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STOCHASTIC MODELING OF ACTIVE LIFE AND ITS EXPECTANCY

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Abstract

The concept of “active” (or “disability-free”) life, and its average value, has proven to be a useful index of public health and of quality of life for populations. A question of great interest in recent years is whether recent trends towards longer life expectancy have been accompanied by comparable increases in *active* life expectancy.

Past research on patterns and trends of active and “inactive” life has focused almost exclusively on the expectancy—or, the *average* value—of years spent with and without disability. This measure is useful for actuarial calculations, for example analysis of the insurance value of programs that provide long-term care services. However, when considering broader issues of equity and efficiency in the financing and provision of services, or of targeting of programmatic resources, it is also useful to analyze the full frequency distribution of time spent in each activity status, in addition to the average values of each. Nevertheless, to our knowledge no past research has attempted to trace out the frequency distribution that underlies the calculations of Active Life Expectancy (ALE). Similarly, the uncertainty (or, the “margin of error”) in our calculations of active life expectancy traceable to sampling error has received little attention.

This paper addresses two related phenomena: *variability* in active life, which is to say the relative likelihood that someone will spend an additional 0, 1, 2, ... or more of his or her years in various functional statuses such as “active” or “inactive;” and *uncertainty* about the average value of additional years spent in each such status. Our concern with both phenomena leads us to present our findings in the form of intervals, or measures of dispersion, as well in the more conventional form of point estimates. Linking the two areas of analysis is a recognition of several sources of randomness, or stochasticity, that are inevitably present when analyzing the dynamics of functional status. In general, we find that the variability in years of active life is substantial. This variability is obscured in analyses that address only the expected value of active life. In contrast, uncertainly related to sampling error appears to be quite small, at least for the combination of survey data and model specification employed here.

Stochastic Modeling of Active Life and its Expectancy

When the number of older Americans begins its substantial increase early in the next century, public and private institutions alike will be faced with a dual challenge: rapidly rising health care costs, coupled with an increased demand for health and related services. The process of planning for these challenges can be informed with estimates of Active Life Expectancy (ALE). An index of population health, ALE integrates information about mortality and morbidity, representing the average amount of time we can expect members of a population group to live without significant disability. Researchers have demonstrated that the magnitude of health care costs and the use of health care services depends on both the number of older persons and their functional status (Laditka 1995; Lubitz, Beebe, and Baker 1995).

Past research on the patterns of active and "inactive" life has focussed almost exclusively on the expectancy—or, the *average* value—of years spent with and without disability. This measure is useful for actuarial calculations, for example analysis of the insurance value of programs that provide long-term care services. However, when considering broader issues of equity and efficiency in the financing and provision of services, or of targeting of programmatic resources, it is also useful to analyze the full frequency distribution of time spent in each activity status, in addition to the average values of each. Furthermore, individual members of a population group would undoubtedly take great interest in knowing their actuarial chances of living 0, 1, 2, ... additional years free of disability, as well as the average of that distribution. However, to our knowledge no past research has attempted to trace out the frequency distribution that underlies the calculations of ALE.

The information needed to compute an estimate of ALE is rarely, if ever, obtained in population censuses. Instead, most research on ALE uses survey data as a basis for estimating

the key parameters used in the computations; in most cases those parameters are estimates of transition or prevalence rates specific to persons of a given age, sex, and possibly racial or educational group. Even when the survey data sources represent large samples from the relevant populations, sampling error large enough to introduce nonnegligible uncertainty into the resulting estimates of ALE must be assumed to be present. In the case of analyses that are used to quantify the value of future financial obligations for a large population—for example, future costs for long-term care obligations incurred through the Medicare and Medicaid programs—small variations in the values of key parameters might imply differences of many millions of program dollars. Again, we are unaware of any past research that addresses uncertainty in estimates of ALE that can be traced to sampling variability.

This paper addresses two related phenomena: *variability* in active life, which is to say the relative likelihood that someone will spend an additional 0, 1, 2, ... or more of his or her years in various functional statuses such as "active" or "inactive;" and *uncertainty* about the average value of additional years spent in each such status. Our concern with both phenomena leads us to present our findings in the form of intervals, or measures of dispersion, as well in the more conventional form of point estimates. Linking the two areas of analysis is a recognition of several sources of randomness, or stochasticity, that are inevitably present when analyzing the dynamics of functional status.

Background

Our research is linked to past efforts in two areas of demographic analysis and methodology: multistate life tables, and cohort-component population forecasting. Many researchers who study ALE have employed multistate life table methods to calculate the average

length of active and inactive life (Crimmins, Hayward, and Saito 1994, 1996; Land, Guralnik, and Blazer 1994; Manton, Corder, and Stallard 1993; Rogers, Rogers, and Belanger 1989). While alternative computational techniques can be found with which to arrive at numerical values for the key elements for this central (perhaps paramount) tool in the demographer's toolkit, virtually all provide only a set of measures of central tendency, for example the proportion of a cohort surviving to a specified age (or, age and identified status), or the expected number of person-years lived in, or beyond, a given age interval. Moreover, these computational techniques virtually always treat the calculations as deterministic, ignoring the random nature of the vital events that, when enumerated, constitute the "occurrences" of occurrence/exposure rate; and, they treat the transition rates, or intensities, as fixed quantities whose values are known without error.

It has been argued, however, that the multistate life table should be viewed as a tabular summary of a random process; for example, Hoem and Funck Jensen (1982) characterize the standard columns of a multistate life table as "... tabulations of values of functions defined for Markov chains with a continuous time parameter and a finite state space" (Hoem and Funck Jensen 1982: 155). In other words, life table entries represent, in general, the expected values of random variables. For instance l_x, the proportion of a cohort surviving to age x, is the expected value, in the population, of the indicator variable for the event "alive at age x." A recognition that the life table is a tabular summary of individual realizations of a random process leads naturally to consideration of a broader set of summary indices—e.g., frequency distributions, as well as averages, of time spent in each state—than would generally be produced by conventional computational algorithms. However, analytical expressions for only a limited range of summary indices can be found in the existing literature.

A concern with uncertainty, and a willingness to link uncertainty to various types of stochasticity, is commonly encountered in the population forecasting literature. Researchers in this area emphasize that all forecasts are uncertain. In addition, these researchers argue that policymakers need to learn to accept uncertainty, and need information about the uncertainty associated with forecasts if they are to use this information as a basis for decision making (Stoto 1988). Further, it is stressed that demographers need to develop better methods to assess and report uncertainty (Keyfitz 1972; Stoto 1988). The methodological approaches that have been used can be classified into two general categories. In the first category, researchers examine the variability associated with underlying demographic rates such as fertility and mortality (Keyfitz 1985). Researchers in this category often examine errors in past population forecasts, and use these errors to construct confidence intervals for their projections (Cohen 1986; Keyfitz 1981; Stoto 1983). In the second category, the model parameters are treated as a random process (Alho 1990; Alho and Spencer 1985; Cohen 1986; Lee 1992; Lee and Tuljapurkar 1994; Tuljapurkar 1992).

