Working Paper No. 262

Health Uncertainty and Precautionary Saving: Evidence from Korea

by

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October 2005

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Health Uncertainty and Precautionary Saving: Evidence from Korea

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ABSTRACT

This paper considers a model of precautionary behavior under health uncertainty and derives testable equations for changes in consumption and medical expenditures. Under this framework, individuals who face future health uncertainty will exhibit precautionary behavior by depressing consumption and at the same time increasing medical care expenditures. In testing the precautionary motive, the paper uses the conditional variance of health disturbances as the direct measure of health uncertainty. Empirical findings suggest that the uncertainty about future health outcomes motivates elderly Koreans to hold down their levels of overall spending during the early years of retirement.

JEL Classification: D91; I19
Keywords: health; uncertainty; savings; Korea

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1. Introduction

The saving caused by uncertainty is often called precautionary saving. In examining precautionary saving, economists have traditionally paid close attention to earnings uncertainty and lifespan uncertainty in particular.\(^1\) However, uncertain future health is increasingly found to represent an important motive for precautionary saving especially among elderly individuals.\(^2\) This implies that, among the aging population, precautionary savings against health uncertainty could account for a large share of aggregate savings. For example, Palumbo (1999) estimates that precautionary saving arising only from uncertain future out-of-pocket medical expenditure can be as much as 7 percent of annual consumption of a typical American couple during its early years of retirement.

Faced with growing uncertainty about future health outcomes, however, an individual may not only reduce her current consumption but also purchase extra medical care (thereby increasing investment in health) as a precaution against future periods of illness. If this is the case, the effect of health uncertainty on aggregate savings can be positive or negative depending on the amount of foregone consumption and additional medical expenditures. In fact, Picone et al. (1998) characterize an elderly individual’s response to health uncertainty as a pattern of the precautionary behavior in terms of medical care purchases and consumption. They derive time paths of consumption and medical care expenditures within a stochastic dynamic framework based on the Grossman (1972) health capital model by numerical simulation. Their simulation results suggest that, confronted by health uncertainty, elderly individuals exhibit precautionary behavior by notching up
medical expenditures and holding down consumption during early retirement. These results have a number of important policy implications, but beg empirical support.

In this paper, we find empirical evidence that uncertainty about future health outcomes does indeed motivate elderly Koreans to hold down their levels of consumption and purchase extra medical care early in old age. We also find that the amount of foregone consumption tends to be far greater than that of additional medical expenditures, thereby increasing overall saving, faced with growing uncertainty about future health outcomes. Our model is a simplified version of the Picone et al. (1998) model. Since their model does not have a closed-form solution, it does not provide comparative statistic results. We modify their model to derive testable equations – the changes in consumption equation and the changes in medical expenditures equation – to be used in empirical testing. We then test these equations on household level panel data from Korea to examine the pattern of precautionary behavior under health uncertainty among Korean elderly households.

Previous empirical studies tend to use proxy variables as a measure of health uncertainty when they try to determine the quantitative effects of health risk on precautionary saving. For example, variables such as the number of days ill (Guiso et al., 1996) or health insurance coverage (Starr-McCluer, 1996) are used to measure health uncertainty. Since we obtain from our model closed-form equations relating consumption and medical expenditures changes to the conditional variances of health disturbances, we try to directly measure these conditional variances instead of resorting to proxy variables of health uncertainty in our empirical testing. The conditional variances of health disturbances are estimated using a multinomial logit model since an individual’s health status is measured by categorical variables in our
data, and its movement across time can be appropriately captured by the employment of the multinomial logit.

This paper is organized as follows: Section 2 introduces the model this paper considers. In Section 3, we give a brief description of the data, followed by the explanation of the method for obtaining conditional health variances. We then present the empirical results on precautionary behavior under health uncertainty. Section 4 contains our conclusions.

