Progress in Estimating Active Life Expectancy

October 9, 2002

National Center for Health Statistics

Hyattsville Maryland

Summarizing the lifetime health experiences of a population is a difficult task requiring the application of clear definitions, high quality data and complex methodologies. For many, life expectancy at birth is the gold standard of summary measures. It is based upon good data, it is accepted and understood by many, and it correlates well with other measures of population well-being. However, life expectancy is one dimensional, measuring only length of life, and at a time when quality-of-life has gained more importance the quest for measures that incorporate health status has gained momentum. The development of a summary measure also satisfies a need among decision makers, the media, and perhaps the public at large, to reduce a complex process down to a single number that can be used for public health surveillance and decision-making.

The National Center for Health Statistics has a long history of involvement in the development and use of summary measures. For many decades, NCHS has coordinated the federal vital statistics program providing the mortality data used to generate estimates of life expectancy. One of the earliest methods for estimating healthy life expectancy was developed at NCHS by Daniel Sullivan. NCHS also has been a leader in developing and fielding some of the longitudinal health surveys used in research on active life expectancy.

In the late 1990's researchers in the aging program at NCHS began working on estimates of active life expectancy and lifetime cost and use of care for the elderly population using data from longitudinal health surveys. Through discussions with colleagues in and outside of government, it became apparent that there were common issues, concerns and experiences that if shared might facilitate the work at NCHS and within the broader community as well. Toward that end, NCHS invited a small and distinguished group of scholars, who have been in the forefront of research in the field, to spend a day discussing their work, its application and the role NCHS might play in furthering scholarship in this area.

The program was divided into two parts; the first, a set of presentations and discussion devoted to methodologies for estimating health transitions and active life expectancy. The second half of the program focused on substantive findings using health transition methods.

Part 1: Advances in Methods

In the three decades since Sullivan (Sullivan, 1971) developed a single index for mortality and morbidity, there has been considerable progress in developing new approaches for estimating composite measures of health expectancy. Much of the new work blossomed as new national longitudinal data sets became available, allowing for the employment of statistical techniques that included time as well as important covariates. Two major methodological innovations that take advantage of the new longitudinal data have been the employment of multi-state life tables and, more recently, development of micro-simulation techniques.

Dr. Liming Cai, National Center for Health Statistics, reported on development of a semi-Markov process (SMP) model to estimate active life expectancy (SMP Model) that seeks to improve on standard multi-state life table approaches (MSLT). This study used data on vital and functional status from the 1992 to 1999 waves of the Medicare Current Beneficiary Survey (MCBS), a continuing longitudinal survey conducted by the Center for Medicare and Medicaid Services (CMS) with a rotating panel design. Respondents are interviewed annually for up to 4 years. The study generates estimates of active life expectancy based upon a person's vital status (alive or dead) and on a five-category functional status variable.

There are three phases in this approach; estimating transition parameters, running a micro-simulation, and calculating sampling variances. The model uses two steps to generate a set of overall event risks (regardless of event type) and relative transition probabilities conditional on the occurrence of a particular event. Initially, parameters are estimated from a set of 5 time-dependent hazard models (for each of the possible starting functional states) with age and sex as covariates. The parameters from the models are used to generate a series of "survival" or non-event probabilities, over a 20-year interval, for each starting functional status, age, and sex. Then separate multinomial logistic regression models are fit to each starting state to predict the relative hazards for those that had a change in state over the 20-year interval, conditional on starting age and sex.

In the simulation phase a hypothetical representative cohort of 100,000 older persons from age 65 to 85 is run through the transition parameters to simulate life histories from which summary statistics such as active life expectancy can be calculated. The third and final phase of the procedure is estimation of variance and standard errors. Variances are obtained using a bootstrap approach because there are no available formulae for computing variances for the summary indicators. Standard deviations of the bootstrap estimates are used as the standard errors for the point estimates of life expectancies.

Dr. Cai obtained estimates for total and active life expectancy for older adults and compared them to those using other sources or methods. For total life expectancy at age 65, the SMP model estimate matches the estimate from vital statistics; the MSLT estimate is significantly lower. However, at age 85, the MSLT estimate is closer to the vital statistics estimate. Active life expectancy (ALE) is defined as either having no functional limitations or only Nagi limitations. Estimates of ALE from the SMP model are slightly higher than those obtained from the MSLT method, for the total population and for men and women. For the total population and for men age 65 or older, similar estimates of the proportion of remaining life spent in an active state were obtained from the two methods. For women age 65 or older, the SMP model produces a slightly lower proportion of remaining life spent in an active state.