A single component of a cohort-component population projection can be represented, in simplified form, as

$$n_{a+\tau}(t+\tau) = n_a(t) S_a(\tau), \qquad (1)$$

where a denotes age, t denotes (calendar) time, $n_a(t)$ represents the number of persons (of a given sex, or sex and race, and so on, group) alive at time t, and $S_a(\tau)$ represents the probability of surviving τ additional periods given survivorship to age a. In this expression we disregard both fertility and net migration as sources of population change. The survival probability (which corresponds to the l_x column of a life table) is, in turn, determined by a sequence of age-specific mortality rates $\mu_t(a)$, $\mu_{t+1}(a+1)$, ... , $\mu_{t+\tau-1}(a+\tau-1)$.

Lee and Tuljapurkar (1994) identify several sources of error in demographic forecasts, each of which can be associated with elements of (1). The first is uncertainty due to individual level randomness, i.e., the fact that survivorship (or nonsurvivorship) for τ additional years is a random variable with probabilities *S* and 1 - *S*, respectively. In large populations this source of error is negligible and can be disregarded. However, while stochastic variability in the number of survivors of a given age to some period—a *period* phenomenon—may be small, stochastic variability in the number of years survived after the baseline period—a *cohort* phenomenon—is generally substantial, and is (as noted above) likely to be a topic of some interest to members of the cohort in question. A second source of error identified (and also disregarded) by Lee and Tuljapurkar (1994) is data errors of several types. For example, the size (or share) of the population in group *a*, $n_a(t)$, may be measured with error, as may be the values of vital rates in the baseline year, that is $\mu_t(a)$. The final source of errors identified, the one upon which they focus their analysis, is uncertainty due to changing future values of vital rates, represented implicitly in (1) by $\mu_{t+1}(a + 1), \ldots , \mu_{t+\tau-1}(a+\tau-1)$. Lee and Tuljapurkar treat vital rates as realizations of stochastic processes, and present interval estimates of the size and composition of the future population incorporating this source of stochastic variation. In our analysis, we undoubtedly have sampling errors present in our estimates of the initial distribution of population characteristics [i.e., the $n_a(t)$], although to date we have not dealt with that source of error. Furthermore, we do not view our estimates as "projections," although they could be viewed as projections of cohort survivorship in the assumed absence of trends in transition rates. A source of stochasticity that is investigated in our work is uncertainty about the values of transition rates due to sampling variability in the parameters of the underlying model of transition rates.

Laditka and Wolf (forthcoming) present estimates of ALE based on a discrete-time Markov chain model of functional status and mortality. Most of the summary indices they present are standard life-table quantities such as age-specific survivorship and residual life expectancy. Here, we extend that analysis by presenting interval as well as point estimates of ALE, as well as depicting the entire frequency distribution of remaining years of life in each functional status state. We also investigate the degree of uncertainty in our estimates of ALE that can be traced to sampling variability in the estimates of model parameters.

Our approach is analytically simple and computationally intensive. Our summary indices of active life and its expectancy are based on large samples of individual disability life-histories generated by a computer using microsimulation techniques; in effect, we use "analog" techniques to develop our estimates of the distribution and expectation of years of active life . Each life history is a realization of a stochastic process for which we have obtained parameter estimates using survey data. These parameter estimates also are subject to sampling error. To investigate this source of variability, we treat the parameters as random variables. For each of a series of independent samples from the sampling distribution of the model parameters, we repeat the process of simulating a large sample of individual life histories; the between-sample variability in estimated ALE is presented as an indicator of uncertainty in ALE.

There are several sources of variability not included in this analysis. First, we do not examine the uncertainty associated with our initial distribution, or radix population. While this is theoretically important, it is beyond the scope of the present study. Second, we do not examine the variability associated with the Monte Carlo procedure used in the microsimulation procedure. Because of the large size of the sample, the uncertainty associated with the Monte Carlo technique is a substantially less important source of variability in this instance.

Methodology

"Active life" is defined as the part of life spent free of disability, represented here as one of a set of discrete functional-status states between which transitions can occur at random times. The model of functional status used here is identical to that presented in Laditka and Wolf (forthcoming). The model assumes that month-to-month transitions within the set of discrete states is described by a first-order Markov chain.

Consistent with previous research (e.g., Katz et al. 1963, 1983), our measure of functional status reflects impairments in Activities of Daily Living (ADLs). We use the following five ADLs: bathing, eating, dressing, transferring, and using the toilet. Individuals are coded as impaired in an ADL if they report any difficulty performing that activity, or report that they receive any help carrying out that activity. The final functional status variable summarizes the five indicators of ADL difficulty, as follows: individuals are coded as "unimpaired" if they exhibit no ADL limitations; individuals limited in one or two ADLs are "moderately impaired," and individuals with three or more ADL limitations are "severely impaired." Completing the state space is the absorbing state "dead."

The model assumes that the probability of making a transitions between any two states depends on the value of selected covariates. These covariates take account of several additional factors shown by prior research to influence the trajectory of functional status among older persons. Age, measured in years, appears as a covariate in the model, as does *Low Education*, a dichotomous variable indicating those persons who completed less than 12 years of schooling, and *Nonwhite*, also a dichotomous variable, which captures racial differences in functional status dynamics. Separate models are estimated for males and females.

Transition Probabilities and Their Standard Errors

The fundamental building blocks of our model are one-month transition probabilities, written in the general form

$$p_{ij}(age,t) = pr(STATUS_{t+1} = j \mid STATUS_t = i; age_t). \quad (2)$$

Thus, the probability of occupying any functional status state next month (at t+1) depends on the status occupied in month t, and on age in month t. The monthly transition probabilities are arranged in a 4×4 matrix as follows:

$$P(age,t) = \begin{bmatrix} p_{UU}(age,t) & p_{UM}(age,t) & p_{US}(age,t) & p_{UD}(age,t) \\ p_{MU}(age,t) & p_{MM}(age,t) & p_{MS}(age,t) & p_{MD}(age,t) \\ p_{SU}(age,t) & p_{SM}(age,t) & p_{SS}(age,t) & p_{SD}(age,t) \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (3)$$

Note that $p_{DU}(t) = p_{DM}(t) = p_{DS}(t) = 0$ while $p_{DD}(t) = 1$ due to the absorbing nature of death. Thus there are 12 unknown probabilities contained in the monthly transition matrix. The assumed probabilistic structure of this model, while rather restrictive, is consistent with virtually all past research on active life expectancy.

