Review of Economic Studies (1999) **66**, 395–421 0034-6527/99/00180395$02.00

Uncertain Medical Expenses and Precautionary Saving Near the End of the Life Cycle

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First version received October 1993; *final version accepted May* 1998 (*Eds.*)

This paper introduces a dynamic, structural model of household consumption decisions in which elderly families consider the effects of uncertain future medical expenses when deciding current levels of consumption. The model with uncertain medical expenses implies a potentially important role for precautionary saving incentives to explain slow rates of dissaving among elderly Americans during retirement. Rather than just simulating the stochastic dynamic model, preference parameters are estimated using panel data on health, wealth and expenditures for retired families. The health uncertainty model predicts consumption levels closer to observed expenditures than a life cycle model with uncertain longevity. However, elderly families typically dissave their financial assets more slowly than even the baseline health uncertainty model predicts is optimal.

I. INTRODUCTION

The life-cycle model of consumption, originally proposed by Modigliani and Brumberg (1954) and Ando and Modigliani (1963), is the dominant framework in economics for analysing consumption, saving, and wealth accumulation. One implication of the simple life-cycle hypothesis is that a retired household should divide its lifetime wealth by the number of years it expects to live and spend that amount each year.[1] Empirical research, however, finds saving behaviour that is inconsistent with this simple life-cycle implication. According to early studies, the elderly engage in no dissaving, but instead continue to amass wealth as they grow older (White (1977), Mirer (1979), Danziger *et al.* (1982, 1983)). More recent articles report less dramatic conclusions: on average, wealth increases during the first few years of retirement and then decreases with age, although too slowly to be consistent with the simple life cycle model (King and Dicks-Mireaux (1982), Diamond and Hausman (1984), Hamermesh (1984), Hurd (1987)). This underspending puzzle can be explained, at least in part, by modelling sources of uncertainty confronting the elderly.

In this paper I propose a dynamic, structural model of household consumption decisions in which elderly families consider the impact of uncertain future medical expenses when choosing their current levels of consumption. Uncertainty regarding future health care expenses, including those incurred during possible nursing home residences, effectively introduces random shocks to the pension incomes of retired households in the model. These random shocks provide the incentive for the elderly to engage in precautionary behaviour with respect to current consumption. That is, households optimally maintain additional financial wealth to offset potentially large future out-of-pocket medical

1. This implication holds strictly only when the household discounts the future at a rate equal to the real interest rate and each agent knows its horizon with certainty. If the rate of time preference exceeds the real interest rate, the family's consumption should decrease with age.

expenses in the health uncertainty model.[2,3] By ignoring sources of uncertainty, the standard life-cycle model misses precautionary motives for household saving and, therefore, overpredicts household consumption expenditures if such motives are important.

Even in the presence of Medicare and private health insurance, out-of-pocket expenditures for health care represent an important source of risk to the elderly's wealth holdings. My calculations from the National Medical Care Expenditure Survey indicate that nearly 10% of elderly households spend a fifth or more of their incomes on out-of-pocket medical expenses. Furthermore, these figures neglect what perhaps is the most important contributor to health care costs—nursing home expenses. The likelihood that a typical sixty-five year old person enters a nursing home during her lifetime is 43%. Once admitted, the average stay in a long-term care facility exceeds one year. Because nursing home costs are virtually uninsured, admission to a long-term care facility can quickly deplete one's financial wealth. In their examination of IRS tax files, Feenberg and Skinner (1994) find that 2 or 3% of elderly families incur medical expenses exceeding 40% of their adjusted gross incomes.

Previous researchers have examined the potential for uncertain longevity to explain the slow rate of dissaving evidenced among elderly Americans. Davies (1981), Skinner (1985), and Engen (1993) report that modelling lifespan uncertainty helps to explain households' consumption decisions. My health uncertainty model, therefore, also includes uncertain longevity. However, Davies (1981) concludes that elderly Americans spend their financial assets much more slowly than is optimal under a life-cycle model that includes only uncertain lifespans.[4] Indeed, the results I present in this paper confirm his conclusion and reveal that health uncertainty provides another important precautionary motive for consumption and saving decisions.

My analysis builds primarily on previous research by Kotlikoff (1988) and Hubbard, Skinner and Zeldes (1994, 1995), in which aspects of health uncertainty are incorporated into life-cycle consumption models. Kotlikoff (1988) examines the implications of different financing mechanisms for random health expenditures for macroeconomic saving rates with his model, largely abstracting the distribution of medical expenses observed among families in the U.S. In their simulation papers, Hubbard, Skinner and Zeldes build a life-cycle model that incorporates uncertainty regarding annual earnings, medical expenses and longevity to explain the distribution of wealth holdings in the U.S. (their 1994 paper) and to study the consequences of a resource-tested Medicaid programme for saving decisions by low- and middle-income families (their 1995 paper). These authors simulate their models for a given specification of household preferences, whereas I actually estimate preference parameters under alternative model specifications and compare predictions from the estimated models to actual household consumption data. My methodology, therefore, naturally allows alternative models to be compared using statistical criteria to gauge the accuracy of their predictions relative to the data.

2. It is well known that if "prudent" households do not know their future incomes with certainty, then they will reduce their current consumption levels to self-insure against possible low draws. Prudence is the term used by Kimball (1990) to describe utility functions that have a positive third derivative. Building on work by Leland (1968) and Sandmo (1970), Kimball shows that such a condition on the utility function is sufficient to imply precautionary behaviour by optimizing agents who face income uncertainty.

3. The most important feature of the model investigated in this paper is uncertainty about future out-of-pocket medical expenses, but I use the term "health uncertainty model" throughout the paper for brevity. The primary role health status plays is to forecast future out-of-pocket medical expenses, but I also investigate utility functions that depend on health status explicitly.

4. Neither Skinner (1985) nor Engen (1993) examines dissaving during retirement.

Ample econometric literature exists about estimating structural dynamic models with discrete choice variables.[5] However, along with contemporaneous work by Lillard and Weiss (1996) and Gourinchas and Parker (1997), this paper joins Hurd (1989) by estimating a continuous control, stochastic dynamic programming model. My statistical method is to estimate the coefficient of relative risk aversion by choosing values for which the actual levels of consumption observed for a sample of elderly retired families are closest to the consumption levels predicted by the health-uncertainty model. In addition, I estimate preferences under a life-cycle model with uncertain longevity. I use three years of data for two separate samples (elderly couples and elderly persons living alone) from the Panel Study of Income Dynamics (PSID) to estimate many alternative model specifications.

From a policy standpoint, it is important to understand why retirees dissave slowly. If the elderly save for precautionary reasons due to medical expense risk, then changes in government health insurance programmes influence their saving decisions by increasing or decreasing exposures to such risk. Identifying a model better capable of explaining the consumption decisions of elderly Americans and estimating parameters for that segment of the population allows a better understanding of the effects of reforming many policies, such as Medicare and Medicaid (which finances much long term care in the U.S.).

The paper is organized as follows. Section II provides detail about how the health-uncertainty model is specified. Section III briefly describes numerous sources of data used to parameterize the probability distributions for randon variables in the model (details appear in the Appendix). In Section IV, I derive a procedure to estimate the preference parameters for two samples of elderly families from the PSID and discuss several estimation issues. Estimation results are presented in Section V and Section VI summarizes the paper's contributions.

II. A LIFE-CYCLE MODEL WITH UNCERTAIN OUT-OF-POCKET MEDICAL EXPENSES

The consumption model proposed in this paper differs from the standard life-cycle model in two primary respects. First, households incur out-of-pocket medical expenses randomly each year. Second, each household is uncertain about its longevity (it does not know its date of death exactly). I estimate the probability distributions for these random variables using publicly available data sources and incorporate them in the health-uncertainty model. Thus, the model allows the role of precautionary saving during retirement to be investigated under parameterizations of medical expense and lifespan risks consistent with available micro data.

In the health uncertainty model, each household finds itself in good, fair, or poor health each year. Denote by $h_t = 1, 2$, or 3, the discrete health status of the household in year t. The household knows h_t at the beginning of period t in this model, but future health outcomes are uncertain and household health status follows a Markov process. Transition probabilities from this year's health status to next year's depend on the family's current health status and other household characteristics.[6] Each family is assumed to know the probability distribution for next year's health outcome conditional on this year's health status.

5. Eckstein and Wolpin (1989) provide a thorough survey of recent work.

6. Section 3 of Appendix B describes how I use health data for a sample of elderly couples and single persons from the PSID to estimate parameters of the Markov health model. Among couples, h_t measures the household's health status, not just the health of the household head.

Each period a family incurs out-of-pocket medical expenses, m_t, drawn from a distribution whose mean depends on current health status, h_t, the age of the head of the family, i_t, and other household characteristics, X_t. Health care expenses are not another consumption good subject to household choice in this model. Rather, I follow Kotlikoff (1988) and Hubbard, Skinner and Zeldes (1994, 1995) by assuming that medical expenses cover required health care and are incurred exogenously each year. Realized out-of-pocket medical expenses (in logs) are the sum of a deterministic function of observable characteristics (h_t, i_t and X_t) and an unpredictable element, denoted by ε_t. The disturbance term allows households with identical observable characteristics to incur different medical expenses. This model contains the intuitive implication that even if a family correctly guesses its health status next year, it cannot predict its out-of-pocket medical expenses with certainty.[7] Household data on out-of-pocket expenses show substantial variability even after controlling for observable household characteristics. As Section III and Appendix B describe, I use several data sources to parameterize the distribution of out-of-pocket medical expenses facing elderly Americans.

In an important simulation paper, Kotlikoff (1988) examines the consequences of health uncertainty for saving decisions under different financing schemes for health care. However, in his paper, random variables follow highly stylized probability distributions that are not based on empirical observation. Perhaps most importantly, Kotlikoff imposes the simplifying assumption that medical expenses are incurred independently over time. In concluding his paper, Kotlikoff (1988) suggests future researchers incorporate distribution functions for medical expenses estimated from micro data into the life-cycle framework, which I do explicitly in this paper. My model incorporates temporally dependent health outcomes and distributions of family medical expenses based on econometric analysis of household data.

According to the health uncertainty-model, families know the values of the nonstochastic variables, i_t and X_t, in all future periods. Each household knows m_t when deciding about c_t, but it does not know its future out-of-pocket medical expenses. The outcomes of the random variables, h_t and ε_t, are known at the beginning of period t, as well. Finally, the family is assumed to be able to evaluate distribution functions for $m_{t+1}, m_{t+2}, \ldots, m_L$, and, therefore, can rationally account for uncertainty about future medical expenses when deciding on current consumption expenditures.

A household's problem in period t, upon observing h_t, is to choose consumption in all periods, c_τ $\{\tau = t, t+1, \ldots, L\}$, to

$$\max \{v(h_t, c_t) + E_t[\textstyle\sum_{\tau=t+1}^{L} \beta^{(\tau-t)}(\prod_{j=t+1}^{\tau} s_{j-1}^{j})v(h_\tau, c_\tau)]\}, \tag{1}$$

where β is the discount factor, L is the maximum attainable age (assumed to be 100 years) and s_j^{j+1} denotes the household's probability of surviving to age $j+1$, conditional on having lived to period j. As detailed below, utility each period, $v(h_t, c_t)$, depends on health status and consumption expenditures. If b denotes the time preference rate, then β equals $1/(1+b)$. Because the model assumes the household is uncertain about its lifespan, utility k periods in the future is effectively discounted by the product of β raised to the power k and the product of the next k conditional survival probabilities.[8]

7. Kotlikoff (1988) and Lillard and Weiss (1996), for example, assume that each health status outcome is associated with only one level of medical expenses. However, a household in good health overall may be involved in an accident or suffer some other injury that results in large medical expenses. On the other hand, a household seemingly in poor health may happen to be lucky, in terms of out-of-pocket expenses actually incurred this year.