In summary, the SMP Model offers an alternative to MSLT for estimating status-based total and active life expectancy with covariates that takes account of duration in state effects and allows for examination of particular pathways as well as average values.

Discussion of Dr. Cai's talk centered on model specifications and data limitations. Some attendees expressed concern over the issue of left-censoring, specifically the baseline state presents a problem because there is no information on how long the person has been in that particular state before observation begins. Dr. Cai indicated he was exploring that problem using an iterative imputation strategy. Several observers noted that the reliability of self-reports of functional limitation is an issue that needs to be considered in analyses based on survey data.

Dr. Scott Lynch, Princeton University, offered an alternative way of estimating transition parameters using Bayesian statistics (A Bayesian Approach). This approach allows for efficient inclusion of covariates in the multi-state life table, a necessary condition when addressing a variety of critical research questions related to inequality, such as race or class differences in active life expectancy. In addition, confidence intervals can be computed using the Bayesian approach, a distinct advantage since most estimates of measures such as active life expectancy are now derived from sample data.

The approach presented is a hybrid of traditional modeling techniques such as hazard models with Bayesian Markov Chain Monte Carlo (MCMC) estimation methods. The models used in this exercise are commonly used in life course research and the statistical methods employed in the model have been used extensively in Bayesian statistics over the last decade.

A summary of the approach is as follows. First a framework is developed; in this example, the function status variable has three categories--healthy, disabled and dead—and a bivariate probit model is used to predict the outcome state with age, starting state and other covariates as the predictors. In the second step, Bayesian methods, specifically MCMC, are employed to estimate the model. Unlike traditional approaches, the goal here is to obtain a probability distribution for the parameters of interest that describes posterior uncertainty regarding the parameters' true values. The MCMC runs produce a set of possible parameter values containing values in proportion to an underlying probability. Once the parameter values are obtained, functions can be used to generate distributions of other quantities; in this exercise, the simulated values are used to generate a distribution of life table values from which are obtained empirical confidence intervals for total, active and disabled life expectancies

The data used in this example came from the National Long Term Care Survey, 1989 and 1994 analytic files. Thus, there is one 5-year interval. The functional status of persons 65 years of age and older was identified as either healthy or disabled if one or more ADL limitations were recorded at each of the two points in time. The outcome variable included death as well as healthy and disabled. Covariates included age, sex, race, starting state, and interaction between age and starting state.

Results for total, active, and disabled life expectancy were presented as empirical confidence intervals, for the four major race/sex groups for 5 age intervals. The intervals include values comparable with results from other studies that used the NLTCS.

In summary, Lynch stressed again that his objective was to describe an application that can be used to estimate MSLT components, specifically active and disabled life expectancy. He argued that the Bayesian approach is conceptually straightforward; it involves estimating well-known hazard models using MCMC methods and then uses repeated life table calculations to generate distributions of life tables. The approach allows for comparisons across such important demographic variables as sex, race, education and SES that can't easily be made using other techniques. Unfortunately, the software to do MCMC estimation is not readily available.

The discussion focused on issues related to missed transitions when the survey interval length is more than a year or two and on the interpretation of statistical error estimates based upon derived measures such as ALE.

Dr. Douglas Wolf, Syracuse University, approaches the topic of health expectancy from a desire to better understand the process of moving from one functional state to another. Unfortunately, we aren't able to measure the continuous process so we must fall back on observations at discrete points in time. Much of his work has involved evaluating some of the data problems that emerge from modeling transitions with limited information on the process.

Dr. Wolf is interested in understanding why, according to recent survey data, the prevalence of disability (measured primarily by limitations in functional status) has been declining in recent years. He argued that, if other factors are held constant, decline in the prevalence of disability could result from 1) falling rates of onset of disability, 2) rising rates of recovery from disability, or 3) a change in the mix of disabled and non-disabled who age into the elderly population. There could be a combination of factors, perhaps contradictory, at work; for example, onset rates could be rising but recovery from disability could be rising at a faster rate, overcoming the increase in newly disabled.

The exploratory work presented at the workshop (Disability Transition Rates) focuses on the trend in transition rates—disability and recovery—during the 1980's and early 1990's using data from the New Haven EPESE project. The study tracks a sample of roughly 2,800 persons age 65 and older first interviewed in 1982 and then followed over a period of 12 years, annually until 1989 then a follow-up in 1989/90 and one in 1994.

