Analyzing health risks, early retirement and saving behavior with a structural life-cycle model

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December 9, 2011

Abstract

This paper proposes a structural life-cycle model to analyze the relationship between health risks, early retirement and saving behavior for employees in Germany. I rely on the framework of a dynamic programming discrete choice model with a discretized saving decision. The model accounts for both forward looking behavior and unobserved heterogeneity which is specified semi-nonparametrically. Health and labor market risks are modelled as a joint stochastic process. This becomes relevant when simulating two counterfactual policy experiments: the first one changes pension benefits of early retirees and the second one introduces a saving subsidy encouraging precautionary savings. My results point to a trade-off between the hedging of health risks and an employee's incentive to remain in the labor force (?). Health-related poverty can be reduced at lower costs by increasing pension benefits than by a saving subsidy (?).

Keywords: Early Retirement, Saving Decision, Dynamic Programming Discrete Choice, EM Algorithm.

JEL Classification:

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1 Introduction

The strong association between health and socio-economic status is a very robust finding and has been discussed by a large body of literature (see ... for overviews). While there is dissent about whether or not and to what extent income or income inequality affect health in developed countries, strong evidence suggests that a substantial share of income inequality can be explained by health (Lit). In particular, health has been found to be one of the main determinants of both an individual's employment status and early retirement (Lit). Unemployment and early retirement reduce a household's expected lifetime income with potentially long-lasting impacts on wealth accumulation. As has been pointed out by Deaton (2003), this is due to the fact that individuals cannot fully insure their earnings against health risks. From a public policy perspective, understanding the complex relationship between health, unemployment, early retirement, and saving behavior is highly relevant because policy interventions that aim at reducing social inequality could adress the link between health risks and inequality. This may be more efficient than increasing means-tested benefits.

This paper proposes a structural life-cycle model to investigate the relationship between health risks, early retirement and saving behavior for employees in Germany. I rely on the framework of a dynamic programming discrete choice model with a discretized saving decision. The model accounts for both forward looking behavior and unobserved heterogeneity which is specified semi-nonparametrically. The paper is inspired by a tradition of structural dynamic retirement models (e.g. Rust and Phelan (1997), van der Klaauw and Wolpin (2008), Nardi, French, and Jones (2010), French and Jones (2011), and Haan and Prowse (2011)), but extends the existing literature in three different ways. First, I take more seriously the dual causality between health and employment. Second, I quantify the implications of health risks for both a household's expected consumption path and wealth accumulation. Third, I perform two counterfactual policy experiments: the first one changes pension benefits of early retirees and the second one introduces a saving subsidy encouraging precautionary savings. My results point to a trade-off between the hedging of health risks and an employee's incentive to remain in the labor force (?). Health-related poverty can be reduced at lower costs by increasing pension benefits than by a saving subsidy (?).

DPDC models provide an excellent framework for the estimation of life-cycle models. Under the assumption of revealed preferences, microdata can be used to estimate parameters characterizing the preferences and beliefs of forward looking individuals. Starting with Wolpin (1984), ... a literature on structural life-cycle models has evolved that applies increasingly complex models (see ... for an overview of the literature). Unlike reduced form approaches being often used for ex-post evaluations of public policy interventions, the big advantage of structural models lies in the estimation of parameters with economic meaning and the possiblity to perform ex-ante counterfactual policy experiments. However, these advantages come at a cost. In particular, estimating these kinds of models typically requires solving a dynamic programming problem that is nested in the estimation criterion. If the state space is large and if unobserved heterogeneity is allowed for, computation can be burdensome. This paper resorts to an estimation approach which has been proposed by Arcidiacono and Jones (2003) for the estimation of finite mixture models with time constant unobserved heterogeneity. They show that additive separability can be reintroduced to the log-likelihood function through an EM algorithm allowing one to estimate the parameters of the model sequentially during each maximization step (see e.g. Arcidiacono (2004,2007) for other applications).

Previous studies have used structural models to investigate the link between health and the economic situation of households. For example, Bound, Schoenbaum, Stinebrickner, and Waidmann (1999) and Disney, Emmerson, and Wakefield (2006) show that older workers being in good health are more likely to be employed, and Blau and Gilleskie (2008) estimate that bad health halves the employment probability of older employees who have health insurance. A few studies have modelled wealth accumulation within the framework of a life-cycle model. Rust and Phelan (1997) and van der Klaauw and Wolpin (2008) look at the effects of employment on wealth accumulation, Nardi, French, and Jones (2010) use a similar model to show that health costs can explain a large share of households' saving behavior over the life-cycle in the US, and French and Jones (2011) analyze the effects of life expectancy on optimal saving behavior of retirees. Finally, Haan and Prowse (2011) use a life-cycle model to estimate the effects of an exogenous increase in life expectancy on employment, retirement behavior and savings in Germany.

