

DOES AGE OR LIFE EXPECTANCY BETTER PREDICT HEALTH CARE EXPENDITURES?

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SUMMARY

It is an unresolved issue whether age or (expected) remaining life years better predicts health care expenditures. We first estimate a set of hazard models to predict life expectancy based on individual demographic characteristics and health conditions, and then use regression analyses to compare the predictive power of age and life expectancy in explaining health care expenditures. This paper differs from previous studies in that it uses predicted life expectancy to address the censoring of death; as a result, this paper goes beyond the large health care expenditures at the end of life and the results apply to both deceased and survivors. We find that age has little additional predictive power on health care expenditures after controlling for life expectancy, but the predictive power of life expectancy itself diminishes as health status measures are introduced into the model. These results are not of esoteric interest only for their statistical properties; we show that using life expectancy rather than age results in lower projections of future health care expenditures. This result suggests that increases in longevity might be less costly than models based on the current age profile of spending would predict. Copyright © 2007 John Wiley & Sons, Ltd.

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INTRODUCTION

Longevity has been steadily increasing for the past century and a half, and this trend is likely to continue well into the future (Oeppen and Vaupel, 2002). This trend – combined with recent decreases in fertility – will substantially increase the number of octogenarians in the US population, both in absolute terms and as a fraction of the general population. Because of the strong positive association between age and health care costs, some researchers predict that these demographic trends will cause a major increase in health care expenditures (Mendelson and Schwartz, 1993; Denton *et al.*, 2002).

When considering the consequences of increased longevity for health care costs, however, it is important to ask whether it is age itself that determines medical spending or whether ages proxies for something else unmeasured. Individuals typically receive intensive medical services as death nears (Lubitz and Prihoda, 1984; Lubitz and Riley, 1993; Scitovsky, 1994, 1988; Garber *et al.*, 1998). Some estimates suggest that 5% of decedents account for 27% of total services, and Medicare payments for beneficiaries in their final year of life are about seven times greater than payments for the average surviving Medicare enrollee (Lubitz and Riley, 1993). This suggests that proximity to death may be a better indicator of health status and therefore a better predictor of health care expenditures than age.

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Disentangling whether it is age or proximity to death matters quite a bit for forecasting purposes. If it is age that matters, then the demographic trends among the elderly will result in substantially higher health care spending (Mendelson and Schwartz, 1993). However, if increases in longevity merely forestall mortality, then health care spending need not rise by as much (Miller, 2001; Lubitz *et al.*, 1995, 2003). In a head-to-head comparison of both methods, Miller (2001) found that cost projections for 2070 based on age exceed those based on proximity to death by about 15%. Using the proximity to death method, Lubitz *et al.* (1995) found that a 7.7% increase in life expectancy beyond age 65 between 1990 and 2020 is associated with only a 2.0% increase in lifetime Medicare payments, and Lubitz *et al.* (2003) found that the expected cumulative health expenditures for healthier elderly persons, despite their greater longevity, are similar to those for less healthy persons. Zweifel *et al.* (1999a,b) studied two samples of deceased individuals and found that age has no effect on health care expenditures for sub-samples of individuals aged 65+ after controlling for proximity to death,¹ where proximity to death is measured by a set of dummies for each period before death. Stearns and Norton (2004) found a similar result. Seshamani and Gray (2004a) used a 29-year longitudinal data set to also conclude that proximity to death matters.

Most of these studies are *retrospective* in the sense that they focus attention on a sample of decedents and then ask whether proximity to death is a more fundamental determinant of health care expenditures than age. In a forecasting exercise, however, we are interested in predicting *prospectively*. Given a cohort that is alive today, is age or proximity to death a better predictor of health care costs? It is not known exactly how long each person has to live, but one can form expectations. More fundamentally, however, age is likely a proxy for morbidity that is not measured by the analyst. Proximity to death contains most, if not all, of the information conveyed by age; therefore age should have little or no power² to predict health care expenditures when proximity to death is included in the model. Furthermore, when direct measures of health status are added to the model, the predictive power of both age and proximity to death should diminish.

Most prior research focuses on time-until-death as the measure for proximity to death. It refers to the actual length of time from a given age to death, whereas life expectancy refers to the expected length of time from a given age to death. Given demographic characteristics and health status, how long an individual is going to live has a probability distribution. Life expectancy is the mean of the distribution and time-until-death would be the realization of a draw from the distribution. Time-until-death has the advantage that it is observable, but – in a cohort of individuals – it may take a long time for everyone to die and hence is subject to severe right censoring.³ Two methods have been used in addressing the right-censoring problem in the literature. Stearns and Norton (2004) use a set of time-to-censoring dummies, and Zweifel *et al.* (2004) top-code time-until-death to 43 months for all survivors in their study. Both of these methods mitigate the right-censoring problem to some extent and allow analysis of survivors and deceased together. But questions remain on how much information on time-until-death for survivors these measures actually contain, and as a result they would tend to find significant effects of age on health care expenditures which are driven primarily by survivors. This also means that, for given time-until-death, the expenditures are averaged across different years and may not be comparable, if the health care delivery system is changing. For example, studies of end-of-life spending often aggregate data over many years to generate sufficiently precise estimates. Furthermore, it is not obvious that time-until-death is a better indicator of health status and predictor of health care expenditures than life expectancy because, on the one hand, time-until-death is affected by health and non-health shocks that may or may not be related to the health status for the period we are concerned with, and therefore

¹ Seshamani and Gray (2004b) found that the result is sensitive to model specification.

