages applications significantly. The effects of arthritis and cardiovascular conditions are not significant but the effect of musculoskeletal conditions is significant, and it leads to a relatively longer duration until SSDI application.

In-Sample and Out-of-Sample Predictions

Table 5 and Table 6 show model predictions of SSDI application rates for men and women, respectively. The first column of each model gives the predicted application rates, and the next column gives the difference between the life table and the predicted rates. The option value and dynamic programming models produce similar predictions. Separate analyses of men and women change the values but not the general pattern.

We test the fitted distributions resulting from the option value and dynamic programming models versus the distribution estimated using life table methods in the original data. First, as in Table 2, we estimate the hazards of application and the implied distribution of time to application in the original data. Then we compare the fitted distributions from option value and dynamic programming in Tables 5 and 6 using a multinomial likelihood ratio test based on the discrete periods. (The Pearson chi-square goodness of fit is a Taylor Series approximation to this, but we use the actual likelihood ratio.) We prefer this metric for comparing predictive power across our models to comparing log-likelihood values based on non-nested hypotheses. To avoid small cells, we consider the first 15 periods (30 years) for men and the first 11 (22 years) for women. The critical values of the chi-square test statistics are 25.0 (5 percent) and 30.6 (1 percent) for men and 19.7 (5 percent) and 24.7 (1 percent) for women. The results are as follows: for men, dynamic programming normal, 63.3, option value normal, 41.7, option value Weibull, 39.5; for women, dynamic programming normal, 41.5, option value normal, 29.5, and option value Weibull, 26.6. The conclusions are that none of the fitted distributions are precise, but the option value models fit better than the dynamic programming model, and there is little difference between the two option value models.

In all the models, we underestimate the application rate in the first period. In the next several periods, we overestimate the application rates. This suggests that individuals who apply in the earlier periods are expected to do so, but they are not expected to apply for SSDI immediately in the first period. This overapplication problem in the first period resembles the problem that LSW encountered with the age 65 retirement effect. As they also point out, this kind of a pattern is clearly not related to the earnings or benefit streams (LSW, 1992). In our case, it may be due to our inability to identify cases where the onset condition is so severe that no real choice of application is feasible. For some significant minority of workers, the onset condition compels immediate application. This overapplication problem in the first period could also be the reason for our failure to estimate the discount factor β (its estimate goes to zero to fit early application better). Also after the first period, the predictions are very similar among the three sets of results. Both the option value and the dynamic programming models overestimate the number of people who choose not to apply for SSDI, but the option value models are more accurate.

We also test out-of-sample predictive performances of our models based on revised data. To do so, we randomly divided our data set into two separate samples: two-thirds of the data were used for parameter estimation only, and the rest was used to assess the predictive performance[13]. This is done separately for men and women. The distributions of spell length by gender for our two-thirds samples are given in Appendix Table 3A. These distributions are very similar to those for the original samples. The fitted distributions resulting from the option value and dynamic programming models using the two-thirds sample are compared to the distribution estimated using life table methods in the one-third sample. These comparisons are presented in Tables 7 and 8. We consider the first 12 periods (24 years) for men and the first 11 periods (22 years) for women. The critical values of the chi-square test statistics are 21.0 (5 percent) and 26.2 (1 percent), and 19.7 (5 percent) and 24.7 (1 percent), respectively. The test statistics are: for men, dynamic programming normal, 24.1, option value normal, 17.5, option value Weibull, 16.7; for women, dynamic programming normal, 20.9, option value normal, 14.7, and option value Weibull, 12.3. The Weibull version of the option value model provides the best out-of-sample forecasts for both men and women even though there is little difference between the Weibull and the normal version of the option value model in terms of predictive performance.

Note that, for both models, the test statistic is less than the critical value at the five percent significance level for both samples. Therefore, we cannot reject the null hypothesis that the option value model is empirically correct.