2. The Model

In order to evaluate the importance of the precautionary motive under health uncertainty, we begin with a simplified version of the Picone et al. (1998) model from which it is relatively simple to obtain closed-form equations for consumption and medical expenditures changes. At each stage of the life-cycle, individual $i$ chooses consumption and medical expenditures to maximize the lifetime utility:

$$\max_{C_{i,t},M_{i,t}} E_t \left\{ \frac{1}{1+\rho} \right\} U(C_{i,t+1}, H_{i,t+1}) ,$$

where $E_t$ denotes the expectation conditioned on information set available at time $t$, $C_{i,t}$ is real consumption, $H_{i,t}$ is the health stock, $M_{i,t}$ is the real (out-of-pocket) medical expenditures, $\rho$ indicates the subjective rate of time preference, and $T$ is the end time. Since we only consider retired individuals with no labor income, the per-period budget constraint becomes:

$$W_{i,t+1} = (1 + r)(W_{i,t} - C_{i,t} - M_{i,t}) ,$$

where $W_{i,t+1}$ is the real stock of wealth at the beginning of period $t+1$, and $r$ is
the real interest rate. In this framework the health stock, $H_{i,t}$, has the consumption aspect only; it generates the direct utility when it enters the utility function as a separate argument. The health stock at the beginning of the period $t+1$ evolves:

$$H_{i,t+1} = (1 - \delta)H_{i,t} + \lambda M_{i,t} + \eta_{i,t+1},$$

(3)

where the health stock depreciates at the rate of $\delta$ and will increase at the end of period $t$ by a fraction of medical expenditures during $t$ ($0 \leq \lambda \leq 1$). An exogenous random shock, $\eta_{i,t}$, is assumed to be normally distributed and allows for the introduction of uncertainty into the health evolution process. Each individual is assumed to have no bequest motive, hence exhausts his or her assets before time $T+1$ (i.e., $W_{i,T+1} = 0$).

The maximization problem can be considered as a dynamic programming problem. Solving the problem yields the following first-order conditions:

$$U_C(C_{i,t}, H_{i,t}) = \left( \frac{1+r}{1+\rho} \right) E_t \left[ U_C(C_{i,t+1}, H_{i,t+1}) \right],$$

(4)

$$U_H(C_{i,t}, H_{i,t}) = \left( \frac{1+r}{1+\rho} \right) E_t \left[ U_H(C_{i,t+1}, H_{i,t+1}) \right],$$

(5)

$$U_C(C_{i,t}, H_{i,t}) = \left( \frac{1+r}{r+\delta} \right) U_H(C_{i,t}, H_{i,t}),$$

(6)

where $U_C$ and $U_H$ are the first derivatives of $U$ with respect to $C$ and $H$, respectively.

We assume a constant absolute risk aversion (CARA) utility function in which consumption and health stock are separable:

$$U(C_{i,t}, H_{i,t}) = -\frac{1}{\alpha} e^{-\alpha c_{i,t}} - \frac{1}{\gamma} e^{-\gamma h_{i,t}},$$

(7)

where $\alpha$ and $\gamma$ are the coefficients of absolute risk aversion with respect to consumption and health stock, respectively. If $\alpha$ and $\gamma$ are positive, the utility
function implies that the marginal utility is convex in both consumption and health stock \((U''_m > 0\), with respect to both \(C\) and \(H\)), and an increase in uncertainty raises the expected marginal utility.

Substituting Eq. (7) into the first-order conditions of Eq. (4) – (6) and using a Taylor series expansion, we can derive the following equations for changes in consumption and changes in medical expenditures:

\[
\Delta C_{t,t+1} = \frac{r - \rho}{\alpha} + \frac{\gamma^2}{2\alpha^3} Var_{t,t}(\eta_{t+1}) + \varepsilon_{t,t+1} \tag{8}
\]

\[
\Delta M_{t,t+1} = \frac{(r - \rho)\delta}{\gamma\lambda} - \frac{1 - \delta}{2\gamma\lambda} Var_{t,t}(\eta_{t+1}) + \xi_{t,t+1} \tag{9}
\]

where \(Var_{t,t}\) denotes the variance conditioned on the information set available at time \(t\), and \(\varepsilon_{t,t}\) and \(\xi_{t,t}\) are expectation errors. The conditional variance terms in the above equations represent health uncertainty. The strength of the precautionary motive depends on the degree of risk aversion with respect to consumption and health stock, on the depreciation rate of health stock, and on the fraction \(\lambda\).

Since we assume that individuals are risk-averse, i.e. \(\alpha\) and \(\gamma\) are positive, future health uncertainty has a positive effect on changes in consumption and a negative effect on changes in medical expenditures. This implies that individuals who face future health uncertainty will exhibit precautionary behavior by depressing consumption and increasing investment in health, in advance. The effect of this precautionary behavior on overall saving depends on the relative size of coefficients for conditional variance terms in Eq. (8) and Eq. (9). That is, the growing uncertainty about future health outcomes results in a higher level of household saving when \(\gamma^3\lambda\) is greater than \(\alpha^3(1 - \delta)\). In the next section, we will test the existence of such precautionary behavior under health uncertainty and determine the effect of future
health uncertainty on overall household saving, using household level panel data from Korea.