Wolf first discussed some of the important data issues that arise when dealing with longitudinal health data (for example the absence of an institutional sample at baseline and variability in the follow-up interval) and the strategies for dealing with them. Then he described his procedure for deriving transition rates from a Markov transition matrix using maximum likelihood techniques.

Results of particular interest in this preliminary inquiry include trends in the onset of disability and in recovery from disability which both declined over the interval of interest. Wolf noted that the downward trend in mortality and in onset of disability might be expected given published results on disability prevalence and mortality. However, the downward trend in recovery from disability was unexpected. If these preliminary results reflect what was actually happening within the US population during this time period, there is an interpretation that would reconcile it with the overall downward trend in prevalence. During the 1980s, disability onset rates fell in the United States, but those who became disabled were increasingly worse-off and less likely to recover --perhaps previously in nursing homes-- thus causing overall recovery rates to fall at the same time. The trends in onset were sufficiently large, however, to outweigh the trends in recovery, resulting in declining prevalence of disability. Further research is needed to validate an explanation relying on unmeasured heterogeneity in the population.

In the discussion that followed, the importance of the observation interval was again emphasized. It was suggested that when you have varied time intervals in the data, a continuous time hazard model might be more computationally efficient, although Dr. Wolf demurred. It was noted that interval drift in scheduled follow-ups might be highly correlated with disability. In response to a question regarding the optimal follow-up interval, Wolf indicated that while a 6-month interval might be best, an annual follow-up would be sufficient. A participant observed that the Medicare Current Beneficiary Survey collected some monthly transition data that might provide valuable information relating to optimal intervals.

Dr. Yasuhiko Saito, Nihon University, offered some specific remarks related to methodological aspects of the three presentations then turned to several cautionary remarks emerging from the participants work. First, there are basically two methods of estimating transition schedules which in turn are the basis of estimating health expectancy. One is based on multinomial logistic regression model generating a transition probability (qx in life table function) and the other based on a hazard model that produces a transition rate (mx in life table function). There are differences between these estimates although the differences may be smaller than measurement error. Saito asked participants to be aware of the important difference between population-based and status-based life tables when evaluating analyses and interpreting results, a concern echoed by several other participants. He also noted that when we estimate health expectancy based on a multivariate model we should pay attention to the interaction between variables included in the model; ignoring interaction effects might cause bias in the estimates. He also issued a cautionary remark relating to the availability of longitudinal data and computer programs. While it is good that the data and programs are available to those working in the field, it is also the cause that some researchers, without appropriate knowledge on estimating health expectancy could produce problematic health expectancy estimates using these new aids.

On a positive note, Dr. Saito noted that the authors in the workshop showed standard errors for their health expectancy estimates, a development that researchers are increasingly addressing as an important component of their work

Regarding the question of the ideal panel survey interval, he proposed that NCHS test the desirability of a one- or two-year interval by computing health expectancy using data from the MCBS survey, which has a one-year design. In addition, Saito suggested a study evaluating a variety of methods used to compute health expectancy. Perhaps one data set could be prepared and then disseminated to researchers who use distinctive methods; the results could then be compared. Others, including Saito and his colleagues, have attempted this exercise but he believes none of these attempts have been comprehensive.

Saito also asked about the possibility of NCHS conducting an LSOA III. He felt it would be very interesting to see the changes in prevalence of disability over 20 years, the transition probabilities among health states in three-time periods. Computing active life expectancy and comparing the results to previous estimates would tell us if there is additional evidence of morbidity compression.

Part 2: New Findings on Active Life Expectancy and Related Issues

Applying the new methodologies in search of answers to real world problems will, in the end, be the true test of their relevancy. During the second half of the workshop, three projects were presented that used health transition models to address important substantive issues.

Dr Constantijn (Stan) Panis, RAND Corporation, talked about a project undertaken for the Center for Medicare and Medicaid Services (CMS) that employed micro-simulation and multi-state techniques to forecast future health care costs under dynamic conditions (Health Status and Medical Expenditures). The goal of the micro-simulation model was to predict the health status and costs of Americans aged 65 or older through 2020, and to evaluate the effects on health status and costs of likely upcoming medical breakthroughs.