² It would be ideal if proximity to death or age also contains information other than health status that is correlated with health care expenditures, such as treatment intensity.

³ For example, Seshamani and Gray (2004a) still have 10% of right censoring even with a 29-year longitudinal sample.

contains more noise. On the other hand, time-until-death may contain information on unobserved health characteristics that are not captured by the models used to estimate life expectancy.

In this paper, we take a prospective view and ask whether age or life expectancy better predicts future health care expenditures using a longitudinal data set of Medicare beneficiaries. We also examine how their predictive power changes when health status measures are available. In the end, we compare the projections of future health care expenditures by age and life expectancy. This paper differs from previous studies in that it uses predicted life expectancy to address the censoring of death; as a result, this paper goes beyond the large health care expenditures at the end of life, and the results apply to both deceased and survivors. Our validity check supports this approach and shows that projections by life expectancy closely follow the adjusted actual health care expenditures while projections by age do not. Our results also show that socioeconomic characteristics and health status can be successfully used to predict life expectancy at the individual level. We find that age has little additional predictive power on health care expenditures after controlling for life expectancy, but the predictive power of life expectancy itself diminishes as health status measures are introduced into the model. This result suggests that increases in longevity might be less costly than models based on the current age profile of spending would predict.

DATA

The primary data source for this study is the 1992–1999 Medicare Current Beneficiary Survey (MCBS). The MCBS is a nationally representative sample of aged (65 years of age or older), disabled and institutionalized Medicare beneficiaries in the United States. The MCBS attempts to interview each respondent 12 times over three years, regardless of whether he or she resides in the community, a facility, or transitions between community and facility settings. The disabled (under 65 years of age) and oldest-old (85 years of age or older) are over-sampled. The first round of interviewing was conducted in 1991. Originally, the survey was a longitudinal sample with periodic supplements and indefinite periods of participation. In 1994, the MCBS switched to a rotating panel design with limited periods of participation. Each fall a new panel is introduced, with a target sample size of 12 000 respondents, and each summer a panel is retired. Institutionalized respondents are interviewed by proxy. The MCBS contains comprehensive claim-based/self-reported information on the health status, health care utilization and expenditures, health insurance coverage, and socioeconomic and demographic characteristics of the entire spectrum of Medicare beneficiaries.

For health status measures, we focus our attention on major disease conditions, functional status, and risk factors that have strong effects on both health care expenditures and survival. Our disease variables include dummies of ever having diabetes, cancer (excluding skin cancer), heart disease (myocardial infarction, heart attack, angina, coronary heart disease, congestive heart failure, or other heart condition), hypertension, stroke, lung disease (emphysema, asthma, or chronic obstructive pulmonary disease), Alzheimer's disease, and osteoarthritis. Functional status is typically measured by limitations in Activities of Daily Living (ADL) in empirical studies. We have two dummy variables for functional status: 1 or 2 ADLs and 3 or more ADLs. Risk factor measures include ever-smoked, underweight (defined as Body Mass Index (BMI) less than 20), normal weight (defined as BMI greater than 20 and less than 30), and obese (defined as BMI over 30).

Our analysis excludes enrollees under age 65 years old (16 840 observations) and enrollees with missing values for the variables of interests (444 observations). Respondents under 65 are eligible for Medicare only if they are disabled or with kidney failure and are not a representative sample of their age cohorts. More than 98% of the elderly population is enrolled in Medicare, and therefore MCBS can also be treated as a representative sample of the entire elderly population, not just the aged Medicare beneficiaries. These exclusions yield a sample size of 83 412. All expenditures are adjusted using medical CPIs and are in 1999 dollars.

METHODS AND RESULTS

Predicting life expectancy and time-until-death

To predict life expectancy, we first estimate a set of proportional hazard models in the following form:

$$\ln h_j(t) = \gamma' \text{Age}(t) + X_j \beta$$

where $\ln h_j$ is the log hazard of onset of outcome j (including death, diabetes, cancer, heart disease, Alzheimer's disease, stroke, hypertension, osteoarthritis, lung disease, 1 or 2 ADLs, 3 or more ADLs, and nursing home residency)⁴; $\text{Age}(t)$ is a piecewise-linear spline transformation of age at time t ; X_j are demographic characteristics, health status, and risk factors that affect the onset of outcomes. Demographic characteristics include age, gender, race, and education. Health status includes disease conditions and functional status. The baseline duration dependency is the dependency on respondent age, $\gamma' \text{Age}(t)$. The hazard of onset is assumed to be linear in age, with potentially different slopes before and after age 77,⁵ i.e. the baseline log hazard is piecewise linear.⁶

Our outcomes are annual transitions and each transition requires two contiguous interview years. All explanatory covariates are measured with a one-year lag, i.e. as of the first interview of an interview pair. In light of large gender differences in mortality risks, we allow for a full gender interaction with age. The model does not control for marital status because that inclusion would require an auxiliary model of marital status in order to project future marital status. The model specifications do not control for household income because we are not convinced that the quality of income data in the MCBS is sufficiently high.

