HEALTH CONDITIONS AND FUNCTIONAL STATUS TRANSITIONS IN OLDER AMERICANS

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ABSTRACT

This study analyzes the longitudinal impact of several specific health conditions on functional limitations of older Americans. The research, building upon a newly developed two-stage longitudinal model, uses data from six waves of the Survey of Asset and Health Dynamics among the Oldest Old (AHEAD). We model the longitudinal influences of five serious health conditions (hypertension, diabetes, cancer, heart disease, and stroke) and arthritis on an older American's number of functional limitations. Analytic results demonstrate an inverse-U shaped nonlinear pattern of transitions in the number of functional limitations for each of the health conditions considered in the analysis. Those with stroke, diabetes and heart disease have higher number of functional limitations at most observation time points than do those with other health conditions. While the presence of each condition has strong adverse impact, comorbidity exerts an even more significant influence on an older American's functional disability.

Keywords: Health conditions, population aging, longitudinal analysis, two-step regression model

INTRODUCTION

During recent decades, the mean age of the population has sharply increased in the United States. Given the significant impact of such demographic changes on the demands for health services and on fundamental social aspects of life, studies analyzing the health of older persons have become topics of tremendous interest. Much of this research concerns the relationship of health measures as integral variables, used either as explanatory or dependent (Crimmins, Hayward, and Saito, 1996; Land, Guralnik, and Blazer, 1994; Liang, Liu, and Gu, 2001; Liu, Liang, Muramatsu, and Sugisawa, 1995). An older person's ability of performing activities of daily living has long been considered a function of morbidity, as well as of some other demographically and socially related factors, such as age and socioeconomic status. However, studies on the impact of specific health conditions on functional status are rare, and rarer is research concerning the longitudinal trend of such impact.

Several conceptual frameworks have influenced the measurement of health in survey research. The World Health Organization (WHO) defines health as "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (WHO, 1980). The obvious importance of this definition to health measurement is the expansion of the concept "health" to dimensions beyond "what ends at the skin." Following in the footsteps of the WHO model, Nagi (1965) developed a four-stage process to describe the change in health. His framework of health is sequential: Ill health begins with disease, which leads to impairment, in turn causing functional limitations, and finally resulting in disability.

Although they have been influential in designing health studies, neither the WHO nor the Nagi conceptual model has gained full academic acceptance (Verbrugge, 1990). One reason for this skepticism may be the difficulty in using these definitions for modeling the associations among various health measures and concepts. Blaxter (1989) develops a useful conceptualization by specifying a schema for categorizing measures of health as differentially defined by medical, social and subjective assessment approaches. The medical approach defines ill health as a deviation from physiological norms. The social approach, on the other hand, indicates illness with a notion of disability or functional disorder. Such disorders translate into difficulties in performing tasks mandatory for social integration. The subjective approach considers ill health in terms of an individual's general perceptions. This schema is useful for specifying three general domains of health measurement that are in congruence with three measures of health often used in studies of older persons. Health conditions, both serious and chronic, represent the medical approach, whereas functional status denotes the social approach, and self-assessed health mirrors the subjective approach. Surveys of older persons often contain measures of such health dimensions. The most frequently used health indicators include the existence of serious and chronic conditions or disorders, various measures of functional abilities, usually obtained through questions asking about difficulties in performing daily tasks like Activities of Daily Living (Katz & Akpom 1976) and Instrumental Activities of Daily Living (Lawton & Brody 1969), and self-rated health.

There are substantial studies investigating the underlying structural linkages among these health measures. These studies share some striking similarities, viewing self-rated health as a function of both health conditions and functional status, and convincingly demonstrating empirical support that health conditions influence physical and social functioning health which, combined, affect self-assessments of health (Bennett & Liang 1991; Johnson & Wolinsky 1993; Liang & Whitelaw 1990). This specification is appropriate, particularly since self-assessments of health result from a culmination of an individual's evaluation on a number of health and non-health related factors (Bergner 1985; Blaum, Liang & Liu 1994; Idler & Kasl 1995; Mossey & Shapiro 1982). Nonetheless, these prior studies have not addressed the discrete nature of illnesses and the possible non-linearity of the linkages among some of the health indicators, thus leading to some specification biases in estimating the interrelationships among health measures. Furthermore, no one has so far examined the longitudinal processes of linkages among various health measures as an older person ages over time.

The most complex examination of the structure underlying health measures has been conducted by Johnson and Wolinsky (1993). The model they have developed reflects a flow of causality adhering to socially relevant factors associated with health measurement. That is, "the scheme reflects a natural progression from body to mind as the diseases of old age are detected, take their physical toll, limit the elder person's abilities and dampen their sense of well-being" (Johnson & Wolinsky, 1993:107). A unique contribution of this research is the consideration of chronic illnesses individually, rather than as an *en masse* measure of the number of chronic disorders. This approach is preferable since Chappell (1981) demonstrates little underlying structure or homogeneous construct among health conditions. Their results confirm that although a disease acts both directly and indirectly on self-rated health, their precise influences depend upon the specific illness.