8. Because households, not just individuals, are the decision units in my health uncertainty model, I compute appropriate survival probabilities for elderly couples using published age- and gender-specific mortality rates for individuals. This implies survival probabilities for couples exceed those for singles, at all ages, which means effective discount rates vary by family size, also. Naturally, effective discount rates vary by age because actuarial survival rates do.

Utility each period is assumed to depend on current health status and consumption excluding out-of-pocket medical expenses, as follows

$$v(h_t, c_t) = \delta(h_t)u(c_t), \tag{2}$$

where $\delta(h_t)$ is a function that decreases as health becomes more poor and takes values between zero and one; and $u(c_t)$ is a utility function exhibiting constant relative risk aversion (denoted γ). I follow Kotlikoff (1988) and Viscuzi and Evans (1990) by modelling the effect of health status on the utility of consumption as a multiplicative constant. $\delta(h_t)$ is a vector of parameters measuring the "disutility" of fair and poor health outcomes, relative to good health. I experimented with several specifications of $\delta(h_t)$, however, incorporating health-state-dependent utility turns out not to improve the health-uncertainty model's ability to fit PSID consumption data, nor does it significantly affect estimates of γ. Therefore, most of the results reported in this paper ignore health-state-dependent utility by setting all three elements (good, fair and poor health) of the disutility parameter equal to one.

In a given health state, household utility of consumption, $u(c_t)$, is represented by constant relative risk aversion, where γ denotes the coefficient of relative risk aversion. This functional form is popular in the literature because its positive third derivative implies precautionary behaviour on the part of rational agents who face uncertain future incomes. Papers in the life-cycle simulation literature typically define c_t as total family consumption, while most Euler equation estimation papers control for family size explicitly or model consumption per adult equivalent. I consider both definitions in the health-uncertainty and life cycle models estimated here, using adult equivalence scales estimated by Slesnick (1993).

In equation (1), expectations are taken with respect to the density function of h_t and the density function for medical expenses, m_t, conditional on health. That is, expected utility during any future period is the integral over the three possible health states and all possible medical expense draws for each health outcome.

Consumption expenditures and medical expenses are financed out of financial wealth each period. Each year wealth is augmented by accrued interest, at rate r, and nonstochastic income (social security and pension payments). Financial wealth (W_t) cannot be negative in the model and consumption is bounded (slightly) above zero in the model. If a family's medical expenses in period t are so large that consumption above the minimum level cannot be attained, the family receives $\underline{c} - (W_t - m_t)$ from the government.[9] Naturally, in this case, the family owns no assets to carry into period $t + 1$. Imposing such a stylized Medicaid programme for medically-needy simply rules out the possibility of a negative asset position after medical expenses are incurred.

Conceptually, my health-uncertainty model is the same as the retirement phase in the Hubbard, Skinner and Zeldes (1995) model. Both models incorporate household longevity and out-of-pocket medical expenses as exogenous, stochastic events and neither includes explicit bequest motives. Our papers focus on the contribution of precautionary saving motives to explain observed consumption behaviour. Hubbard, Skinner and Zeldes carefully model the pre-retirement phase of the life cycle, while I focus on the retirement period exclusively. Finally, my goal is to estimate the preferences under the health-uncertainty model for a sample of elderly households, while Hubbard, Skinner and Zeldes simulate their model's implications for a given set of parameter values. I explicitly compare the ability of the estimated health-uncertainty model to fit PSID consumption data

9. Most states set the maximum allowable resources for Medicaid eligibility at \$2000. I use this value for $\underline{c}$ in the model. Estimation results are not very sensitive to this parameter value.

relative to alternative life-cycle model specifications using statistical criteria, rather than presume the health-uncertainty model works better.

No closed-form solution exists for the optimal consumption plan $\{c_t, t = 1, 2, \ldots, L\}$ under the health-uncertainty model (see Zeldes (1989) and Deaton (1992) for excellent discussions). Optimal consumption (the control variable) instead is calculated for a large number of combinations of the state variables: the age of the householder (or the number of periods away from L), the health status of the family, and the household's wealth minus medical expenses (discretionary financial wealth). The approximated consumption function is a matrix in which the optimal value of c_t is computed for each possible combination of i_t, h_t and $W_t - m_t$. Therefore, the procedure is feasible only for discrete state variables. By definition, age and the health status of the household are discrete variables, but discretionary wealth is continuous. I make $W_t - m_t$ discrete by assuming arbitrary maximum and minimum values over which it is allowed to range and then dividing the range into a finite number of values. I settle on the grid specification through experimentation.

Appendix A describes numerical techniques to exploit the recursive nature of the dynamic programming problem to approximate optimal consumption plans. The intuition underlying the solution procedure is that a household surviving to period L has an easy decision to make: consume all remaining wealth. Knowing the period-L decision allows one to numerically integrate the expected value (at time $L-1$) of surviving to period L and, therefore, allows one to find the consumption decision that maximizes the period-$L-1$ value function. The same logic is carried back until the optimal consumption choice in the first period is computed for a large number of combinations of wealth and health. Taylor and Uhlig (1990) refer to the numerical solution algorithm as the Euler equation grid method, which is described further by Baxter, Crucini and Rouwenhorst (1990), as well as Appendix A.

III. CHARACTERIZING THE DISTRIBUTIONS OF THE RANDOM VARIABLES IN THE HEALTH-UNCERTAINTY MODEL

Before the health-uncertainty model can be solved for optimal consumption, I must parameterize the distributions for all random variables in the model: the household's future health status, its future out-of-pocket medical expenses, and the number of years it will remain alive. To accomplish this, I employ several sources of household and individual data. Appendix B describes the exact procedures and data used to estimate probability distributions needed to completely specify the health-uncertainty model. Here I simply introduce the data and methods used.

I construct a longitudinal database from the PSID to estimate a Markov model for household health transitions over time. By incorporating an estimated dynamic model of health outcomes (described in Section 3 of Appendix B), my health-uncertainty model captures two important characteristics of the data: the persistence of poor and good health states over time and the general deterioration of health that occurs as people age.

Section 1 of Appendix B explains how I estimate the distribution of out-of-pocket expenses for health care provided to elderly members living at home using data from the National Medical Care Expenditure Survey of 1977 (NMCES). The NMCES carefully catalogues annual expenses on health care (these are recorded as they occur during the survey year) and distinguishes between out-of-pocket expenditures and those paid for by Medicare and other third parties. Thus, NMCES data is most appropriate for my application. Several variables are used to explain the distribution of out-of-pocket medical expenses incurred for health care received by elderly persons living in the community: income, age, family size, retirement status, race and health status. A histogram of the least squares residuals is used to represent the distribution of the stochastic element of out-of-pocket medical expenses.

Because the NMCES data omits expenses incurred for health care received during periods of institutionalization, the regressions just mentioned ignore the impact of potential nursing home admissions on the distribution of out-of-pocket medical expenses. Expenses incurred during residences in intermediate care and skilled nursing facilities, however, represent a large, virtually uninsured risk to the wealth of elderly Americans. As Section 2 of Appendix B describes, results from two empirical studies allow me to parameterize the distribution of nursing home expenses across the elderly population. Cohen, Tell, and Wallack (1986) report age-specific probabilities of nursing home admissions for elderly persons. Liu and Manton (1984) estimate distribution of lengths of stay in long-term care facilities for admitted patients. After correcting the Liu and Manton results for censoring bias due to nursing home deaths and adjusting entry rates across poor and good health states, I combine results from the two papers to describe the probability density function for out-of-pocket medical expenses incurred for long-term care that elderly Americans face.

Including potential nursing home expenses in the distribution of out-of-pocket medical expenses is important, even though (by definition) none of the elderly PSID heads of household for whom the health uncertainty model is being estimated reside in a nursing home. As Kotlikoff (1988) explains, prudent forward-looking families might respond to the possibility of a nursing home admission in the future by reducing expenditures today. Every elderly person faces the possibility of requiring an expensive nursing home admission during their lives, though most will not actually experience one. Explicitly incorporating this risk implies a precautionary motive potentially capable of explaining some of the empirical reluctance to dissave financial wealth relative to standard life-cycle predictions.

Lifespan uncertainty is incorporated into the health-uncertainty model by estimating the probability that one or both members of a typical elderly couple survive to the following year, conditional on having survived to the current year.[10] This is done by "aging" a hypothetical cohort of couples through their retirement years and allowing the proper number of males and females to leave the cohort each year. The proper exit frequencies come from age- and gender-specific estimates of mortality tables for individuals published by the U.S. Department of Health and Human Services (1985). Implementing standard nonparametric survival analysis to the hypothetical cohort gives the correct age-specific mortality probabilities for elderly households. Published life tables provide relevant survival probabilities for the sample of single elderly persons.[11]

IV. ESTIMATING THE HEALTH-UNCERTAINTY MODEL BY MAXIMUM LIKELIHOOD

This section describes a novel approach to estimating the coefficient of relative risk aversion for the health-uncertainty and life-cycle models of consumption. I detail the econometric procedure, provide some motivation for the approach to estimation and relate the paper's methods to some other recent contributions to the literature.

10. Appropriately, I create new life tables for couples using published mortality rates for individuals.

11. Because I am unaware of appropriate estimates, I do not adjust the published actuarial mortality rates for differences in marital status or wealth.

My estimation procedure requires first using numerical methods to solve the health-uncertainty model for a given value of the coefficient of relative risk aversion (γ) by computing optimal consumption as a function of the model's state variables—household age, health and wealth (or, "cash on hand," in Deaton's (1992) terminology). I observe values of the state variables (age, health and wealth) for two samples of retired families in the Panel Study of Income Dynamics (PSID), so I can use the solution matrix from the health-uncertainty model to predict a consumption level for each household during each year of the panel data.[12] Denote by $c^p(a_{it}, h_{it}, W_{it}; \gamma)$ the level of consumption predicted for household i during year t according to the optimal decision under the health uncertainty model parameterized with a value of γ given the family's observed age, health and wealth. Predicted consumption is a function of the coefficient of relative risk aversion (γ) because the approximated consumption function depends on household preferences according to the health-uncertainty model.

In principle, effective household discount factors, which could depend on perceived mortality rates, subjective time preference, consumption equivalent scales or anticipated interest rate movements, also determine optimal consumption expenditure by age, health and wealth. I only have access to three years of panel data, which, in practice, turns out to be insufficient for accurately estimating effective discount factors in this context. Consequently, as described below, in this paper I examine the sensitivity of estimated risk aversion to alternative maintained assumptions about household discounting under both the health-uncertainty and life-cycle models of consumption.