We write each of the first three rows of (3) as a multinomial logistic regression, with covariates representing age, race, and education, for example

$$\ln\left[\frac{p_{ij}(age,t)}{p_{iU}(age,t)}\right] = \beta_{ij0} + \beta_{ij1} Age_t + \beta_{ij2} Nonwhite + \beta_{ij3} Low\,Education, \quad (4)$$

with $I = U, M,$ or S and $j = M, S,$ or D. The coefficients corresponding to the probabilities found in the first column of (3) are normalized to zero. There are therefore nine sets of unknown regression coefficients, with four coefficients in each set, to be estimated; each set corresponds to one of the allowable combinations of the i and j subscripts. A more detailed discussion of the

estimation techniques used, and the data used in the estimation, can be found in Laditka and Wolf (forthcoming).

The maximum-likelihood algorithm used to estimate the logistic regression coefficients in (4) produces a (column) vector of estimated regression coefficients, $\hat{\beta}$, and a matrix of their variances and covariances, Σ. Variances of the transition probabilities can be derived using the relationship

$$V = \text{var}(P_{col}) = J_1 \Sigma J_1', \tag{5}$$

where P_{col} denotes the P-matrix rearranged as a column vector, and J_1 is a matrix a typical elements of which is

$$\frac{\partial p_{ij}}{\partial \beta_{rst}}.$$

Sampling errors in the elements of the β vector propagate through the P-matrix in a limited way: every element of β_{rst}, for a given r (row) influences the variances of all transition probabilities in that row of P.

We also present estimates of one-year transition probabilities, to facilitate their comparison to the annual rates used in most past research on ALE. The one-year transition probabilities are simply the twelfth power of P. Variances for $R = P^{12}$ are obtained analogously to those for P, using

$$W = \text{var}(R_{col}) = J_2 V J_2'. \tag{6}$$

In the derivation of the transformation matrix J_2 we make use of the fact that

$$\frac{\partial P^m}{\partial p_{ij}} = \sum_{j=0}^{m-1} P^{m-j} 1_{ij} P^j,$$

where 1_{ij} is a matrix whose i,j^{th} element equals 1, while all other elements equal 0. The propagation of sampling errors in β through R is extensive: in general, the derivative of every element of R with respect to every element of P is nonzero.

Variability in Years of Active and Inactive Life

We investigate the degree of variability in the length of active (or of inactive) life by producing a frequency distribution of the number of years spent in each functional status; we also summarize this variability using conventional summary statistics such as standard deviations. These summary measures are obtained using a large sample of individual functional status histories generated by a computer using microsimulation techniques.

A sample of simulated functional status histories for 100,000 men exactly 70 years old, and an analogous sample for women, were created for this analysis. The gender, racial, and functional status composition of these cohorts were based on the average characteristics of individuals aged 65 to 74 in the 1989 wave of the National Long-Term Care Survey (NLTCS). The NLTCS is useful for this purpose since it includes the institutionalized population. In the microsimulation procedure, functional status transition matrices (the *P*s) were used to simulate each person's survivorship and functional status, month by month, from exact age 70 onward until death. For example, for someone with ADL code i in month t, the model generates the four transition probabilities $p_{i1}(t+1)$, $p_{i2}(t+1)$, $p_{i3}(t+1)$, and $p_{i4}(t+1)$, corresponding to possible states occupied in the next month. These four probabilities are then mapped into subsets of the 0,1 interval: subset 1 is the interval from 0 to $p_{i1}(t+1)$, while subset 2 is the interval from $p_{i1}(t+1)$ to $[p_{i1}(t+1) + p_{i2}(t+1)]$, and so on. Next, a computer-generated random number from the uniform (0,1) distribution is drawn. Finally, a particular value (1, 2, 3 or 4) for the next month's functional status is assigned, depending on the subset into which the random number falls. The

preceding steps were repeated for each successive month until the individual was simulated to die (i.e., to make a transition into state 4).

The data file produced by the microsimulation is treated as though it represented longitudinal survey data. Summary statistics of interest are derived by tabulation of the simulated life histories. For example, each person's "active life" is a count of the number of months in which the simulated functional status code equals one (i.e., "unimpaired"). ALE for the simulated cohort is the sample average of active life, so coded. Other summary statistics (for example, the frequency distribution of active life) are similarly obtained.

Uncertainty in Estimates of Active Life Expectancy

As discussed above our estimates of the parameters of our model of functional status transitions embody sampling error, and this error produces errors in our calculated transition probabilities. We investigate the empirical consequences of this type of error by repeating the microsimulation exercise ten times. Each "run" of the microsimulation uses a different vector of model parameters, $\beta^*_m, m = 1, \ldots, 10$. The β^*'s are generated as draws from a multivariate normal distribution with mean, $\hat{\beta}$, and variance Σ. We present the minimum, maximum, and standard deviation of the 10 independent estimates of ALE based on the 10 different values of the underlying parameters. Note that the SD of ALE is not the standard error of our estimate of the mean of active life; rather, it is an estimate of the likely size of errors in our estimate of ALE attributable to our ignorance of the true value of β.

Results

Transition Probabilities and Their Standard Errors

Tables 1 and 2 present illustrative computed values of one- and twelve-month transition probabilities implied by our estimates of β (for completeness, the estimates of β for men and women are also included as appendix tables A-1 and A-2). Table 1 pertains to men, while Table 2 presents the transition probabilities for women. Also shown in these tables are standard errors, i.e., the square roots of the variances produced by equations (5) and (6). Several anticipated patterns are exhibited in these tables. For instance, the probability of dying increases with age and with the severity of disability. The probability of dying is larger for males who are moderately impaired than for those who are unimpaired, and several times larger for those who are severely impaired than for the unimpaired. Men with less education have uniformly higher chances of dying than those with more education only if they are also unimpaired. Analogous results can be seen for women.

As a general rule the transition probabilities are quite precisely estimated: the point estimates of the probabilities tend to be many times larger than their standard errors. These findings reassure us that our description of the dynamics of functional status is not greatly influenced by sampling errors in the parameters of the model.

The probabilities shown in Tables 1 and 2 are point estimates, and the small standard errors displayed for most of those point estimates are based on analytic methods. We now consider the life-cycle implications of our estimated functional status transition matrices, examining both the frequency distribution and average amount of time spent in each functional status recognized by the model.

Patterns of Active Life and Active Life Expectancy

Years of Remaining Life. Figures 1 to 3, and Tables 3 and 4, illustrate the main results of our microsimulation analysis. In these results the transition probabilities used are those implied by $\hat{\beta}$, our central estimates of the model parameters. Figure 1 shows the frequency distribution for remaining years of unimpaired life among 70-year old white men, while Figures 2 and 3 present analogous frequency distributions for years spent in the "moderately impaired" and "severely impaired" states, respectively. In all three figures the frequency distributions are quite skewed, particularly for the impaired states. At age 70, a substantial percentage of white males is simulated to have zero remaining years of active life; this reflects the fact that many men begin this age interval in an impaired state and never return to the unimpaired state. It is also noteworthy that Figure 1 shows the modal value of residual unimpaired years of life to be one, while its mean (from Table 3) is nearly nine. In Figures 2 and 3 we see that most 70-year old white men can expect to spend no years of their remaining lifetime in an impaired state. Thus, the *average* number of years of life spent unimpaired, and especially the average number of years spent impaired, appear to be very poor descriptions of "typical" life experiences of older men.