The predicted application rates from the option value and dynamic programming models are similar overall. However, the comparison of the predictive performance of the two models based on the multinomial likelihood ratio test suggests that the option value model is superior to the dynamic programming model. Note that the option value models provide a better fit out-of-sample than in-sample. This point is very important in the context of policy analysis, since policy simulations require models that are able to predict actual responses to future policy changes. Given the estimation cost of dynamic programming models, the option value model clearly has an additional advantage since it is able to produce good predictions even though it is computationally less intensive. This conclusion is similar to that of LSW for retirement who find that the more complex dynamic programming model does not produce better predictions than the option value model.

Comparison with Hazard Models

In this section, we discuss hazard model results. The hazard model is based on Burkhauser *et al*. (2002). We define new variables in order to make the hazard specification comparable to the option value and dynamic programming approaches. Hazard models are explicitly reduced form models of the time until an event occurs, here application for SSDI. In the same way that one might compare structural models of wages or macroeconomic outcomes with models designed exclusively to make predictions, one can compare hazard models with option value and dynamic programming models. A priori, hazard models would be expected to have higher likelihood functions in sample because they impose little in the way of assumptions, but they would be suspect as the basis for policy simulations of substantial changes in program rules. Because hazard models are available in standard computer packages and they have been used in empirical research before, at least a brief comparison is useful for practical policy analysis. We nevertheless prefer structural modeling a priori because it is based on the utility theoretic basis of individual behavior.

Here, the hazard rate is defined as the probability of applying for SSDI benefits once a work limiting condition first begins to bother the worker. Note that this probability is time-dependent, it is conditional on not having applied earlier, and the spell starts when the worker becomes eligible. An interval hazard that controls for unobserved heterogeneity is used to estimate the transition to SSDI application. The unobserved heterogeneity, due to omitted variables or differences in the distribution functions across individuals, is integrated out of the likelihood function by assuming a log normal form. We define $\ln W_t$ as the logarithm of the current earnings in the no application state. LnD_t is the natural logarithm of a weighted average of current income in the "applied and rejected" and "applied and accepted" states, where the weights are based on the probability of acceptance, i.e. $\ln D_t = \ln[\alpha(t) * B_t + (1-\alpha(t)) * Y_t]$. The variable we use in the hazard model is the difference $\{\ln W_t - \ln D_t\}$.

The last columns in Tables 5 and 6 show the predicted application rates using the hazard model[14]. The hazard model predicts the first period application relatively well for men. However, it overestimates the application rates for almost all other periods as the economic and policy incentives are captured only indirectly. Moreover, uncertainty about the future is not fully modeled. The multinomial likelihood ratio test statistic is 74.2 for men and 62.9 for women for the in-sample predictions and the option value models fit better than the hazard model.

Conclusions

In this paper, we model the timing of SSDI applications. We do so using two dynamic structural models, option value and dynamic programming. These models enable us not only to describe but also to explain how timing to SSDI application is affected by both health conditions and policy variables.

We then investigate whether the results from the estimated models differ qualitatively or quantitatively. The aim is to see which of these models performs better in terms of predictive performance. The measure we use to evaluate the predictive performance is a multinomial likelihood ratio test based on the difference between the optimal timing predictions and the life table application rates. Our predictive power comparisons using both in-sample and out-of-sample data show that the option value model performs better than the dynamic programming model in terms of predictive power even though it may be less consistent with theoretical individual behavior. In addition, its computational simplicity is an advantage over the dynamic programming approach. Nevertheless, dynamic programming is clearly theoretically preferred in terms of allowing for a more complete model including several other issues such as savings, appeals, return to work, transitions from SSDI into retirement, etc.

All our models underestimate the risk of an "immediate" application following the onset. This suggests that for a significant subset of our sample unobserved severity of a work limitation may be limiting their choice of timing over and above the observed health measures. However, our results also show that while the severity of a work limiting health condition significantly affects the timing of SSDI applications, as do policy variables such as employer accommodation and the relative value of income in the application state to income in the work state. We conclude that while the road to disability benefit status begins with a health condition, the SSDI application decision is affected by the personal and economic characteristics of individuals, as well as by government policies and labor market conditions they face.