A sample log-likelihood function for γ can be derived based on deviations between the natural log of consumption actually observed for a family, $\ln(c^a_{it})$, and the natural log of its predicted expenditure according to the health-uncertainty model and given its observed state vector. Three years of data are available for each family ($t = 1, 2, 3$) and the difference between actual and predicted log-consumption levels can be represented by a serially correlated, normally distributed error term

$$\begin{aligned} \ln(c^a_{it}) &= \ln(c^p(a_{it}, h_{it}, W_{it}; \gamma)) + \eta_{it}, \qquad t = 1, 2, 3, \\ \eta_i &= (\eta_{i1}, \eta_{i2}, \eta_{i3}) \sim \text{iid } N((0, 0, 0), \Omega), \end{aligned} \tag{3}$$

where Ω is a three-by-three covariance matrix to be estimated. For household i, the trivariate normal density function describes the likelihood of observing a vector of errors over the panel, $\eta_i = (\eta_{i1}, \eta_{i2}, \eta_{i3})$. Under the standard regularity conditions and as long as the error vector η_i is uncorrelated with the function $\ln(c^p(\cdot))$, maximizing the sample log-likelihood function with respect to the parameter γ produces consistent and asymptotically normal estimates.[13]

12. I solve the health-uncertainty and life-cycle models for three different income groups (nonasset income is the appropriate definition) and use the appropriate solutions to predict consumption levels for the sample households. It might be preferable to solve the models using each family's actual income process, but that increases the computational burden substantially.

13. A number of numerical techniques might have been employed to maximize the sample log-likelihood function with respect to the coefficient of relative risk aversion. Recall, the health-uncertainty model does not yield a closed-form solution for predicted consumption as a function of either the observable state variables or the model parameters. This makes it difficult to use analytical derivatives in an optimization algorithm for the likelihood function. Furthermore, preliminary results indicated the possibility of multiple local maxima for some particular model specifications. Therefore, the preference parameter, γ, is estimated using a grid search. Experimentation using a (Nelder and Mead) simplex algorithm under GQOPT closely replicated my estimation results, but took significantly longer than my grid search algorithm to converge. Finally, I truncated grid searches at $\gamma = 25{\cdot}00$, which binds the estimate under some life-cycle model specifications. Larger values of γ simply do not generate very different predictions for household expenditures because the numerical algorithm produces essentially the same approximation to the optimal expenditure function at such extreme parameter values.

Thus, the statistical criterion upon which estimates of γ are based in this paper come from adding a disturbance term to model-predicted consumption levels based on the optimal solution algorithm and observed information about age, assets and health for each family in the sample. At least two justifications exist for "adding an error term" to form the statistical criterion for estimation. First, as shown by MaCurdy (1985) and Altonji (1986), the existence of multiplicative preference shocks, unobserved by the econometrician, to a utility function exhibiting constant relative risk aversion results in an additive error term for optimally chosen log-consumption levels. In the context of the health-uncertainty model or the life-cycle model with uncertain longevity, multiplicative preference shocks could result from, for example, differences between perceived mortality rates among retirees and actuarial rates published in life tables; differences between actual adult equivalence scales for family consumption and estimated functions based on previous economic research (I use Slesnick (1993)); or, anticipated movements in real interest rates during the survey period. Second, total consumption levels are not directly observed in the PSID data I study in this paper. As described below and in detail in Appendix D, I impute total consumption expenditures from the set of information directly available from the PSID survey. Thus, random errors from the imputation procedure would result in additive disturbances to log consumption in the sample. To summarize, both of these justifications for random deviations between model-predicted consumption and that observed in the micro data reasonably supports the assumption that the errors to be uncorrelated with the optimal consumption function. In these cases, γ should be estimated consistently by this paper's methods.

While the statistical formulation for estimating γ in (3) allows a general time-series correlation structure in consumption-errors for each family under the health-uncertainty or life-cycle models, consistent estimation requires independence among errors across families. Thus, consistent estimates do not necessarily follow in the presence of aggregate shocks to consumption expenditures, such as those operating, for example, through unanticipated macroeconomic shocks to real interest rates during the sample period. Simultaneous consideration of random income realizations and random real interest rates poses too complex a problem for numerical analysis given current computational constraints (consult, for example, Ludvigson and Paxson (1997)). Thus, a limitation in this and virtually all other papers in the precautionary saving literature follows from abstracting from the effects of unanticipated movements in real interest rates on family consumption decisions in the presence of income risk.

The sample log-likelihood value provides a metric for measuring the distance between actual and predicted consumption levels in the data—the determinant of the covariance matrix of prediction errors.[14] Holding covariances constant, larger estimates for the error variance terms result in smaller log-likelihood values. Thus, models which predict consumption closer to observed levels on a household-by-household (and year-to-year) basis, yield smaller estimated error variances and obtain larger sample log-likelihood values. In comparing predictions from different model specifications in Section V below, I report both sample log-likelihood functions and estimated variances for the log-prediction errors under different model specifications.

14. The estimator does not depend critically on the prediction errors being normally distributed and, thus, could be relabeled quasi-maximum likelihood. Because maximizing the sample log-likelihood function is equivalent to minimizing the determinant of the covariance matrix, Ω, my estimation procedure is the same as Hurd's (1989) nonlinear GLS.

Nearly all previous papers in the large body of recent microeconomic research on consumption and saving fall into one of two disjoint sets. The first set comprises econometric papers in which the objective is to estimate structural preference parameters by directly examining Euler equations consistent with intertemporal optimization and considering their ability to explain variation in consumption growth rates among samples of families.[15] The second set comprises simulation papers in which the objective is to contrast behavioural implications from specific models of intertemporal optimization to benchmark models, taking preference parameters as given, rather than estimating them directly.[16] Thus, the former set of papers achieves its econometric goals without explicitly modelling the stochastic environment families face in their lives.[17] On the other hand, in the latter set, substantial effort is allocated to modelling "realistically" the economic environment facing families, but key preference parameters are imposed from "outside" the specific modelling environment. Furthermore, the simulation papers do not use statistical criteria for evaluating the predictive performance of alternative model specifications, as the econometric papers do.

A motivation for my approach is to bridge these two parallel strands in the existing consumption literature. It involves investigating "fully specified" structural models for retirement expenditure decisions based on intertemporal optimization under uncertainty, but also estimating preference parameters using microdata and evaluating alternative model specifications using statistical criteria. Estimation is particularly important for my application because none of Euler-equation estimation papers consider retired families exclusively, as I care to. Thus, to the extent the current generation of retirees in the U.S. exhibit different preferences, or attitudes toward risk, than Americans of "prime age," appropriate parameters cannot be extracted from the existing literature.

The empirical approach of this paper receives further motivation based on results from two very recent studies. Independently and based on different specific analyses, Carroll (1997) and Ludvigson and Paxson (1997) demonstrate how specification and approximation biases in linearized Euler equations severely damage their ability to produce consistent estimates of structural preference parameters from consumption models using micro data.[18] My approach substitutes an approximate numerical solution to the optimal consumption function from a well-defined dynamic programme (based on the exact Euler equation) for apparently biased Euler equations using log-linear consumption growth rates employed in many previous studies. The cost to my approach, relative to estimating linearized Euler equations, is that one must explicitly specify the stochastic environment facing households to derive the relevant intertemporal budget constraints and to numerically solve for optimal consumption rules.

In addition to Hurd (1989), two other recent contributions to the consumption literature implement estimation strategies similar to mine. First, Lillard and Weiss (1997) estimate parameters from a consumption model in which retired families optimally consider the impact of social security benefit rules for surviving spouses when making their spending decisions. By assuming a quadratic form for household utility, however, Lillard and

15. Browning and Lusardi (1996) identify 25 relevant papers in their survey of the literature. Deaton (1992) and Attanasio and Weber (1995) thoroughly discuss many econometric issues arising in the Euler equation studies.

16. Again, Deaton (1992) and Browning and Lusardi (1996) cite many simulation papers in their survey. Particularly useful examples appear in Zeldes (1989) and Hubbard, Skinner and Zeldes (1995).

17. As discussed by Browning and Lusardi (1996), essentially the same Euler equations arise from many different, and perhaps competing, stochastic specifications of underlying life-cycle models.

18. Virtually all papers employing micro data estimate linear approximations to the exact Euler equations consistent with intertemporal optimization under uncertainty.

Weiss (1997) ignore precautionary saving during retirement, which, given the presence of uncertain medical expenses, provides the motivation for this paper. Second, Gourinchas and Parker (1997) use simulation methods to estimate preference parameters for families during the "prime-age" phase of their life cycles. Gourinchas and Parker (1997) model intertemporal allocations between ages 25 and 65 years, but "turn off" the model during retirement to avoid the relevant issues directly faced in this paper. These four papers take the same general empirical approach to studying life cycle consumption allocations, but focus on different specific behavioural motivations for saving during different life-cycle phases and, thus, complement each other well.

To summarize at an intuitive level, the health-uncertainty and life-cycle models investigated in this paper imply different nonlinear functions relating the state variables (age, wealth and health) to optimal consumption levels during retirement. Furthermore, each model specification implies a nonlinear function relating state and control variables that depends on the preference parameter, γ. Thus, my empirical strategy involves selecting the value of γ for each model specification providing the best fit to the empirical function relating age, health and wealth to levels of expenditure among two samples of retirees in the PSID. Identification of γ comes from sample variation in age, health and wealth and the (implicit) functional form of the optimal consumption policy rule derived from the stochastic life-cycle model. Because the empirical approach taken in this paper derives from the simulation branch of the consumption literature, it should be mentioned that I require the same set of ancillary assumptions to estimate the coefficient of relative risk aversion consistently. That is, all other restrictive elements built into the health-uncertainty model (deterministic real interest rate, no bequest motive, rational expectations *etc.*) play a role in estimation. In presenting the econometric results below, I analyse the sensitivity of estimates for γ with respect to many other modelling elements.

As introduced above, estimation requires micro data on financial wealth, nonasset income, consumption, health status, and the age of the household head. I construct a database for two samples of retired, elderly families from the PSID, observed during the years 1984 through 1986. The first sample contains elderly couples living together (both retired); the second contains elderly, retired individuals living alone. All families are white and none contain individuals other than the respondent and his spouse. The reason for choosing homogeneous samples is that allowing heterogeneous preferences based on additional observed characteristics in the health-uncertainty model increases computational complexity (by increasing the dimension of the state vector). A natural alternative to modelling preference-heterogeneity is to select a sample of households most likely to exhibit similar preferences toward the timing of consumption and similar attitudes toward risk. I compare estimation results across the two samples of elderly couples and single individuals.

Total consumption expenditures are not directly available from the PSID, so I modify Skinner's (1987) procedure for imputing this variable to households in the sample. Skinner's idea involves using information available in the PSID (food consumption at and away from home, house value or rent, and utility expenditures) to estimate total consumption for each family based on regressions using the same variables and measured total consumption for families in the 1982–83 Consumer Expenditure Survey. In this paper, I actually undertake the empirical analysis using three different imputation procedures for PSID consumption, all described in Appendix D. First, I follow Skinner's procedure exactly; second, I modify his procedure to allow explicitly for flexible Engel-curves for food and other consumption items; third, I apply estimates from Attanasio and Weber's (1995) structural (AIDS) demand system for food and nonfood expenditures to my PSID sample. For the remainder of this paper, "actual" or "observed" consumption refers to the imputed values from the flexible-Engel-curve modification to Skinner's procedure. As discussed in part B of Section 5 below, my estimation results are quite robust across these three different imputation procedures.

