NBER WORKING PAPER SERIES

HEALTHY-TIME MEASURES OF HEALTH OUTCOMES AND HEALTHCARE QUALITY

Marguerite Burns
John Mullahy

Working Paper 22562
http://www.nber.org/papers/w22562

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2016

John Mullahy's work has been supported in part by the Health & Society Scholars Program, by NICHD grant P2C HD047873 to the Center for Demography and Ecology, and by the Robert Wood Johnson Foundation Evidence for Action Program (grant 73336), all at the University of Wisconsin-Madison. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Healthy-Time Measures of Health Outcomes and Healthcare Quality
Marguerite Burns and John Mullahy
NBER Working Paper No. 22562
August 2016
JEL No. I1

ABSTRACT

The purposes of this paper are to describe some conceptual and empirical foundations of "healthy-time" measures of health outcomes or healthcare quality, and to explore how to expand the empirical opportunities for measuring such outcomes using U.S. national survey data. To these ends, the paper provides an overview of Grossman's seminal health production framework, surveys some of the healthy-time outcome/quality measures in use across a variety of contexts and applications, explores how data from the U.S. Medical Expenditure Panel Survey (MEPS) might be used to develop ongoing healthy-time measures for U.S. samples, describes an econometric strategy for studying such outcomes, and presents estimates of regression models describing two sets of healthy-time outcome measures obtained from 2011 and 2012 MEPS data.

Marguerite Burns
Department of Population Health Sciences
University of Wisconsin
WARF Building
Madison WI 53726
meburns@wisc.edu

John Mullahy
University of Wisconsin-Madison
Dept. of Population Health Sciences
787 WARF, 610 N. Walnut Street
Madison, WI 53726
and NBER
jmullahy@facstaff.wisc.edu

> *...consumers demand health, defined broadly to include illness-free days in a given year and life expectancy...* (Grossman, 2016)
>
> *What generally matters to patients are outcomes that encompass the whole cycle of care -- including health status achieved (e.g., survival, functional status, quality of life); the time, complications, and suffering involved in getting care; and the sustainability of benefits achieved...* (Porter et al., 2015)

1. Introduction

Economists examining health questions often encounter data on concepts like work-loss days, restricted-activity days, bed-disability days, and school-loss days, these often reported over a two-week recall or lookback period. Other familiar measures, like EVGFP self-assessed physical health or mental health, may or may not have defined recall periods or timeframes, while yet other measures are tied tightly to specific time windows, e.g. how many days in the past 30 days physical health or mental health has been not good.

Regardless of the particular metric, a fundamental motivation for analyzing or reporting such measures is that they are intended to describe individuals' "health", and -- in most cases -- to provide a time reference for the period during which that health was being experienced. That is, they are oriented to characterizing and measuring what we will call "healthy time." As we suggest in Section 2, such notions of time-denominated health are essentially those that characterize Grossman's seminal work on the demand for health (Grossman, 1972), and notion that "time being healthy is what people value" is challenging to challenge.

Indeed patient-centered and/or value-based healthcare is -- or at least ought to be -- based on the premise that the health outcomes or healthcare quality dimensions of interest are those that matter to patients. Measures used to assess the value of such healthcare

should logically attempt to capture such dimensions of health status (Lynn, et al., 2015; Porter et al., 2015). Section 3 describes how some prominent measures currently in use that point towards quantifying value or patient-centeredness are fundamentally about "time being healthy."

In reality, "time being healthy" will often be operationalized in available data by measures of time not spent in contact with the healthcare system. As such, its nature as truly healthy time is perhaps questionable. Downstream research might usefully explore the extent to which time spent outside of healthcare system contact is or isn't healthy and how this might vary with individuals' characteristics, including health status. But such considerations are beyond the scope of the present paper.

The purposes of this paper are to describe some conceptual and empirical foundations of "healthy-time" measures of health outcomes or healthcare quality, and to explore how to expand the empirical opportunities for measuring such outcomes using U.S. national survey data. To these ends, here is the plan for the paper. Section 2 gives a brief overview of Grossman's health production framework. Section 3 surveys some of the healthy-time measures in use across a variety of contexts and applications. Section 4 explores how data from the U.S. Medical Expenditure Panel Survey (MEPS) might be used to develop ongoing healthy-time measures for samples of the noninstitutionalized civilian population in the U.S. Section 5 describes an econometric strategy for studying such outcomes in reduced-form settings. Section 6 presents estimates of regression models describing two sets of healthy-time outcome measures obtained from 2011 and 2012 MEPS data. Section 7 concludes.

2. Health Measurement in Time: Grossman's Health Production Framework

Many discussions of health in health economics begin with Grossman's (1972) model of the demand for health. This work is best known for its emphasis on health as a valued commodity that cannot be purchased on markets, for its development of the notion of investment in health capital stocks as a special form of human capital, and for its careful assessment of the roles of medical care and schooling in the demand-investment framework.

A less-often emphasized feature of Grossman's framework is its careful distinction between health capital and health status. Health capital, a stock, is at time (subscripts "i" index time periods in Grossman's notation) generated via some investment-depreciation process $H_{i+1} - H_i = I_i - \delta_i H_i$, with investment "production" given by $I_i = I_i\left(M_i, TH_i; E_i\right)$ wherein M represents medical care utilization, TH is time devoted to investment in health capital (including, but not limited to, time spent engaged in medical care), and E is schooling or some other feature of non-health human capital.

Health status, conversely, is a flow that in Grossman's framework is at any time "i" proportional to health capital stocks, $h_i = \phi_i H_i = \phi_i\left(I_{i-1} - \left(1 - \delta_{i-1}\right)H_{i-1}\right)$. As a flow, health status is necessarily defined by some time frame or time denomination. In Grossman's framework, this translates into considering poor health or sickness as a particular form of time use within individuals' overall time budgets. Grossman's original exposition is characteristically clear:

> ...The time constraint requires that Ω, the total amount of time available in any period, must be exhausted by all possible uses: $TW_i + TL_i + TH_i + T_i = \Omega$,

where TL_i is time lost from market and nonmarket activities due to illness or injury.

...If sick time were not added to market and nonmarket time, total time would *not* be exhausted by all possible uses. My model assumes that TL_i is inversely related to the stock of health; that is, $\partial TL_i / \partial H_i < 0$. If Ω were measured in days (Ω=365 days if the year is the relevant period) and if ϕ_i were defined as the flow of healthy days per unit of H_i, h_i would equal the total number of healthy days in a given year. Then one could write $TL_i = \Omega - h_i$. (Grossman, 1972)

For present purposes the important point is that the component shares of the period-i time budget $TW_i + TL_i + TH_i + T_i = \Omega$ are, or result from, choices made in period i as well as in periods prior to i. As such, at a fundamental level the time share components result from individuals' purposive time-allocation decisions, and resultant period-i healthy time that emerges ($h_i = \Omega - TL_i$) is allocated to labor supply, further investments in downstream health, and time engaged in other forms of household production or investment.