3. Empirical Results

3.1. Description of the Data

Data from the Korean Household Panel Study (KHPS) were used to estimate the effect of health uncertainty on changes in consumption and medical expenditures. The KHPS is a nationwide panel survey conducted over the period of 1993-1998. It chose a representative sample of non-institutional Korean households, and interviewed each household member aged 18 and older once a year between August and October. For each household, the survey contains detailed information on household income and consumption, household assets, ownership of the dwelling, and household size. It also includes information on individual household members’ characteristics such as age, gender, marital status, health status, education, employment, smoking habits, and drinking habits.

Data from the survey in 1998 were not available to us, and the survey in 1995 did not have the question on self-assessed health status. Subsequently, we used the four-year panel data composed of 1993, 1994, 1996, and 1997 waves. The number of respondents was 10,460 from 4,547 households in the 1993 wave, 8,567 from 3,625 households in 1994, 6,729 from 2,833 households in 1996, and 6,320 from 2,724 households in 1997. After excluding individuals from the original data due to missing or internally inconsistent responses, we have constructed a working sample of a
balanced panel composed of 4,950 individuals.

The KHPS breaks down consumption into two types: nondurable consumption and durable goods consumption. Items under the heading of nondurable consumption include expenditures on food, housing, clothing/footwear, and cultural/recreation. We consider only these expenditures and do not include durable goods consumption. Medical expenditures include out-of-pocket expenses on medication, doctor’s office visits and hospitalization, and do not include health insurance premiums. Both consumption and medical expenditures have been adjusted using the consumer price indexes and are expressed in 1995 constant prices.

In the KHPS, the self-assessed health status was measured by asking each individual to describe his or her general health status as 5 categories: “excellent”, “good”, “average”, “poor”, or “very poor”. A description of the variables included in this study is presented in Table 1.

3.2. Conditional Variances of Health Disturbances

In order to estimate Eq. (8) and Eq. (9), the conditional variances must be determined first. In measuring health uncertainty, previous studies employed proxy variables for health risk; for example, Guiso et al. (1996) used ‘number of days ill’ and Starr-McCluer (1996) used ‘health insurance coverage’. This study uses the conditional variance of health disturbances as the direct measure of health uncertainty and directly calculates the conditional variance as follows: From the definition of conditional variance,
For $j = 1, \ldots, 5$, \hfill (10)

where $H_{it}$ is (latent) health, $S_{it}$ is the health status of individual $i$ at year $t$ represented by the discrete values from 1 (very poor) to 5 (excellent); $H_k$ is the (latent) health score corresponding to the health status $k$; and $P$ is the transition probability of health status.

Since we do not have a continuous measure of health in the KHPS, latent health scores ($H_k$) are obtained from the information contained in the self-assessed health status. It is generally believed that empirical distributions of self-assessed health are skewed to the lower level of health status. The sample distribution of self-assessed health in the KHPS also exhibits a skewed distribution to the lower level. Therefore, as in Wagstaff and van Doorslaer (1994) and Kakwani et al. (1997), we assume that underlying the responses is a continuous latent self-assessed health variable with a standard lognormal distribution. Following the method suggested in Wagstaff and van Doorslaer (1994), we first divide up the area under the standard lognormal distribution in proportion to the numbers in each response category for pooled four-year data, and then obtain the corresponding latent health scores for each category. Note that the latent health scores obtained by this method indicate ‘ill-health’ not ‘health’.

To estimate the transition probabilities of future health status given current health status, a multinomial logit model is employed. Following Palumbo (1999), the Markov transition probability of the individual’s health status in year $t$ conditioned
that his or her health status in year $t-1$ is $j$ is:

$$P(S_{i,t} = k \mid S_{i,t-1} = j) = \frac{\exp(\beta_{kj}X_{i,t})}{\sum_{j=1}^{5} \exp(\beta_{kj}X_{i,t})}, \quad k = 1, \ldots, 5,$$

where $X_{i,t}$ is a vector of individual $i$'s characteristics in year $t$. We estimate the coefficients for five different multinomial logit models (i.e., one for each of the five health statuses being considered). The explanatory variables are age, age squared, gender, marital status, education, smoking, and drinking.