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Table 1: 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 $1,000 (1967 dollars).

Source: Authors' calculations using HRS data.

Table 2: Distribution of Spell Length

	Men (N=592)					Women (N=493)				
Spell length	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.

Table 3: Estimation Results for Men (N=592)

Parameter	Dynamic Programming Normal	Option Value Normal	Option Value Weibull
κ	1.431	1.509	0.384
	(7.706)	(12.145)	(3.617)
β	0.850*	0.850*	0.850*
γ	0.407	0.456	0.585
	(6.093)	(9.045)	(4.626)
Education	0.081	0.238	0.114
	(2.443)	(11.408)	(2.493)
Married[a]	-0.125	0.035	-0.198
	(-4.276)	(1.908)	(-3.987)
Black[b]	-0.132	-0.102	-0.253
	(-4.164)	(-5.331)	(-5.259)
Accommodation	0.093	0.100	0.256
	(3.711)	(5.522)	(5.069)
White Collar	0.008	0.004	0.062
	(0.237)	(0.169)	(0.986)
Arthritis[c]	0.075	0.167	0.179
	(1.687)	(5.665)	(2.018)
Cardiovascular[c]	-0.119	-0.086	-0.259
	(-3.225)	(-4.089)	(-4.771)
Musculoskeletal[c]	0.016	0.057	0.061
	(0.550)	(3.082)	(1.215)
- log Likelihood	-1,054.871	-1,108.966	-1,058.458

Note: κ is the relative value of income in the non-work state to income in the work state, γ is risk aversion parameter of the utility function (with respect to income variability) where the coefficient of relative risk aversion=γ-1, and β is the discount factor.
* denotes the parameters that are set outside the model. T-values are in parentheses. All monetary values are in $1,000 (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.

Table 4: Estimation Results for Women (N=493)

Parameter	Dynamic Programming Normal	Option Value Normal	Option Value Weibull
κ	2.123	2.007	1.798
	(7.334)	(25.598)	(9.807)
β	0.850*	0.850*	0.850*
γ	0.520	1.678	1.046
	(3.211)	(22.708)	(7.414)
Education	0.068	0.114	0.102
	(1.739)	(4.047)	(1.841)
Married[a]	0.002	0.024	0.041
	(0.063)	(1.266)	(0.832)
Black[b]	-0.186	-0.080	-0.306
	(-4.642)	(-3.842)	(-5.495)
Accommodation	0.074	0.042	0.080
	(2.618)	(2.194)	(1.595)
White Collar	0.089	0.067	0.193
	(2.447)	(2.398)	(2.693)
Arthritis[c]	0.030	0.042	0.098
	(0.758)	(1.748)	(1.593)
Cardiovascular[c]	0.015	0.016	-0.014
	(0.268)	(0.538)	(-0.176)
Musculoskeletal[c]	0.117	0.091	0.263
	(3.660)	(4.551)	(5.166)
- log Likelihood	-848.340	-854.105	-884.685

Note: κ is the relative value of income in the non-work state to income in the work state, γ is risk aversion parameter of the utility function (with respect to income variability) where the coefficient of relative risk aversion=γ-1, and β is the discount factor.
* denotes the parameters that are set outside the model. T-values are in parentheses. All monetary values are in $1,000 (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.

Table 5: Application Rates for Men (N=592)