The presence of one of eight target diseases and five functional states constituted the health states. Transition probabilities were obtained using data from the Medicare Current Beneficiary Survey (MCBS) for the population age 65 and over. Discrete (annual) hazard models were employed for each condition and functional state, controlling for a set of standard demographic characteristics, risk factors and functional status. Disease presence was modeled as absorbing, that is once identified as "ever had," return to a non-diseased state was impossible. To estimate the health status of incoming cohorts of 65 year olds, the project predicted disease prevalence and functional status through 2020 based upon data from the National Health Interview Survey, 1990-1996.

Estimated health expenditures under the assumption of a status quo level of medical technology were a function of predicted risk factors, conditions, functional status and interactions among disease and disability. Not surprisingly, data from the MCBS show that expenditures increase with an increase in ADL limitations, the number of chronic conditions, and the number of ADLs by condition.

Panis then outlined an approach taken to estimate the impact of future medical innovations. The project first identified 34 key trends and technologies based upon the work of four panels of experts in the areas of improved disease prevention, better risk stratification and detection of sub-clinical disease, better treatment regimes, and lifestyle changes and better care management. For each breakthrough the panels provided estimates of the target population, the probability of the breakthrough entering clinical practice, its impact on mortality and morbidity, and its cost

Each of these breakthroughs were then simulated within the model to predict effects on the prevalence of the specific disease, on related diseases, on disability and on the societal costs; they will be compared to the status quo projections or to other breakthrough scenarios.

In the future, RAND plans to develop ways of making the model more sophisticated including incorporating demographic trends that differentially affect disease, disability, and costs and correlated shocks and heterogeneity.

Dr. Mark Hayward, Penn State University, and his colleagues used multi-state models of heart disease life expectancy and associated functional limitation to better understand apparent differences between adult whites, blacks and Hispanics in length and quality of life (Race differences - PowerPoint slides; PDF Tables). Cause-specific mortality and disease reporting data show an apparent paradox; although adult blacks report lower rates of heart disease compared to whites, they have significantly higher rates of heart disease mortality. Hispanics by contrast apparently have lower rates of heart disease mortality and morbidity compared to whites. Blacks and Hispanics, have different mortal outcomes even though they have roughly equivalent socio-economic status.

The project used data from Waves 1 and 2 of the Health and Retirement Survey (HRS) and AHEAD to estimate morbidity, disability, and mortality for persons 50 years of age and older, and to model disease onset, life with heart disease and other fatal diseases and functional limitations. Population and status-based, Markov-based multi-state life tables were calculated separately for whites, blacks and Hispanics, using self-reports of 1) no fatal chronic disease 2) heart disease, 3) other fatal disease but no heart disease, 4) other fatal disease and heart disease, and 5) death.

Hayward then discussed several important data limitations and necessary adaptations that are required to estimate health state transitions.

Results show blacks have a higher rate of heart disease onset and Hispanics a lower rate than whites, although the differences were not statistically significant. Hispanic women have substantially lower rates of heart disease onset than all other race/sex groups. Among persons with heart disease, blacks and Hispanics are more likely to die than whites; the overall excess mortality among blacks is primarily from heart disease.

Estimates of life expectancy with and without several fatal chronic diseases show that persons surviving to age 50 with no conditions experience elevated life expectancy and compressed morbidity. Persons with co-morbid conditions have relatively low life expectancy. Race/ethnic differences in total and active life expectancy among those with heart disease at age 50 show that whites live more years with heart disease than blacks or Hispanic, but proportionately fewer years with heart disease and a major functional limitation.

The study offers several important policy-relevant conclusions. First, heart disease has less pernicious consequences for whites than for blacks or Hispanics. Whites live longer with heart disease primarily because of lower heart disease-related mortality. They also incur fewer functional problems with heart disease. Second, the research suggests that differential mortality from heart disease identified in vital statistics reflects higher death rates among blacks relative to whites after disease onset rather than differences in onset. Finally, postponing disease onset past middle age has considerable benefits for extending life and compressing morbidity; this is particularly true for black men.

Discussion centered on some of the challenges presented by the HRS/AHEAD data and the steps taken to deal with them in this as illustrated in this research. One of the major problems was the change in questions on functional status across survey waves; RAND is providing information for users on how to use survey data based on questions that changed between waves. Some skepticism was voiced related to the findings that heart disease onset did not differ by race/ethnicity; Survey linkages with Medicare data may offer additional insight into potential differentials.

Finally, **Eric Stallard,** Duke University, discussed the connection between definitions of health and methodology, then presented results from a project looking at long term care cost and use that employed federal eligibility standards for tax deductible long term care insurance.(Policy Applications).