Implementing empirically this time-allocation framework is challenging. The MEPS data we use (described in Section 4) contain no useful measures of date-specific labor supply, TW, nor do they permit distinction between productive investment time (T) and sick time (TL).[1] What we can reasonably draw from the MEPS data, however, is

[1] While it may or may not be important to draw sharp distinction between health capital and healthy time (i.e. "health status") in a particular application, some measures of health (continued)

information for a 365-day accounting period on elements of a time vector $\mathbf{t} = \left[\mathbf{TH}, \mathrm{TN}, \mathrm{TD} \right]$ measuring: a vector of health-capital (specifically, medical care utilization) investments, **TH**; time spent alive -- healthy or ill -- but not using medical care, TN; and time possibly deceased during the 365-day accounting period (TD). For the most part it is not possible to distinguish which aspects of **TH** represent investments in health while healthy (e.g. preventive healthcare utilization) from the "investments" that arise from the use of healthcare while unhealthy. In any event, the relevant time budget for present purposes is $\mathbf{TH} + \mathrm{TN} + \mathrm{TD} = \Omega = 365$. Previewing our empirical analysis, our interest is in estimating models of features of the distributions of period-two time allocations $\mathbf{t}_2$ given period-one covariates $\mathbf{x}_1$.

In Grossman's framework, the **TH** time allocations or investments might variously be conceived as factor demands for productive health investments, as components of time budgets within which health outcome flows are present, or in some sense as indicators of healthcare utilization per se. Moreover, as suggested by Grossman's human capital

---

(cont.)
elicited via familiar survey questions will often be difficult to interpret because of the lack of correspondence to either health capital or healthy time. For instance, compare a survey question: "In general, would you say your health is EVGFP?" with an alternative: "Over the past week, would you say your health is EVGFP?" The former version provides no time-frame anchor within which a respondent can interpret unambiguously what is meant by "in general"; as such it is challenging to interpret a response to such a question as a measure of healthy time or a health flow.

investment process $I_i = I_i\left(M_i, TH_i; E_i\right)$, the **TH** time inputs into health investment will to some degree be complementary with the medical care inputs (M) purchased or otherwise obtained by individuals. As such, the extent to which M is responsive to incentives like insurance generosity and the extent to which insurance generosity may be endogenously determined by unobserved illness propensities suggests that the **TH** time inputs will themselves be influenced by possibly self-selected insurance generosity. Some implications of this econometric analysis are considered in Section 6.

3. Healthy-Time Measures in Practice

The notion that healthiness is a flow corresponding to some form of time use or time allocation within a given time budget or time frame is both conceptually (in the context of Grossman's model) as well as intuitively appealing. While such measures are hardly common in empirical work -- or in the datasets that support such work -- applications are increasingly prominent. This section reviews some of these measures, and in so doing points the way to this paper's measurement innovations discussed in Section 4.

Two prominent measures of health status from the Behavioral Risk Factors Surveillance System (BRFSS) have been adopted as summary measures of health-related quality of life in population health contexts (CDC, 2000). The same questions (apart from slightly different punctuation) are also administered in the Medicare Health Outcomes Survey (HOS). These are measures of physically and mentally healthy time in the 30 days preceding the survey, based on the following survey questions (see Figure 1):

Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 was your physical health not good?

Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?

Characterizing healthiness via time allocations also appears in the context of disease-specific clinical outcomes. For instance, in a randomized trial comparing deep-brain stimulation and medication against medical management for patients suffering from Parkinson's symptoms (Deuschl et al., 2006) the main outcome studied is a multidimensional time allocation measure based on subjects' diaries. The dimensions of clinical interest are: (1) mobile with troublesome dyskinesias; (2) mobile without troublesome dyskinesias; (3) neither fully mobile nor fully immobile; (4) immobile; and (5) sleeping. The first and fourth measures are considered negative outcomes, the second and fifth positive outcomes, and the third an ambiguous outcome. By construction, these time uses add up to 24 hours in one diary day; see Figure 2.

In similar spirit, and of central interest in this paper, are measures that are based on information on individuals' healthcare utilization and mortality experiences over some predefined time window. We refer to such measures generically as utilization-based healthy-time measures. One early example of such a measurement approach is ESCAPE (2005) that examines using a randomized trial the safety and efficacy of pulmonary artery catheters for patients with congestive heart failure. The main endpoint in this study is *days alive out of the hospital* (DAOH) during the six months following randomization. The

ESCAPE trial adopts the terminology of "days well" being days on which subjects were neither in the hospital nor deceased.

Building on the DAOH concept, MedPAC, 2015, considers an indicator of care-related, patient-centered outcomes which they call *healthy days at home* (HDAH). The idea in defining HDAH is that over one calendar year, time not spent engaged in various encounters with the healthcare system or time not deceased constitutes a positive outcome from a patient's perspective. Using Medicare patients' encounters and mortality experiences, multiple forms of healthcare-related time allocation are defined: days not alive; days in an SNF; days with an ED visit; days with an outpatient observation stay; and days with receipt of home health care. Adding up all these measures, adjusting for double-counting, and subtracting from 365 yields the HDAH metric (see Figure 3). This measure is in fact silent on the question of whether the "days at home" are actually "healthy", but the basic premises underlying this measure's definition are conceptually sound and intuitively appealing; its use as a patient-centered outcome or care-quality indicator holds promise.

Similar in spirit is the Dartmouth Institute (2016) measure of *contact days* (CD), defined as "the number of days a patient spends per year in an inpatient setting or having a clinician visit, procedure, imaging study, or lab test in an ambulatory setting." Based in this particular example on Medicare encounters, it is argued that the CD measure is patient-centered and yields increased appreciation of "how much of the older adult's daily life is being occupied by health care." For our subsequent purposes it is useful to define the complementary measure of *noncontact days* (NCD), equal to 365 minus CD, as well as a measure of *noncontact days alive* (NCA), equal to NCD minus the number of days in the accounting period the individual was deceased.

The final utilization-based measure we discuss is that of *days residing in the community* (DRC). This measure is discussed by Mathematica Policy Research (2016) in the context of designing outcome measures for dual-eligible Medicare-Medicaid beneficiaries (see also Fenton et al., 2002). The stated goals in considering measures like DRC "are to develop measures that are meaningful, outcomes-based... and take into consideration preferences of key measure users and stakeholders, including consumers, state Medicaid agencies, health plans, and providers."