The present research contributes to one of the linkages of health measures within the longitudinal context, building upon the prior work by Johnson and Wolinsky (1993) and Liang and Associates (Bennett & Liang 1991; Liang & Whitelaw 1990). Specifically, we analyze the longitudinal impacts of five serious health conditions (hypertension, diabetes, cancer, heart disease, and stroke) and arthritis on an older American's number of functional limitations, using a newly developed two-stage longitudinal regression model. Longitudinal data come from the first six waves of the Survey of Asset and Health Dynamics among the Oldest Old (AHEAD). The effects of the level of comorbidity are considered and examined simultaneously. As planners, policy-makers, and health care providers are concerned about the costs of social welfare programs as the U.S. adult population ages, the results derived from this study will provide important information with policy implications.

CONCEPTUAL FRAMEWORK

In Johnson and Wolinsky's model (1993: Figure 3, pp. 114), it is questionable whether body disability and functioning should be treated as the cause and the effect. While functioning encompasses all body functions, activities and participation, disability serves as an umbrella term for impairments, activity limitations or participation restrictions (World Health Organization, 2001). Functional limitations in performing various social and physical activities should be regarded as the components, domains, or constructs of disability (Katz & Akpom 1976; Verbrugge 1990; World Health Organization, 2001). In this study, the number of functional limitations is used to measure functional status and, among those with any sign of functional loss, the severity of disability (Verbrugge 1991). As a person's limitations to various daily activities generally follow a hierarchical pattern, a greater number of activity limitations reflect a higher degree of disability (Katz & Akpom 1976; Kempen & Suurmeijer 1990; Liang, Liu and Gu, 2001; Liu, Liang, Muramatsu, & Sugisawa 1995; Spector, Katz, Murphy, & Fulton 1987).

While limitations of physical and social functioning reflect disability, we view the presence of any health condition (e.g. heart disease, diabetes, arthritis) as an indication of morbidity. Serious and chronic conditions vary considerably among people and over time; functional status fluctuates substantially according to the severity of health conditions and their progressive processes. Using these notions, we develop and test a longitudinal causal model on the relationship and its changing patter over time between health conditions and the number of functional limitations. The model is based on the underlying hypothesis that the precise way that health conditions function to influence an older person's physical and social functioning varies over specific diseases and over time. As a result, we consider five specific serious health conditions – high blood pressure, diabetes, heart disease, cancer, and stroke – and one chronic disease – arthritis – to represent health conditions. These diseases are widely believed to be among the leading conditions for disability and are the most frequently self-reported conditions among adults (Ferraro & Farmer 1999; Liang, Liu & Gu 2001; Radloff 1977). Other health conditions, such as fractured bones, hip replacement, mental disorders, and the like, are combined into one state – other diseases.

Some other factors can influence an individual's sense of self when it comes to health (Cockerham, Sharp & Wilcox 1983). Accordingly, we consider a number of control factors in the longitudinal model. They include socio-demographic characteristics (age, gender, education, veteran status, and ethnicity), social integration (marital status), and health behaviors (smoking cigarettes and drinking alcohol).

DATA, MEASURES, AND METHODS

Data

Data used for this study come from the Survey of Asset and Health Dynamics among the Oldest Old (AHEAD), a nationally representative investigation of older Americans. This survey, conducted by Institute of Social Research (ISR), University of Michigan, is funded by National Institute on Aging as a supplement to the Health and Retirement Study (HRS). At present, the Survey consists of six waves of investigation. The Wave I survey was conducted between October 1993 and April 1994. Specifically, a sample of individuals aged 70 or older (born in 1923 or earlier) was identified throughout the HRS screening of an area probability sample of households in the nation. This procedure identified 9,473 households and 11,965 individuals in the target area range. AHEAD obtains detailed information on a number of domains, including demographics, health status, health care use, housing structure, disability, retirement plans, and health and life insurance. Survival information throughout the six waves has been obtained by a link to the data of National Death Index (NDI). The present study uses data of all six waves (1993, 1995, 1998, 2000, 2002 and 2004).

Measures

We measure the number of functional limitations by a score of activities of daily living (ADL), instrumental activities of daily living (IADL), and other types of functional limitations (Liu, Engel, Kang, and Cowan, 2005). A score of one is given to an individual who has any difficulty with a specific physical or social activity, and the number of items for which difficulties are reported is then summed. As a result, the score ranges from 0 (functional independence) to 15 (maximum disability).