Predicted consumption from the life-cycle model is attained by "turning off" health uncertainty in the model of Section II. That is, what I refer to as the life-cycle model in this paper simply is the health-uncertainty model with future medical expenses equal to their mean values with probability one in all time periods. The only state variables for the life-cycle model are wealth and age for each household. Note, all life cycle model specifications examined in this paper include uncertain household longevity, unless specifically mentioned below.

V. ESTIMATES FROM HEALTH-UNCERTAINTY AND LIFE-CYCLE CONSUMPTION MODELS

This section reports maximum likelihood estimates of the coefficient of relative risk aversion (γ) under several health-uncertainty and life-cycle model specifications. The relative success of the two consumption models for predicting actual consumption levels among retired elderly families in my PSID sample is determined by comparing their maximized sample log-likelihood values and summary statistics for actual and predicted levels of (log) annual consumption expenditures. First, I discuss estimates from baseline model specifications. Second, I examine the sensitivity of estimation results to several alternative model specifications. Third, I present results from a broad specification search. Across all specifications investigated, the health-uncertainty model outperforms the life-cycle model for predicting consumption levels during retirement.

A. *Estimates from baseline model specifications*

First, I report estimation results for baseline specifications of health-uncertainty and life-cycle models, which maintain parameter values similar to those appearing in the related simulation literature, such as Kotlikoff (1988) and Hubbard, Skinner and Zeldes (1995). Uncertain longevity is parameterized using published life table estimates for age- and sex-specific mortality rates; the real interest rate is 3%; time preference is 0%; and, utility from annual consumption expenditures *per adult equivalent family member* takes the constant relative risk aversion form (health-state-dependent utility is ignored in the baseline case). Thus, the only important departure relative to the simulation literature is that the latter imposes a CRRA utility function for *total family* consumption expenditures, not spending per adult equivalent member. In Section B below, I examine the sensitivity of estimation results to alternative specifications for health-uncertainty and life-cycle models.

Estimates for coefficients of relative risk aversion, sample log-likelihoods values, and predicted consumption levels from baseline health-uncertainty and life-cycle model specifications appear in Table 1. Panel A contains results from the sample of retired, elderly couples in the PSID; panel B shows results from the sample of retired, elderly individuals living alone. Across both subsamples, baseline health-uncertainty specifications predict consumption levels closer to actual values than life-cycle models do. Among PSID elderly couples, Table 1 indicates larger log-likelihood values for health-uncertainty models (+3·94 vs. −12·70), closer predicted to actual consumption levels (\$18,247 vs. \$19,225) on average, and smaller average squared deviations of predicted from actual consumption levels

TABLE 1

CRRA *estimates and consumption predictions from baseline health-uncertainty and life-cycle model specifications*

A. PSID elderly couples ($N = 142$)	Health-uncertainty model	Life-cycle model
γ	7·00	24·00
Standard error	(1·89)	(3·32)
LL_N	3·94	−12·70
Avg. Actual consumption	15,115	—
Avg. Predicted consumption	18,247	19,225
Avg. η^2	0·134	0·152

B. PSID elderly singles ($N = 144$)	Health-uncertainty model	Life-cycle model
γ	6·25	25·00
Standard error	(1·03)	(2·12)
LL_N	−186·64	−192·13
Avg. Actual consumption	8,999	—
Avg. Predicted consumption	8,597	8,604
Avg. η^2	0·230	0·243

Notes: As described in the text, PSID consumption expenditures have been imputed using the CEX-based, flexible-Engel-curve procedure described in Appendix D.

Baseline model specifications include: adult equivalent scales for household consumption; uncertain longevity parameterized using published life table estimates for mortality probabilities; 0% time preference rate; 3% real interest rate; and, no health-state-dependence in the utility derived from consumption expenditures.

Standard errors are estimated by evaluating the inverse second derivative from a high-order polynomial approximation to the sample log-likelihood function at the estimated parameter value.

η^2 is the squared difference between the natural log of actual consumption expenditures imputed to PSID families and annual consumption levels predicted according to health uncertainty or life cycle models.

Because log-likelihood functions are extremely flat, grid searches have been truncated at $\gamma = 25{\cdot}00$ under life cycle model specifications.

(0·134 vs. 0·152). Among PSID sample of elderly who live alone, the best baseline health-uncertainty model specifications yield larger log-likelihood values (−186·64 vs. −192·13) and closer consumption predictions (measured as average squared deviations from actual consumption; 0·230 vs. 0·243) than the life-cycle model. However, on average, the health-uncertainty model with $\gamma = 6{\cdot}25$ and the life-cycle model with $\gamma = 25{\cdot}00$ predict (nearly) identical levels of consumption ($8597 vs. $8604).

Table 2 shows how the health-uncertainty model yields closer predictions for actual consumption levels than the life-cycle model for nearly all observable characteristics among the sample of elderly couples in the PSID.[19] According to Table 2, the baseline health-uncertainty model overpredicts actual consumption levels among PSID elderly couples by about 13%, on average. This average discrepancy is small relative to the average 19% overprediction coming from the baseline life-cycle model. Average squared deviations between log-actual and log-predicted consumption levels measure the variance of prediction errors or average "distance" between actual and predicted consumption from

19. To conserve space, I report some results, such as those in Tables 2 and 3, only for the PSID couples' sample when they are qualitatively similar among the sample elderly individuals who live alone. Also, I only discuss results pertaining to 1985 consumption levels in the PSID data because they represent the same patterns as data from the other two years, 1984 and 1986.

TABLE 2

Comparing deviations from actual consumption levels for predicted values based on estimated baseline health-uncertainty and life-cycle models

1985 Consumption levels among sample of PSID elderly couples ($N = 142$)				
Household category	Health-uncertainty model		Life-cycle model	
	η	η^2	η	η^2
Total sample	−0·13	0·13	−0·19	0·15
Asset bracket				
< 5k	0·07	0·06	0·02	0·08
5–15 k	0·01	0·07	−0·09	0·09
15–30 k	−0·18	0·15	−0·27	0·18
30–60 k	−0·16	0·09	−0·23	0·12
60–90 k	−0·24	0·14	−0·29	0·15
90–120 k	−0·17	0·21	−0·21	0·21
120–180 k	−0·51	0·35	−0·55	0·37
> 180 k	−0·59	0·47	−0·60	0·49
Income bracket				
< 7·5 k	0·12	0·09	0·11	0·11
7·5–17·5 k	−0·06	0·09	−0·16	0·11
> 17·5 k	−0·37	0·23	−0·39	0·25
Age bracket				
65–69	−0·15	0·12	−0·21	0·14
70–74	−0·12	0·13	−0·16	0·15
75–79	−0·09	0·13	−0·18	0·15
80–84	−0·22	0·17	−0·33	0·20
85–89	−0·20	0·22	−0·33	0·25
Health status				
Good	−0·21	0·16	−0·26	0·18
Fair	−0·13	0·13	−0·21	0·14
Poor	−0·06	0·13	−0·12	0·16

Notes: η is the average deviation between log-actual and log-predicted consumption based on the estimated baseline health-uncertainty or life-cycle models. η^2 refers to average squared deviations. Health-uncertainty model is best baseline specification, with estimated $\gamma = 7{\cdot}00$; life-cycle model is best baseline specification, with estimated $\gamma = 24{\cdot}00$.

the two structural models. These columns of results in Table 2 also reveal the dominance of health-uncertainty vs. life-cycle models to predict consumption among retirees in the PSID across nearly all observable characteristics (wealth, income, age and health status). In fact, Table 2 indicates only a single category of families for whom the life-cycle model predicts closer consumption levels than the health-uncertainty model: families with wealth below $5000. On the other hand, for all other wealth categories and all age, income and health categories, the baseline health-uncertainty model overpredicts consumption levels to a lesser extent than does the baseline life-cycle model.

In the baseline specifications, which are chosen for their similarity to models in the existing literature, estimated coefficients of relative risk aversion (7·00 and 24·00) far exceed values used for simulations, which typically fall between 1 and 3. Along with the fact that both dynamic structural models systematically overpredict consumption levels relative to the PSID data, this suggests the possibility of misspecification (or, at least, room for improvement) in the baseline specifications. The following section reports on the sensitivity of CRRA estimates and prediction performance of the health-uncertainty relative to the life-cycle model for alternative model specifications.

B. *Sensitivity of estimation results to alternative model specifications*

Results from the sensitivity analysis appear in Table 3, which shows how CRRA parameter estimates and log-likelihood values vary across alternative health-uncertainty and life-cycle model specifications. Each row of Table 3 (after the first) refers to healthy-uncertainty and life-cycle model estimates when a single aspect of the models is modified from its baseline value. For example, the second and third rows of Table 3 show how estimation results change if consumption among the sample of PSID elderly couples is imputed using Skinner's (1987) original methodology or the "structural demand system" approach based on Attanasio and Weber's (1995) work. For both the health-uncertainty and life-cycle models, estimated CRRA parameters vary only slightly relative to the baseline estimates

TABLE 3

CRRA *estimates from baseline and several alternative health-uncertainty and life-cycle model specifications*

	Sample of PSID elderly couples ($N = 142$) γ, LL_N (standard error)			
Model specification	Health-uncertainty model		Life-cycle model	
1. Baseline	7·00, (1·89)	3·94	24·00 (3·39)	−12·70
2. Using Skinner-imputed data	6·75 (1·80)	−35·49	25·00 (3·81)	−48·12
3. Using Attanasio/Weber-imputed data	9·00, (2·09)	−179·26	25·00, (3·42)	−188·56
4. With health-state-dependent utility	6·75, (1·93)	0·41	n/a	n/a
5. Without adult equivalent scales equivalent scales	6·50, (2·17)	16·90	25·00 (2·94)	7·78
6. $r = 0\%$	6·75, (0·96)	9·85	25·00, (2·75)	−6·18
7. Mortality rates/4	1·50, (0·22)	21·57	1·25, (0·20)	18·47
8. Mortality rates/10	2·00, (0·23)	23·45	1·25 (0·19)	20·07
9. Mortality rates/100	3·25, (0·29)	27·29	2·00, (0·21)	21·47
10. $b = -10\%$	4·25, (0·31)	23·51	3·50, (0·25)	15·95

Notes: Baseline model specifications include: adult equivalent scales for household consumption; uncertain longevity parameterized using published life table estimates for mortality probabilities; 0% time preference rate; 3% real interest rate; and, no health-state-dependence in the utility derived from consumption expenditure.

Each row of this table refers to the maximum likelihood estimates based on baseline model specifications with a single parameter adjusted as shown.

Row 4 reports results based on the following function: δ (good health) = 1·00; δ (fair health) = 0·70; δ (poor health) = 0·40. Other functions lead to qualitatively similar results.

Row 5 results refer to CRRA utility as a function of total family expenditures, rather than consumption per adult equivalent member.

Rows 7 through 9 come from model specifications in which perceived mortality rates (age-specific) are smaller than published actuarial rates by factors of four, ten and a hundred, respectively.

Results based on the PSID sample of elderly singles are not reported because of their qualitative similarity to these. Standard error estimates come from evaluating inverse second derivatives for high-order polynomial approximations to the sample log-likelihood function.