In all these cases, the presumed goal is to utilize existing data to characterize outcomes that are likely to be considered important by patients and other stakeholders, and ultimately to understand the factors -- treatments, quality initiatives, provider incentives, etc. -- that produce these time-allocation outcomes. For the DAOH, HDAH, NCA, DRC, and kindred utilization-based healthy-time measures the basic premise is that any given day within the accounting period has positive value if the individual is alive and not in contact with the healthcare system on that day. While no single such measure may be conceptually ideal, these measures trade off some conceptual purity for the ability to use available data on healthcare utilization and mortality to compute the respective metrics.

The next section builds on these frameworks and explores how such measures may be built on MEPS data. Among other things, to the extent that the measures we derive are sound -- plausible, reliable, robust, etc. -- the ability to define utilization-based health-time measures from MEPS greatly expands the scope of such measures from that of Medicare-encounter or clinical-EMR contexts.

4. Healthy-Time Measures Based on MEPS Data

Our empirical analysis uses data from the Medical Expenditure Panel Survey (MEPS). Specifically we utilize the two-year Longitudinal Data files for MEPS panels 15 and 16, covering 2010-2011 and 2011-2012, respectively (these are MEPS data files HC-148 and HC-156, respectively). To these files is merged information on the dates of various forms of healthcare system contact from the 2011 and 2012 Household Component Event files (MEPS files HC-144xx and HC-152xx, respectively). In the spirit of Grossman's time-allocation framework, the analytical strategy we pursue here is to use baseline measures obtained in year one of each two-year panel as conditioning covariates ($\mathbf{x}_1$) and time-use measures from year two of each panel as outcomes ($\mathbf{t}_2$).

MEPS affords potentially many different ways to proceed with respect to defining the time-allocation outcome measures. We focus here on two. The first mimics closely the spirit of the *days alive and out of hospital*, DAOH, measures described above. The second is essentially an amalgam of the NCD and the HDAH measures, in which the TN time use is *noncontact days alive*, or NCA. We refer to the sets of time-allocation outcomes in these two measurement approaches as Outcomes A and Outcomes B, respectively.

To compute these measures, we define the timing of various types of year-two healthcare utilization (e.g. dates of an inpatient stay) from the Household Component Event files. Date of death, if relevant, is obtained from the in-scope timing indicators in the Longitudinal Data files. Since multiple types of healthcare may have been reported for any given calendar date, we use the following hierarchy to assign a unique type of utilization (or death) to each calendar date:

Death > Inpatient Stay > E.R. Visit > Outpatient Visit >

Office-Based Visit > Dental Visit > Noncontact

For example, if on a particular date an individual made a dental visit and an E.R. visit, the utilization type assigned for that date was E.R. Visit. Our analytical sample contains observations on N=20,421 respondents ages 18 and above with nonmissing relevant data. Future work will add data from survey years prior to 2010 to our samples. Basic summary statistics for Outcomes A and B are displayed in Table 1; graphical depictions are provided in Figure 4.

Obtaining this analytical sample was not straightforward, and it is important for readers to appreciate some of the key issues confronted and decisions made in arriving at this sample. Among these are the following:

1. A minor point is that 2012 is a leap year and 2011 is not; we use 2012 data only for January 1 through December 30.

2. The specific timing of the dates of home healthcare contacts is not provided in the Event files. As such we ignore home healthcare in our analyses.

3. The utilization-type hierarchy we use (displayed above) is admittedly arbitrary, and reasonable alternatives can certainly be imagined.

4. We explored the use of summaries of inpatient stay nights (*ipngtdy2*), zero-night hospital stays (*ipzeroy2*), and home health provider days (*hhtotdy2*) that are provided in the Longitudinal Data files, particularly insofar as computation of a "days alive and out of the hospital" measure was concerned. In conjunction with our calculated year-two mortality timing, however, the totals of these

categories exceeded 365 days in a nontrivial number of cases. As such we elected not to pursue further a measure based on these variables.

5. The Longitudinal Data files for panels 15 and 16 provide information on the timing of when respondents may become "out of scope" for MEPS. (Indeed, this is how date-of-death is computed.) In principle information on the person disposition status (*pstatxx*) might be used to compute specific dates on which a respondent became institutionalized in a healthcare facility, for instance. However, determining the date on which such a respondent might have re-joined MEPS as in scope is more problematic. Thus, while institutionalized status would be an interesting dimension of healthcare system contact to consider, further exploration will be required before it can be determined whether this is reasonable to pursue. (Only a small number of respondents are so identified, it should be noted.)

6. The episodic nature of some forms of time spent in contact with the healthcare system is not addressed with the means-based analytical methods we use (described in the next section). That is, three four-day inpatient stays over the course of a 365-day accounting period would be treated as the same "outcome" as two six-day stays or one twelve-day stay. This also appears to be a feature of some of the other utilization-based time-allocation measures in use (e.g. HDAH). Whether or not this is problematic depends presumably on the questions at hand.

7. Other than death and institutionalization in a healthcare facility, other reasons for respondents to fall out of scope include some forms of military service, other forms of institutionalization, moving outside the U.S., etc. For simplicity, we

elected to define our sample to consist of respondents who either were in scope for the entire two-year MEPS survey period, or who died at some point during the two-year period.

8. Finally, while we plan to supplement our sample with panels prior to panel 15 (i.e. initial survey years prior to 2010), using samples after panel 16 encounters challenges. Specifically, after 2012 the MEPS public use files eliminated for confidentiality reasons specific date information for several key measures on which our measurement approach relies, instead providing only month and year data. For our proposed methods to be useful going forward, having ready access to specific date information is essential, and we will explore possible alternatives. (Accessing the specific date information is presumably possible through approved Census Research Data Center protocols or by working through the MEPS On-Site Data Center, but neither of these is ideal.)

5. Econometric Strategies

With M types of time allocation t_m of interest, the key measurement features are $t_m \in [0,\Omega]$ and $\sum_{m=1}^{M} t_m = \Omega$, where $\Omega = 365$ in our MEPS applications. One might be interested in general properties of a marginal or joint distribution, i.e. $f(t_m|\mathbf{x})$ or $f(\mathbf{t}|\mathbf{x})$ (where $\mathbf{x}$ represents exogenous covariates of interest, treatments, etc.). Or one might be interested more narrowly in particular features of such distributions, like conditional means $E[t_m|\mathbf{x}]$.

As any particular t_m will represent a fraction of the the overall fixed time budget Ω, approaching such modeling using fractional regression methods is intuitively appealing. In the case where only two forms of time allocation are of interest -- e.g. healthy and sick, along the lines of the BRFSS health days measures -- then the analytical setting is a univariate outcome model. In this instance, the original work of Papke and Wooldridge (PW, 1996) on estimation of conditional mean models for fractional univariate outcomes is directly applicable. In the PW framework one specifies conditional mean functions $E\left[t_m \middle| \mathbf{x}\right] = G\left(\mathbf{x},\boldsymbol{\beta}\right) \in \left(0,1\right)$, with the logical choice of functional forms for $G\left(...\right)$ being the class of univariate distribution functions. Specifying $G\left(...\right)$ as a logit or probit function gives rise to fractional logit (FLOGIT) or fractional probit (FPROBIT) specifications. Estimation of such models is generally undertaken using quasi-ML.