	Dynamic Programming		Option Value N		Option Value W		Hazard	
Period	Predicted	Difference	Predicted	Difference	Predicted	Difference	Predicted	Difference
1	0.143	0.137	0.192	0.088	0.152	0.128	0.165	0.115
2	0.116	0.004	0.128	-0.009	0.116	0.003	0.128	-0.009
3	0.099	-0.035	0.098	-0.034	0.101	-0.037	0.103	-0.039
4	0.077	-0.019	0.071	-0.013	0.078	-0.020	0.088	-0.030
5	0.059	-0.023	0.052	-0.016	0.061	-0.026	0.077	-0.041
6	0.045	0.003	0.042	0.006	0.051	-0.003	0.069	-0.021
7	0.032	0.004	0.029	0.007	0.037	-0.001	0.062	-0.026
8	0.024	0.001	0.022	0.003	0.029	-0.004	0.058	-0.032
9	0.019	0.006	0.018	0.007	0.025	0.000	0.051	-0.026
10	0.015	0.014	0.014	0.015	0.021	0.008	0.048	-0.019
11	0.011	0.013	0.011	0.012	0.016	0.007	0.044	-0.021
12	0.008	0.021	0.010	0.019	0.014	0.015	0.039	-0.011
13	0.007	0.002	0.008	0.000	0.011	-0.002	0.030	-0.021
14	0.005	0.020	0.008	0.017	0.010	0.015	0.021	0.004
15	0.004	0.061	0.006	0.059	0.007	0.057	0.011	0.053
never apply	0.333	-0.203	0.284	-0.155	0.262	-0.133	0.000	0.129
Test of predicted versus life table distributions of time to application:								
Test statistic[a]	63.296		41.701		39.513		74.239	

Note: Dynamic programming model is the model estimated under normality assumption. Option Value N and Option Value W refer to the models with normal distribution and Weibull distribution assumptions, respectively. The last two columns show the hazard model results.

[a] The test statistics shown are multinomial likelihood ratio statistics for the null hypothesis that the discrete distribution of time to application in Table 2 estimated using life table techniques is equal to the fitted distributions resulting from the models in this table. Critical chi-square values are 24.996 (0.05) and 30.578 (0.01).

Source: Authors' calculations using HRS data.

Table 6: Application Rates for Women (N=493)

	Dynamic Programming		Option Value N		Option Value W		Hazard	
Period	Predicted	Difference	Predicted	Difference	Predicted	Difference	Predicted	Difference
1	0.133	0.129	0.141	0.121	0.134	0.127	0.136	0.126
2	0.112	0.008	0.117	0.003	0.112	0.008	0.119	0.002
3	0.097	-0.036	0.102	-0.041	0.101	-0.040	0.106	-0.045
4	0.080	-0.022	0.081	-0.023	0.085	-0.027	0.097	-0.039
5	0.060	-0.013	0.062	-0.015	0.063	-0.016	0.091	-0.044
6	0.048	0.005	0.051	0.002	0.054	-0.002	0.085	-0.033
7	0.037	0.022	0.040	0.019	0.043	0.016	0.082	-0.022
8	0.028	-0.005	0.032	-0.009	0.035	-0.012	0.075	-0.052
9	0.023	0.055	0.027	0.051	0.030	0.048	0.067	0.011
10	0.017	-0.004	0.020	-0.008	0.022	-0.010	0.056	-0.044
11	0.013	0.048	0.016	0.044	0.018	0.043	0.043	0.018
never apply	0.325	-0.181	0.276	-0.132	0.260	-0.116	0.000	0.144
Test of predicted versus life table distributions of time to application:								
Test statistic[a]	41.461		29.516		26.505		62.940	

Note: Dynamic programming model is the model estimated under normality assumption. Option Value N and Option Value W refer to the models with normal distribution and Weibull distribution assumptions, respectively. The last two columns show the hazard model results.

[a] The test statistics shown are multinomial likelihood ratio statistics for the null hypothesis that the discrete distribution of time to application in Table 2 estimated using life table techniques is equal to the fitted distributions resulting from the models in this table. Critical chi-square values are 19.675 (0.05) and 24.725 (0.01).

Source: Authors' calculations using HRS data.