He began by observing that the fundamental relationship examined in the workshop is quite straightforward. Total life expectancy at any age can be decomposed into that portion of life spent in an active state (ALE) and that portion spent in a disabled state (DLE). How those two components are measured forms the crux of the problem. Stallard argued that different definitions of disability are needed for different policy applications, and the choice of a disability definition may restrict the form of dynamic life table model used. A variety of applications were provided as examples of diversity in approach.

Stallard then reported on a multi-state life table analysis that employs definitions of disability consistent with the criteria legislated in the federal government's Health Insurance Portability and Accountability Act of 1996 (HIPAA) for tax qualified long term care insurance. Data came from the 1984,'89, and '94 waves of the National Long-Term Care Survey with a combined sample of roughly 36,000 individuals age 65 years and older. The functional status variable has 5 HIPAA compatible categories. Simple prevalence estimates over the period 1984-94 for all levels of disability combined suggest a decline in disability rates at all ages. A set of age-specific transition matrices indicates that recovery of function occurred primarily at younger ages and that at older ages persistence in state decreases and mortality increases. Estimates of life spent in non-disabled and disabled states for both sexes combined shows that the years of chronic disability above age 65 are split evenly between mild/moderate and severe disability. Above age 85, however, severe disability accounts for about two-thirds of those years.

Stallard also presented estimates of average lifetime costs of long-term care for persons in each of the disabled categories, using additional information from the NLTCS. At age 65, the expected cost of LTC services (inflated to 2000 dollars) was approximately $60,000 for both sexes combined; for women the estimated cost was $80,000, for men $30,000. Of that amount, less than 10 percent was incurred during episodes of mild or moderate disability, episodes not eligible for tax-qualified LTC insurance benefits under HIPAA, and the rest, over 90 percent was incurred during episodes of severe disability. When considering HIPAA requirements, Stallard concluded the criteria effectively target the high-cost disabled subpopulation. Severe disability accounts for the overwhelming majority of purchased LTC services and a large majority of unpaid LTC services. Females outspend males nearly 3 to 1 when lifetime costs are considered.

In her closing comments, **Dr. Eileen Crimmins**, University of Southern California, presented a perspective from which to evaluate the workshop papers (Crimmins comments) . Each of the papers integrated mortality and disability, some also examined disease and health care costs. Although a number of different methodologies were used, all of the papers touched on important policy issues. There are several reasons why researchers are drawn to health expectancy measures; they can efficiently monitor population health change over time, summarize or highlight population subgroup differences, evaluate the use of resources, measure the effect of intervention or gauge the effect of health input factors.

The attractiveness of these measures derives from the fact that mortality change and health change are not necessarily the same. The measures appear to be easy to interpret because they are often in a commonly used metric, years of life. Moreover, the procedures standardize across age groups so that different populations can be compared. Finally, they are widely used by international and government agencies to set aims and priorities.

When comparing approaches to estimating healthy life, it is important to consider the definition or dimension of health problems to be used in the indicator, and the specific methods employed. The dimension of health to be used in estimating healthy life can be at any stage of health but it is clear that there is an order to health change leading from disease onset to functional loss and disability. It is important to understand, however, that for individuals the process of health change can involve repeated movements that are bi-directional; for instance, an individual can have a disease and become disabled, then return to full functioning with the disease still present.

Two approaches employed in much of the work on health expectancy are the Sullivan method and the multi-state life table. Although the presenters only briefly mentioned the Sullivan method, over the years it has proven to be a useful tool in monitoring trends in healthy life and in comparisons across subpopulations. However, because of its limitations, it doesn't add to an understanding of the past or predict the future.

Multi-state approaches are attractive for reasons made clear in the presentations. They help us understand the process of health change. In addition, they offer the possibility of insight into how past processes and potential future medical and technological developments will affect individual life cycles, population health, and costs. Although these approaches may do a better job of describing reality, they still are models or estimates of an unmeasured reality-- individual health histories--based upon estimates of current patterns of health transitions.

In summary, Crimmins emphasized that measures of health expectation are simply tools that enhance our understanding of the implications of health change for population health and individual life cycles. Years of life in a health state needs to be thought of as an estimate derived from a model. Their use and usefulness depend on definitions of health, the method of estimation, and the value of the underlying data.