When the time allocation outcomes are multivariate ($M \geq 2$), a generalization of the PW estimator to the multivariate fraction or share context suggested by Mullahy, 2015, and Murteira and Ramahlo, 2016, may be useful.[2] Normalizing $\Omega = 1$, the essence of the multivariate fractional logit (MFLOGIT) model for multivariate time-share outcomes t_m is a set of $M \geq 2$ conditional means

$$E\left[t_m \middle| \mathbf{x}\right] = \xi_m\left(\mathbf{x};\boldsymbol{\beta}\right) \in \left(0,1\right), \quad m=1,...,M,$$

[2] Among other applications, the MFLOGIT method has been used to study empirically health-related time allocation (Mullahy and Robert, 2010).

having the property $\sum_{m=1}^{M} E\left[t_m \middle| \mathbf{x}\right] = 1$, and accommodating $\Pr\left(t_m = 0 \middle| \mathbf{x}\right) \geq 0$ and $\Pr\left(t_m = 1 \middle| \mathbf{x}\right) \geq 0$, m=1,...,M. The M conditional means are specified to have multinomial logit (MNL) functional forms,

$$E\left[t_m \middle| \mathbf{x}\right] = \xi_m\left(\mathbf{x};\boldsymbol{\beta}\right) = \frac{\exp\left(\mathbf{x}\boldsymbol{\beta}_m\right)}{\sum_{k=1}^{M}\exp\left(\mathbf{x}\boldsymbol{\beta}_k\right)}, \quad m=1,...,M,$$

with a required normalization one one of the outcomes' $\boldsymbol{\beta}_m$ ($\boldsymbol{\beta}_M = \mathbf{0}$ is used here).[3,4,5]

---

[3] Estimation is via quasi-ML using a MNL quasi-likelihood function where the observed shares $t_{im} \in \left[0,1\right]$ take the place of the usual binary indicators that would typically populate a multinomial logit likelihood function. The asymptotic distribution of $\hat{\boldsymbol{\beta}}$ follows from the quasi-ML arguments in PW. Specifically, given correct specification of the conditional first moments $\sqrt{N}\left(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}\right)$ is asymptotically $N\left(\mathbf{0}, \mathbf{V}\right)$, where the true asymptotic covariance matrix **V** manifests underdispersion relative to the MNL covariance matrix; inference using sandwich estimators accommodates such differences; Mullahy, 2015, provides details.

[4] If features of $f\left(\mathbf{t} \middle| \mathbf{x}\right)$ beyond simply its marginal conditional means are of interest then -- at the risk of jeopardizing robustness of conditional mean estimates -- models like negative hypergeometric distributions can be used to accommodate the restrictions $\sum_{m=1}^{M} E\left[t_m \middle| \mathbf{x}\right] = 1$, $\Pr\left(t_m = 0 \middle| \mathbf{x}\right) \geq 0$, and $\Pr\left(t_m = 1 \middle| \mathbf{x}\right) \geq 0$ and provide a comprehensive picture of the relationship between covariates and outcomes. This model is a Dirichlet mixture of multinomials or multivariate negative hypergeometric, a multivariate version of

(continued)

6. Results

This section reports the results of an empirical exercise examining determinants or correlates of the time-allocation shares in Outcomes A and B. The analysis is based on the 2010-2012 MEPS data as described in Section 3. The main objective of this empirical analysis is not so much to provide definitive estimates of the determinants or correlates of such outcomes, but instead to provide proof-of-concept estimates in which such outcomes might be characterized as the product of some "treatment" process of interest. A wide array of interesting questions might be posed such that exploiting MEPS's longitudinal structure might be exploited fruitfully, and at a minimum the estimation strategy pursued here should be suggestive as to how such questions might be addressed. That said, we believe the estimates presented here are also of intrinsic interest.[6]

(cont.)
the beta-binomial distribution (Heckman and Willis, 1977; Liu et al.,. 2013).

[5] One advantage of MFLOGIT-type estimation strategies is that inferences based thereon can be fully classical in the sense that the full joint covariance matrix of the parameter estimates and their corresponding partial effects is a by-product of this approach that estimates jointly all outcomes. In contrast, when such multivariate outcomes are neither considered nor modeled jointly, undertaking proper inference may be more challenging; for instance, in the Deuschl et al., 2006, study of Parkinson's interventions, it does not appear that the reported inferences accommodate the inherent jointness of the outcomes.

[6] Beyond the scope of this particular analysis, one might consider settings in which time-allocation outcomes like these might be modeled in contexts: with actual exogenous or random treatment assignment (e.g. the Deuschl et al., 2006, study); with exogenous policy changes (e.g. Medicare quality-improvement initiatives, along the lines of MedPAC, 2015); or with others in reduced-form settings in which exogeneity of RHS covariates is plausible

(continued)

To this end we exploit the longitudinal structure of the MEPS data and model time-allocation patterns (Outcomes A and B) in each MEPS panel's second year $\mathbf{t}_2$ as a function of year-one baseline characteristics $\mathbf{x}_1$ that include individual and family demographics and baseline indicators of chronic disease. As such this exercise can be interpreted roughly as one relying on Grossman's health production framework in which $\mathbf{t}_2$ are the period-two time allocations arising from period-one health capital stocks, constraints, etc., i.e. $\mathbf{x}_1$. From an econometric perspective, the MFLOGIT point estimates of the parameters β -- as with standard multinomial logit models -- are not themselves particularly interesting or informative.[7] Instead we present estimates of each covariate's average partial effect (APE), which indicate how, averaged over the sample, the means of the t_m conditional on $\mathbf{x}$ vary with the components x_k. The estimated APEs for Outcomes A and B along with their

---

(cont.)
(or is "induced" via control functions). In such cases, it will be useful to recall the discussion in Section 2 that considered how models of such outcomes -- in part consisting of measures of healthcare utilization -- have important commonalities with many healthcare utilization models in which exogeneity of RHS covariates like health insurance status may be tenuous, and in which problems of "postdiction" -- does health status predict utilization or does utilization predict health status -- may readily arise (see Manning et al., 1982).

[7] The parameter point estimates are available on request.

corresponding estimated bootstrap .95 confidence intervals are presented in Tables 2 and 3, respectively.[8]

For Outcomes A, the results in Table 2 suggest unsurprisingly that age and race/ethnicity have prominent associations with DAOH and time deceased. Of the year-one chronic diseases, cancer, diabetes, emphysema, joint pain, M.I., and stroke have particularly large negative associations with DAOH and mortality. Similar stories emerge in Table 3 for the APEs for Outcomes B, although the specific forms of time allocated to healthcare used in that outcome's definition obviously permit a more nuanced assessment of how individual demographics and chronic illnesses affect time allocated to healthcare utilization.