Because log-likelihood functions are extremely flat, grid searches have been truncated at $\gamma = 25{\cdot}00$ under life cycle model specifications.

across PSID consumption imputations. Health-uncertainty models predict consumption levels better than life-cycle models using all three imputation procedures for PSID consumption levels.[20]

The fourth row of Table 3 shows the inability of modelling health-state-dependent utility of consumption to improve consumption predictions relative to the baseline health-uncertainty model. This occurs despite the fact that poor-health families in the PSID indeed report lower levels of expenditure than those in good health. Though this empirical pattern seems to provide a potentially important role for health-state-dependence in utility and, therefore, in consumption levels, closer examination reveals the problem such a specification encounters. Recall, health deteriorates with age, intuitively and among elderly respondents in the PSID. When dynamically optimizing families forecast a future deterioration in their health, they forecast a future decline in marginal utility when their preferences are health-state-dependent. The rational response, then, is to substitute for more current consumption (when health seems relatively good) at the expense of lower future consumption. Thus, health-state-dependent utility tends to increase expenditures among the young, healthy retired families according to this health-uncertainty model (relative to the baseline) specification. Of course, Table 2 indicates that such a tendency simply exacerbates problems for the health-uncertainty model by resulting in even larger overpredictions for consumption than occur in the baseline specification.

The fifth through tenth rows of Table 3 reflect the same result: alternatives to the baseline specification which tend to reduce predicted expenditures early during the retirement period tend to increase log-likelihood values and reduce estimated CRRA parameters relative to baseline. Removing adult equivalent scales, increasing real interest rates, reducing perceived mortality rates (increasing life expectancy) and introducing negative discount rates represent several ways to shift retirement consumption levels from early to very old ages according to the dynamic models.[21]

The latter three of these effects are standard, but the first one might warrant closer inspection. Modelling utility as a function of expenditures per adult equivalent implies that utility from spending $10,000 is lower (and marginal utility is greater) for a two-person household than a single individual. Optimizing retired couples, therefore, forecast smaller households and lower marginal utility in the future than today. Rationally, they respond by shifting consumption expenditures from the future to the present, which increases consumption predictions for health-uncertainty and life-cycle models during the early periods of retirement. Consistent with the health-state-dependent utility result described above, removing this tendency from the baseline specifications improves the ability of both health-uncertainty and life-cycle models to predict retirement consumption.

All of the alternative specifications shown in rows five through ten of Table 3 reduce estimated CRRA parameters and increase log-likelihood values relative to baseline. In fact, health-uncertainty and life-cycle model specifications in which retired Americans have "optimistic" life expectancies (relative to published data based on death certificates) or negatively discount the future, result in CRRA estimates in the range of values from the empirical Euler equation literature. However, none of the alternative specifications in Table 3 (or any of the numerous unreported specifications) changes the primary result

20. In none of the dozens of health-uncertainty or life-cycle model specifications estimated, have I discovered important differences in results depending on which of the three procedures is used to impute consumption expenditures to elderly families in the PSID.

21. Table 3's seventh row, for example, considers an alternative specification in which retired Americans perceive their age- and sex-specific mortality rates to be just a fourth as large each year as the statistics published by the U.S. Department of Health and Human Services (1985).

that health-uncertainty models better predict consumption levels among PSID retirees than life-cycle models do.

Table 3 compares estimates from health uncertainty and life-cycle model specifications when several alternative specifications are examined one-at-a-time. However, the possibility remains for some combination of alternatives to allow a life-cycle model to outperform the best health-uncertainty model, in terms of ability to predict PSID retirement consumption levels. To investigate this possibility, I estimate health-uncertainty and life-cycle models under dozens of combinations of alternatives suggested by Table 3.[22]

TABLE 4

CRRA *estimates and consumption predictions from the best health-uncertainty and life-cycle specifications*

A. Sample of PSID elderly couples ($N = 142$)		
Estimation results	Health-uncertainty model	Life-cycle model
γ	4·00	11·00
Standard error	(0·62)	(0·93)
LL_N	28·43	21·66
Avg. actual consumption	15,115	—
Avg. predicted consumption	15,698	15,436
Avg. η^2	0·102	0·114
Best model specification		
Adjustment factor for annual mortality rates	10	100
Adult equivalence scales for utility of consumption	Off	On
Real interest rate	0%	3%
Rate of time preference	0%	−10%

B. Sample of PSID elderly singles ($N = 144$)		
Estimation results	Health-uncertainty model	Life-cycle model
γ	3·00	25·00
Standard error	(0·51)	(2·12)
LL_N	−181·38	−192·13
Avg. actual consumption	8,999	—
Avg. predicted consumption	8,328	8,604
Avg. η^2	0·215	0·243
Best model specification		
Adjustment factor for annual mortality rates	4	None
Adult equivalence scales for utility of consumption	n/a	n/a
Real interest rate	0%	3%
Rate of time preference	0%	0%

Notes: η^2 is the squared difference between the natural log of actual consumption expenditures imputed to PSID families and annual consumption levels predicted according to health-uncertainty or life-cycle models.

These results are based on a broad specification search with respect to alternative parameters imposed under health uncertainty and life cycle consumption models.

Note, many different specifications of the life-cycle model yielded nearly the exact same fit for the sample of elderly singles as the baseline case presented above ($\gamma = 25{\cdot}00$; $LL_N = -192{\cdot}13$).

Table 4 documents significantly greater log-likelihood values, closer average predicted consumption levels and smaller average squared deviations of prediction errors from modified health-uncertainty and life-cycle models relative to their baseline specifications.

22. In fact, I also examined more time preference rates than appear in Table 3 (−10%, −5%, 0%, 5% and 10%) in combination with all other alternative specifications. Also, I tried models in which retirees' perceptions about age- and sex-specific mortality rates were just half the published statistics.

However, precautionary saving from explicit uncertainty about future medical expenses implies a reluctance to dissave financial wealth during retirement under the health-uncertainty model that cannot be adequately mimicked by any life-cycle model permutations—even those imposing large coefficients of relative risk aversion, negative (subjective) time preference rates and the failure to recognize the possibility of death before a hundred years of age.

As suggested by Table 3's results, the principle modification of health-uncertainty and life-cycle model (relative to baseline) to improve their predictive abilities is increasing perceived life expectancies (decreasing perceived annual mortality rates) compared to published statistics. However, the best-fitting health-uncertainty model involves a different combination of alternative specifications than does the best-fitting life-cycle model. For example, once sufficiently "optimistic" life expectancies are incorporated into the health-uncertainty model (dividing published mortality rates by an adjustment factor of ten), no further discounting (via negative subjective time preference rates or positive real interest rates) improves the health-uncertainty model's fit to the data. The resulting CRRA estimate, 4·00, is near the range of estimates available from the contemporary Euler equation estimation literature in this case. On the other hand, the best-fitting life-cycle specification "turns off" mortality risk altogether (essentially, all individuals think they will live to one hundred years), but still requires a 3% real interest rate and two unusual values for preference parameters: an estimated CRRA equal to 11·00 and a time preference rate of negative 10%.

Finally, Panel B of Table 4 shows qualitatively similar results hold for the PSID sample of elderly individuals living alone. Under the health-uncertainty model, the best specification yields $\gamma = 3{\cdot}00$ and $LL_N = -181{\cdot}38$. The best specification imposes a real interest rate and a time preference rate equal to 0% and adjusts individual mortality rates downward by a factor of four relative to their actuarial values. These parameter values are very similar to those reported for PSID elderly couples. For the PSID sample of elderly singles, many different specifications of the life-cycle model with uncertain longevity returned log-likelihood values near the baseline case (−192·13) and all required γ to be 25·00. Thus, none of the dozens of alternative specifications investigated outperformed, or differed very significantly from the baseline life-cycle model.

To summarize the empirical results, precautionary incentives implied by a dynamic model in which retirees' face uncertain medical expenses in the future helps to reduce predicted consumption levels toward values observed among elderly families, on average, compared to life-cycle models. Even when unusual parameters are imposed, such as large coefficients of relative risk aversion and negative time preference rates, life-cycle models cannot adequately mimic the reluctance to consume early during retirement to the extent evidenced among families in the data. Note, however, the best fitting health-uncertainty model also requires adjusting age- and sex-specific mortality to much less than their actuarial values to overcome a systematic tendency to overpredict consumption levels in the baseline specification.

VI. CONCLUSIONS

This paper introduces a dynamic, structural model of household consumption decisions during retirement in which families consider the effects of potential future shocks to their wealth levels when determining how much to spend currently. Explicitly, shocks take the form of exogenous expenses incurred out-of-pocket to finance health care during old age. Additionally, the health-uncertainty model incorporates the possibility of a person living past her life expectancy, as well as the possibility of dying prematurely, which also will affect the timing of consumption expenditures. Using panel data from samples of elderly retirees in the PSID, I estimate the coefficient of relative risk aversion under the health-uncertainty and life-cycle consumption models. In contrast, the existing literature tends to estimate dynamic models without fully specifying the stochastic environment facing forward-looking families or to simulate "complete" life-cycle models without subjecting them to standard empirical testing using formal statistical criteria.

The health-uncertainty model predicts consumption expenditures much closer, on average, to observed expenditures during retirement than life-cycle models with uncertain longevity. This result obtains in the baseline model specifications, which are parameterized to closely match the existing simulation literature, and for every alternative specification investigated in the sensitivy analysis. I conclude, therefore, that uncertain out-of-pocket medical expenses represents an important motive for precautionary saving among elderly Americans. Simulations (unreported) of the health-uncertainty model using the estimated coefficient of relative risk aversion imply that precautionary saving arising only from uncertain future out-of-pocket medical expenses amounts to approximately 7% of annual consumption during the early years of retirement for a typical couple.

On the other hand, improvements in the ability of the health-uncertainty model to fit the PSID consumption data can be gained by adjusting downward (substantially) annual mortality rates relative to published actuarial estimates. This result indicates that the substantial precautionary saving implied by the health-uncertainty model still is inadequate to explain completely the apparent reluctance of elderly Americans to spend down their financial assets during their early retirement years. Besides being consistent with systematic "optimism" about life expectancy during old-age, this pattern also is consistent with an altruistic motive for inter-generational bequests. In principle, the health-uncertainty model can be modified to include such objectives explicitly, but the empirical examination estimation of such a model, which adds complexity relative to the current framework, is left for future research.

Including an explicit parameterization of health uncertainty into the retirement phase of an otherwise standard life-cycle consumption model moves us in the correct direction by generating a precautionary motive for saving in old-age, but does not seem to move us far enough toward the data. Additionally, baseline health-uncertainty specifications, which most closely follow models previously used in the simulation literature, yield large, and arguably implausible, estimates for the coefficient of relative risk aversion. Alternative health-uncertainty model specifications, which arbitrarily adjust perceived mortality rates substantially below their actuarial values, improve the model's fit to the panel consumption data and yield parameter estimates closer to those reported in some previous studies (γ around 3 or 4).[23]

The general estimation methodology developed in this paper, however, is readily applicable to a very wide class of alternative life-cycle-type models for family consumptions decisions. The paper's contribution, therefore, may be particularly important in light of recent research by others, such as Carroll (1997) and Ludvigson and Paxson (1997), documenting inherent econometric difficulties with the log-linearized Euler equation methodology so frequently applied in the past.