The results of the multinomial logit estimation are presented in Table 2. The estimates for direct effect of age indicate that individuals are less likely to move into better health status as they are aging: age significantly decreases the probabilities of transition into good health from very poor health and transition into (or remaining in) excellent health from poor, average, or excellent health. It is also observed that high school graduates are more likely to move into better health status than individuals who didn’t finish high school. This is in accord with the general notion of a positive relationship between education and health status. On the other hand, the effect of smoking is not so pronounced in our estimation results. Smoking is found to deteriorate health status in a statistically significant way only when smokers are in ‘good health last year.’ In fact, drinking appears to have more significant effects on health status, but the direction of their effects is not so consistent. For example, drinkers with good or excellent health are more likely to slip into worse health status whereas drinking is found to actually increase the probability of better health next period for individuals with very poor or poor health.

After calculating the health transition probabilities given current health status and the (latent) health scores, the conditional health variance for each individual in Eq.
(10) can be determined. Substituting these variances into Eq. (8) and Eq. (9), we are now ready to test the prediction of the model.

3.3. Precautionary Behavior of Consumption and Medical Expenditures

In order to test the prediction of our model, we estimate Eq. (8) and Eq. (9). However, the estimation faces a number of complications. For one, the disturbance terms in these equations are the expectation errors, and are correlated with the conditional variances. In addition, Eq. (8) and Eq. (9) have the conditional variances as the only explanatory variables, and do not include other factors such as household characteristics as additional control variables. Subsequently, an omitted variable bias is likely to be present in the estimation of these equations. It is also likely that health uncertainty is affected by the changes in consumption or medical expenditures, in which case health uncertainty becomes endogenous.

Given a relatively short time period covered by this study, we may safely assume that individual-specific effects omitted from Eq. (8) and Eq. (9) are constant over time. Under this assumption, we first take first-differences of each of Eq. (8) and Eq. (9) to eliminate an omitted variable bias. We then employ the generalized method of moments (GMM) estimation to take into account non-zero correlations between the right-hand-side variables and the disturbances and also the potential endogeneity of conditional variances. Since we consider only households with no labor income, we select households headed by a person at least 65 years old in 1993, the beginning year of the panel.\(^5\)

In the GMM estimation, the lagged values of the conditional variances are used as
instruments. To test the validity of the overidentifying restrictions, we use the Sargan/Hansen test ($J$-statistic). Under the null of instrument validity, the $J$-statistic follows a chi-square distribution with degrees of freedom equal to the number of instruments less the number of parameters to be estimated. The test results indicate that the used instruments are valid. The estimation results based on these instruments are provided in Table 3. According to them, the estimated coefficients for future health variances in Eq. (8) and Eq. (9) have theoretically correct signs, and are significant at the 1% level.

Our results indicate that Korean elderly households exhibit precautionary behavior of consumption and medical care expenditures under health uncertainty. That is, faced with growing uncertainty about future (out-of-pocket) medical expenditures, elderly households tend to reduce current consumption and invest more in health by increasing current expenditures on medical care. However, it appears that households reduce their spending on nondurable consumption to a far greater extent than they increase spending on medical care. Therefore, our results regarding Korean elderly households suggest that uncertainty about their future health motivates retired individuals to hold down their levels of spending during the early years of retirement. This is in line with the substantial precautionary saving among elderly Americans implied by Palumbo (1999)’s findings based on the health uncertainty model.

It should be noted that health insurance can substantially weaken precautionary motives for saving by reducing uncertainty about future out-of-pocket medical expenditures. In fact, Chou, et. al (2003) found that the introduction of National Health Insurance (NHI) in Taiwan reduced saving by an average of 8.6-13.7 percent. At the same time, different types of arrangements for insuring uncertain medical
expenditures may have potentially quite different effects on savings. For example, the simulation results of Kotlikoff (1986) indicate that switching from the actuarially fair insurance arrangement to a Medicaid-type program with an asset test substantially reduces steady state wealth. In Korea, however, NHI covering all members of the population was already in place during the period this study covers. The insured fraction of the population ranges between 96 and 98 percent during this period.