7. Summary

This paper has described some conceptual and empirical foundations of "healthy-time" measures of health outcomes or healthcare quality, and has explored how to expand the empirical opportunities for measuring such outcomes using U.S. national survey data from MEPS. Existing utilization-based time-allocation measures were seen to be more-or-

[8] The APE of covariate x_k on outcome t_m is given by

$$\widehat{APE}_{mk} = \sum_{i=1}^{N} \widehat{PE}_{mki} = \sum_{i=1}^{N} \frac{\delta \hat{E}\left[t_{im} \middle| \mathbf{x}_i \right]}{\delta x_{ik}},$$

where "δ" denotes either "Δ" or "∂". Note that $\sum_{m=1}^{M} \widehat{APE}_{mk} = 0$ due to the adding-up restriction. The confidence intervals are computed as $\left[.025, .975 \right]$ C_2 percentile confidence intervals as described in Hansen (2016, Chapter 10.5); the CIs presented here are based on 1,000 bootstrap replications.

less conceptually well grounded in economic theory. As such, their use as patient-centered outcome measures is both intuitively plausible as well as conceptually defensible. We are encouraged by our preliminary investigations into the utility of MEPS data for characterizing and assessing the determinants of such outcomes, although further conceptual work and scrutiny of the details of MEPS measures is necessary before we could advocate comfortably one particular or dominant set of healthy-time measures from MEPS.

Acknowledgments

Thanks are owed to participants at the Bari Health Econometrics Workshop for helpful comments and discussion.

References

Centers for Disease Control and Prevention. 2000. *Measuring Healthy Days*. Atlanta: CDC.

Dartmouth Institute for Health Policy & Clinical Practice. 2016. *Our Parents, Ourselves: Health Care for an Aging Population*. Hanover, NH: Dartmouth Institute.

Deuschl, G., C. Schade-Brittinger, P. Krack, et al. 2006. "A Randomized Trial of Deep-Brain Stimulation for Parkinson's Disease." *NEJM* 355: 896-908.

The ESCAPE Investigators and ESCAPE Study Coordinators. 2005. "Evaluation Study of Congestive Heart Failure and Pulmonary Artery Catheterization Effectiveness." *JAMA* 294: 1625-1633.

Fenton, W.S. et al. 2002. "Cost and Cost-Effectiveness of Hospital vs. Residential Crisis Care for Patients Who Have Serious Mental Illness." *Archives of General Psychiatry* 59: 357-64.

Grossman, M. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80: 223-255.

Grossman, M. 2016. "'A Theory of the Allocation of Time' Turns Fifty: Its Impact on the Field of Health Economics." *Health Economics* 25: 3-7.

Hansen, B.E. 2016. *Econometrics*. (Online textbook) Dept. of Economics, UW-Madison. http://www.ssc.wisc.edu/~bhansen/econometrics/Econometrics.pdf. (Accessed 28 June 2016).

Heckman J.J. and R.J. Willis. 1977. "A Beta-Logistic Model for the Analysis of Sequential Labor Force Participation by Married Women." *Journal of Political Economy* 85: 27-58.

Liu, C.-F., J.F. Burgess, Jr., W.G. Manning, and M.L. Maciejewski. 2013. "Beta-Binomial

Regression and Bimodal Utilization." *Health Services Research* 48: 1769-1778.

Lynn, J., A. McKethan, and A.K. Jha. 2015. "Value-Based Payments Require Valuing What Matters to Patients." *JAMA* 314: 1445-1446.

Manning, W.G., J.P. Newhouse, and J.E. Ware, Jr. 1982. "The Status of Health in Demand Estimation; or, Beyond Excellent, Good, Fair, and Poor." in V. Fuchs, Ed. *Economic Aspects of Health*. Chicago: University of Chicago Press for NBER.

Mathematica Policy Research. 2016. *Quality Measure Development and Maintenance for CMS Programs Serving Medicare-Medicaid Enrollees and Medicaid-Only Enrollees: Dual Enrollees and Medicaid HCBS Technical Expert Panel, April 13, 2016 Meeting Summary*. Contract No. HHSM-500-2013013011I.

Medicare Payment Advisory Committee (MedPAC). 2015. "Next Steps in Measuring Quality of Care in Medicare." Chapter 8 in *June 2015 Report to the Congress: Medicare and the Health Care Delivery System*. Washington, DC: MedPAC.

Mullahy, J. 2015. "Multivariate Fractional Regression Estimation of Econometric Share Models." *Journal of Econometric Methods* 4: 71-100.

Mullahy, J. and S.A. Robert. 2010. "No Time to Lose: Time Constraints and Physical Activity in the Production of Health." *Review of Economics of the Household* 8: 409-432.

Murteira, J.M.R. and J.J.S. Ramalho. 2016. "Regression Analysis of Multivariate Fractional Data." *Econometric Reviews* (in press).

Papke, L.E. and J.M. Wooldridge. 1996. "Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates." *Journal of Applied Econometrics* 11: 619-632.

Porter, M.E. et al. 2015. "Standardizing Patient Outcome Measures." *NEJM* 374: 504-506.

Figure 1

Healthy-Days Measures, 2014 BRFSS (Sample Frequencies)

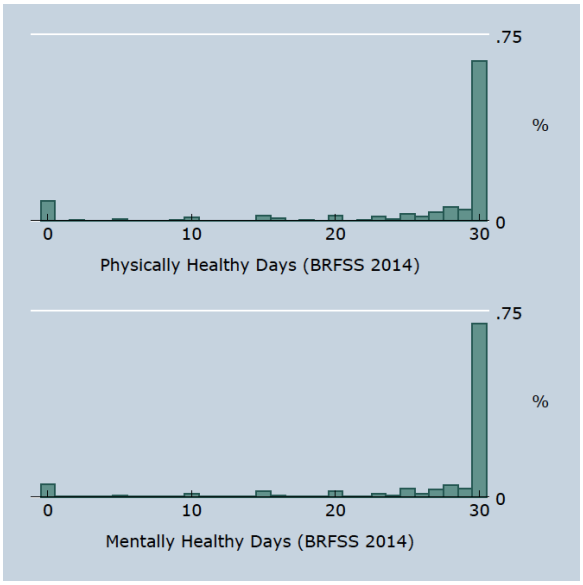


Figure 2

A Randomized Trial of Deep-Brain Stimulation for Parkinson's Disease: Changes in Patients' Diaries from Baseline to Six Months in the Neurostimulation and Medication Groups
(Reproduced from Deuschl et al., 2006, Figure 2B)