We apply the hazard estimates to all individuals in our MCBS 1992–1999 sample to predict their life expectancy based on demographics, disease conditions, and risk factors in the year when they were interviewed. In other words, we simulate the lifetime disease and disability profile and survival curve for each individual in our sample. For example, for a person of 65 years old in 1992, we first predict the mortality rate and probabilities of having the listed conditions in 1993 when this person is 66 years old; then a random draw process is used to determine what conditions manifest for this person in 1993. If the predicted probability of onset of one condition is greater than the random draw, this person will get the condition in 1993; the process is repeated until the mortality rate is close to one or the effect of an additional iteration on life expectancy is negligible. Then we can construct a synthetic survival curve for this person (conditional on being alive in 1992) by accumulating the mortality rates. Life expectancy is calculated as area under this survival curve. Demographic characteristics and risk factors are held constant over this process.

To predict time-until-death for each individual, a random draw process is used to determine not only the onset of illnesses but also whether a person is going to die in the next period. If the predicted mortality rate is greater than the random draw, this person is predicted to die in the next period. We repeat this process until everyone in our sample dies and time-until-death is calculated as the number of years between the year of death and the year in which this person was interviewed. Essentially, the predicted time-until-death is the predicted life expectancy with some noise.

The National Center for Health Statistics (NCHS) publishes period life tables by year, age, gender, and race. We merged the time-until-death⁷ estimates from 1992–1999 NCHS period life tables with 1992–1999 MCBS data by year, age, gender, and race. Our estimates of mean life expectancy and time-until-death by

⁴The corresponding log-likelihood function is: $\ln L_j(\beta, \gamma) = \sum_{i=1}^N h_j(t)^{y_i} S_j(t)^{y_i} S_j(c)^{(1-y_i)}$, where $y_i = 1$ indicates that person i had onset of outcome at $t + 1$; all x 's are measured at t ; $S(t)$ is the survival function, $S(t) = \exp(-\int h(t) dt)$; c indicates the time of censoring and is always 1 under our data structure.

⁵We experimented with more general formulations using more nodes, and the results were not significantly different.

⁶ γ is a vector of two age slopes and $\text{Age}(t)$ is a spline transformation, $\text{Age}(t) = \begin{pmatrix} \min(A, 77) \\ \min(0, A - 77) \end{pmatrix}$, where A is age at time t .

⁷It is called life expectancy, but according to our definition, it should be time-until-death because it is based on how long an individual actually lived from a given age.

age are compared with those from NCHS (Figure 1). Empirical confidence intervals are also calculated. The predicted life expectancy and time-until-death are based on the probabilities of death and illness onsets between 1992 and 1999 and do not incorporate the effects of likely technology advancements beyond 1999. The NCHS statistics are from 1992–1999 period life tables in which time-until-death estimates are based on the death rates observed for the population in each given year. The predicted life expectancy and time-until-death are at the individual level while the NCHS statistics are at the aggregate level. Because both the predicted and the NCHS statistics are for the same population under the same medical technologies and practice of medicine, we expect them, on average, to be the same.

Our estimates of life expectancy and time-until-death using MCBS match well with the population level statistics (Figure 1), indicating that they are well constructed. The variation in NCHS estimates of time-until-death stems mostly from gender difference. Predicted time-until-death has much larger variation than predicted life expectancy, and the extra variation is only due to the random draw of death and therefore is entirely noise, unlike the actual time-until-death that may contain information on unobserved health characteristics not captured by the estimation models. Therefore, predicted time-until-death is inferior to predicted life expectancy as an indicator of health status and a predictor of health care expenditures.

Figure 2 shows the distributions of life expectancy and time-until-death. The distribution of predicted time-until-death from our hazard models is fairly close to the distribution of time-until-death from life