Table 3 shows the average and standard deviation of number of remaining years of life in total, and in each of three functional status categories—unimpaired, moderately impaired, and severely impaired—at ages 70, 80, and 90, for a number of different population groups. The averages in each case represent conventional "life expectancies" specific to the indicated statuses. The standard deviations summarize the dispersion of the distributions of years of remaining life about each respective mean. The patterns exhibited by the averages shown in this tabulation are described in detail in Laditka and Wolf (forthcoming). We briefly review these patterns here. First, females live notably longer than males in both absolute and relative terms;

however, the gap in total life between males and females narrows at the oldest ages. Second, while the total life expectancy for females is greater than that of males, women live a greater percentage of years in an unimpaired state compared with males. Third, more education is positively associated with total life expectancy for both racial groups. Finally, the total life expectancy of nonwhite males exceeds that of white males, in all ages, by a considerable margin. However, nonwhite males can expect to spend a greater percentage of their lives in an impaired state compared with white males.

Next we focus on the variability in patterns of active life, represented in Table 3 by the standard deviation of years spent in each status. First, for males, the magnitude of the standard deviation for nonwhites is higher relative to the mean, compared with whites. For females, the opposite is true; the size of the standard deviation relative to the mean is generally smaller for nonwhites compared with whites. Second, the size of the standard deviation relative to the mean is greater for the impaired states, compared with the total and unimpaired years of remaining life.. Finally, for both males and females, there are no notable differences in the size of the standard deviation relative to the mean for whites in the high and low education categories compared with whites overall.

Judging by the figures shown in Table 3, we cannot escape the conclusion that variability in the remaining years of life in each functional status is quantitatively significant. For the two impaired states, the standard deviation exceeds the mean in all groups, and at all ages. For total and for unimpaired years of remaining life, variability grows in relative importance at successively older ages: for most groups shown, by age 90 the standard deviation is nearly as large, and in some cases is larger, than the mean number of years of life remaining in total, and in the unimpaired state.

Duration of Functional Status Episodes. Our microsimulation approach allows us to investigate the duration of functional status episodes (or spells), i.e., the number of consecutive months that someone has a given functional status. This type of information is not obtained using conventional multistate life-table techniques. Means and standard deviations for the length of functional status episodes are presented in Table 4. Note that the simulated functional status history for one person can contribute two or more (as well as one, or even zero) observations to the pool of functional status episodes of a given type.

Several interesting patterns can be found in Table 4. First, females spend a longer mean length of time in each functional status state. Second, for both males and females, persons with more education have longer spells of unimpairment and shorter episodes of impairment compared with individuals with less education. For males, spells in a severely impaired state, on average, exceed those spent in a moderately impaired state by about three months; for females, this difference is about six months.

Table 4 also reveals substantial amounts of variability in the length of functional status episodes. Again, the standard deviations are larger relative to the mean duration of a spell for nonwhites compared with whites. There are no substantial differences between the size of the standard deviation relative to its mean between males and females. Overall, the magnitudes of the standard deviation indicates that there is substantial individual variability in average length of time spent in each functional status state: in most cases the standard deviation is nearly as large as the mean, and in a few cases it is greater.

Uncertainty in Estimates of Active Life Expectancy

In Tables 5 and 6 we turn our attention to uncertainty in our estimates of ALE that is traceable to sampling variability in the estimated parameters of the model. These tables

summarize the results of 10 independent simulations, each using a different (but identically distributed) vector of parameter values β^*. The averages and SDs of the β^*s used in the 10 simulations are shown in Appendix Tables A-1 and A-2, for reference.[1]

Table 5 quantifies our uncertainty about ALE by presenting the lowest and highest values of ALE obtained in the ten independent simulations, as well as the SD of the ten values, for each of four life expectancies: total (TLE), unimpaired (ULE), moderately impaired (MLE) and severely impaired (SLE). Paralleling the structure of Table 3, these figures are shown for ages 70, 80, and 90, for a number of different population groups. The patterns of functional status are similar to those just reviewed; e.g., females live notably longer than males, whites with more education live longer than whites with less education. We focus on the uncertainty associated with these estimates, where uncertainty is reflected in the range of the estimate (the difference between the minimum and maximum value) and its standard deviation. The major findings regarding uncertainty are as follows. First, for males the ranges of estimates of TLE, ULE, MLE, and SLE is greater for nonwhites than whites. For example, the difference between the minimum and maximum values for TLE for nonwhite males at age 70 is 2.1 years, while the comparable figure for white males is .5 years. A related finding is that for nonwhite males at all ages and functional status categories, the magnitude of the standard deviation relative to the maximum (or minimum) estimate of remaining life expectancy generally exceeds that of whites. These findings are also true for females, but the effect is less pronounced. A second finding is that the ranges of estimates of TLE, ULE, MLE, and SLE are generally larger, and the standard deviations greater, for the two education categories when considered separately rather than together. More generally, the more we disaggregate the groups being examined the greater the range of uncertainty associated with average life expectancy within group. In addition, for both

males and females the size of the standard deviation relative to the maximum (or minimum) life expectancy is larger for MLE and SLE compared with TLE and ULE. Thus, there is greater uncertainty associated with the two impaired categories compared with total and unimpaired life expectancy.

Combining our findings for the mean number of years lived in each functional status from Table 3 with our estimates of the uncertainty about those means from Table 5, we can examine the *relative* uncertainty about total life expectancy and its components (e.g., unimpaired life expectancy). Table 6 displays the coefficient of variation—that is, the SD (from Table 5) divided by the mean (from Table 3)—for TLE, ULE, MLE, and SLE by sex, race, and (for whites only) education at age 70. The ratios shown have been multiplied by 100, allowing the entries in the table to be interpreted as an index of uncertainty relative to the mean in percentage terms.

The results found in Table 6 are consistent with those already shown: in general, the larger the population group and the more universal the phenomenon, the less relative uncertainty about the value of ALE. Thus, total life expectancy, which is computed for everyone, has a smaller coefficient of variation than does active life expectancy, which in turn has a smaller coefficient of variation than does either of the impaired functional statuses. The same is true for whites and for nonwhites, but for each index the coefficient of variation is larger for nonwhites (the smaller group) than for whites (the larger group). This is partly a sampling phenomenon (that is, it is a manifestation of the relative prevalence of whites and nonwhites in the simulated data base) and partly reflects the relative variability of the relevant regression coefficients. These two "sources" of relative uncertainty are, however, related: the relative imprecision of the regression coefficients for the variable "nonwhite" in our model of transition probabilities itself is due, in part, to the relative prevalence of nonwhites in the sample used to estimate that model.