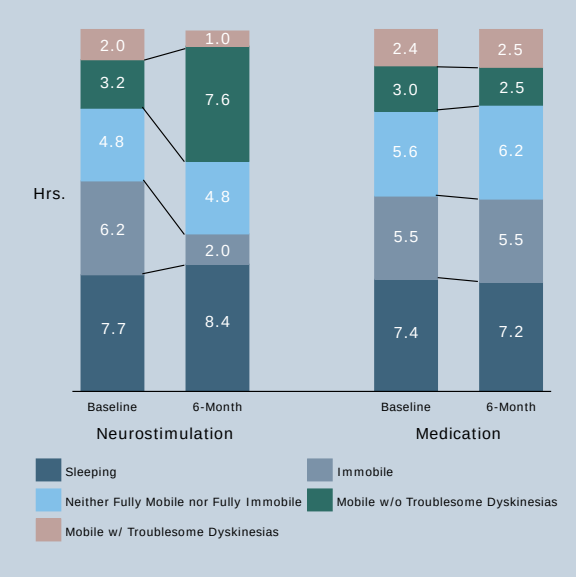


Figure 3

MedPAC Healthy Days at Home Measures, by Age,
Beneficiaries with at Least One Chronic Condition
(Source: MedPAC, 2015, Table 8-5)

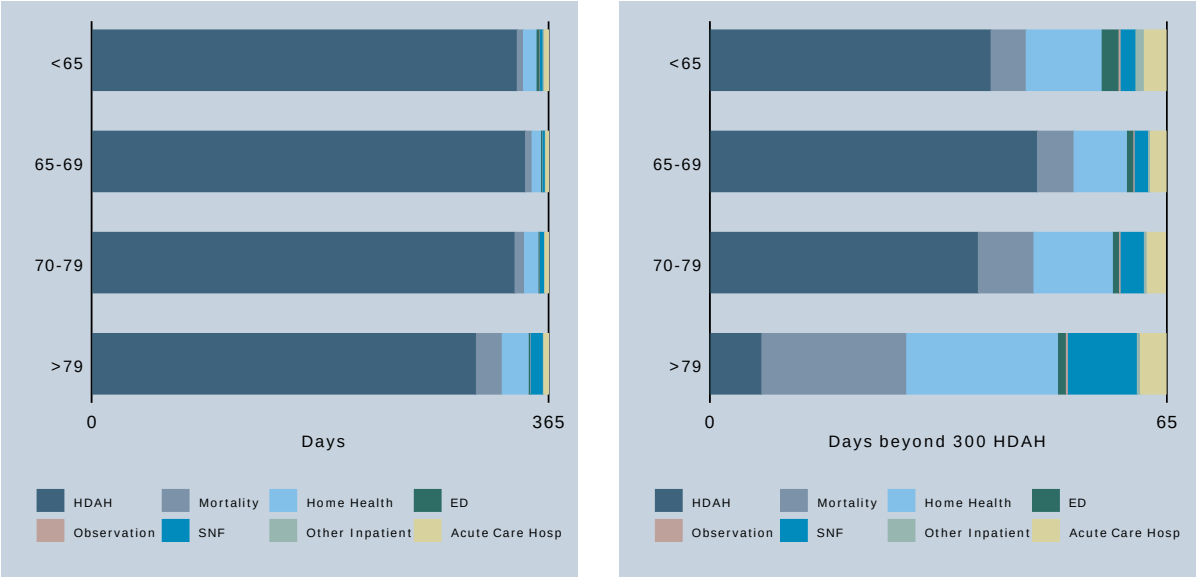
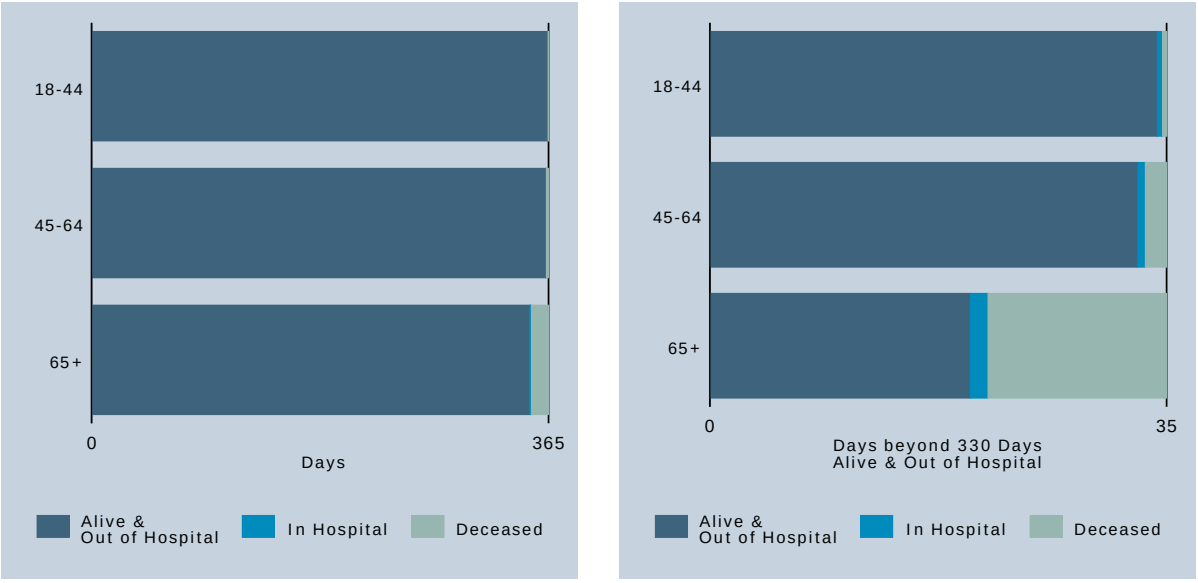


Figure 4

Healthy-Time Outcomes: Time-Budget Shares
(MEPS, 2012-2013; N=20,421; Sample Means)