Table 7: Application Rates for Men, Out-of-Sample Predictions (N=197)

	Dynamic Programming		Option Value N		Option Value W	
Period	Predicted	Difference	Predicted	Difference	Predicted	Difference
1	0.135	0.131	0.174	0.092	0.139	0.127
2	0.109	0.014	0.118	0.005	0.106	0.017
3	0.094	-0.019	0.093	-0.019	0.096	-0.022
4	0.070	-0.023	0.064	-0.016	0.070	-0.023
5	0.056	-0.019	0.048	-0.011	0.058	-0.020
6	0.044	0.006	0.041	0.009	0.050	0.001
7	0.033	-0.003	0.030	0.001	0.041	-0.011
8	0.026	0.008	0.024	0.009	0.031	0.002
9	0.020	0.005	0.019	0.006	0.025	0.000
10	0.016	0.014	0.016	0.014	0.021	0.008
11	0.011	0.017	0.011	0.017	0.015	0.013
12	0.008	0.039	0.009	0.039	0.012	0.036
never apply	0.349	-0.226	0.311	-0.188	0.289	-0.166
Test of predicted versus life table distributions of time to application:						
Test statistic[a]	24.140		17.508		16.700	

Note: Dynamic programming model is the model estimated under normality assumption. Option Value N and Option Value W refer to the models with normal distribution and Weibull distribution assumptions, respectively.

[a] The test statistics shown are multinomial likelihood ratio statistics for the null hypothesis that the discrete distribution of time to application in Appendix Table 3A estimated using life table techniques is equal to the fitted distributions resulting from the models in this table. Critical chi-square values are 21.026 (0.05) and 26.217 (0.01).

Source: Authors' calculations using HRS data.

Table 8: Application Rates for Women, Out-of-Sample Predictions (N=164)

	Dynamic Programming		Option Value N		Option Value W	
Period	Predicted	Difference	Predicted	Difference	Predicted	Difference
1	0.146	0.121	0.153	0.114	0.154	0.113
2	0.120	0.013	0.125	0.007	0.126	0.006
3	0.100	-0.039	0.105	-0.043	0.107	-0.046
4	0.080	-0.027	0.081	-0.029	0.088	-0.036
5	0.057	-0.017	0.062	-0.022	0.064	-0.024
6	0.044	0.032	0.049	0.027	0.051	0.025
7	0.034	0.025	0.038	0.021	0.040	0.019
8	0.023	-0.002	0.028	-0.008	0.029	-0.008
9	0.020	0.058	0.025	0.052	0.027	0.051
10	0.016	-0.001	0.022	-0.006	0.023	-0.007
11	0.012	0.063	0.016	0.059	0.017	0.058
never apply	0.323	-0.223	0.263	-0.164	0.234	-0.134
Test of predicted versus life table distributions of time to application:						
Test statistic[a]	20.858		14.701		12.262	

Note: Dynamic programming model is the model estimated under normality assumption. Option Value N and Option Value W refer to the models with normal distribution and Weibull distribution assumptions, respectively.

[a] The test statistics shown are multinomial likelihood ratio statistics for the null hypothesis that the discrete distribution of time to application in Appendix Table 3A estimated using life table techniques is equal to the fitted distributions resulting from the models in this table. Critical chi-square values are 19.675 (0.05) and 24.725 (0.01).

Source: Authors' calculations using HRS data.

Appendix Tables

Appendix Table 1A: In-Sample Estimation Results for Men (N=395)

	Dynamic Programming	Option Value	
Parameter	Normal	Normal	Weibull
κ	1.449	1.237	0.354
	(6.327)	(10.504)	(2.158)
β	0.850*	0.850*	0.850*
γ	0.437	0.596	0.820
	(5.262)	(10.475)	(5.397)
Education	0.113	0.267	0.184
	(2.618)	(10.216)	(3.130)
Married[a]	-0.121	-0.002	-0.190
	(-3.256)	(-0.061)	(-3.128)
Black[b]	-0.092	-0.108	-0.260
	(-2.462)	(-4.506)	(-4.300)
Accommodation	0.134	0.153	0.357
	(4.411)	(6.210)	(5.334)
White Collar	0.050	0.029	0.073
	(1.036)	(0.946)	(0.876)
Arthritis[c]	0.001	0.138	0.182
	(0.023)	(3.475)	(1.602)
Cardiovascular[c]	-0.223	-0.165	-0.378
	(-4.689)	(-5.755)	(-5.469)
Musculoskeletal[c]	-0.013	-0.003	-0.013
	(-0.334)	(-0.097)	(-0.199)
- log Likelihood	-687.170	-720.098	-681.095

Note: κ is the relative value of income in the non-work state to income in the work state, γ is risk aversion parameter of the utility function (with respect to income variability) where the coefficient of relative risk aversion=γ-1, and β is the discount factor.