Finally, Table 7 shows the minimum and maximum for the mean length of spells in each functional status state, and the standard deviation of the means, paralleling the information presented in Table 4. Here, again, females are shown to experience longer spells in all functional status states compared with males. Again we focus our discussion on the results related to uncertainty. First, for both males and females, with only one exception, the size of the standard deviation relative to the maximum of the average length of a spell is larger for nonwhites compared with whites. Second, the ranges of the intervals are somewhat larger for nonwhites compared with whites. For instance, the difference between the maximum and minimum mean duration of unimpairment is 9.5 months for nonwhite males compared with 6.9 for white males. There are no other notable differences between subgroups.

Conclusions

As the number of older Americans increases substantially early in the next century, it is likely that estimates of ALE will be used to help plan for and develop health care policies. It is vital for policymakers to have a measure of the degree of variability, and of uncertainty, associated with estimates the length of active—and inactive—life, and of its average.

This study has investigated two sources of variability present in empirical studies of active life and its expectancy. The first is variability in the patterns of remaining years of "active" and of "inactive" life. Most past research has examined only the average number of years spent in any status, no doubt a reflection of the fact that conventional multistate life table techniques generally used in ALE research produce estimates of only these averages. We use, instead, microsimulation techniques that permit us to calculate not only the average but also the full frequency distribution of remaining years lived in each status. The second source of

variability examined is sampling variability: our distributions of remaining years of life in each functional status rely on estimates of transition probabilities that are, in turn, estimates from a model whose parameters are functions of sample data. Like all sample statistics these model parameters are subject to sampling error, and those sampling errors propagate throughout our simulated functional status life histories.

Our findings can be summarized most compactly with the observation that *variability* of active life (and of inactive life) about its expected value is vastly more important that is *uncertainty* about active (or inactive) life expectancy due to sampling error in the underlying model parameters. Variability in the patterning of remaining life across functional categories is revealed by our histograms for the distribution of years lived in each status from age 70 onward (Figures 1 to 3) and in the large SDs obtained for these frequency distributions (Table 3). A similar pattern emerges whether we examine the frequency distributions of length of individual functional status episodes (in Table 4) or the more aggregated distributions of time in a given status, summed over episodes (as in Table 3).

In contrast, our indicators of the degree of uncertainty in ALE due to sampling variability suggest that this type of variability, while obviously present, is relatively small. This conclusion is most strongly indicated by the coefficients of variation shown in Table 6: in most cases the uncertainty in ALE is summarized by a number only 2 or 3 percent as large as the mean to which it corresponds. The exceptional cases—for example, the coefficient of variation for average years spent severely impaired, among nonwhite males, which is about 0.15—pertain to groups, and to outcomes, that are comparatively uncommon in our data. The pattern of sampling variability uncovered appears both in the relative precision of the underlying model parameters (see Appendix Tables A-1 and A-2), which translates into relative precision of the transition

probabilities (see Tables 1 and 2), and in the data base of simulated functional status life histories upon which our estimates are ultimately based.

It is important to note that the model used in our analysis (a more detailed rendition of which can be found in Laditka and Wolf, forthcoming) is a very simple one. An important question, but one we cannot at this point address, is the extent to which our conclusions, summarized above, are specific to the combination of model specification, estimation technique, and data sources used in this research. We have assumed that functional status dynamics can be represented, at the individual level, as a first-order Markov chain. This should be viewed as a baseline model, against which more complex (that is, more realistic) models, yet to be developed, should be compared. Nevertheless, our Markovian model is in its most fundamental respects identical to that used, explicitly or implicitly, in nearly all past research on active life expectancy.

One of the major limitations of this study is the absence of other ALE estimates with which to compare our results. We hope that more ALE researchers will employ stochastic modeling approaches, such as those now employed in the field of population forecasting. This would provide policymakers with additional information about the degree of uncertainty associated with ALE estimates. In addition, it would allow researchers to compare both ALE estimates and their degree of precision across studies which use different methods and data. Our suggestion in this area echoes the argument of other researchers: we need to focus more on comparing the results of different demographic methods (Ahlburg and Land 1992; Cohen 1986; Land 1986). Further, employing stochastic modeling approaches would allow researchers to better gauge the accuracy of their models, and ultimately, help them to build better models.

Our study reinforces the usefulness of employing microsimulation techniques in ALE research. First, consistent with the conclusions of other researchers, microsimulation allows us

to calculate useful indices of active and inactive life patterns—calculations that would not be feasible using other methods (Pflaumer 1988). Second, microsimulation generates a distribution of values in addition to a mean value. We have highlighted this feature of microsimulation in our examination of variability in active and inactive life. Finally, microsimulation allows us to examine the life-cycle implications of our model of functional status transitions, and the degree of uncertainty associated with these estimates.

There are several ways in which the research presented here might be usefully extended. We have not examined the variability associated with the radix population. Researchers have proposed various approaches (e.g., bootstrapping) which could be used to examine this third source of variability (Wolf et al. 1995). In addition, the methods presented here could be used to examine disability trends in new studies examining the functional status patterns of older persons.

Endnotes

1. Ten is an admittedly small sample of βs to use in this analysis. Readers will note that for several of the regression coefficients, the average value (in the sample of 10) is dissimilar to the "true" value (that is, the value of $\hat{\beta}$ that represents the expected value). In all cases, however, the average values shown are well within one standard deviation of the "true" value.