Structural life-cycle models usually assume a one-way relationship between health and employment running from health to employment. This assumption not only contradicts the theoretical literature where health often has been modelled as an endogenous variable (e.g. Grossman (1972), Willis and Rosen (1979)), it is also at odds with empirical findings showing that unemployment can have detrimental effects on both mental and physical health (Clark and Oswald (1994), Morris, Cook, and Sharper (1994), Virtanen, Vahtera, Kivimaki, Liukkonen, Virtanen, and Ferrie (2005), Böckerman and Ilmakunnas (2009)). Since my research question adresses the effects of health risks and since forward looking households may take into account the correlation between health and labor market risks when making their decisions, I have to take the dual causality seriously. Haan and Myck (2009) propose an approach that models health and employment risks jointly in a model with state dependencies while allowing unobserved heterogeneity to affect both processes. I resort to this approach when setting up the transition density functions for health and employment.

Average pension benefits of early retirees in Germany have declined nominally from 738 EUR to 647 EUR between 2000 and 2008, and each year around 160,000 new early retirees are registered at the German statutory pension insurance scheme (DRV 2009a). Given that pension benefits are the only income source of every other early retiree and that individuals who are in bad health usually cannot compensate reductions in the level of pension benefits by delaying retirement, there is a serious concern regarding old age poverty. Quantifying the implications of health risks for both a household's expected consumption path and wealth accumulation provides important information about health-related poverty risks in the population. Counterfactual policy experiments can give insights about the options available to policy makers who aim at raising welfare of risk averse households.

The paper is structured as follows. After presenting the data and some descriptive statistics, I outline the institutional framework in Germany. Then, I proceed by describing the life-cycle model and the estimation approach. Subsequently, I discuss the results, present two counterfactual policy experiments, and check the sensitivity of my estimates. A final section summarizes the findings and concludes with a discussion about the policy implications.

2 Model and specification

Basic ideas: The model assumes that individuals maximize expected life-time utility by making two decisions in each period of time. First, they make a discretized saving decision by choosing the saving rate. Second, they decide whether they stay in the labor force or whether they go into retirement. If they stay in the labor force, the employment status is modelled jointly with the health status as a stochastic process. Individuals have rational expectations and face a dynamic programming problem with a finite horizon. They take into account the correlation of future labor market and health risks when making their decisions. Wages are estimated within the model and individuals face a budget constraint. Pension benefits are a deterministic function of an individual's employment and wage history. After retirement, individuals are assumed to dissave the actuarially fair annuity value of their accumulated wealth. Unobserved heterogeneity is accounted for semi-nonparametrically by assuming that there is a finite number of types. The model is set up at the individual level. Thus, a sample of single household is most suitable for estimating the model because couple households would require strong assumptions regarding the partner's behavior.

I specify a DPDC model of individuals' early retirement and saving decision. All individuals are finitely lived and die not later than period T which is set to be 100. Discrete time is indexed by t, and there is a number of N households being indexed by n. Each individual n receives a utility flow $U(s_{nt}, c_{nt})$ in period t where s_{nt} is a vector of state variables, and c_{nt} is a vector of choice variables that indicate whether an individual retires or stays in the labor force and what share of net income is saved. Note that the saving decision is discretized. Every period t an individual observes the state variables s_{nt} and makes the decision c_{nt} that maximizes expected life-time utility

$$E\left\{\sum_{j=0}^{T-t} f_{nt+j}\beta^j U(s_{nt+j}, c_{nt+j})\right\} \tag{1}$$

where $\beta \in (0,1)$ is the time discount factor and f_{nt+j} is the survival probability of the individual for period t+j given survival until period t. Life expectancy can be a deterministic function of the state variables. I estimate the survival probabilities conditional on the individual's health status. Thus, individuals who are in bad health take into account a lower life expectancy when making their decisions.

The individuals' beliefs about the future states are captured by a Markov transition density function $q(s_{nt+1}|s_{nt}, c_{nt})$. Let $V(s_{nt})$ be the value function of the individual's dynamic programming problem. Applying Bellman's principle of optimality, the value function can be represented as

$$V(s_{nt}) = \max_{c_{nt} \in D(s_{nt})} \left\{ U(s_{nt}, c_{nt}) + f_{nt+j}\beta \int V(s_{nt+1}, c_{nt+1}) q(s_{nt+1}|s_{nt}, c_{nt}) ds_{nt+1} \right\} \quad (2)$$

where $D(s_{nt})$ is the choice set available to individual n in period t. Only individuals being eligible for early retirement (bad health or age > 60) can make the retirement decision. Other individuals make only a saving decision.