Dichotomous variables indicate the existence of six specific diseases or disorder – hypertension, diabetes, heart disease, cancer, stroke and arthritis – with the presence of a given disease or disorder coded "1." We also construct a variable indicating the presence of any other diseases, such as fractured bones, hip replacement, mental disorders, and the like. An older person is viewed as "without any physical disease or mental disorder" if each of these variables is zero. Table 1 presents distributions of AHEAD respondents at six waves by specific health conditions and the number of functional limitations.

<Table 1 about here>

With respect to control variables, first, we consider six socio-demographic and social integration variables. Veterans status is a dichotomous variable with 1 = veterans and 0 = nonveteran. Age is defined as the actual years of age reported by respondents at the AHEAD Wave I survey. Gender is indexed as a dichotomous variable (women = 1; men = 0). Educational attainment, an approximate proxy for socioeconomic status, is measured as the total number of years in school, assuming the influence of education on health status to be a continuous process (Liu, Hermalin, & Chuang 1998). Ethnicity is specified as a dichotomous variable (white = 1; others = 0), as is marital status (“currently married” = 1; else = 0). Among them, age and marital status are viewed as time-dependent variables.

Next, we consider two time-dependent variables measuring health behaviors, “smoking cigarettes” and “drinking alcohol,” measured as dichotomous (“currently or previously smoking cigarettes” or “currently drinking alcohol” = 1; else = 0). Whereas the negative effect of smoking on health has been well documented, moderate drinking has been observed to produce a protective effect on health (Duffy 1992). The AHEAD data set does not contain reliable and useful information on the amount of alcohol consumption. However, there is evidence that heavy drinking is not common among older persons (Koong, Malison & Nakashima 1990; Liu et al. 1998). Therefore, we expect most drinking older Americans to be moderate drinkers; hence drinking alcohol is likely to be favorably linked with an older person’s health status.

Table 2 presents the means, standard deviations, and coding schemes for the aforementioned variables at Wave I.

<Table 2 about here>

Methods

Although the number of functional limitations is a continuous variable, a considerable proportion of the AHEAD respondents have reported no functional problem at all. This distribution suggests that the linearity assumption, which is widely applied in measuring health status, does not hold in this context. As a result, an application of the least squares regression leads to biased estimates of the effects on the number of functional limitations (Amemiya, 1985; Heckman, 1976; Maddala, 1983). Additionally, as the distribution of health status among functionally dependent persons is often skewed (Blaum, Liang and Liu, 1995), the direct use of a linear regression approach is inappropriate.

Instead, we use a two-stage longitudinal regression model to estimate the effects of health conditions on the number of functional limitations. The relationship can be viewed as a joint distribution of two sequential events – the likelihood of having any functional limitation and the conditional density function on the number of functional limitations among those having at least one limitation. For this reason, a two-step procedure is developed with the first equation estimating the likelihood of having a nonzero number of functional limitations. Let I be the number of respondents at baseline and J the number of time points, then the two-stage nonparametric model is given by

$$\Pr(\mathrm{Y} > 0) = \Phi(\mathbf{X}'\boldsymbol{\beta}_1 + \mathbf{Z}'\boldsymbol{\gamma}_1) \qquad (1a)$$

$$\log(\mathbf{Y} | \mathbf{Y} > 0) = (\mathbf{X}'\boldsymbol{\beta}_2 + \mathbf{Z}'\boldsymbol{\gamma}_2 + \boldsymbol{\varepsilon})\boldsymbol{\xi}, \qquad (1b)$$

where $\mathbf{Y}$ represents the $(n \times 1)$ vector of observed outcome data within the framework of a block design $(n = I \times J)$. The matrix $\mathbf{X}$ is an $(n \times p)$ matrix for p -1 independent variables and $\mathbf{Z}$ is a $(n \times r)$ design matrix for the random effects. The matrices $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are parameters for $\mathbf{X}$ and $\mathbf{Z}$, respectively. The random effects are assumed to be normally distributed with mean 0 and variance matrix $\mathbf{G}$. Φ denotes the cumulative normal distribution function (probit function), $\boldsymbol{\xi}$ serves as a nonparametric adjustment factor for selection bias from high mortality, and $\boldsymbol{\varepsilon}$ is the error term for the OLS model which, after retransformation, is not normally distributed (Manning, Duan & Rogers 1987). This two-stage model derives much more efficient estimates than those obtained from a single OLS regression (Heckman 1976; Maddala 1983).