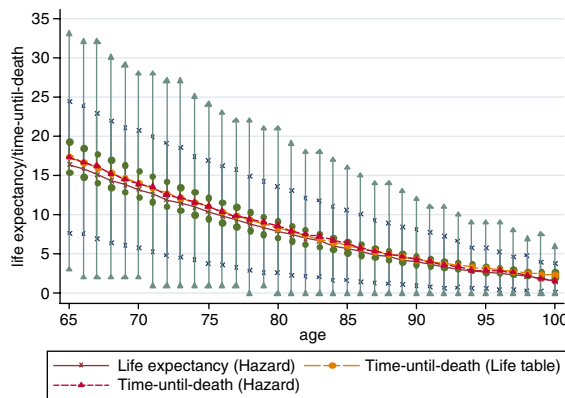


Figure 1. Life expectancy and time-until-death by age

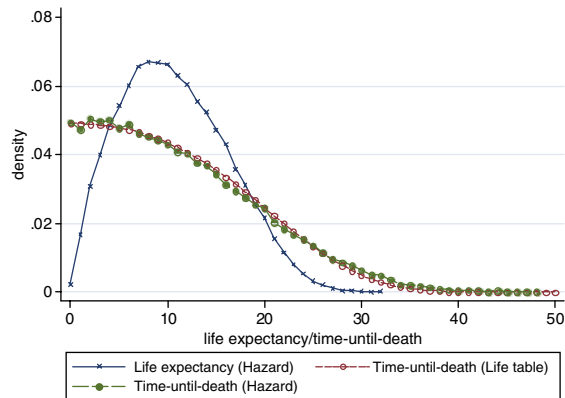


Figure 2. Distributions of life expectancy and time-until-death

Table I. Description of independent variables

Variables or groups of variables	
Total health care expenditures	
Age	
Age ²	
Male	
Race	White, Black, and Other (omitted group)
Hispanic	
Education	Less than high school (omitted group), High school, Some college, and College or higher
Married	
Region	Northeast, Midwest, South, West, and Other (omitted group)
Urban	
Insurance	Private, Employer, Medicaid, Medicare HMO, and Medicares A and B (omitted group)
Died	
Year	1992–1999 (omitted year: 1992)
Life expectancy	
Disability	Non-disabled (omitted group), 1 or 2 ADLs, 3 or more ADLs, and Nursing home
Obesity	Obese, Normal weight (omitted group), and Underweight
Ever smoked	
Health conditions	Diabetes, Cancer, Heart, Alzheimer's, Stroke, Hypertension, Osteoarthritis, and Lung disease
Interaction of health conditions and disabilities	

tables, which, from another perspective, proves the validity of our hazard estimates. The distribution of life expectancy, however, is very different from the distribution of time-until-death.

Modeling health care expenditures

Independent variables. Table I lists all the independent variables in our regression analyses and Table II lists the summary statistics of variables used in our analysis. We will estimate seven specifications in terms of covariates:

- (1) Age only: constant, age, and age².
- (2) Life expectancy only: constant and life expectancy.
- (3) Age and life expectancy: constant, age, age², and life expectancy.
- (4) Baseline⁸ plus age and age².
- (5) Baseline plus life expectancy.
- (6) Baseline plus age, age², and life expectancy.
- (7) Full model: all in (6) plus disease conditions, functional status, and risk factors.

Comparison among specifications (1)–(3) shows how age or life expectancy alone predicts health care expenditures. Comparison among (4)–(7) shows the predictive power of age and life expectancy in explaining health care expenditures at the presence of other demographic characteristics and health measures.

It may well be true that health care expenditures have a beneficial effect on life expectancy and health status; therefore, time-until-death and life expectancy could be potentially endogenous. But we expect that our approach actually mitigates this endogeneity problem to some extent: (1) The predicted life expectancy in year t is based on the demographics and health status in year t , and therefore it would not be correlated with health care expenditures after year t (actual time-until-death would); (2) The

⁸Baseline: constant, gender, race, Hispanic origin, education, married, region, urban, insurance, died and year dummies.

Table II. Descriptive statistics

Variable	Mean	Standard deviation
Age	75.11	7.47
Male	0.41	0.49
<i>Race</i>		
White	0.90	0.30
Black	0.08	0.27
Other	0.02	0.14
Hispanic	0.05	0.23
<i>Education</i>		
Less than high school	0.39	0.49
High school	0.33	0.47
Some college	0.15	0.35
College or above	0.14	0.35
<i>Risk factors</i>		
BMI	25.69	4.84
Ever smoked	0.59	0.49
<i>Disease conditions</i>		
Diabetes	0.17	0.37
Cancer	0.18	0.39
Heart	0.39	0.49
Alzheimer's	0.04	0.20
Stroke	0.12	0.32
HBP	0.54	0.50
Osteoarthritis	0.55	0.50
Lung disease	0.14	0.35
<i>Disability</i> ^a		
Non-disabled	0.68	0.47
1 or 2 ADLs	0.17	0.37
3 or More ADLs	0.09	0.28
Nursing home	0.07	0.25
Total health care expenditures (\$1999)	8923	17 577
Nonzero health care expenditures	0.97	0.17
Total sample size	83 412	

^aThe four disability categories are mutually exclusive.

predicted life expectancy is based on the hazard estimates and the health status of each individual in year t and is correlated with individual health care expenditures to the extent that the expenditures affect individual health measures in year t ; (3) The predicted life expectancy is mostly based on chronic conditions which will not be cured by the use of medical services. We expect this effect of expenditures on health status and predicted life expectancy to be small.