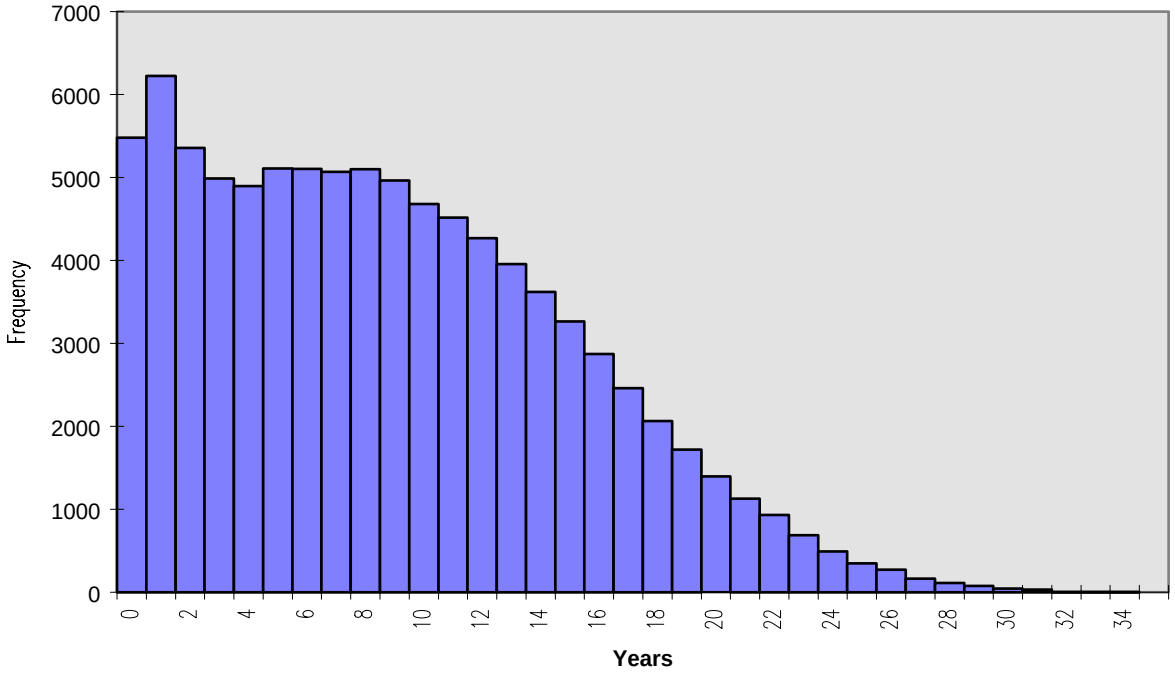

Figure 1: Frequency Distribution for Remaining Years of Unimpaired Life, White Males, Age 70

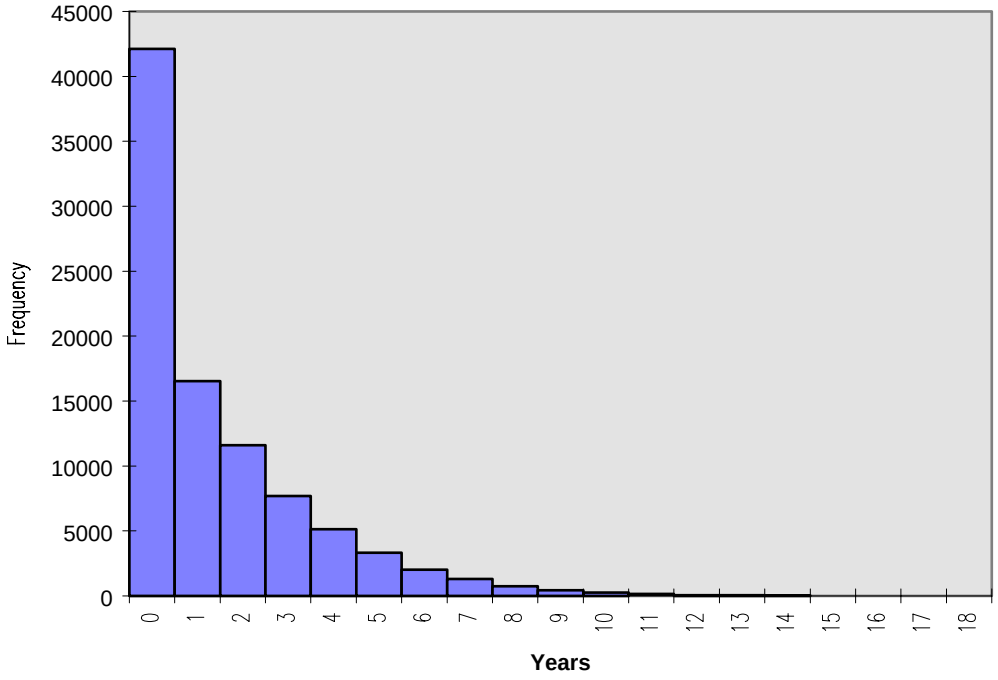

Figure 2: Frequency Distribution for Remaining Years of Moderately-Impaired Life, White Males, Age 70

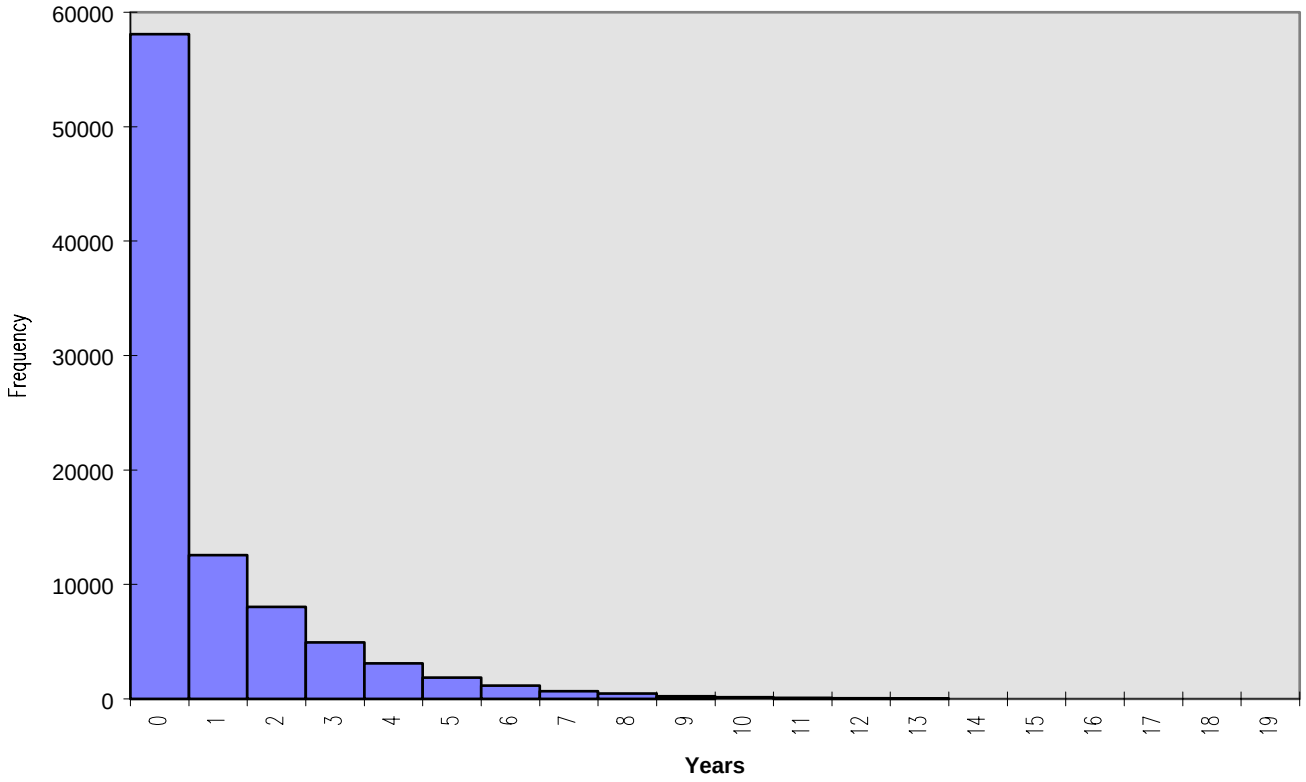

Figure 3: Frequency Distribution for Remaining Years of Severely Impaired Life;