Finally, many simulation studies in public finance (for instance Summers (1981) and Auerbach and Kotlikoff (1987)) examine the implications of fiscal policy reform in life-cycle model settings. The economic environment in which the analyses take place are such

23. Ludvigson and Paxson (1997) survey parameter estimates from several different approaches to Euler equation estimation in the recent consumption literature.

that families are assumed to make decisions when all economic variables are known with certainty, all households are assumed to live to their life expectancies and altruistic bequests are ignored. An important lesson to be learned from this paper, however, is that such a simple life-cycle model specification is not at all consistent with observed consumption decisions of retired Americans. The standard life-cycle model simply cannot explain why elderly families spend so little of their incomes and wealths during their early retirement years. This paper suggests that models incorporating precautionary behaviour on the part of rational, forward-looking families, such as Engen and Gale (1993) and Hubbard, Skinner and Zeldes (1995) and others, are more appropriate for policy analysis in a dynamic context.

APPENDIX

A: *Numerical solution technique for the health-uncertainty model*

The health-uncertainty model that I investigate is quite similar to stochastic life-cycle models analysed by Kotlikoff (1988), Zeldes (1989), and Hubbard, Skinner and Zeldes (1994, 1995), among others. Thus, I employ essentially the same numerical solution algorithm as these authors. Taylor and Uhlig (1990) discuss many different solution algorithms for stochastic dynamic programming problems. The algorithm I describe above and employ in this paper is the discrete-state, Euler equation approach utilized by Baxter, Crucini and Rouwenhorst (1990). The only difference is that not only do I iterate on the Euler equation to find optimal consumption at each wealth, health and age "node," but I also evaluate the value function itself for many intermediate consumption levels to identify potential multiple local maxima, as described by Hubbard, Skinner and Zeldes (1995).

The premise is to descretize the state space and then exploit the recursive nature of the dynamic programming problem. Two of the state variables in the health-uncertainty model, age and health status, are discrete variables, by assumption. Discretionary wealth (wealth minus out-of-pocket medical expenses), however, is defined to be continuous. At each age, I divide the maximum feasible range of the natural log of (discretionary) wealth into a finite number of grid points. Then I solve for optimal consumption for each possible combination of age, health and discretized wealth. This procedure effectively increases the search intensity for optimal consumption at low levels of wealth, where the consumption function is most likely to exhibit nonlinearities (see Hubbard, Skinner and Zeldes (1994, 1995)).

Applying the terminal asset condition defines optimal consumption for any wealth level and medical expense outcome during the final year of life

$$c_L = W_L - m_L, \quad \text{if } W_L - m_L \gtrsim \underline{c},$$
$$c_L = \underline{c}, \quad \text{otherwise.}$$

The period L consumption function holds for each of the three possible health states. When the medical expense in period L is adequately small to allow consumption above the level guaranteed by Medicaid, the individual chooses to consume all remaining wealth. Otherwise, Medicaid pays for medical bills exceeding $W_L - \underline{c}$ and consumption equals the minimum level.

During period $L-1$, the household searches for c_{L-1} that maximizes the following value function

$$J_{L-1}(W_{L-1} - m_{L-1}, h_{L-1}) = \delta(h_{L-1})u(c_{L-1}) + \beta s^L_{L-1}(\textstyle\sum_{h_L=1}^{3} \delta(h_L)u(\underline{c})G(\varepsilon^*_L)f(h_L))$$
$$+ \beta s^L_{L-1}(\textstyle\sum_{h_L=1}^{3} \sum_{\underline{\varepsilon}_L}^{\varepsilon^*_L} D(h_L)u(W_L - m(\varepsilon_L))g(\varepsilon_L)f(h_L)),$$

where $\underline{\varepsilon}_L$ gives the minimum medical expense disturbance and $\varepsilon > \varepsilon^*_L$ are those medical expense disturbances for which $W_L - m(\varepsilon^*_L) = \underline{c}$ and occurs with probability $1 - G(\varepsilon^*_L)$. The medical expense disturbance, ε_L, is a continuous random variable, but $g(\cdot)$ denotes the density function associated with a discrete representation of ε_L. Appendix B reports the discrete representation for the distribution of the medical expenses disturbance, which is estimated using data from the National Medical Care Expenditure Survey.

For a guess of c_{L-1}, associated current utility level plus the expected value for period L is computed, conditional on that consumption choice. The expected value function is computed by integrating over all three possible health outcomes in period L and each possible medical expense, conditional on health. An updated guess of c_{L-1} comes from a univariate optimization routine, which runs until the globally maximizing value of consumption between $\underline{c}$ and $W_{L-1} - m_{L-1}$ is found. Optimal consumption is such that current marginal utility equals the expected marginal utility next period at interior solutions, though optimal corner solutions are allowed.

In fact, the solution algorithm allows for multiple local interior maxima for consumption as a function of age, health and wealth and chooses optimal consumption as the globally maximizing value after corner solutions are allowed. Hubbard, Skinner and Zeldes (1994, 1995) carefully document the possibilities of multiple local maxima and discontinuities in optimal consumption as a function of wealth. My solution algorithm appropriately deals with these possibilities.[24]

Once c_{L-1} and $J_{L-1}(W_{L-1}-m_{L-1},h_{L-1})$ are known for all possible values of W_{L-1} and h_{L-1}, the household's $L-2$ problem may be solved by repeating the procedure. When necessary for calculating the expected value of consumption next period, optimal consumption is interpolated between values in the consumption grid. The recursion continues until the $t=1$ problem is solved.

B. *Estimating the empirical distributions for out-of-pocket medical expenses and household health status*

The elderly face two types of risks regarding out-of-pocket medical expenses: first, those associated with health care services received while living in the community; and, second, those incurred during residences in nursing homes. By design, data on community-based health care expenses exclude periods of institutionalization, so I must estimate distributions of the two random variables separately using separate sources of data.[25] Section 1 of this Appendix describes the estimation of the first distribution using the 1977 National Medical Care Expenditure Survey. Section 2 describes an application of studies by Cohen, Tell and Wallack (1986) and Liu and Manton (1984) to parameterize nursing home risk. Section 3 describes the data and procedure used to estimate the Markov transition probabilities for next year's health status, conditional on the household's current health status. Together, these different sources of health expenditure data, allow a realistic model of random out-of-pocket medical expenses during retirement to be incorporated into the life-cycle framework of this paper.

1. *Expenses incurred for community-based health care.* The National Medical Care Expenditure Survey's Person File (NMCES) details health care expenses incurred by 40,320 persons representing the civilian, noninstitutionalized U.S. population in 1977. This survey is useful for my purposes because it provides individual characteristics, such as age and income and health status and total health care expenses paid for out-of-pocket. I only use the NMCES sample of households in which the head is older than sixty-four years, reports at least a dollar of income and contains no missing health data. The sample consists of 2821 families with average out-of-pocket medical expenses of \$405·56 and a standard deviation of \$658·65. The household reporting the largest health care liability incurred \$8537·25 of expenses paid out-of-pocket. Only eleven households report of figure greater than \$5000. Using self-reported indicators of health status for each NMCES respondent, I estimate a family health index. According to the constructed index, 29·2% of the sample households are in good health, 43·7% are in fair health, and 27·1% are in poor health. Exposure to risky total and out-of-pocket expenses for community-based health care increases among those in more poor health, as average and standard deviations of out-of-pocket expenses increase as health becomes worse.

The health-uncertainty model requires the distribution of medical expenses to be estimated. Therefore, the following specification is estimated by ordinary least squares regression

$$m_i^{cb}=\pi_0+\pi_1\,\text{Age}_i+\pi_2\,\text{Income}_i+\pi_3\,\text{Retired}_i+\pi_4\,\text{Fam Size}_i$$
$$+\pi_5\,\text{Nonwhite}_i+\pi_6\,\text{Fair Health}_i+\pi_7\,\text{Poor Health}_i+\varepsilon_i,$$

where m_i^{cb} is the natural log of community-based out-of-pocket medical expenses for household i, Age is age of the householder, Income is family income, Retired equals 1 only if the householder is not working, Fam Size is the number of household members, Nonwhite equals 1 only for households headed by nonwhite persons, and Fair and Poor Health are dummy variables indicating the household's health status.[26] The regression results, available on request, provide evidence that household health status is important for predicting average community-based medical expenses. Community-based medical expenses are positively correlated with the age of

24. Both of these possibilities are less likely to be a problem in my model than they are for Hubbard, Skinner and Zeldes (1993). This follows from my assumption that retirement income is nonstochastic and positive for all families, while Hubbard, Skinner and Zeldes include stochastic (and possibly very low) income and medical expenses during the working phase of the life cycle. Thus, it is much more likely for a family to draw a medical expense larger than "cash on hand" in their model than it is in mine.

25. A more detailed description of the empirical procedures and results introduced in this Appendix is available from the author upon request.

26. Before deciding upon this specification for the log medical expense regression I fit many equations by ordinary least squares. This rather parsimonious model fit the data very nearly as well as more general ones.

the householder and the family size, holding the other variables constant. Retirees and households headed by nonwhite persons spend less out-of-pocket on health care, *ceteris paribus*. The coefficient estimate on family size is less than one, suggesting that elderly couples are more likely to recuperate at home while single persons require professional assistance for longer periods after an illness. Finally, the income elasticity of medical expenses is estimated to be 0·37 for the elderly sample.

The estimated regression coefficients are used to predict average medical expenses in the future. In order to choose consumption optimally in period t according to the health-uncertainty model of the paper's text, a family must know the entire distribution of out-of-pocket expenses for community-based health care. I use a nonparametric distribution based on a histogram of the regression residuals to characterize the density function for community-based out-of-pocket medical expenses across families in the health-uncertainty model.

2. *Expenses related to nursing home admissions.* The NMCES contains no information about nursing home expenses, thereby ignoring an important, generally uninsured (except through Medicaid) risk to elderly persons. In this section, I describe how to use results from three published sources to calculate the distribution of nursing home expenses.

Cohen, Tell and Wallack (1986) estimate age-specific probabilities of nursing home admission, which I directly incorporate into my health-uncertainty model. Their double-decrement life table analysis allows for an elderly person to drop out of her age-cohort for either of two reasons—nursing home admission or death—using published mortality rates and the Current Medicare Survey of 1977 to estimate nursing home admission rates for elderly persons. Their research indicates, for example, that 4·84% of elderly aged 65–69 are admitted to nursing homes before turning seventy; nursing home admissions occur with increasing frequency as the cohort ages; and, the lifetime risk of a nursing home admission for a typical sixty-five year old is 43·12%.[27]

Liu and Manton (1984) combine samples from two separate components of the 1977 National Nursing Home Survey—current residents and discharged patients—to estimate the distribution of lengths of stay for nursing home admissions. According to their study, the average stay of a nursing home admission is approximately 456 days, over half of the entrants are discharged in their first three months of residence. Nearly three-quarters of admitted patients reside in a nursing home less than one year.

For the purpose of representing nursing home risk in my health-uncertainty model, Liu and Manton's length of stay distribution is inappropriate. Published life tables for the U.S. give conditional mortality probabilities that characterize lifespan uncertainty in my model. To use these probabilities I need the length of stay distribution for persons *discharged alive to the community*. Liu and Manton underestimates this length of stay distribution because patients who die as nursing home residents should be considered censored observations for length of stay to live discharge—the event I care to measure. Fortunately, Liu and Manton (1986, Table B-2) report the fraction of live and dead discharges by length of stay, which enables me to correct for the censoring bias by applying the Kaplan–Meier estimator for survival rates. My calculations imply, for example, that 27% of all nursing home entrants receive live discharges within one month of admission; 62% receive live discharges within one year of admission (again, the full set of estimates I develop for the model are available upon request).