4. Conclusions

The simple life-cycle hypothesis fails to explain the apparent reluctance of elderly families to spend down their incomes and wealth. This paper identifies health uncertainty as an important motive for such reluctance. We find empirical evidence that uncertainty about future health outcomes motivates elderly Koreans to hold down their levels of overall spending during the early years of retirement.

The model developed in this paper characterizes an elderly individual’s response to health uncertainty as a pattern of precautionary behavior in terms of consumption and medical care purchases, and provides testable equations for changes in consumption and medical expenditures. We test these equations on household level panel data from Korea to examine the pattern of precautionary behavior under health uncertainty among Korean elderly households.

Our empirical results indicate that Korean elderly households exhibit precautionary behavior of consumption and medical care expenditures as predicted by our model. That is, faced with growing uncertainty about future (out-of-pocket)
medical expenditures, elderly households tend to not only reduce current consumption but also invest more in health by increasing current expenditures on medical care. However, the magnitude of additional medical expenditures is found to be too small to reverse a fall in overall spending of elderly Koreans driven by their decisions to cut down on nondurable consumption.

Since we obtain from our model closed-form equations relating consumption and medical expenditures changes to the conditional variances of health disturbances, we try to directly measure these conditional variances in our empirical testing. The conditional variances of health disturbances are estimated using a multinomial logit model. The results of the multinomial logit estimation indicate that individuals are less likely to move into better health status as they are aging. It is also observed that high school graduates are more likely to move into better health status than individuals who didn’t finish high school. Although the effects of smoking and drinking are sometimes found to be significant for the individuals of specific health status, they are not generally pronounced and consistent in our estimation results.
Table 1. Description of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>0 if female, 1 if male</td>
</tr>
<tr>
<td>Age</td>
<td>age in years</td>
</tr>
<tr>
<td>Age Squared</td>
<td>$\text{Age}^2/100$</td>
</tr>
<tr>
<td>Education</td>
<td>0 if not graduated from high school, 1 if graduated from high school</td>
</tr>
<tr>
<td>Marital Status</td>
<td>0 if single, 1 if married</td>
</tr>
<tr>
<td>Household Size</td>
<td>number of household members</td>
</tr>
<tr>
<td>Smoking</td>
<td>0 if non-smoker, 1 if current smoker</td>
</tr>
<tr>
<td>Drinking</td>
<td>0 if non-drinker, 1 if current drinker</td>
</tr>
<tr>
<td>Health Status</td>
<td>1 if ‘Very Poor’, 2 if ‘Poor’, 3 if Average’, 4 if ‘Good’, 5 if ‘Excellent’</td>
</tr>
<tr>
<td>Consumption</td>
<td>annual consumption expenditures on food, housing, clothing and footwear, and cultural and recreation (10 thousand Won)</td>
</tr>
<tr>
<td>Medical expenditures</td>
<td>annual medical expenditures (10 thousand Won)</td>
</tr>
</tbody>
</table>
Table 2. Multinomial Logit Estimation