We extend Duan's (1983) and Liu's (2000) retransformation method to estimate the above two-equation model. Here, we are not particularly interested in understanding the correlation coefficients between the two equations per se; instead, we seek to look at the overall prediction bias of the two models (Manning et al. 1987). Our preliminary data analysis demonstrates that the retransformation approach behaves more efficiently than an extension of the Heckman's model in the context of health distribution. In the construct of the retransformation method, the expected number of functional limitations at various time points can be expressed by the following joint distribution:

$$\mathbf{E}\left(\hat{\mathbf{Y}}\middle|\mathbf{S}=1\right)=\Phi\left(\mathbf{X}'\hat{\boldsymbol{\beta}}_1+\mathbf{Z}'\hat{\gamma}_1\right)\exp\left(\mathbf{X}'\hat{\boldsymbol{\beta}}_2+\mathbf{Z}'\hat{\boldsymbol{\gamma}}_2\right)\hat{\boldsymbol{\xi}}, \qquad (2).$$

where the first equation component on the right (the probit model) derives the probability of $Y_i > 0$ from equation (1a), and the second predicts the number of functional limitations among those with at least one limitation, at each time point. Veteran status, age, gender and education are used as the control variables in estimating the mixed models and are rescaled to be centered about their means for analytic convenience. Specification of different sets of covariates at two different estimation stages helps reduce the occurrence of collinearity (Winship and Mare 1992). The estimate of ξ at time t is thus given by

$$\boldsymbol{\xi}_{\mathbf{t}} = \frac{\sum_{\mathbf{i}=1}^{\mathbf{n_t}} \exp\left[\log\left(\mathbf{Y_{it}}\middle|\mathbf{Y_{it}}>0\right)-\left(\mathbf{X}'_{\mathbf{2it}}\hat{\boldsymbol{\beta}}_5+\mathbf{Z}'_{\mathbf{2it}}\hat{\boldsymbol{\gamma}}_5\right)\right]}{\mathbf{n_t}}. \qquad (3)$$

As defined, the nonparametric random-effects model does not depend on the specification of a given selection process. Rather, it estimates an unknown error distribution by the empirical cumulative density function of the estimated regression residuals, and then takes the desired expectation with respect to the expected error distribution. The SAS PROC MIXED procedure with repeated measures is used to compute both fixed and random effects at the second stage and derive the predicted number of functional limitations at each time point (Littell, Milliken, Stroup, Wolfinger, and Schabenberger 2006). Because intervals between two adjacent time points are unequally spaced in the AHEAD longitudinal data, we use REPEATED/TYPE = SP in executing the SAS PROC.MIXED procedure to represent the autoregressive error structure of the data (Littell et al. 2006). For analytic simplicity without loss of generality, between-individuals random effects are not further specified with the presence of a specific residual variance/covariance structure. Statistically, a combination of both error types is often found to fit the data about the same as does a model of either type (Hedeker and Gibbons 2006). Hence, in the estimation process the variable "time" is treated as a series of dichotomous variables, with the last time point, time five (time = 0, 1, 2, 3, 4, and 5), used as the reference.

RESULTS

As indicated earlier, the effects of specific health conditions on the number of functional limitations are analyzed by two stages and they are time-dependent. The mixed model at the second stage, time is treated as five dichotomous variables. Additionally, when we analyze the longitudinal impact of each specific condition, other specific health conditions, together with control variables, are fixed as sample means. These specifications lead to a large number of regression models and, in each model, a large number of covariates; therefore, we do not present the detailed results of these regression models here.

To summarize, all regression coefficients of health conditions, for both probit and random-effects regression models, are statistically significant, either from the main effects or from the interaction between a condition and time, except those of cancer in the second-stage mixed models. At baseline, those with the six specific health conditions record close proportions of having any functional limitations, ranging from 0.7571 among those with high blood pressure to 0.8275 among those with stroke, other things being equal. At the five successive time points, over 90% of those with the six conditions have at least one functional limitation. Among older persons having functional limitations, those with stroke display the strongest positive effects on the number of functional limitations, followed by, in order, diabetes, heart disease, arthritis, high blood pressure, and cancer. Of the control variables, veterans, older persons, women or lowly educated persons are expected to have a higher number of functional limitations than do their nonveteran, younger, male and highly educated counterparts, other things equal. All regression coefficients, except those of veteran status, are statistically significant. Detailed results of the two-step regression models are available upon request.

Table 3 demonstrates three sets of mean number of functional limitations in older Americans at six time points, 1993, 1995, 1998, 2000, 2002 and 2004, derived from, respectively, observed data, the conventional linear mixed regression model, and the two-stage mixed model. All three sets demonstrate an inverse-U shaped nonlinear pattern of transitions in the number of functional limitations, reflecting the strong impact of the "survival–of-the-fittest" effect. It is evident that compared to the observed data, the conventional one-step linear mixed model systematically overestimates the number of functional limitations at every subsequent time point and this overestimation increases as the survey progresses. In contrast, the nonparametric two-stage model derives the closest set of estimates to describe transitions in the number of functional limitations in older Americans.