In our sample, each individual can have multiple observations in the span of several years; therefore, the error terms may not be i.i.d. In our model estimation, we address this issue by clustering observations from the same individuals and computing robust standard errors.

Dependent variable. Our primary dependent variable is total health care costs by Medicare beneficiaries. The reason that we use this aggregate measure as our primary dependent variable is that we are most interested in how well life expectancy and age, as general indicators of health status, can predict total health care costs, and its implications on future total health care spending. Total health care costs include both program spending and out-of-pocket spending and consist of health care spending on

inpatient, outpatient, physician, pharmaceutical, facility, home care, and hospice care. The cost data are based on Medicare claims data, linked to the MCBS, combined with respondent self-reports. For services covered by Medicare, the data capture the spending both by Medicare, other payers including Medicaid, and by the beneficiary. Spending for services not covered by Medicare is based on self-reports and may be under-reported.

Model specification. The distribution of medical expenses has the following characteristics (Duan *et al.*, 1983): first, about 20% of the population has zero expenses; second, the remaining 80% has positive expenses that are highly skewed, but the positive expenses are approximately log normally distributed through most of their range; third, the far-right tail of the distribution is too long even for a lognormal transformation. The econometric and statistical literatures provide a number of models for dealing with these kinds of data. In our data set, there are only 2215 observations with zero total expenditure, less than 3% of the total sample size.⁹ Hence, we do not model zero expenditure explicitly, which should not make much of a difference.

We consider two types of models in our analysis:

(1) *Linear/log-linear models*

$$Y = X\beta + \epsilon$$

where Y denotes health care expenditures or log transformation of health care expenditures. The advantage of ordinary least-square (OLS) model is that we do not have to assume a distribution for the error term and can avoid retransformation from log scale to normal scale comparing with the lognormal specification. Past research shows that log-transformed models fit health care costs better than non-log-transformed models. The disadvantage is that it could provide biased estimate of the mean response of the untransformed outcome variable in the presence of heterogeneity in the log-scale error term. Even the non-parametric smearing retransformation does not always work well.

(2) *Generalized linear models (GLMs)*

$$E(Y) = \exp(X\beta)$$

where Y denotes health care expenditures and has a Gamma/Gaussian distribution. Because of the possibility of long right tail of the distribution even after the log transformation, Gamma with log link is widely used to model health care expenditures. Gamma with log link is generally more robust to distributional assumptions than lognormal but can be very imprecise. Gaussian with log link is equivalent to a non-linear least-square (NLS) specification (from now on, we will refer this model as NLS). One drawback of NLS is that it allows for negative Y although negative predicted values are not allowed, but the fact that we have less than 3% of zero expenditure limits the effect of this truncation problem. NLS is quite appealing here in that, first, it allows for zero Y without introducing another step in the estimation (for example, the Probit model in the two-part model); second, no distributional assumption is necessary for the estimation; and third, it minimizes the sum of squared error, which is consistent with our interest in the mean.

There has been extensive literature comparing lognormal and GLMs with log link. The primary finding is that no single estimator is dominant or nearly dominant under all circumstances (Manning *et al.*, 2001; 2002). We compare the goodness of fit of these models using split-sample validation under specifications (4), (6), and (7). Given the large retransformation bias in the lognormal model, we compare only simple OLS, Gamma with log link, and NLS directly. We estimate all three models using data from year 1992 to t , predict the health care expenditures for year $t + 1$ to 1999, and then compute

⁹The reason we only have 3% zero expenditure is that we have a much sicker population (aged 65 or above) and medical spending has been growing rapidly in the last two decades.

both mean absolute prediction error (MAPE) and root-mean-squared prediction error (RMPE). Our results¹⁰ show that NLS consistently outperforms OLS and gamma distribution with log link under specifications (4) and (6) in terms of both MAPE and RMPE. OLS and NLS outperform gamma with log link for all cases and have similar goodness of fit under specification (7) in terms of both MAPE and RMPE. Overall, NLS has better goodness of fit than gamma with log link and simple OLS. Therefore, NLS is our preferred model and most of the subsequent analysis will be based on it. We will also show results from OLS and lognormal to check the robustness of the results from NLS.

Results

Because life expectancy is estimated from auxiliary hazard models, the standard errors obtained directly from the regression models may be understated.¹¹ The standard errors of our estimates are computed using bootstrap replications. We sample the 1992–1999 MCBS sample 1000 times, predict life expectancy for individuals in each of these bootstrap samples, and run our regression analyses. Standard errors are then computed across the results for these 1000 replications. These yield standard errors of the estimation, that is, we take the hazard estimates as given and computed variations that arise because of differences in the population of respondents and the randomness in the model transition. Also in all our regression analyses, observations are clustered by individuals and robust standard error estimation method is used for correcting non-i.i.d. errors.

Estimates from NLS are summarized in Table III, and we compare the predictive power between age and life expectancy under various model specifications. All findings here are consistent with our hypothesis. Age is a strong predictor of health care expenditures when life expectancy and health status are not included in the model. Both age and age² are statistically significant under ‘Baseline plus Age’ and they together have significant positive effects on health care expenditures.