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Poor Health This Year</th>
<th>Average Health This Year</th>
<th>Good Health This Year</th>
<th>Excellent Health This Year</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conditioned on Very Poor Health Last Year</strong> (N = 821)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.073 (0.501)</td>
<td>-0.054 (0.063)</td>
<td>-0.202 (0.067)***</td>
<td>-0.014 (0.200)</td>
</tr>
<tr>
<td>Age Squared</td>
<td>0.072 (0.046)</td>
<td>0.046 (0.059)</td>
<td>0.190 (0.063)***</td>
<td>-0.097 (0.220)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.823 (0.233)***</td>
<td>0.895 (0.294)***</td>
<td>0.917 (0.339)***</td>
<td>0.640 (0.758)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.100 (0.270)</td>
<td>0.604 (0.300)**</td>
<td>0.839 (0.358)**</td>
<td>-0.181 (0.719)</td>
</tr>
<tr>
<td>Marital Status</td>
<td>0.328 (0.215)***</td>
<td>0.906 (0.311)***</td>
<td>1.122 (0.376)***</td>
<td>0.120 (0.741)</td>
</tr>
<tr>
<td>Smoking</td>
<td>0.171 (0.237)</td>
<td>0.122 (0.296)</td>
<td>-0.412 (0.369)</td>
<td>0.122 (0.846)</td>
</tr>
<tr>
<td>Drinking</td>
<td>0.741 (0.231)***</td>
<td>1.268 (0.272)***</td>
<td>1.454 (0.314)***</td>
<td>0.605 (0.662)</td>
</tr>
<tr>
<td><strong>Conditioned on Poor Health Last Year</strong> (N = 2634)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.0008 (0.040)</td>
<td>-0.028 (0.041)</td>
<td>-0.068 (0.044)</td>
<td>-0.150 (0.067)***</td>
</tr>
<tr>
<td>Age Squared</td>
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<td>-0.006 (0.038)</td>
<td>0.028 (0.041)</td>
<td>0.099 (0.065)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.517 (0.195)***</td>
<td>0.438 (0.200)**</td>
<td>0.164 (0.217)</td>
<td>-0.016 (0.352)</td>
</tr>
<tr>
<td>Education</td>
<td>0.390 (0.224)*</td>
<td>0.890 (0.222)***</td>
<td>0.698 (0.236)***</td>
<td>0.840 (0.353)**</td>
</tr>
<tr>
<td>Marital Status</td>
<td>0.302 (0.182)*</td>
<td>0.637 (0.197)*</td>
<td>0.521 (0.219)**</td>
<td>0.418 (0.374)</td>
</tr>
<tr>
<td>Smoking</td>
<td>0.087 (0.195)</td>
<td>0.209 (0.201)</td>
<td>0.099 (0.219)</td>
<td>-0.142 (0.368)</td>
</tr>
<tr>
<td>Drinking</td>
<td>0.629 (0.183)***</td>
<td>0.659 (0.185)***</td>
<td>0.698 (0.198)***</td>
<td>0.522 (0.309)*</td>
</tr>
<tr>
<td><strong>Conditioned on Average Health Last Year</strong> (N = 5291)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.0008 (0.040)</td>
<td>-0.028 (0.041)</td>
<td>-0.068 (0.044)</td>
<td>-0.150 (0.067)***</td>
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<td>Age Squared</td>
<td>-0.016 (0.036)</td>
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<td>Gender</td>
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</tr>
<tr>
<td>Drinking</td>
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<td>0.659 (0.185)***</td>
<td>0.698 (0.198)***</td>
<td>0.522 (0.309)*</td>
</tr>
<tr>
<td><strong>Conditioned on Good Health Last Year</strong> (N = 4641)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.076 (0.039)*</td>
<td>0.058 (0.038)</td>
<td>-0.013 (0.039)</td>
<td>-0.009 (0.051)</td>
</tr>
<tr>
<td>Age Squared</td>
<td>-0.081 (0.037)**</td>
<td>-0.105 (0.037)</td>
<td>-0.036 (0.038)</td>
<td>-0.046 (0.051)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.373 (0.230)</td>
<td>0.208 (0.220)</td>
<td>-0.055 (0.224)</td>
<td>-0.087 (0.271)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.031 (0.216)</td>
<td>0.333 (0.206)</td>
<td>0.328 (0.210)</td>
<td>0.227 (0.244)</td>
</tr>
<tr>
<td>Marital Status</td>
<td>0.588 (0.224)***</td>
<td>0.655 (0.215)***</td>
<td>0.512 (0.219)**</td>
<td>0.627 (0.285)**</td>
</tr>
<tr>
<td>Smoking</td>
<td>0.557 (0.249)**</td>
<td>0.614 (0.239)**</td>
<td>0.411 (0.243)*</td>
<td>0.449 (0.284)</td>
</tr>
<tr>
<td>Drinking</td>
<td>0.373 (0.210)</td>
<td>0.528 (0.200)***</td>
<td>0.556 (0.203)***</td>
<td>0.795 (0.236)***</td>
</tr>
<tr>
<td><strong>Conditioned on Excellent Health Last Year</strong> (N = 1463)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.007 (0.052)</td>
<td>-0.006 (0.050)</td>
<td>-0.046 (0.050)</td>
<td>-0.127 (0.056)**</td>
</tr>
<tr>
<td>Age Squared</td>
<td>-0.007 (0.049)</td>
<td>-0.037 (0.047)</td>
<td>-0.005 (0.047)</td>
<td>0.073 (0.054)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.358 (0.299)</td>
<td>0.303 (0.283)</td>
<td>0.068 (0.281)</td>
<td>-0.409 (0.311)</td>
</tr>
<tr>
<td>Education</td>
<td>0.043 (0.277)</td>
<td>0.551 (0.261)***</td>
<td>0.566 (0.260)***</td>
<td>0.432 (0.287)</td>
</tr>
<tr>
<td>Marital Status</td>
<td>0.121 (0.319)</td>
<td>0.556 (0.306)*</td>
<td>0.374 (0.303)</td>
<td>0.227 (0.338)</td>
</tr>
<tr>
<td>Smoking</td>
<td>-0.013 (0.299)</td>
<td>0.136 (0.282)</td>
<td>-0.069 (0.280)</td>
<td>-0.333 (0.308)</td>
</tr>
<tr>
<td>Drinking</td>
<td>0.360 (0.259)</td>
<td>0.441 (0.245)*</td>
<td>0.523 (0.244)**</td>
<td>0.456 (0.266)*</td>
</tr>
</tbody>
</table>