<Table 3 about here>

Figure 1 further illustrates deviations in the predicted number of functional limitations derived from the two types of mixed models. In Panel A, which compares the observed curve with the predicted values derived from the conventional one-step linear mixed model, there are distinct and systematic separations between the two growth curves. At each time point following the baseline survey, the predicted number of functional limitations obtained from the conventional one-equation mixed model is considerably higher than the corresponding observed number. In Panel C, the two curves almost coincide, thereby demonstrating the strong model fitness of the nonparametric two-stage model which builds upon empirical data rather than strong assumptions on error distributions.

<Figure 1 about here>

Table 4 presents the mean number of functional limitations across six time points by each condition type and the total number of health conditions representing comorbidity, derived from the two-stage mixed regression model.

<Table 4 about here>

Table 4 displays that variations in the number of functional limitations across the six health conditions are consistent over the 11-year time period. Those having a stroke have the highest number of functional limitations at almost all time points, consistent with all levels of comorbidity. Older Americans with diabetes or heart diseases also have relatively higher number of functional limitations at most observation time points than do those with other diseases. Arthritis, regarded as a less life-threatening disease than serious health conditions, is shown to be a significant predictor for the severity of disability, controlling for the confounding effects of serious health conditions and comorbidity. At some time point, their effects are even stronger than those of cancer and hypertension. However, differences in these health measures across health conditions are not as large as might be expected based on prior research.

It is interesting to note the influence of the total number of health conditions on the number of functional limitations. For each condition type at each time point, an increase in the total number of health conditions is accompanied by a considerable enhancement in the number of functional limitations, other things being controlled. This result suggests that comorbid conditions pose substantial barriers to functional abilities whatever the main condition is. For example, among older Americans who only have stroke, the predicted numbers of functional limitations at baseline, Wave III and Wave IV are, respectively, 3.31, 6.10 and 4.38; these figures uplifted to 3.61, 7.01 and 5.51 with the presence of one more condition, and to 5.82, 8.90 and 9.15 with at least two more conditions, other things being equal.

DISCUSSION

Linkages among health measures often involve difficult mechanisms. An older person's functional status can be considered to be a function of an array of inputs, including health conditions and the level of comorbidity, as well as other demographically and socially related factors, such as age and socioeconomic status.

Blaxter's (1989) conceptualization of health measures is particularly enlightening to identify various areas of health measurements, the medical, the social, and the subjective, while the work of Johnson and Wolinsky (1993) is important to the understanding of the interrelationships between the measures from a sociological perspective. In view of these earlier theoretical and empirical works, we build upon our understanding of health status measurements by concentrating on the linkages between two widely used health measures, particularly on the influences of health conditions on the number of functional limitations. At the same time, we consider the discrete nature of specific serious health conditions as well as the role of arthritis in the conceptualization.

Our analysis demonstrates that there are some variations in the number of functional limitations associated with specific health conditions. In particular, those with stroke, diabetes and heart disease have relatively higher number of functional limitations than other specific diseases; the impact of stroke is especially noteworthy. These associations are highly consistent over the six observation time points. However, differences in these health measures are not as sizable as would be anticipated from results of other studies. In our analysis, the number of health conditions, considered a less informative measure of disease by Johnson and Wolinsky (1993), proves a more significant predictor than specific health conditions on functional status and its transitions among older Americans (see Table 4). The implication of this finding is that besides variations by specific type of health conditions, a higher level of comorbidity tends to exacerbate functional disability whatever the specific conditions.

REFERENCES

Amemiya, T. (1985). *Advanced econometrics*. (Cambridge, MA: Harvard University Press)

Bennett, J., & Liang, J. (1991, November). Health and loneliness in the American elderly. (Paper presented at the 44th Annual Scientific Meeting of the Gerontological Society of America, San Francisco, CA)

Bergner, M. (1985). Measurement of health status. *Medical* Care, 23 (5), 696-705

Blaum, C., Laing, J., & Liu, X. (1994). The relationship of chronic diseases and health status to the health services utilization of older Americans. *Journal of the American Geriatrics* Society, 42, 1087-1093

Blaxter, M. (1989). A comparison of measures of inequality in morbidity. (In J. Fox (Ed.), *Health inequalities in European countries* (pp.199-230). Aldershot: Gower.)

Burkhardt, C. (1985). The impact of arthritis on quality of life. *Nursing Research*, 34, 11-16

Chappell, N. (1981). Measuring functional ability and chronic health conditions among the elderly: A research note on the adequacy of three instruments. *Journal of Health and Social Behavior*, 22, 90-102

Cockerham, W., Sharp, K., & Wilcox, J. (1983). Aging and perceived health status. *Journal of Gerontology*, 38, 349-355.