2.1 State variables and budget constraint

Individuals are facing uncertainty about their future health and the employment status. Following Haan and Myck (2009), health and labor market risks are modelled as a joint stochastic process taking into account the interdependence between health and employment status.

$$Prob(h_{nt} = 1) = \Lambda(\pi_0 + \pi_1 h_{nt-1} + \pi_2 e_{nt-1} + \mu_n) \quad (3)$$

$$Prob(e_{nt} = 1) = \Lambda(\zeta_0 + \zeta_1 h_{nt-1} + \zeta_2 e_{nt-1} + \nu_n) \quad (4)$$

where $\Lambda(\cdot)$ is the logistic distribution function, h_{nt} indicates good health and e_{nt} indicates employment. Time-constant unobserved heterogeneity is captured by μ_n and ν_n. The parameters of the health and employment equation are denoted as $\theta_h = (\pi_0, \pi_1, \pi_2, \mu_n)$ and $\theta_e = (\zeta_0, \zeta_1, \zeta_2, \nu_n)$. Note that the retirement and saving decision is made given expectations about future health and employment risks. Bad health raises presumably the risk of unemployment which in turn affects labor income. Thus, bad health involves three different dimensions: first it raises the likelihood of unemployment, second it opens up the option of early retirement for individuals aged below 63, and third it reduces life expectancy.

The individuals' gross labor income is modelled by a Mincer type equation:

$$\log(w_{nt}) = \psi_0 + \psi_1 \log(educ_n) + \psi_2 ex_{nt} + \psi_3 ex_{nt}^2 + \omega_n + \eta_{nt} \quad (5)$$

where w_{nt} is gross labor income, $educ_n$ is years of schooling, ex_{nt} is work experience which depends on the individual's employment history, ω_n is unobserved heterogeneity, and η_{nt} is i.i.d. $N(0, \sigma_\eta)$. Note that selection into the labor market is captured by the correlation of ν_n and ω_n. The vector containing the parameters of the wage equation is denoted by $\theta_w = (\psi_0, \psi_1, \psi_2, \psi_3, \omega_n)$.

Period t's consumption is constrained by the household's budget constraint:

$$\begin{aligned} y_{nt}(s_{nt}, c_{nt}) &= TT_t\left(s_{nt}, c_{nt}, nl_{nt}, w_{nt}, pb_{nt}\right) \\ W_{nt+1} &= (1 + r_t)\left(W_{nt} + b_{nt} y_{nt}(s_{nt}, c_{nt})\right) \\ W_{nt} &\geq 0 \end{aligned} \tag{6}$$

where $y_{nt}(s_{nt}, c_{nt})$ is net income, $TT_t(\cdot)$ is a function applying the rules and regulations of the German tax and transfer system, nl_{nt} is non-labor income which is assumed to be exogenous, and pb_{nt} is pension benefits. W_{nt} is period t's wealth, r_t is the real interest rate, and b_{nt} is individual n's saving rate (choice). Following Haan and Prowse (2011), I assume that retirees dissave the actuarially fair annuity value. This considerably simplifies estimating the model while a detailled modelling of the retirees' saving decisions is not relevant for my research question.

Note that the model contains the following state variables $s_{nt} = (h_{nt}, e_{nt}, w_{nt}, W_{nt})$. Since only h_{nt}, e_{nt}, and w_{nt} are stochastic, the transition density function $q(s_{nt+1}|s_{nt}, c_{nt})$ refers only to these three variables.

2.2 Utility and choice probabilities

The individuals have preferences about consumption and leisure time. The preferences are represented by the following time separable random utility model:

$$U(s_{nt}, c_{nt}) = \frac{1}{\alpha_{1n}}((1 - b_{nt}) y_{nt}(s_{nt}, c_{it}))^{\alpha_{1n}} + \alpha_{2n} l(s_{nt}, c_{nt}) + \epsilon_{nt}(c_{nt}) \tag{7}$$

where $\epsilon_{nt}(c_{nt})$ is an i.i.d. error term that follows a type 1 extreme value distribution. Thus, the model follows the framework of Rust (1987,1994) and Rust and Phelan (1997). $y(s_{nt}, c_{nt})$ is net income, $l(s_{nt}, c_{nt})$ is leisure time, and b_{nt} is the saving decision (saving rate) of the individual. Note that both period t's net income and leisure time depend on the state and decision in period t. The vector containing the parameters of the utility function is denoted by $\theta_U = (\alpha_{1n}, \alpha_{2n})$.