The health-uncertainty model requires the distribution of nursing home expenses incurred during a one-year period. However, a nursing home admission could begin this year but carry over into next year. Assuming that nursing home admissions are distributed uniformly across the calendar year, the expected cost this year to a nursing home resident with length of stay i (LOS_i, measured in days) is

$$E(m^{\mathrm{nh}} \mid LOS_i) = (1-n_i)n_i(c^{\mathrm{ac}}+c^{\mathrm{nh}}) + n_i\left(\frac{n_i}{2}\right)(c^{ac}+c^{nh}) - \text{Medicare Benefit},$$

where m^{nh} denotes the total cost incurred this year for a nursing home admission; c^{ac} is the average cost of one year of acute care received in nursing home; c^{nh} is the average cost of one year of nursing home care; n_i is the fraction of the year spent in a nursing home for LOS_i; and, i indexes different nursing home lengths of stay (there are seven possible lengths of stay). Recall that the uniform distribution implies that the probability that a nursing home stay of length n_i occurs entirely during the current (calendar) year is $(1-n_i)$. The total cost of a nursing home admission of length i which occurs entirely during the current year is the product of the fraction of the year spent in the facility, n_i, and the total cost of a year of nursing home care, $c^{\mathrm{ac}}+c^{\mathrm{nh}}$. Finally, the expected cost this year of a nursing home stay which partly carries over into next year is one-half of the total nursing home cost, $n_i\,(c^{\mathrm{ac}}+c^{\mathrm{nh}})$. I assume that Medicare pays for the first thirty days of nursing home care.

Deflating Rivlin and Wiener's (1988) figures on average daily nursing home costs to 1977 dollars yields an estimate of \$39·40 for the average daily nursing home cost and \$51·36 for average monthly acute care expenses. Medicare part B benefits have been subtracted from the acute care expenses. The average cost of nursing home

27. The full set of results I use are available in a more detailed version of this Appendix upon request.

care for one year is \$14,381 in 1977 and the average cost of acute care received in a nursing home for one year is \$616.

Unfortunately, we do not have estimates of the probability of nursing home admission by health status. Rivlin and Weiner (1988) report that disabled elderly persons enter long-term care facilities more frequently than nondisabled persons, providing evidence that health matters for nursing home admission rates. Therefore, I assume that households in good health are half as likely as those in fair health to be admitted to a nursing home at all ages. Households in poor health are assumed to enter nursing homes twice as often as those in fair health. Finally, the health-uncertainty model also accounts for the fact that a person who resides in a nursing home only for a portion of the year incurs community-based medical expenses for the rest of the year. For example, a seventy-year old household in fair health faces an annual nursing home admission rate of about 1·4%. Conditional on admission, the household incurs nursing home expenses of \$3,390 this year with probability 9% (during a 135-day length of stay). Finally, this household pays community-based medical expenses accruing during the other 230 days of the year.

3. *Estimating a Markov process for household health status.* This section describes a multinomial logit model applied to a sample of elderly families from the PSID to estimate Markov transition probabilities for household health status over time as functions of observable characteristics. Multinomial logit estimates and additional analysis are available upon request.

Consistent with the NMCES work reported above, household health status is assumed to obtain one of three outcomes each period: good ($h_{it} = 1$), fair ($h_{it} = 2$) or poor ($h_{it} = 3$). Denote by $p_i(k|j)$ the probability that household i draws health status k in period t, conditional on having drawn health status j in period $t-1$. I allow transition probabilities for health to vary with several household characteristics: age, marital status, race and education. Let x_{it} be a vector of these characteristics for household i in year t. Then define the index variables $v_i(k|j)$ as follows

$$\begin{aligned} v_i(k|j) &= \exp(\beta'_{kj}\, x_{it}), \qquad \text{for } k = 1 \text{ or } 2, \\ &= \exp(0'\, x_{it}) = 1, \quad \text{for } k = 3. \end{aligned} \tag{B-1}$$

The Markov transition probabilities for the health status of household i in year t are then defined by

$$p_i(k|j) = \frac{v_i(k|j)}{\sum_{j=1}^{3} v_i(k|j)}.$$

Thus, to allow a dynamic representation for categorical outcomes of household health, I substitute transition probabilities in place of the static probabilities usually specified in discrete choice models and I estimate the parameters maximum likelihood under multinomial logit. The estimated coefficients measure differences in health transition fitted values across families with different characteristics. The multinomial logit coefficients are estimated relative to the health transition into poor health because b_{3j} is normalized to 0 for $j = 1, 2$, and 3.

I estimate the coefficients in (B-1) for three different multinomial logit models—one for each of the three health states being conditioned upon ($j = 1, 2, 3$). That is, I create three different data sets and estimate a different multinomial logit specification for each. The first data set includes the current health status and household characteristics for all elderly families in good health last year. The second and third data sets include families in fair and poor health last year. Consider the estimation of the vectors b_{11} and b_{21}, the effects on health transition fitted values of household characteristics, conditional on a family having been in good health last year. The data used to estimate these coefficient vectors consist of: (i) 1985 health status and household characteristics for all families in good health in 1984; (ii) 1986 health status and household characteristics for all families in good health in 1985; and (iii) 1987 health status and household characteristics for all families in good health in 1986.

In the Panel Study of Income Dynamics, 623 households were singles or couples headed by a person at least sixty-five years of age in 1984. The file containing current health and household characteristics for families in good health the previous year contains 401 observations; the file of families in fair health the previous year contains 668 observations; the file of families in poor health the previous year contains 750 observations.[28]

In general, the multinomial logit estimates imply that nonwhites, singles and households in which the head does not hold a high school degree are less likely to move into (or remain in) good health. Estimated coefficients for the dummy variable indicating single households and the dummy variable indicating high school education for the head are significantly different from zero in all three multinomial logit specifications. Coefficients for the age and race of the household head differ significantly from zero only for health transitions from fair health last

28. The total number of observations in the three data files do not add up to 623 * 3 because a few with missing variables were deleted.

year. Finally, the estimated coefficient for the age of the household head squared does not differ significantly from zero in health transitions from any of the three states last year. Consider, as the base-case, a white couple headed by a seventy-year old with a high school degree. Conditional on the base household being in good health this year, the probability of it being in good health next year is 66% and the probability of it being in fair health next year is about 33%. The base household remains in fair health over 72% of the time while moving to good health over 17% of the time. Finally, if the base household finds itself in poor health this year, the probability is four-tenths of a percent that it will be in good health next year and is about 39% that it will be in fair health next year.

C. *Two samples of elderly families from the* PSID

I estimate the health-uncertainty model on two samples of elderly families from the PSID, waves 1984 through 1986: a sample of single elderly persons and a sample of elderly couples. As mentioned in the text, the sample selection criteria are strict. The reason for restricting the sample is that modelling preference heterogeneity in the health-uncertainty model would introduce substantial computational burden. Thus, I choose the elderly samples from the PSID to be homogeneous in observable characteristics. To be included in my panel data set, a household satisfied the following requirements:

(i) age of the head of the household at least sixty-five in 1984;
(ii) white head of the household in 1984;
(iii) household consists of head only (single households) or only head and wife (elderly couples) in 1984, 1985, and 1986 (no changes to head or wife across years);
(iv) head and wife (if present) retired in 1984;
(v) no missing data for the household in 1984, 1985 or 1986.

In the 1987 PSID family-individual file, 145 elderly couples satisfy the above five selection criteria. However, I deleted one elderly couple claiming to own $9,530,000 of financial wealth in 1984 and another that received income exceeding $128,000 in 1984. My sample includes 143 PSID elderly couples. I believe observation number 143 warrants extra attention. In particular, this couple owned only $1000 of financial wealth in 1984, received, on average, an annual income of under $6500, but spent $45,856 in 1985 and $9377 in 1986. I interpret number 143 as containing a coding error and, thus, drop it from the working sample of PSID elderly couples, leaving 142 complete observations.

In the 1987 PSID family-individual file, 147 elderly singles' satisfy the above five selection criteria. However, I delete three additional elderly people from the PSID singles sample. One deleted observation reports $16 total consumption expenditures in 1984, $1736 in 1985 and $11,512 in 1986. The second deleted observation reports −$33,000 in financial wealth in 1984 and total consumption expenditures exceeding income during all three years of data. The third deleted observation reports financial wealth equal to −$8200 in 1984 and total consumption in excess of income during all three years of observation. The working database of PSID elderly singles contains 144 complete observations for 1984 through 1986. Summary statistics for the sample of elderly samples that appear are available upon request.

D. *Imputing consumption expenditures to households in the* PSID

The PSID does not directly report total consumption expenditures—the variable this paper requires for empirical implementation. However, I apply three imputation procedures to the PSID data and investigate the sensitivity of model estimates among them. This Appendix describes the three imputations employed.

1. *An imputation procedure due to Skinner* (1987). The PSID contains information about each household's expenditure on food consumed at home, food consumed away from home and annual utility payments. Additionally, it contains the market value of homeowners' homes and the annual rent paid by non-homeowners. Finally, households record the number of automobiles they own during each year of the survey. This information, along with much more detailed consumption data, also is available in the Consumer Expenditure Survey (CEX). In fact, it is possible to construct a measure of total consumption on nondurable goods and services for a cross-section of CEX families.[29] Skinner's idea is to regress this measure of total household consumption on

29. Total annual consumption is defined to be expenditures on all nondurable goods and services plus the imputed service flow from the most important durable good, each family's stock of owner-occupied housing. Stocks of other durables goods are unavailable in the CEX, so housing, the most important consumer durable, is the only service flow that can be included in total consumption.

the set of explanatory variables found in the PSID for the CEX cross-section and then to use those least squares coefficient estimates to inflate the PSID numbers up to an imputed value of total consumption.

In his original paper, Skinner (1987) documents two reasons his imputation procedure can be usefully applied to the PSID. First, data from the CEX implies that the few available consumption variables in the PSID explain 80% of the variation in total consumption expenditures. On the other hand, food consumption alone explains only a quarter of the variation in total consumption expenditures across CEX households. Second, the estimated regression coefficients for total consumption expenditures on its components are stable across different cross-sections (years) of CEX data.

To allow for potential spending differences among elderly and nonelderly households, I fully interact a dummy variable indicating elderly households with each of the PSID consumption variables and include all variables in the regression equation. Thus, I essentially impute total consumption for PSID elderly families using a CEX consumption regression estimated only for elderly families. Excluding the interactive variables barely changes the adjusted R-squared because essentially the same regression fits data for the elderly and non-elderly subsamples in the CEX.

2. *A flexible-Engel curve adaptation of Skinner's procedure.* Following the suggestion of a referee, I modify the CEX regression on which imputed consumption levels in the PSID are based. The modified regression equation allows more flexibility with respect to the "effects" of each consumption category for total expenditures. In particular, the modified imputation equation fully interacts annual income and family size with all consumption categories available in the PSID. The model is estimated on a CEX subsample comprised only of elderly couples and single people, which corresponds to the PSID sample on which imputations will be performed. Overall, F-statistics for statistical significance for both the income-interaction effects and the family size-interactions imply p-values of 0%. The adjusted R-squared of the flexible regression model increases slightly (to 0·77 from 0·74) relative to Skinner's (1987) original specification.