Crimmins, E.M., M.D. Hayward & Y. Saito. (1996). Differentials in active life expectancy in the older population of the United States. *Journal of Gerontology: Social Sciences*, 51B, S111-S120.

Duan, N. (1983). Smearing estimate: A nonparametric retransformation method. *Journal of the American Statistical Association*, 78, 605-610

Duffy, J. (Ed.) (1992). *Alcohol and illness*. (Edinburgh, Scotland: Edinburgh University Press)

Ferraro, K., & Farmer, M. (1999). Utility of health data from social surveys: Is there a gold standard for measuring morbidity? *American Sociological Review*, 64, 303-315

Fox, J. (1987). Effect displays for generalized linear models. (In C. Clogg (Ed.), *Sociological methodology 1987* (pp. 347-361). Washington, DC: American Sociological Association.)

Heckman, J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5, 475-492

Idler, E., & Kasl, S. (1991). Health perceptions and survival: Do global evaluations of health status really predict mortality? *Journal of Gerontology: Social Sciences*, 46, S55-S65

Johnson, R., & Wolinsky, F. (1993). The structure of health status among older adults: Disease, disability, and functional limitation, and perceived health. *Journal of Health and Health Behavior*, 34, 105-121

Katz, S., & Akpom, C. (1976). A measure of primary sociological functions. *International Journal of Health Services*, 6, 493-508

Kemper, G., & Suurmeijer, T. (1990). The development of a hierarchical polychotomous ADL-IADL scale for noninstitutionalized elders. *The Gerontologist*, 30, 497-502

Koong, S., Malison, M., & Nakashima, A. (1990). A prevalence survey of behavioral risk factors in Taipei City, Taiwan. *International Journal of Epidemiology*, 19, 154-159.

Land, K.C., J.M. Guralnik & D.G. Blazer. 1994. Estimating increment-decrement life tables with multiple covariates from panel data: The case of active life expectancy. *Demography*, 31, 297-319.

Lawton, M., & Brody, E. (1969). Assessment of older people: Self-monitoring and instrumental activities of daily living. *The Gerontologist*, 9, 179-186

Liang, J., Liu, X. & Gu, S. (2001). Transitions in functional status among older people in Wuhan, China: Socioeconomic differentials. *Journal of Clinical Epidemiology*, 54, 1126-1138

Liang, J., & Whitelaw, N. (1990). Assessing the physical and mental health of the elderly. (In S. Stahl (Ed.), *Legacy of longevity: Health and health care in later life* (pp. 35-54). Newbury Park, CA: Sage Publications.)

Liu, X., Engel, C., Kang, H., & Cowan, D. (2005). The effect of veteran status on mortality among older Americans and its pathways. *Population Research and Policy Review*, 24, 573-592

Liu, X., Engel, C., & Liang, J. (2006). Decomposition of causal effects in multinomial logit models. (Working paper at Deployment Health Clinical Center, Walter Reed Army Medical Center)

Liu, X., Hermalin, A., & Chuang, Y. (1998). The effect of education on mortality among older Taiwanese and its pathways. *Journal of Gerontology: Social Sciences*, 53B, S71-S82

Liu, X., Liang, J., Muramatsu, N., & Sugisawa, H. (1995). Transitions in functional status and active life expectancy among older people in Japan. *Journal of Gerontology: Social Sciences*, 50B, S383-S394

Maddala, G. (1983). *Limited-dependent and qualitative variables in econometrics*. (Cambridge: Cambridge University Press)

Manning, W., Duan, N., & Rogers, W. (1987). Monte Carlo evidence on the choice between sample selection and two-part models. *Journal of Econometrics*, 35, 59-82

Mossey, J., & Shapiro, E. (1982). Self-rated health: A predictor of mortality among the elderly. *American Journal of Public Health*, 72, 800-807

Nagi, S. (1965). Some conceptual issues in disability and rehabilitation. (In B. Sussman (Ed.), *Sociology and rehabilitation* (pp. 100-113). Washington, DC: American Sociological Association.)

Petersen, T. (1985). A comment on presenting results from logit and probit models. *American Sociological Review*, 50, 130-131

Radloff, L. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, 1, 385-401

Spector, W., Katz, S., Murphy, J., & Fulton, J. (1987). The hierarchical relationship between activities of daily living and instrumental activities of daily living. *Journal of Chronic Diseases*, 40, 481-489

Verbrugge, L. (1990). The iceberg of disability. (In S. Stahl (Ed.), *The legacy of longevity: Health and health care in later life* (pp. 55-75). Newbury Park, CA: Sage Publications.)