After controlling for life expectancy, the effect of age on health care expenditures diminishes. Life expectancy then becomes a very strong predictor itself of health care expenditures. As shown in ‘Baseline plus Age and Life Expectancy’ model in Table III, the coefficients of age and age² change from 0.1340 to 0.0124 and from -0.0007 to -0.0001 , respectively, while the variances stay about the same. The marginal effect of age on health care expenditures is actually negative for individuals aged 65 or older. Age adds little additional predictive power to the model once life expectancy is included.

After controlling for health status, both age and life expectancy have little predictive power on health care expenditures as shown in Table III. The negative marginal effect of age on health care expenditures in both cases is consistent with the findings from the literature that doctors are more aggressive in treating younger patients.

The coefficients on most of the other covariates make intuitive sense. Under specification ‘Baseline plus Age’, males spend more than females; married individuals have lower health care expenditures; whites spend more than nonwhites; the better-educated spend more than the less educated; urban residents spend more than rural residents. Under specification ‘Baseline plus Age and Life Expectancy’, males no longer spend more than females, which probably can be explained by the fact that males have shorter life expectancy than females and are generally in worse health than females at a given age. The gaps between married and unmarried and between white and nonwhite are also somewhat reduced. Health status further reduces the gaps in most cases as expected.

The results above are robust to model specifications. Estimates on goodness of fit from OLS and lognormal are also calculated and summarized in Table IV. For the OLS model, age alone can explain 4.5% of the variation in health care expenditures while life expectancy explains 6.7% (a 50.2%

¹⁰ Not included in the paper due to limited space.

¹¹ Please see Murphy and Topel (1985) for a detailed discussion.

Table III. Estimates form NLS

	Baseline plus age	Baseline plus age and life expectancy	Full model
Age	0.1340*** (0.0162)	0.0124 (0.0171)	0.0140 (0.0209)
Age ²	-0.0007*** (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
Male	0.0683*** (0.0202)	-0.0354* (0.0204)	0.0441** (0.0208)
Married	-0.0654*** (0.0217)	-0.0495** (0.0222)	0.0064 (0.0215)
White	0.5577*** (0.0629)	0.5308*** (0.0654)	0.1724*** (0.0539)
Black	0.3726*** (0.0690)	0.3730*** (0.0712)	0.2986*** (0.0585)
Hispanic	-0.4929*** (0.0527)	-0.3365*** (0.0509)	0.1082** (0.0477)
High school	0.1177*** (0.0205)	0.1565*** (0.0198)	0.0385** (0.0182)
Some college	0.1338*** (0.0325)	0.1605*** (0.0321)	0.0441 (0.0321)
College or above	0.1270*** (0.0310)	0.2173*** (0.0297)	0.0470 (0.0303)
Urban	0.2553*** (0.0169)	0.2373*** (0.0167)	0.2217*** (0.0151)
Died	0.8699*** (0.0584)	0.7760*** (0.0597)	0.4204*** (0.0626)
Region	Yes	Yes	Yes
Insurance	Yes	Yes	Yes
Year	Yes	Yes	Yes
Life expectancy	No	-0.0834*** (0.0030)	-0.0080* (0.0046)
Health measures	No	No	Yes
Constant	1.4285** (0.6779)	8.0331*** (0.7281)	6.2693*** (0.9226)
ln <i>L</i>	-927 011	-925 710	-917 037

Note: Bootstrapped standard errors in parentheses: *10%; **5%; ***1%.

Table IV. Predictive power of life expectancy and age with OLS and lognormal models

<i>R</i> -squared	Age only	Life expectancy only	Age and life expectancy	Baseline plus age	Baseline plus life expectancy	Baseline plus age and life expectancy
Lognormal	0.0636	0.0862	0.0916	0.1333	0.1608	0.1612
OLS	0.0448	0.0673	0.0733	0.1299	0.1461	0.1477

increase); 'Baseline plus Age' can explain 13.0% of variation in health care expenditures while 'Baseline plus Life Expectancy' explains 14.6% (a 12.5% increase); and adding age to 'Baseline plus Life expectancy' model almost has no effect on *R*-squared while adding life expectancy to 'Baseline plus Age' model increases *R*-squared from 13.0 to 14.8%. For the lognormal model, age alone can explain 6.4% of variation in health care expenditures while life expectancy explains 8.6% (a 35.5% increase); 'Baseline plus Age' can explain 13.3% of variation in health care expenditures while 'Baseline plus Life Expectancy' explains 16.1% (a 20.6% increase); and adding age to 'Baseline plus Life expectancy' model

almost has no effect on R -squared while adding life expectancy to ‘Baseline plus Age’ model increases R -squared from 13.3 to 16.1%.

Our split sample validation with NLS model further confirms the conclusion that life expectancy is a better indicator of health status and a better predictor of health care expenditures. Once life expectancy enters the model, there is no gain to include age in predicting health care expenditures.