Notes: All coefficient estimates are relative to the health transition into very poor health this year. Standard errors are in parentheses. ***Statistically significant at the 1-percent level. **Significant at the 5-percent level. *Significant at the 10-percent level.
<table>
<thead>
<tr>
<th>Conditional variance conditioned on the information at $t$: $Var_{t,j} (\eta_{j,t+1})$</th>
<th>Dependent variable $\Delta C_{i,t+1}$ (Eq. (8))</th>
<th>Dependent variable $\Delta M_{i,t+1}$ (Eq. (9))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.8641***</td>
<td>-0.000648***</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td>(0.000101)</td>
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<tr>
<td>Sargan/Hansen statistic</td>
<td>6.119</td>
<td>1.667</td>
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<tr>
<td>[$p$-value]</td>
<td>[0.190]</td>
<td>[0.434]</td>
</tr>
</tbody>
</table>

*Notes:* Sample size = 81. Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors are in parentheses.

***Statistically significant at the 1-percent level.
Acknowledgements

The authors would like to thank Michael D. Hurd for extremely valuable comments and suggestions on an earlier draft.
References


Weil, P. (1993) Precautionary Savings and the Permanent Income Hypothesis,
Appendix

We begin with the last-period problem. At period \( T \), substituting Eq. (7) into Eq. (4) – (6) in the text yields:

\[
\exp(-\alpha C_{T-1}) = \left(\frac{1+r}{1+\rho}\right) E_{T-1} \left[\exp(-\alpha C_T)\right], \quad \text{(A1)}
\]

\[
\exp(-\gamma H_{T-1}) = \left(\frac{1+r}{1+\rho}\right) E_{T-1} \left[\exp(-\gamma H_T)\right], \quad \text{(A2)}
\]

\[
\exp(-\alpha C_T) = \left(\frac{1+r}{r+\delta}\right) \exp(-\gamma H_T). \quad \text{(A3)}
\]

Since \( C_T = W_T - M_T \) and \( H_T = (1-\delta)H_{T-1} + \lambda M_{T-1} + \eta_T \), we can rewrite Eq. (A3) as:

\[
\exp(-\alpha(W_T - M_T)) = \left(\frac{1+r}{r+\delta}\right) \exp(-\gamma((1-\delta)H_{T-1} + \lambda M_{T-1} + \eta_T)). \quad \text{(A4)}
\]

By taking logarithmic transformation on both sides and rearranging,

\[
M_T = W_T - \frac{\gamma(1-\delta)}{\alpha} H_{T-1} - \frac{\lambda \gamma}{\alpha} M_{T-1} + \frac{1}{\alpha} \ln \left(\frac{1+r}{r+\delta}\right) - \frac{\gamma}{\alpha} \eta_T. \quad \text{(A5)}
\]

Combining Eq. (A5) with the budget constraint and the health evolution process at the last period yields:

\[
C_T = \frac{\gamma(1-\delta)}{\alpha} H_{T-1} + \frac{\lambda \gamma}{\alpha} M_{T-1} - \frac{1}{\alpha} \ln \left(\frac{1+r}{r+\delta}\right) + \frac{\gamma}{\alpha} \eta_T, \quad \text{(A6)}
\]

\[
H_T = (1-\delta)H_{T-1} + \lambda W_{T-1} - \frac{\lambda \gamma}{\alpha} (1-\delta) H_{T-2} - \frac{\lambda \gamma}{\alpha} M_{T-2} + \frac{\lambda}{\alpha} \ln \left(\frac{1+r}{r+\delta}\right) + \eta_T - \frac{\lambda \gamma}{\alpha} \eta_{T-1}. \quad \text{(A7)}
\]