Table 1. Selected Functional Status Transition Probabilities: White Males (x 100)

	One-Month Transition Probabilities				12-Month Transition Probabilities			
To:	**U**	**M**	**S**	**D**	**U**	**M**	**S**	**D**
High Education, Age = 70								
From:U	99.28	0.47	0.04	0.22	92.44	4.21	0.55	2.81
	[0.05][a]	[0.05]	[0.01]	[0.02]	[0.46]	[0.38]	[0.08]	[0.21]
M	2.71	95.34	1.13	0.82	26.0	57.19	7.67	9.14
	[0.43]	[0.51]	[0.17]	[0.21]	[3.13]	[3.52]	[1.05]	[1.76]
S	3.11	0.40	94.44	2.05	27.17	3.39	50.56	18.87
	[0.33]	[0.06]	[0.56]	[0.26]	[2.14]	[0.39]	[3.57]	[1.94]
High Education, Age = 90								
From:U	97.47	1.46	0.0	1.07	74.57	10.03	2.93	12.46
	[0.18]	[0.17]	[0.0]	[0.14]	[1.53]	[1.04]	[0.50]	[1.28]
M	1.69	92.01	5.29	1.01	11.83	40.13	29.04	19.01
	[0.30]	[0.92]	[0.80]	[0.28]	[1.75]	[3.89]	[2.82]	[2.07]
S	0.11	1.49	93.86	4.54	1.79	8.25	49.34	40.62
	[0.07]	[0.47]	[0.81]	[0.58]	[0.35]	[2.17]	[4.29]	[3.82]
Low Education, Age = 70								
From:U	97.94	0.63	1.16	0.27	79.45	5.65	10.40	4.50
	[0.24]	[0.06]	[0.23]	[0.03]	[2.14]	[0.47]	[1.92]	[0.35]
M	2.86	95.24	1.09	0.81	24.25	56.89	9.67	9.19
	[0.34]	[0.47]	[0.15]	[0.11]	[2.23]	[3.17]	[1.04]	[0.95]
S	1.05	0.75	96.12	2.08	10.14	5.87	63.19	20.80
	[0.11]	[0.11]	[0.41]	[0.26]	[0.85]	[0.79]	[3.09]	[2.18]
Low Education, Age = 90								
From:U	96.70	2.00	0.0	1.31	68.30	13.25	3.66	14.79
	[0.21]	[0.20]	[0.0]	[0.13]	[1.57]	[1.19]	[0.49]	[1.15]
M	1.79	92.08	5.14	0.99	11.95	42.56	26.98	18.51
	[0.33]	[0.80]	[0.76]	[0.31]	[1.96]	[3.04]	[2.40]	[1.97]
S	0.04	2.69	92.80	4.47	1.97	14.14	45.08	38.82
	[0.02]	[0.75]	[0.95]	[0.46]	[0.50]	[3.05]	[3.96]	[2.86]

[a]Standard errors shown in parentheses.

U = unimpaired; M = moderately impaired; S = severely impaired; D = dead

Table 2. Selected Functional Status Transition Probabilities: White Females (x 100)

To:	One-Month Transition Probabilities				12-Month Transition Probabilities			
	U	M	S	D	U	M	S	D
High Education, Age = 70								
From:U	99.49	0.39	0.02	0.10	94.64	3.60	0.41	1.34
	[0.03][a]	[0.03]	[0.01]	[0.01]	[0.28]	[0.25]	[0.05]	[0.14]
M	2.84	95.44	1.18	0.54	26.13	59.00	9.08	5.79
	[0.26]	[0.36]	[0.14]	[0.09]	[1.99]	[2.40]	[0.88]	[0.81]
S	0.05	2.60	96.44	0.91	4.14	19.99	66.08	9.79
	[0.00]	[0.50]	[0.50]	[0.12]	[0.74]	[3.24]	[3.77]	[1.15]
High Education, Age = 90								
From:U	97.41	1.81	0.12	0.66	74.62	13.94	3.52	7.92
	[0.15]	[0.16]	[0.06]	[0.07]	[1.15]	[0.99]	[0.41]	[0.67]
M	1.96	94.29	3.11	0.64	15.19	52.35	21.81	10.65
	[0.23]	[0.43]	[0.33]	[0.12]	[1.47]	[2.41]	[1.83]	[0.97]
S	0.12	1.24	95.80	2.83	2.09	8.77	61.35	27.79
	[0.08]	[0.23]	[0.34]	[0.25]	[0.62]	[1.41]	[2.37]	[2.05]
Low Education, Age = 70								
From:U	99.35	0.53	0.03	0.09	93.38	4.77	0.61	1.25
	[0.04]	[0.04]	[0.01]	[0.01]	[0.35]	[0.33]	[0.06]	[0.11]
M	3.05	95.11	1.23	0.61	27.37	56.77	9.45	6.41
	[0.25]	[0.36]	[0.12]	[0.07]	[1.75]	[2.32]	[0.85]	[0.63]
S	0.01	2.39	96.63	0.97	3.72	18.19	67.55	10.53
	[0.00]	[0.37]	[0.36]	[0.12]	[0.61]	[2.44]	[2.77]	[1.17]
Low Education, Age = 90								
From:U	96.80	2.44	0.20	0.57	69.92	17.81	4.92	7.34
	[0.17]	[0.19]	[0.09]	[0.06]	[1.21]	[1.11]	[0.55]	[0.59]
M	2.10	93.92	3.25	0.73	15.34	50.52	22.46	11.68
	[0.23]	[0.41]	[0.31]	[0.13]	[1.43]	[2.17]	[1.64]	[1.00]
S	0.04	1.14	95.80	3.03	1.30	7.83	61.27	29.59
	[0.02]	[0.21]	[0.30]	[0.22]	[0.23]	[1.28]	[2.10]	[1.79]

[a] Standard errors shown in parentheses.