Projecting future health care expenditures

It is well established in the literature that diffusion of new medical technologies is the main driver of health care expenditure growth (Newhouse, 1992). Our projections are based on medical technologies and practice of medicine in the 1990s and changes in these factors will alter the trajectory of future health care expenditures.

Our projections do not incorporate the growth of health care spending over time; therefore, the annual health care expenditures by age $c(\alpha)$, annual health care expenditures by time-until-death $c(k)$, and annual health care expenditures by life expectancy $c(e)$ are time invariant and not functions of t .

Projections based on expenditures by age. We take Census Bureau annual projections of the residential population (middle series) by single year of age,¹² sex, race, and Hispanic origin from year 2000 to 2080, and estimates of health care expenditures by age using MCBS 1992–1999, to project total health care expenditures in year t :

$$TH(t) = \sum_{\alpha=65}^{100} p(\alpha, t) * c(\alpha)$$

where $p(\alpha, t)$ is the population of age α in year t , and $c(\alpha)$ is the annual health care expenditures for individuals of age α .

Projections based on expenditures by time-until-death. The distribution of time-until-death can be derived from projected period life tables. We have projected period life tables (1996–2080) from Berkeley Mortality Database prepared by the Office of the Chief Actuary in the Social Security Administration.¹³

The time-until-death distribution for individuals of age α in year t is expressed as

$$d(\alpha, k, t) = l(\alpha + k, t) * u(\alpha + k, t) / l(\alpha, t)$$

$d(k, t)$ is the population with time-until-death k in year t :

$$d(k, t) = \sum_{\alpha=65}^{100} d(\alpha, k, t) * p(\alpha, t)$$

where $k = 1, \dots, 40$.

Total health care expenditures in year t are expressed as

$$TH(t) = \sum_{k=0}^{40} d(k, t) * c(k)$$

where k is time-until-death; $l(x)$ is the proportion of a cohort surviving to age x ; $u(x)$ is the force of mortality at age x , and $c(k)$ is the annual health care expenditures for individuals with time-until-death k .

¹²The population projections put all people who are 100 year of age or older in one bracket.

¹³Projected life tables are based on Alternative II forecasts for the 1998 Trustees report. The life expectancies are based on the concept of a period life table. The period life expectancy at a given age for any year represents the average number of years of life remaining if all persons at that age in the population were to experience the mortality rates by age observed in, or assumed for, that year.

Projections based on expenditures by life expectancy. Although our regression analysis shows that life expectancy is a better predictor than age on health care expenditures, no projection on future distributions of life expectancy is available. Given the projected distributions of time-until-death, however, we can derive future distributions of life expectancy by using the empirical distributions of life expectancy conditional on time-until-death in the 1992–1999 MCBS sample because we have estimates of both time-until-death and life expectancy for everyone in our sample.

The distribution of life expectancy for the elderly population in year t is expressed as

$$q(e, t) = \sum_{k=0}^{40} d(k, t) * f(e | k)$$

Total health care expenditures in year t are expressed as

$$TH(t) = \sum_{e=0}^{32} q(e, t) * c(e)$$

where e is the life expectancy; $f(e|k)$ is the empirical distribution of e conditional on k , and $c(e)$ is the annual health care expenditures for individuals with life expectancy e . Note that $f(e|k)$ is not a function of t .

Projection comparison. Figure 3 shows the estimated expenditure–age and expenditure–life expectancy profiles. Health care expenditures increase dramatically as death nears or life expectancy approaches zero.

To validate our conclusion that life expectancy is a better predictor of health care expenditures than age, we use 1992 data to estimate the expenditure profiles and then project per capita expenditures forward from 1993 to 1999 as shown in Figure 4. Actual per capita expenditures are also included, both adjusted and unadjusted. Because medical technology advancements and regulatory changes among other factors, other than demographics and health status of the elderly, also contribute to changes in health care spending, we adjust the actual health care expenditures by spending trend and Balance Budget Act (BBA) of 1997. Clearly, after removing the spending trend and the effect of BBA from actual health care expenditures, the projections by life expectancy follow the actual health care expenditures much closely than the projections by age. The projections by age show a steady increase in health care expenditures because they do not take into account changes in health status for cohorts of the same age over time in predicting health care expenditures. Life expectancy, on the other hand,