Note the fact that if \( x \) is normally distributed with mean \( E[x] \) and variance \( Var[x] \), then \( E[\exp(x)] = \exp(E[x] + \frac{1}{2} Var[x]) \). Thus if we assume that \( \eta \) is normally distributed, we can obtain:
$$E_{T-1}[\exp(-\alpha C_T)] = \exp\left(-\alpha E_{T-1}[C_T] + \frac{1}{2} \left( \frac{\gamma}{\alpha} \right)^2 Var_{T-1}[\eta_T] \right)$$, \quad (A8)$$

$$E_{T-1}[\exp(-\gamma H_T)] = \exp\left(-\gamma E_{T-1}[H_T] + \frac{1}{2} Var_{T-1}[\eta_T] \right)$$.

(A9)

From Eq. (A1) and (A2):

$$\exp(-\alpha C_{T-1}) = \left( \frac{1+r}{1+\rho} \right) \exp\left(-\alpha E_{T-1}[C_T] + \frac{1}{2} \left( \frac{\gamma}{\alpha} \right)^2 Var_{T-1}[\eta_T] \right)$$, \quad (A10)

$$\exp(-\gamma H_{T-1}) = \left( \frac{1+r}{1+\rho} \right) \exp\left(-\gamma E_{T-1}[H_T] + \frac{1}{2} Var_{T-1}[\eta_T] \right)$$.

(A11)

By taking logarithmic transformation on both sides of (A10) and (A11) and rearranging,

$$C_T - C_{T-1} = \left( \frac{r-\rho}{\alpha} \right) + \frac{\gamma^2}{2\alpha^2} Var_{T-1}[(\eta_T)] + (C_T - E_{T-1}[C_T])$$, \quad (A12)

$$M_T - M_{T-1} = \left( \frac{(r-\rho)\delta}{\gamma\lambda} \right) - \left( \frac{1-\delta}{2\gamma\lambda} \right) Var_{T-1}[(\eta_T)] + (M_T - E_{T-1}[M_T])$$.

(A13)

Thus we have obtained the final equations for changes in consumption and medical expenditures as in the text:

$$\Delta C_T = \left( \frac{r-\rho}{\alpha} \right) + \frac{\gamma^2}{2\alpha^2} Var_{T-1}[(\eta_T)] + \varepsilon_T$$, \quad (A14)

$$\Delta M_T = \left( \frac{(r-\rho)\delta}{\gamma\lambda} \right) - \left( \frac{1-\delta}{2\gamma\lambda} \right) Var_{T-1}[(\eta_T)] + \xi_T$$.

(A15)

where $\varepsilon_T$ and $\xi_T$ are expectation errors. By induction, we can derive the equations for consumption and medical expenditures changes at earlier periods.
Following Leland (1968) and Sandmo (1970), ample theoretical literature on precautionary saving exists about relating earnings uncertainty to a lower level of consumption. Empirical findings for various countries tend to be in line with the existence of precautionary saving arising from uncertain future income. For example, see Guiso et al. (1992) for Italy; Kazarosian (1997), and Carroll and Samwick (1998) for U.S.; and Lyhagen (2001) for Sweden. Lifespan uncertainty is another type of uncertainty frequently cited in the precautionary saving literature. A number of studies show that uncertain longevity influences households’ consumption decisions. They include, among others, Davies (1981) and Skinner (1985).

For example, Palumbo (1999) finds that the health uncertainty model tends to predict the consumption of elderly Americans much closer, on average, to observed level than life cycle models with lifespan uncertainty.

A utility function exhibiting constant relative risk aversion (CRRA) is more commonly used in the analysis of health risk. Under the CRRA utility function, however, our dynamic decision problem yields no closed-form solution. For simplicity, we assume a CARA utility function which indicates constant absolute prudence, following Kimball and Mankiw (1989), Caballero (1990), Weil (1993), and Chou et al. (2003).

For a detailed procedure to derive these equations, see the Appendix.

Age 65 is chosen as a cut-off age because the official retirement age was 60 for government officials and 65 for teachers during our sample period.

Household characteristics variables were also tried as instruments for the GMM estimation, but the $J$-statistic rejected their validity.
For simplicity, we delete the subscript $i$ in this appendix.