3. *A structural imputation procedure for PSID consumption levels.* Also following a referee's suggestion, I employ a third procedure to impute total consumption to PSID families—one which, unlike the "reduced form" prediction equations described above, follows directly from a structural model of household expenditures. Attanasio and Weber (1995) estimate an Almost Ideal Demand System (Deaton and Muellbauer (1980)) for food and nonfood expenditures using several cross-sections of household data from the CEX (sampled during the 1980's). Attanasio and Weber generously provided their unpublished parameter estimates to me, which I apply to my sample of elderly singles and couples from the PSID. Readers should consult Attanasio and Weber (1995) for details about estimating the model; here, I describe my use of their estimated parameters. Attanasio and Weber (AW) estimate a two-commodity demand system (food and nonfood expenditures), which results in a single, structural estimation equation for the food budget share, once adding-up constraints are imposed on the system. Budget shares depend on relative prices and total expenditures in theoretically consistent ways. According to their empirical specification, preference parameters, which determine own-price, cross-price and income elasticities of demand, vary by educational attainment, age, family composition and labour supply variables at the household level.

I predict food budget shares for each family in my PSID sample using their parameter estimates, food and nonfood prices (provided by them for 1984 through 1986) and observed household characteristics (from my sample of PSID elderly families). Given information about levels of food expenditure directly available in the PSID, I then impute total expenditures consistent with the predicted budget shares from AW's structural model estimates. That is, imputed total expenditures from this procedure simply equal observed food spending for each family in the PSID divided by its predicted food budget shares based on AW parameter estimates, prices (food and nonfood) and additional PSID data. The resulting levels of total expenditures represents the third imputation investigated empirically using the estimation methods and structural, dynamic consumption models of this paper.

4. *A comparison across three imputation procedures.* Overall, the three procedures impute consistent values for total expenditure among PSID sample families. Acording to Skinner's original procedure, imputed consumption levels average \$11,508 among elderly couples and singles during 1985. The flexible Engel curve procedure imputes \$12,035, on average, while the figures based on Attanasio and Weber's estimates are a little lower, \$10,828. Imputations based on the first two procedures are (linearly) correlated to 0·98; correlations based on the last two imputation procedures are 0·75. Furthermore, within family size and income brackets (the relevant grouping for my purposes), the three procedures result are more similar to one another. For example, regressions of consumption imputed using the AW estimates on consumption imputed using the flexible Engel curve procedure yield intercepts less than \$1000 and slope coefficients above 0·90 (with R^2s larger than 0·92).

Given the reasonable similarity among the three different procedures, it is not too surprising that the estimation results of this paper are insensitive to the choice of which imputation is used for PSID consumption levels. Qualitatively and quantitatively, all estimation results reported in Section IV of this paper's text hold when the health uncertainty and life-cycle models are applied consumption data either based on Skinner's (1987) original imputation procedure or that based on Attanasio and Weber's (1995) estimates. However, consumption data imputed using the flexible Engel curve methodology of Subsection 2 results in the largest log-likelihood values for all health-uncertainty and life-cycle model specifications estimated in this paper. Thus, I adopt this imputation procedure as the baseline case when discussing empirical results for my health-uncertainty and life-cycle models.

Acknowledgements. On this project, I received valuable advice from Jonathan Skinner and Steven Stern. Orazio Attanasio, Guglielmo Weber and Daniel Slesnick generously provided unpublished parameter estimates to me. Manuel Arellano and two anonymous referees made excellent suggestions to improve the paper. I appreciate receiving comments on earlier drafts from Alok Bhargava, Steven Craig, Eric Engen, Chinhui Juhn, Dan Levin, Jim Smith, David Papell and Peter Thompson. The Alfred P. Sloan Foundation and the Office of Sponsored Programs at the University of Houston helped to finance this research.

REFERENCES

ALTONJI, J. G. (1986), "Intertemporal Substitution in Labor Supply: Evidence from Micro Data", *Journal of Political Economy*, **94**, S176–S215.

ANDO, A. and MODIGLIANI, F. (1963), "The 'Life Cycle' Hypothesis of Saving: Aggregate Implications and Tests", *American Economic Review*, **53**, 55–84.

ATTANASIO, O. P. and WEBER, G. (1995), "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey", *Journal of Political Economy*, **103**, 1121–1157.

AUERBACH, A. J. and KOTLIKOFF, L. J. (1987) *Dynamic Fiscal Policy* (Cambridge: Cambridge University Press).

BAXTER, M., CRUCINI, M. J. and ROUWENHORST K. G. (1993), "Solving the Stochastic Growth Model by a Discrete-State-Space, Euler-Equation Approach", *Journal of Business and Economic Statistics*, **8**, 19–22.

BROWNING, M. and LUSARDI, A. (1996), "Household Saving: Micro Theory and Micro Facts", *Journal of Economic Literature*, **34**, 1797–1855.

CARROLL, C. D. (1997), "Death to the Log-Linearized Consumption Euler Equation!" (Mimeo, Johns Hopkins University).

COHEN, M. A., TELL, E. J. and WALLACK. S. S. (1986), "The Lifetime Risks and Costs of Nursing Home Use Among the Elderly", *Medical Care*, **24**, 1161–1172.

DANZIGER, S., VAN DER GAAG, J., SMOLENSKY, E. and TAUSSIG, M. (1982–1983), "The Life-Cycle Hypothesis and Consumption Behavior of the Elderly", *Journal of Post-Keynesian Economics*, 208–227.

DAVIES, J. B. (1981), "Uncertain Lifetime, Consumption, and Dissaving in Retirement", *Journal of Political Economy*, **89**, 561–577.

DEATON, A. S. (1992) *Understanding Consumption* (Oxford: Clarendon Press).

DEATON, A. S. and MUELLBAUER, J. (1980), "An Almost Ideal Demand System", *American Economic Review*, **70**, 312–336.

DIAMOND, P. A. and HAUSMAN, J. A. (1984), "Individual Retirement and Savings Behavior", *Journal of Public Economics*, **23**, 81–114.

ECKSTEIN, Z. and WOLPIN, K. I. (1989), "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models", *The Journal of Human Resources*, **24**, 562–598.

ENGEN, E. (1993), "Estimation of Dynamic Models of Precautionary Saving and Life-Cycle Consumption Using Panel Data" (Mimeo, UCLA).

ENGEN, E. M. and GALE, W. G. (1993), "IRA's and Saving in the Stochastic Life-Cycle Model" (Mimeo, Brookings Institution).

FEENBERG, D. and SKINNER, J. (1994), "The Risk and Duration of Catastrophic Health Care Expenditures", *Review of Economics and Statistics*, **76**, 633–647.

GOURINCHAS, P.-O. and PARKER, J. A. (1997), "Consumption Over the Life Cycle" (Working paper).

HAMERMESH, D. D. (1984), "Consumption During Retirement: The Missing Link in the Life Cycle", *Review of Economics and Statistics*, **64**, 1–7.

HUBBARD, R. G., SKINNER, J. and ZELDES, S. P. (1994), "The Importance of Precautionary Motives in Explaining Individual and Aggregate Saving", *Carnegie–Rochester Conference Series on Public Policy*, **40**, 59–125.

HUBBARD, R. G., SKINNER, J. and ZELDES, S. P. (1995), "Precautionary Saving and Social Insurance", *Journal of Political Economy*, **103**, 360–399.

HURD, M. D. (1987), "Savings of the Elderly and Desired Bequests", *American Economic Review*, **77**, 298–312.

HURD, M. D. (1989), "Mortality Risk and Bequests", *Econometrica*, **57**, 779–814.

KIMBALL, M. S. (1990), "Precautionary Saving in the Small and in the Large", *Econometrica*, **58**, 53–73.

KING, M. A. and DICKS-MIREAUX, L. (1982), "Asset Holdings and the Life-Cycle", *Economic Journal*, **92**, 247–267.

KOTLIKOFF, L. J. (1988), "Health Expenditures and Precautionary Saving", Chapter 6 in *What Determines Saving?* (Cambridge, MIT Press).

LELAND, H. E. (1968), "Saving and Uncertainty: The Precautionary Demand for Saving", *Quarterly Journal of Economics*, **82**, 465–473.

LILLARD, L. and WEISS, Y. (1997), "Uncertain Health and Survival: Effects on End-of-Life Consumption", *Journal of Business and Economic Statistics*, **15**, 254–268.

LIU, K. and MANTON, K. G. (1984), "The Characteristics and Utilization Pattern of an Admission Cohort of Nursing Home Patients (II)", *The Gerontologist*, **24**, 70–76.

LUDVIGSON, S. and PAXSON, C. H. (1997), "Approximation Bias in Linearized Euler Equations" (Mimeo, Princeton University).

MACURDY, T. E. (1985), "Interpreting Empirical Models of Labor Supply in and Intertemporal Framework with Uncertainty", Chapter 3 in Heckman, J. J. and Singer, B. (eds.), *Longitudinal Analysis of Labor Market Data* (Cambridge: Cambridge University Press).

MIRER, T. W. (1979), "The Wealth-Age Relation Among the Aged", *American Economic Review*, **69**, 435–443.

MODIGLIANI, F. and BRUMBERG, R. (1954), "Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data", in Kurihara, K. K. (ed.), *Post-Keynesian Economics* (New Brunswick: Rutgers University Press).

PALUMBO, M. G. (1992), "Health Uncertainty and Optimal Consumption Near the End of the Life Cycle" (University of Virginia Ph.D. Dissertation).

SANDMO, A. (1970), "The Effect of Uncertainty on Saving Decisions", *Review of Economic Studies*, **37**, 353–360.

SKINNER, J. (1985), "Variable Lifespan and the Intertemporal Elasticity of Consumption", *Review of Economics and Statistics*, **67**, 616–623.

SKINNER, J. (1987), "A Superior Measure of Consumption from the Panel Study of Income Dynamics", *Economic Letters*, **23**, 213–216.

SLESNICK, D. (1993), "Gaining Ground: Poverty in the Postwar United States", *Journal of Political Economy*, **101**, 1–38.

SLESNICK, D. (1994), "Is Our Data Relevant to the Theory? The Case of Aggregate Consumption" (Mimeo).

SUMMERS, L. H. (1981), "Taxation and Capital Accumulation in a Life-Cycle Growth Model", *American Economic Review* **71**, 533–554.

TAYLOR, J. B. and UHLIG, H. (1993), "Solving Nonlinear Stochastic Growth Models: A Comparison of Alternative Solution Methods", *Journal of Business and Economic Statistics*, **8**, 1–17.

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES (1985) *U.S. Decennial Life Tables for 1979–81* (DHHS Publication No. (PHS) 85-1150-1).

VISCUSI, W. K. and EVANS, W. N. (1990), "Utility Functions that Depend on Health Status: Estimates and Economic Implications", *American Economic Review*, **80**, 353–374.

WHITE, B. B. (1978), "Empirical Tests of the Life-Cycle Hypothesis", *American Economic Review*, **68**, 547–560.

ZELDES, S. P. (1989), "Optimal Consumption with Stochastic Income: Deviations from Certainty Equivalence", *Quarterly Journal of Economics*, **95**, 275–298.