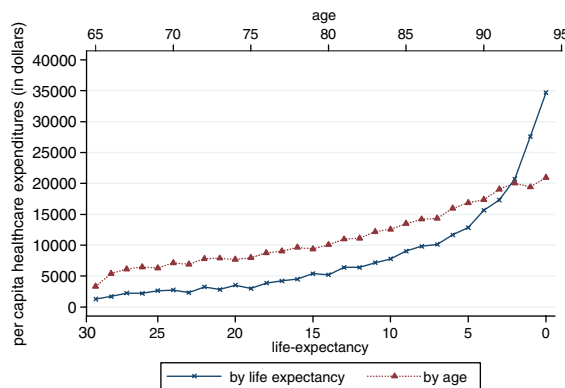


Figure 3. Per capita health care expenditure profiles

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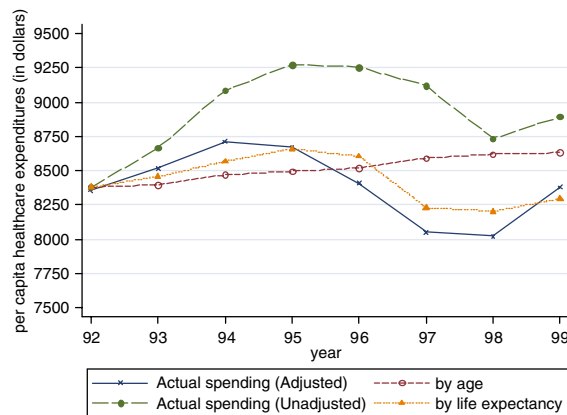


Figure 4. Projecting 1993–1999 health care expenditures using 1992 data

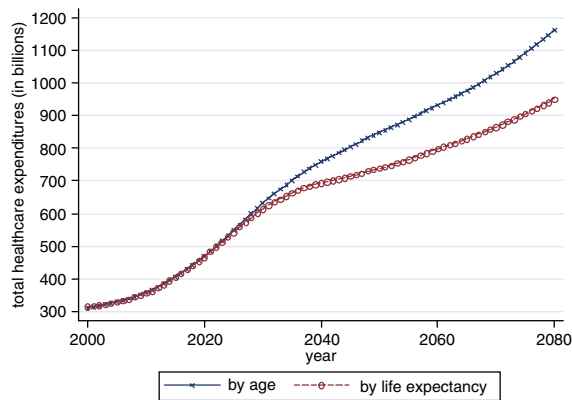


Figure 5. Projections of total health care expenditures

contains more information on health status and projections by life expectancy take into account changes in health status for cohorts of the same age over time.

Miller (2001), using a sample of *deceased* Medicare beneficiaries to estimate costs by time-until-death, found that projected *Medicare* expenditures in 2070 by age are about 15% higher than those by time-until-death. The expenditure profiles are based on deceased Medicare beneficiaries for Medicare expenditures, not total health care expenditures. Stearns and Norton (2004), using two simulated cohorts in 1998 and 2020, respectively, found that using age would over-predict health care expenditures by 9–15% over a 20-year period. In this paper, we solve the censoring problem of death by predicting life expectancy for each individual in our sample and are interested in how differently age and life expectancy, in a prospective framework, project future health care expenditures. Figure 5 shows total health care expenditure projections from 2000 to 2080 by age and life expectancy.¹⁴ Adding gender to the projections does not make much difference, and therefore the results are not reported here. Life expectancy yields significantly lower projected expenditures than age and the

¹⁴The projections by predicted time-until-death are also generated but are not presented because they are very similar to the projections by life expectancy.

gap widens with more gain in life expectancy. In 2040, the projected total expenditures by age are 9% higher than those by life expectancy; in 2070, the projected total expenditures by age are 19% higher and in 2080, the projected total expenditures by age are 22% higher.

DISCUSSION

Health care expenditures increase sharply as the end of life nears, which indicates that life expectancy may be a more fundamental measure of health status and therefore a better predictor of health care expenditures than age. Increasing attention has been paid to this hypothesis in recent years and many studies have already based their health care expenditure projections on life expectancy rather than on age.

The increase in longevity could be due to improved health care, better diet and higher quality food, decreased environmental hazards, and better sanitation. Medical technologies have played an important role in improving life expectancy. If the increase in longevity is due to improvements in health, then future cohorts will be in better health than those of today and projections by age would overestimate health care expenditures. If, however, the increase in longevity is largely because new medical technologies keep people alive in poor health, then projections by life expectancy would underestimate future health care expenditures. The life expectancy approach represents the optimistic path as supported by past experience.

Unlike age, life expectancy is unobservable. Using a set of discrete piecewise linear hazard models, we predict life expectancy conditioning on the information given in the particular period which include demographic characteristics, health status, and risk factors. Using our preferred model, NLS, we find that age has little predictive power on total health care expenditures after controlling for life expectancy while life expectancy itself is a strong predictor of health care expenditures. In other words, age has an effect on health care expenditures only through life expectancy. After we add direct health status measures to the model, neither life expectancy nor age has any predictive power on health care expenditures. The results are robust to model specifications. Using estimated expenditure–age profile, expenditure–life expectancy profile, and projected life tables, we are able to project future health care expenditures. The projections by life expectancy are significantly lower than those by age.

The findings here have strong implications in projecting future health care expenditures. As our results show, projections by life expectancy are much lower than those by age, especially with large life expectancy gains. Our results provide further evidence on the findings by Zweifel *et al.* (1999a, b, 2004), and Stearns and Norton (2004), and show that including life expectancy in projecting future health care expenditures would produce more reliable estimates.

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