Given the finite horizon of the optimization problem, the expected value function for period T is given by

$$v(s_{nT}, c_{nT}) = u(s_{nT}, c_{nT}) \tag{8}$$

and, as has been noted by Rust(1987), it follows from the type 1 extreme value distribution of $\epsilon_{nt}(c_{nt})$ that for all other periods the expected value function is defined recursively as

$$\begin{aligned} v(s_{nt}, c_{nt}) =& u(s_{nT}, c_{nT}) \\ &+ f_{nt+1}\beta \int \left\{ \log \left[\sum_{c_{nt} \in D(s_{nt})} \exp\left(v(s_{nt}, c_{nt})\right) \right] \right\} q(s_{nt+1}|s_{nt}, c_{nt}) ds_{nt+1} \end{aligned} \tag{9}$$

Rust (1987) shows that under the assumtpions of additive separability of the utility function and conditional independence the conditional choice probabilities have the following closed form solution:

$$Prob(c_{nt}|s_{nt}) = \frac{exp(v(s_{nt}, c_{nt}))}{\sum_{j \in D(s_{nt})} exp(v(s_{nt}, j))} \tag{10}$$

The model can be solved recursively by substituting the expected value functions into the conditional choice probabilities. Interpolation methods can be used to approximate the value function in order to reduce computation time (Keane and Wolpin (1994)).

2.3 Unobserved heterogeneity and initial condition

Following Heckman and Singer (1984) and Keane and Wolpin (1997), unobserved heterogeneity is accounted for through a semi-nonparametric approach allowing for a finite mixture of types $m \in 1, ..., M$ where each comprises a fixed proportion of the population. The probability that individual n is of type m is modelled conditionally on time-constant characteristics and the initial values of the state variables:

$$\pi_{mn} = \frac{exp(\gamma_m z_n)}{1 + \sum_{l=1}^{M-1} exp(\gamma_l z_n)}, \ for \ m = 1, ..., M-1 \tag{11}$$

where z_n contains time-constant characteristics and the initial values of the state variables. γ_M is normalized to zero and $\sum_{m=1}^{M} \pi_m = 1$. It follows that the parameters capturing unobserved heterogeneity $(\mu_n, \nu_n, \tau_n, \alpha_{1n}, \alpha_{2n}) = (\mu_m, \nu_m, \tau_m, \alpha_{1m}, \alpha_{2m})$, m being individual n's unobserved type.

2.4 Estimation procedure

The log-likelihood of the sample is given by

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \pi_m(\gamma_m) \prod_{t=1}^{T} L(c_{nt}|\theta_U, \theta_h, \theta_e, \theta_w) L(h_{nt}, e_{nt}|\theta_h, \theta_e) L(w_{nt}|\theta_w) \tag{12}$$

where $L(c_{nt}|\theta_U, \theta_h, \theta_e, \theta_w)$ is the likelihood contribution of the observed decision c_{nt} of individual n in period t. The likelihood contributions of the health, labor, and income transitions are given by $q(s_{nt}|s_{nt-1}, c_{nt-1}) = L(h_{nt}, e_{nt}|\theta_h, \theta_e)L(w_{nt}|\theta_w)$. The log-likelihood is not additively separable such that a two-step estimation is not possible. A direct maximization with respect to all parameters appears to be computationally very expensive, if not numerically infeasible. Arcidiacono and Jones (2003) have proposed an iterative estimator that facilitates estimation substantially. The Expectation-Maximization (EM) algorithm reintroduces additive separability of the log-likelihood at the maximization step. It follows from Bayes rule that the conditional probability Π_{mn} of individual n of being of type m given the observed choices and the parameters $\theta_U, \theta_h, \theta_e, \theta_w$, and γ_m can be written as

$$\Pi_{mn} = \frac{\pi_m(\gamma_m) \prod_{t=1}^{T} L(c_{nt}|\theta_U, \theta_h, \theta_e, \theta_w)L(h_{nt}, e_{nt}|\theta_h, \theta_e)L(w_{nt}|\theta_w)}{\sum_{m=1}^{M} \pi_m(\gamma_m) \prod_{t=1}^{T} L(c_{nt}|\theta_U, \theta_h, \theta_e, \theta_w)L(h_{nt}, e_{nt}|\theta_h, \theta_e)L(w_{nt}|\theta_w)} \tag{13}$$

Using the conditional probabilities, the following additively separable expected log-likelihood function can be derived:

$$\sum_{n=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} \Pi_{mn} \left\{\log(L(c_{nt}|\theta_U, \theta_h, \theta_e, \theta_w)) + \log(L(h_{nt}, e_{nt}|\theta_h, \theta_e) + \log(L(w_{nt}|\theta_w)))\right\} \tag{14}$$

Starting with arbitrary initial values of the parameters, the maximum of the log-likelihood can be found by iteratively maximizing the expected log-likelihood 14, then using the estimates for $\theta_U, \theta_h, \theta_e$,and θ_w to get estimates for γ_m by maximizing 12, and finally using the estimated parameters to update the conditional probablities. Using the updated conditional probabilities the expected log-likelihood is maximized again. Iterating on these steps until convergence yields the maximum of the log-likelihood (see Bolyes (1987) and Wu (1987) for formal proofs). Note that the additive separability of 14 allows stepwise maximization of the expected log-likelihood.

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