Verbrugge, L. (1991). Survival curves, prevalence rates, and dark matters therein. *Journal of Aging and Health*, 3, 217-236

Weinberger M., Darnell, J., & Tierney, W. (1986). Self-rated health as a predictor of hospital admission and nursing home placement in elderly public housing tenants. *American Journal of Public Health*, 76, 457-459

World Health Organization. (1958). *Constitution of the W.H.O., Annex I. The first ten years of the World Health Organization*. (Geneva: Author)

World Health Organization. (1980). *International classification of impairments, disabilities, and handicaps*. (Geneva: Author)

World Health Organization. (2001). *International classification of functioning, disability, and health*. (Geneva: Author)

Table 1. Percentage distribution of AHEAD respondents by health conditions,

Number of functional limitations from Wave I to Wave VI

Health status	Percent (%) and frequency of respondents					
Variables	Wave I	Wave II	Wave III	Wave IV	Wave V	Wave VI
<u>Health conditions</u>[a]						
Hypertension	49.8%	52.2%	54.7%	58.0%	60.5%	64.0%
Diabetes	13.2	14.6	15.7	16.1	17.6	17.9
Cancer	13.4	15.2	16.1	16.9	18.8	19.6
Heart Disease	30.4	32.9	27.2	31.9	38.0	39.4
Stroke	10.1	11.0	12.8	13.0	14.1	14.6
Arthritis	25.8	54.5	63.4	68.8	70.9	72.4
Other conditions	76.5	78.9	100.0	75.1	77.9	74.8
<u>Functional limitations</u>						
No limitation	37.6%	5.6%	1.9%	1.7%	1.4%	12.7%
One limitation	16.3	11.1	4.3	5.0	4.4	13.9
Two limitations	10.3	11.8	8.6	9.1	8.9	11.6
Three limitations	8.3	10.1	8.5	8.7	9.2	11.0
Four and over	27.6	61.4	76.7	75.4	76.0	50.8
Total sample size	8,222	7,000	5,908	4,956	4,056	3,291

[a] The total of the percentages for health conditions does not sum up to 100.0 because a high proportion of the AHEAD respondents had more than one health conditions across the six survey waves.

Table 2. Means (or Proportions), Standard Deviations, and Coding Schemes of Eight Control Variables:

AHEAD Respondents, Wave I (N = 7,380)

Control Variables	Sample Mean Or Proportion	Standard Deviation	Coding Scheme
Veteran status	0.21	0.41	Whether or not subject is a veteran: 1 = yes, 0 = no.
Age	76.16	6.60	Actual number of years from birth to 1993; maximum is 103 years.
Female	0.65	0.48	Whether or not subject is a female: 1 = yes, 0 = no.
Education	10.99	3.66	Actual years of attending school.
White	0.85	0.36	Whether or not subject is a white: 1 = yes, 0 = no.
Currently married	0.55	0.50	Whether or not subject is currently married: 1 = yes, 0 = no.
Smoking cigarettes	0.52	0.50	Whether or not subject is a current or a past smoker: 1 = yes, 0 = no.
Drinking alcohol	0.46	0.50	Whether or not subject is currently drinking alcohol: 1 = yes, 0 = no.
Number of other health conditions	1.79	1.46	Actual number of other health conditions reported in Wave I survey.

Table 3. Predicted number of functional limitations generated from two Regression models and the observed value (n = 8,443)

Time (year)	Observed and predicted number of functional limitations		
	observed	conventional	two-stage
1993	2.4887	2.4996	2.6918
1995	5.1514	5.2571	5.1184
1998	6.1378	6.3934	6.1197
2000	6.1602	6.5138	6.1598
2002	6.3348	6.7521	6.3056
2004	4.9608	5.5154	4.9088

Note: All predicted values derived from the three mixed models are statistically significant relative to value zero.

Table 4. Population estimates of mean number of functional limitations by specific serious health conditions
Classified by number of health conditions in older Americans: AHEAD Wave I to Wave VI

Health	Time Points					
Condition	Wave I	Wave II	Wave III	Wave IV	Wave V	Wave VI
	Persons with one or two health conditions					
Hypertension	1.51	4.22	6.28	5.87	6.04	2.72
Diabetes	1.90	4.87	6.50	5.78	5.46	1.93
Cancer	1.62	3.90	6.49	5.78	5.18	2.52
Heart Disease	1.78	4.43	6.97	6.18	6.59	3.12
Stroke	3.31	6.79	6.10	6.49	8.30	4.38
Arthritis	1.56	4.02	5.52	5.58	5.76	3.10
	Persons with three or four health conditions					
Hypertension	2.49	4.57	5.89	5.78	5.87	4.07
Diabetes	2.76	4.93	5.75	5.91	6.38	4.09
Cancer	2.26	3.85	5.55	5.57	5.66	3.45
Heart Disease	2.52	4.66	5.80	5.93	6.20	4.31
Stroke	3.61	6.63	7.01	7.95	8.13	5.51
Arthritis	2.56	4.59	5.50	5.68	5.82	4.33
	Persons with more than four health conditions					
Hypertension	4.37	6.16	6.58	6.94	6.61	6.60
Diabetes	4.99	6.48	6.62	6.85	6.50	6.63
Cancer	4.03	5.94	6.03	6.42	6.33	6.06
Heart Disease	4.44	6.44	6.79	6.93	6.82	6.69
Stroke	5.82	8.47	8.90	9.08	8.90	9.15
Arthritis	4.35	6.25	6.49	6.80	6.66	6.61