Outcomes A: Days Alive and Out of Hospital



Outcomes B: Noncontact and Alive Days

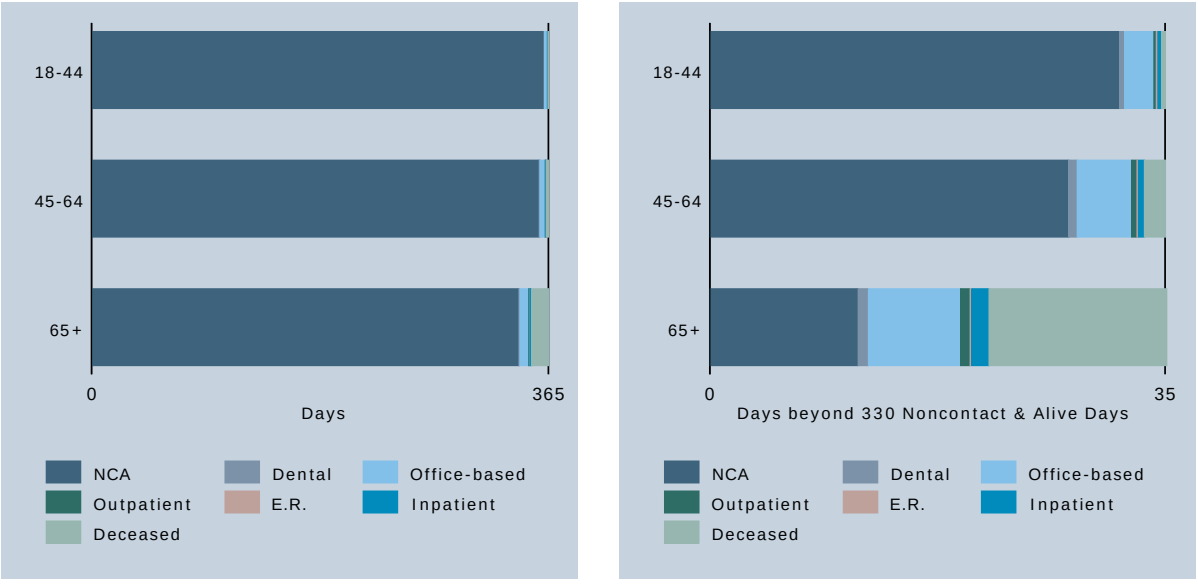


Table 1

Summary Statistics for Outcome Measures, by Age (Total N=20,421)

Outcomes	Days	Ages 18-44 (N=9,159)			Ages 45-64 (N=7,405)			Ages 65+ (N=3,857)		
		Mean	**%=0**	**%=365**	**Mean**	**%=0**	**%=365**	**Mean**	**%=0**	**%=365**
	Deceased	.309	.999	.001	1.634	.994	.003	13.675	.957	.028
Outcomes A	Alive & Out of Hospital	364.3	.001	.860	362.8	.003	.860	350.0	.028	.756
	In Hospital	.410	.862	0	.570	.864	0	1.314	.792	0
Outcomes B	Noncontact & Alive	361.5	.001	.432	357.6	.003	.272	341.4	.028	.116
	Dental Visit	.404	.774	0	.638	.694	0	.787	.665	0
	Office-Based Visit	2.231	.539	0	4.189	.363	0	7.087	.189	0
	Outpatient Visit	.184	.925	0	.409	.853	0	.736	.759	0
	ER Visit	.124	.905	0	.113	.913	0	.137	.892	0
	Inpatient	.285	.944	0	.457	.936	0	1.314	.871	0

Table 2

Estimated APEs and .95 Confidence Intervals: Outcomes A (N=20,421; Hansen C_2 CIs)

Covariate	Days		
	Alive & Out of Hospital	**In Hospital**	**Deceased**
Age	-0.301	0.003	0.298
CI - L	-0.360	-0.002	0.239
CI - U	-0.242	0.007	0.357
Female	0.628	0.153	-0.781
CI - L	-0.295	0.052	-1.806
CI - U	1.678	0.265	0.121
Education	-0.022	-0.037	0.059
CI - L	-0.149	-0.053	-0.070
CI - U	0.115	-0.021	0.181
Family Size	0.088	-0.051	-0.038
CI - L	-0.262	-0.085	-0.345
CI - U	0.413	-0.013	0.331
Non-Hispanic White	5.728	0.206	-5.935
CI - L	3.512	0.101	-8.024
CI - U	7.807	0.321	-3.690
Non-Hispanic Black	4.232	0.293	-4.524
CI - L	1.968	0.123	-6.759
CI - U	6.448	0.456	-2.201
Northeast	0.136	0.113	-0.248
CI - L	-1.348	-0.049	-1.647
CI - U	1.557	0.255	1.199
Midwest	-0.360	0.097	0.263
CI - L	-1.632	-0.049	-1.264
CI - U	1.140	0.224	1.539
West	1.155	0.001	-1.155
CI - L	0.016	-0.134	-2.268
CI - U	2.267	0.116	-0.054
MSA	0.045	0.057	-0.101
CI - L	-1.259	-0.063	-1.244
CI - U	1.229	0.197	1.189
continued			

Table 2 (continued)

Covariate	Days		
	Alive & Out of Hospital	**In Hospital**	**Deceased**
Angina	1.138	0.085	-1.223
CI - L	-0.110	-0.158	-2.748
CI - U	2.684	0.303	0.005
Arthritis	0.833	0.180	-1.013
CI - L	-0.196	0.015	-2.072
CI - U	1.941	0.341	0.023
Asthma	-0.239	0.182	0.056
CI - L	-1.619	-0.027	-1.461
CI - U	1.264	0.349	1.444
Cancer	-2.936	0.141	2.795
CI - L	-4.436	-0.023	1.169
CI - U	-1.305	0.291	4.271
Chronic Bronchitis	0.907	0.064	-0.972
CI - L	-0.490	-0.186	-2.628
CI - U	2.552	0.271	0.398
Coronary Heart Dis.	-0.355	0.022	0.333
CI - L	-1.767	-0.207	-1.318
CI - U	1.350	0.228	1.803
High Cholesterol	2.013	-0.074	-1.940
CI - L	1.010	-0.182	-2.925
CI - U	3.012	0.041	-0.941
Diabetes	-2.425	0.465	1.960
CI - L	-3.698	0.270	0.565
CI - U	-1.053	0.646	3.255
Emphysema	-7.115	0.380	6.735
CI - L	-10.300	-0.004	2.520
CI - U	-2.807	0.688	9.899
Hypertension	-0.157	0.112	0.045
CI - L	-1.217	-0.016	-0.932
CI - U	0.841	0.242	1.098
Joint Pain	-1.558	0.008	1.550
CI - L	-2.542	-0.121	0.515
CI - U	-0.490	0.153	2.510

continued

Table 2 (continued)

Covariate	Days		
	Alive & Out of Hospital	**In Hospital**	**Deceased**
M.I.	-3.720	0.152	3.569
CI - L	-5.905	-0.245	0.665
CI - U	-0.759	0.408	5.746
Other Heart Disease	-0.607	0.243	0.364
CI - L	-1.748	0.037	-0.915
CI - U	0.674	0.422	1.522
Stroke	-2.328	0.747	1.581
CI - L	-3.984	0.376	-0.169
CI - U	-0.478	1.063	3.199

Table 3

Estimated APEs and .95 Confidence Intervals: Outcomes B (N=20,421; Hansen C_2 CIs)