* denotes the parameters that are set outside the model. T-values are in parentheses. All monetary values are in $1,000 (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.

Appendix Table 2A: In-Sample Estimation Results for Women (N=329)

Parameter	Dynamic Programming Normal	Option Value Normal	Option Value Weibull
κ	2.000	2.003	1.994
	(5.440)	(22.359)	(6.160)
β	0.850*	0.850*	0.850*
γ	0.446	1.705	0.818
	(2.477)	(17.804)	(5.574)
Education	0.010	0.085	0.093
	(0.189)	(2.396)	(1.366)
Married[a]	-0.011	0.022	0.033
	(-0.275)	(0.935)	(0.547)
Black[b]	-0.178	-0.057	-0.265
	(-3.584)	(-2.182)	(-3.812)
Accommodation	0.097	0.049	0.099
	(2.743)	(2.137)	(1.664)
White Collar	0.150	0.094	0.260
	(3.290)	(2.911)	(3.160)
Arthritis[c]	0.057	0.048	0.120
	(1.069)	(1.575)	(1.568)
Cardiovascular[c]	0.000	0.030	0.046
	(-0.001)	(0.834)	(0.505)
Musculoskeletal[c]	0.141	0.079	0.243
	(3.231)	(3.164)	(3.830)
- log Likelihood	-573.168	-585.430	-601.594

Note: κ is the relative value of income in the non-work state to income in the work state, γ is risk aversion parameter of the utility function (with respect to income variability) where the coefficient of relative risk aversion=γ-1, and β is the discount factor.

* denotes the parameters that are set outside the model. T-values are in parentheses. All monetary values are in $1,000 (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.

Appendix Table 3A: Distribution of Spell Length (In-Sample)

	Men (N=395)					Women (N=329)				
Spell length	Apply	Censor	Hazard rate	Survival rate	Estimated pmf	Apply	Censor	Hazard rate	Survival rate	Estimated pmf
1	101	30	0.266	1.000	0.266	84	29	0.267	1.000	0.267
2	42	27	0.168	0.734	0.123	37	23	0.181	0.733	0.133
3	23	13	0.122	0.611	0.075	15	19	0.102	0.600	0.061
4	13	23	0.088	0.537	0.047	11	18	0.097	0.539	0.052
5	9	10	0.076	0.489	0.037	7	15	0.082	0.486	0.040
6	11	11	0.112	0.452	0.050	11	13	0.171	0.447	0.076
7	6	6	0.076	0.401	0.030	7	6	0.159	0.370	0.059
8	6	6	0.090	0.371	0.033	2	8	0.067	0.311	0.021
9	4	8	0.074	0.338	0.025	6	3	0.267	0.291	0.078
10	4	8	0.095	0.313	0.030	1	3	0.074	0.213	0.016
11	3	7	0.098	0.283	0.028	4	1	0.381	0.197	0.075
12	4	5	0.186	0.255	0.047	0	0	0.000	0.122	0.022
13	0	4	0.000	0.208	0.000	1	1	0.182	0.122	0.000
14	1	4	0.111	0.208	0.023	0	3	0.000	0.100	0.000
15	2	0	0.333	0.185	0.062	0	1	0.000	0.100	0.000
16	0	4	0.000	0.123	0.000	0	0	0.000	0.100	0.000
Total	229	166				186	143			