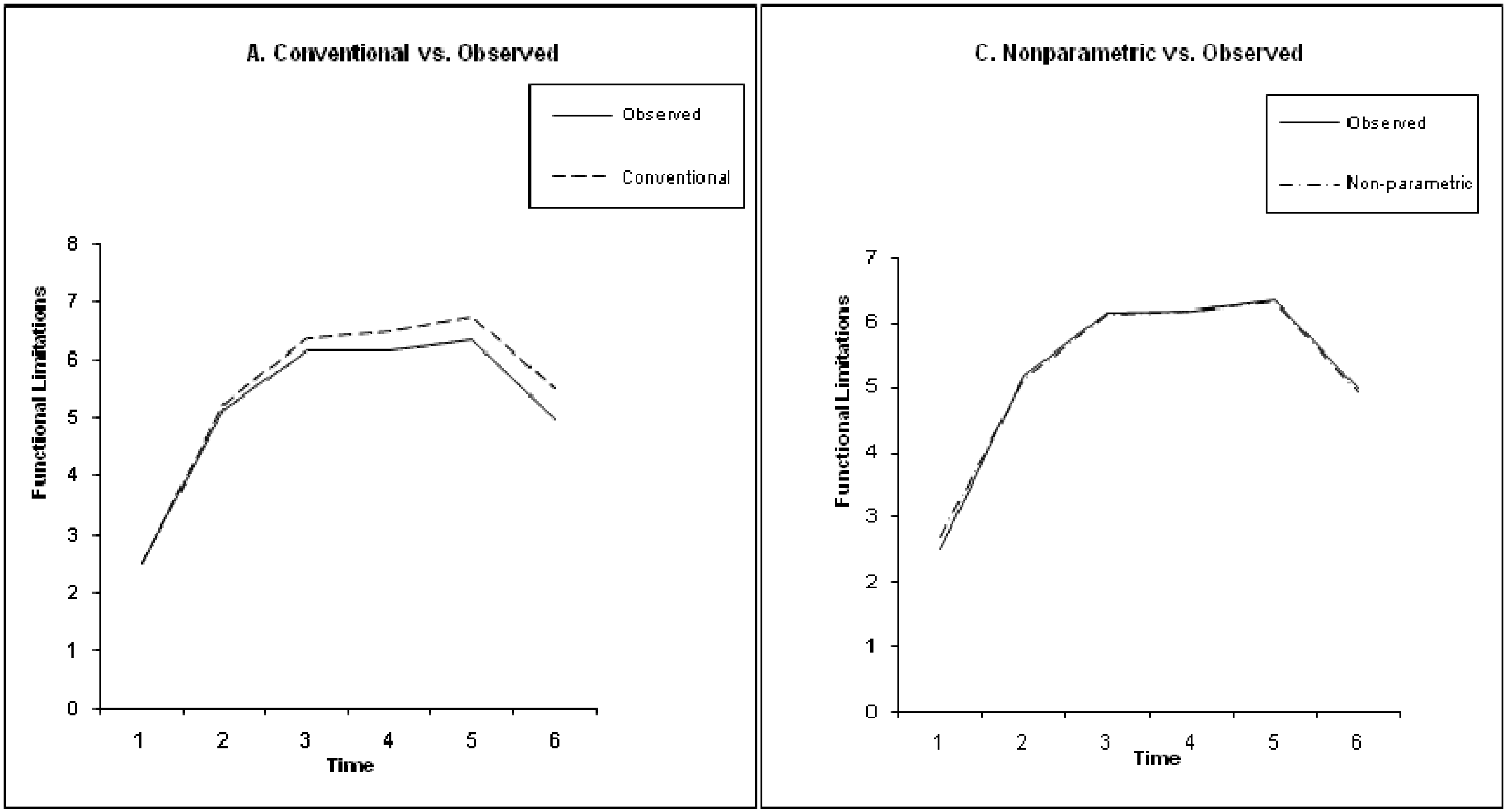

Figure 1: Transitions in the number of functional limitations in older Americans:
Growth curves generated from two regression approaches