Appendices

Appendix 1 Final Program

Wednesday, October 9, 2002
9:00 a.m. to 4:30 p.m.
National Center for Health Statistics
6525 Belcrest Road, Hyattsville, MD
11th floor auditorium

9:00 a.m. **Welcome and Introduction**

Jennifer Madans, Associate Director for Science, NCHS

James Lubitz, Acting Chief, Aging Studies Branch, NCHS

Part I. Advances in Methods

9:30 a.m. **A New 2-Part Method To Estimate Active Life Expectancy**

Liming Cai, National Center for Health Statistics

The multi-state life table method is limited by several key assumptions about the underlying dynamic process. A two-part model is developed to yield new estimates of total and active life expectancy. Our study also highlights the potential of its application in more extensive studies of the dynamic patterns of disability and compares results from the 2-part model to a multi-state model.

9:55 a.m. **A Bayesian Approach to Estimating Multistate Life Tables with Covariates**

Scott M. Lynch, Princeton University

Traditional approaches to estimating multistate life table quantities do not readily allow the inclusion of covariates in estimation nor the construction of confidence intervals on state expectancies. In this research, I develop a Bayesian approach for estimating multistate tables using Markov chain Monte Carlo methods applied to multivariate (possibly discrete time) probit models. The method is relatively easy to apply and is extremely flexible.

10:20 a.m. **Trends in disability transitions and their implications for active life expectancy**

Douglas A. Wolf, Syracuse University.

Most studies of active life expectancy have either used data on state transitions from a single period, or used longitudinal data on state transitions, but ignored intertemporal differences in transition patterns. A few studies have investigated trends in active life expectancy through comparisons of period-specific measures. A completely different strand in the literature investigates trends in the prevalence of disability, and has generally shown a downward such trend in the 1980s and 1990s. Missing from the literature is an attempt to tie these strands together; a downward trend in the prevalence of disability over (say) age 65 could arise because of (1) downward trends in disability onset rates, (2) upward trends in disability recovery rates, or (3) a reduced prevalence of disability among those reaching age 65. Varying mixtures of all three trends could, of course, lie behind the apparent reductions in disability prevalence since 1980. This study attempts to investigate these issues by introducing trend effects into a model of disability transitions. Such a model requires a longitudinal design with frequent follow-ups over a substantial follow-up period. We use the New Haven EPESE data, which come reasonably close to providing these features: baseline data were collected in 1982, with annual follow-ups through 1990 and an additional follow-up in 1994. The statistical basis for the analysis is a generalization of the embedded Markov chain approach found in Laditka and Wolf (1998). We find evidence of significant time trends in all model parameters.

10:45 a.m. **Break**

11:00 a.m. **Discussion and Questions**

Prepared Remarks: Yasuhiko Saito, Nihon University

12:15 p.m. to 1:15 p.m. **LUNCH**

Part II. New findings on active life expectancy and related issues

1:15 p.m. **A Model to Estimate the Impact of Risk Factors and Medical Care Changes on Health and Health Care Costs**

Constantijn W.A. (Stan) Panis, RAND

This presentation discusses a microsimulation model that RAND developed for CMS. The model predicts health status and health care expenditures of individuals age 65 and older through the year 2020. Predicted health status is very detailed and includes cancer, heart disease, stroke, Alzheimer's, diabetes, lung disease, arthritis, hypertension, disability, and mortality. The model is capable of forecasting the effects of a medical breakthrough on a condition, related conditions, longevity, and health care expenditures.

1:40 p.m. **Race Differences in the Burden of Heart Disease**

Mark Hayward, Pennsylvania State University.

2:05 p.m. **Break**

2:20 p.m. **The policy applications of different definitions of disability**

Eric Stallard, Duke University

Active and disabled life expectancy life-table models are frequently constructed using multipurpose survey data without fully considering the impact of varying disability definitions. While the reliability, validity, and cross-survey consistency of a limited set of disability definitions are emphasized, a larger set of disability definitions could accommodate a broader range of policy analyses. The policy issues are illustrated using the definitions of "chronically ill individuals" in the Internal Revenue Code (Sec. 7702B, relating to qualified LTC insurance contracts), "years of healthy life" in *Healthy People 2000*, and "employment disability" in the decennial Census. The choice of disability definition restricts the form of dynamic, but not static, life-table models that can be used in analyzing active and disabled life expectancy.

2:45 p.m. **Discussion and Questions**

Prepared Remarks: Eileen Crimmins, University of Southern California

4:00 p.m. **Conclusion and Next Steps**

Facilitator: Harold Lentzner

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