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

Appendix Table 4A: Hazard model estimates

	Men		Women	
Variables	Coefficient	T-Value	Coefficient	T-Value
Constant	-4.973	-5.383	-4.794	-3.980
$(\ln W_t - \ln D_t)$[a]	-0.255	-4.331	-0.105	-1.191
Age at onset	9.107	5.540	8.353	4.326
Married	-0.017	-0.084	-0.056	-0.289
Education	-6.200	-2.380	-6.068	-1.497
Black [b]	0.486	2.284	0.529	2.086
Other Race [b]	0.705	2.520	0.406	1.112
Two conditions [c]	0.321	1.785	0.710	3.026
Three conditions [c]	0.565	2.433	0.923	3.132
Arthritis [d]	-0.712	-2.117	-0.546	-2.057
Cardiovascular conditions [d]	0.085	0.404	-0.030	-0.099
Musculoskeletal conditions [d]	-0.505	-2.416	-0.754	-3.092
White collar	-0.139	-0.593	-0.472	-1.443
Employer Accommodation	-0.625	-3.051	-0.421	-1.905
SSA records missing	-0.485	-2.228	-0.707	-2.522
Time	-0.096	-0.727	-0.004	-0.023
Time square	0.016	2.190	0.016	1.461
Variance of Heterogeneity	0.832	0.973	1.127	1.112
Log-Likelihood	842.21		640.42	
Sample Size	592		493	

[a] We define W_t as the logarithm of the current earnings in the no application state. D_t is the natural logarithm of a weighted average of current income in the "applied and rejected" and "applied and accepted" states, where the weights are based on the probability of acceptance.
[b] Reference group is white race.
[c] Reference group is one health condition at onset of a disability.
[d] Reference group is all other types of health conditions.
Source: Authors' calculations based on the HRS data.

Endnotes

[1] See Bound and Burkhauser (1999) for a review of this literature. See Burkhauser *et al*. (2002) for a more recent discussion of the employment rates of working age people with disabilities.

[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. To simplify our model, 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 will apply for OASI benefits at 62. This is a simplified model of a labor market exit behavior that ignores the periods after age 62. A fuller model would integrate OASI and SSDI into a model of labor market exit. But this consideration is beyond the scope of this paper.

[3] Note that, one could also follow an alternative modeling strategy by parameterizing the probability of acceptance. This probability can be modeled as an unobserved individual specific variable instead of the random utility framework we set up here in this paper.

[4] A data appendix which 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).

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

[6] 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.

[7] 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.

[8] 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.

[9] In our empirical study, we include both primary and secondary respondents. Note that the secondary respondents are not a random sample 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, in the HRS, 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.

[10] Note that D_d and all other incomes represented here depend on many factors related both to individuals and to the pattern of application. We take those factors into account in our analysis but omit the list of conditioning variables in order to describe the model in a less complex way. A fuller discussion is provided in the unpublished data appendix (see Gumus, 2002).

[11] Note that except the estimated κ in the Weibull version of the option value model for men, the parameter values we obtain are in line with results from previous studies by LSW (1992 and 1997) and Ausink and Wise (1996). In these studies, the value of γ ranges between 0.5 and 1.8, and κ takes values between 1.3 and 3.6.

[12] Following Stock and Wise (1990b), we consider a gamble of receiving \$10,000 or \$20,000 each with .5 probability, thus the expected amount is \$15,000. The certainty equivalent is the amount that would be accepted instead of the uncertain amount. Using our estimates of γ and

holding everything else constant, we calculate the certainty equivalent as $14,589, $15,560, and $15,039 for the dynamic programming, the normal option value, and the Weibull option value models, respectively. These amounts are not very different from the expected amount of $15,000, hence we argue that the individuals in our sample are, in fact, close to being risk neutral with respect to income variability even though the estimated value of the risk aversion parameter of the utility function takes different values in each model. The certainty equivalent amounts for men are $14,491, $14,533, and $14,644 respectively. See Gumus (2002) for more details.

[13] Estimated coefficients for in-sample estimation are presented in Appendix Tables 1A and 2A.

[14] Estimated coefficients of the hazard model are presented in Appendix Table 4A.

IZA Discussion Papers

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