Covariate	Days						
	Noncontact	**Dental Visit**	**Office-Based Visit**	**Outpatient Visit**	**E.R. Visit**	**Inpatient Stay**	**Deceased**
Age	-0.337	0.006	0.025	0.005	-0.002	0.005	0.298
CI - L	-0.394	0.005	0.017	0.003	-0.003	0.001	0.240
CI - U	-0.279	0.007	0.033	0.008	-0.002	0.010	0.356
Female	-0.887	0.118	1.337	0.060	0.046	0.108	-0.782
CI - L	-1.888	0.086	1.106	-0.011	0.035	0.012	-1.697
CI - U	0.042	0.152	1.560	0.142	0.057	0.211	0.233
Education	-0.413	0.098	0.260	0.034	-0.005	-0.032	0.058
CI - L	-0.565	0.087	0.189	0.018	-0.008	-0.046	-0.074
CI - U	-0.265	0.110	0.331	0.049	-0.003	-0.015	0.184
Family Size	0.605	-0.054	-0.440	-0.027	-0.007	-0.044	-0.034
CI - L	0.220	-0.064	-0.523	-0.054	-0.011	-0.077	-0.369
CI - U	0.944	-0.042	-0.350	0.007	-0.002	-0.004	0.367
Non-Hisp. White	4.208	0.220	1.293	0.015	0.022	0.184	-5.941
CI - L	2.160	0.177	1.014	-0.080	0.005	0.063	-8.009
CI - U	6.201	0.265	1.588	0.123	0.037	0.289	-3.885
Non-Hisp. Black	4.443	-0.074	-0.136	0.007	0.035	0.257	-4.531
CI - L	2.392	-0.122	-0.507	-0.137	0.016	0.091	-6.974
CI - U	6.741	-0.031	0.242	0.139	0.054	0.410	-2.394
Northeast	-1.028	0.142	0.791	0.233	0.008	0.104	-0.250
CI - L	-2.409	0.091	0.466	0.129	-0.010	-0.048	-1.597
CI - U	0.316	0.187	1.131	0.339	0.024	0.233	1.128
Midwest	-1.528	0.211	0.665	0.292	0.031	0.067	0.262
CI - L	-2.926	0.165	0.402	0.172	0.013	-0.063	-1.206
CI - U	-0.052	0.256	0.949	0.392	0.048	0.201	1.705
West	-0.094	0.186	1.040	0.023	-0.001	0.002	-1.155
CI - L	-1.207	0.139	0.718	-0.057	-0.018	-0.126	-2.191
CI - U	0.987	0.233	1.374	0.114	0.016	0.117	-0.040
MSA	-0.425	0.099	0.422	-0.051	-0.009	0.064	-0.100
CI - L	-1.639	0.055	0.125	-0.117	-0.025	-0.058	-1.271
CI - U	0.773	0.146	0.723	0.024	0.009	0.182	1.102

continued

Table 3 (continued)

Covariate	Days						
	Noncontact	**Dental Visit**	**Office-Based Visit**	**Outpatient Visit**	**E.R. Visit**	**Inpatient Stay**	**Deceased**
Angina	1.116	-0.065	0.099	-0.015	0.009	0.076	-1.219
CI - L	-0.174	-0.190	-0.572	-0.147	-0.028	-0.151	-2.973
CI - U	2.947	0.042	0.692	0.082	0.043	0.261	-0.029
Arthritis	-0.843	0.007	1.518	0.150	0.032	0.150	-1.014
CI - L	-1.938	-0.039	1.203	0.041	0.014	-0.017	-2.144
CI - U	0.366	0.054	1.837	0.243	0.051	0.305	0.045
Asthma	-1.680	0.035	1.286	0.118	0.061	0.125	0.055
CI - L	-3.199	-0.026	0.849	-0.067	0.034	-0.080	-1.482
CI - U	0.042	0.093	1.674	0.262	0.085	0.285	1.446
Cancer	-4.357	0.097	1.124	0.193	0.032	0.110	2.801
CI - L	-5.851	0.046	0.806	0.092	0.009	-0.053	0.998
CI - U	-2.572	0.154	1.475	0.284	0.057	0.245	4.294
Chron. Bronchitis	0.588	-0.140	0.468	-0.017	0.013	0.058	-0.970
CI - L	-0.861	-0.232	-0.240	-0.160	-0.022	-0.185	-2.585
CI - U	2.333	-0.053	1.086	0.100	0.044	0.253	0.405
Coronary Heart Dis.	-0.767	-0.087	0.482	0.009	0.028	0.000	0.335
CI - L	-2.185	-0.165	-0.094	-0.119	-0.017	-0.210	-1.303
CI - U	1.040	-0.009	0.989	0.107	0.063	0.178	1.682
High Cholesterol	1.331	0.091	0.581	0.009	0.003	-0.072	-1.942
CI - L	0.278	0.053	0.302	-0.077	-0.014	-0.164	-2.924
CI - U	2.360	0.133	0.846	0.090	0.019	0.041	-0.897
Diabetes	-3.567	-0.045	1.096	0.106	0.024	0.428	1.958
CI - L	-4.928	-0.110	0.714	-0.018	0.000	0.218	0.584
CI - U	-2.113	0.014	1.457	0.214	0.046	0.604	3.238
Emphysema	-6.736	-0.035	-0.361	0.034	0.048	0.324	6.725
CI - L	-9.915	-0.173	-0.892	-0.148	-0.002	-0.033	2.694
CI - U	-2.585	0.100	0.138	0.179	0.092	0.613	9.876
Hypertension	-0.873	-0.061	0.733	0.044	0.031	0.084	0.042
CI - L	-1.916	-0.104	0.484	-0.056	0.013	-0.037	-0.997
CI - U	0.221	-0.020	0.978	0.142	0.049	0.215	1.118
Joint Pain	-2.714	0.077	0.986	0.090	0.033	-0.021	1.549
CI - L	-3.770	0.033	0.718	0.012	0.017	-0.149	0.512
CI - U	-1.647	0.115	1.232	0.169	0.049	0.122	2.640

continued

Table 3 (continued)

Covariate	Days						
	Noncontact	**Dental Visit**	**Office-Based Visit**	**Outpatient Visit**	**E.R. Visit**	**Inpatient Stay**	**Deceased**
M.I.	-3.642	-0.098	0.062	-0.017	-0.016	0.149	3.562
CI - L	-5.953	-0.187	-0.470	-0.159	-0.048	-0.173	0.866
CI - U	-0.784	-0.018	0.598	0.100	0.012	0.378	5.844
Other Heart Dis.	-1.721	0.083	0.783	0.247	0.035	0.206	0.368
CI - L	-2.980	0.017	0.356	0.038	0.013	0.020	-0.946
CI - U	-0.305	0.144	1.234	0.388	0.057	0.365	1.554
Stroke	-2.212	-0.129	0.090	-0.042	0.057	0.653	1.584
CI - L	-3.903	-0.224	-0.548	-0.154	0.016	0.297	-0.250
CI - U	-0.238	-0.043	0.632	0.051	0.094	0.942	3.251