U = unimpaired; M = moderately impaired; S = severely impaired; D = dead

Table 3. Summary Statistics for Remaining Years of Life by Status, by Sex, Race, and Education, for Selected Ages

		Total		Unimpaired		Moderately Impaired		Severely Impaired	
Population Group	**Age**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Males	70	11.3	7.1	8.8	6.2	1.5	2.0	1.0	1.8
	80	6.8	4.9	4.6	4.2	1.2	1.6	1.0	1.6
	90	3.8	3.1	1.9	2.4	0.9	1.2	1.0	1.4
Nonwhite	70	11.8	7.4	8.5	6.0	1.8	2.0	1.5	2.2
	80	7.2	5.2	4.3	3.9	1.4	1.6	1.5	2.0
	90	4.4	3.5	1.7	2.2	1.1	1.3	1.6	1.9
White	70	11.3	7.0	8.9	6.2	1.5	2.0	0.9	1.7
	80	6.7	4.8	4.6	4.2	1.2	1.6	0.9	1.5
	90	3.7	3.0	2.0	2.5	0.8	2.2	0.9	1.3
Low Education	70	9.9	6.8	7.2	5.8	1.5	2.2	1.2	1.9
	80	6.2	4.6	3.8	3.7	1.4	1.8	1.0	1.6
	90	3.5	3.0	1.5	2.0	1.0	1.3	1.0	1.3
High Education	70	12.1	7.1	9.9	6.3	1.4	1.9	0.8	1.5
	80	6.9	4.9	4.9	4.4	1.1	1.5	0.9	1.5
	90	3.8	3.1	2.1	2.6	0.8	1.1	0.9	1.3

Table 3. Continued

Population Group	Age	Total		Unimpaired		Moderately Impaired		Severely Impaired	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Females	70	15.2	7.9	11.0	6.5	2.5	2.7	1.7	2.5
	80	9.1	5.8	5.3	4.5	2.1	2.3	1.7	2.3
	90	4.9	3.7	1.9	2.4	1.4	1.8	1.6	1.9
Nonwhite	70	13.9	7.6	8.7	5.7	3.1	3.1	2.1	2.6
	80	8.1	5.5	3.8	3.7	2.4	2.6	1.9	2.3
	90	4.6	3.6	1.4	2.0	1.6	2.0	1.6	1.7
White	70	15.4	7.9	11.2	6.6	2.5	2.7	1.7	2.5
	80	9.2	5.8	5.4	4.5	2.1	2.3	1.7	2.3
	90	4.9	3.9	2.0	2.5	1.4	1.7	1.5	1.9
Low Education	70	14.8	7.8	10.3	6.3	2.6	2.7	1.9	2.6
	80	8.7	5.6	4.8	4.2	2.1	2.3	1.8	2.3
	90	4.6	3.5	1.6	2.2	1.4	1.7	1.6	1.9
High Education	70	15.7	8.0	11.3	6.6	2.4	2.7	1.6	2.4
	80	9.4	5.9	5.8	4.6	2.0	2.3	1.6	2.3
	90	5.0	3.8	2.1	2.6	1.4	1.8	1.5	1.9

Table 4. Average Length (in months) of Functional Status Episodes, by Sex, Race, and Education

Population Group	Unimpaired		Moderately Impaired		Severely Impaired	
	Mean	SD	Mean	SD	Mean	SD
Males	73.8	66.4	16.6	16.3	19.7	19.6
Nonwhite	56.9	51.5	11.9	11.7	18.7	19.0
White	75.9	63.4	17.4	16.8	19.8	19.6
Low Education	85.1	55.1	17.6	16.9	20.9	20.5
High Education	60.9	66.4	17.2	16.7	18.9	18.8
Females	80.5	65.2	19.2	18.5	25.1	24.4
Nonwhite	61.0	52.2	22.0	21.1	24.2	23.7
White	82.5	66.1	18.9	18.2	25.3	24.5
Low Education	74.3	60.6	18.4	17.7	26.2	25.3
High Education	87.0	68.5	19.2	18.5	24.7	23.9

Table 5. Uncertainty of Life Expectancy by Functional Status, by Sex, Race and Education, for Selected Ages

		TLE			ULE			MLE			SLE		
Population Group	**Age**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**
Males	70	11.0	11.4	.126	8.5	9.0	.166	1.4	1.6	.057	0.9	1.1	.088
	80	6.6	6.9	.107	4.3	4.7	.204	1.1	1.4	.095	0.8	1.1	.097
	90	3.5	3.9	.132	1.7	2.2	.183	0.7	1.1	.117	0.8	1.2	.143
Nonwhite	70	10.9	13.0	.638	7.9	9.2	.428	1.5	1.9	.143	1.3	2.0	.226
	80	6.5	8.1	.464	3.6	4.9	.371	1.1	1.6	.140	1.1	1.8	.216
	90	3.3	4.7	.397	1.2	2.1	.238	0.7	1.1	.166	1.1	1.8	.207
White	70	11.0	11.5	.142	8.5	9.1	.175	1.4	1.6	.076	0.8	1.0	.063
	80	6.5	6.9	.123	4.3	4.9	.202	1.1	1.4	.092	0.8	1.0	.082
	90	3.5	3.9	.126	1.7	2.2	.190	0.7	1.0	.094	0.7	1.2	.141
Low Education	70	9.5	10.4	.242	6.8	7.6	.245	1.4	1.8	.106	1.1	1.3	.057
	80	5.9	6.6	.216	3.5	4.1	.181	1.3	1.5	.092	0.9	1.0	.053
	90	3.1	3.7	.250	1.2	1.9	.196	0.8	1.2	.129	0.8	1.1	.097
High Education	70	11.7	12.4	.183	9.4	10.3	.255	1.3	1.5	.082	0.6	0.9	.097
	80	6.7	7.2	.151	4.6	5.3	.259	1.0	1.3	.095	07	1.0	.117
	90	3.5	4.0	.125	1.8	2.4	.228	0.6	1.0	.107	0.7	1.1	.142

Table 5. Continued

		TLE			ULE			MLE			SLE		
Population Group	**Age**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**
Females	70	14.8	15.4	.195	10.6	11.3	.185	2.4	2.5	.043	1.7	1.8	.042
	80	8.7	9.2	.175	5.0	5.4	.163	1.9	2.1	.082	1.6	1.8	.063
	90	4.4	5.2	.231	1.6	2.0	.143	1.2	1.5	.092	1.4	1.7	.108
Nonwhite	70	13.2	14.2	.306	8.2	8.9	.249	2.6	3.5	.267	1.8	2.4	.199
	80	7.7	8.5	.283	3.3	4.1	.251	2.0	2.8	.262	1.6	2.3	.216
	90	4.2	5.3	.425	1.1	1.9	.259	1.2	2.2	.327	1.3	1.8	.173
White	70	14.9	15.5	.197	10.8	11.5	.197	2.3	2.5	.047	1.6	1.8	.063
	80	8.8	9.3	.191	5.1	5.6	.179	1.9	2.0	.053	1.6	1.8	.067
	90	4.4	5.2	.230	1.7	2.1	.163	1.1	1.4	.103	1.4	1.7	.107
Low Education	70	14.4	15.2	.250	9.8	10.7	.244	2.4	2.8	.117	1.8	2.1	.114
	80	8.0	8.9	.241	4.4	5.0	.172	2.0	2.1	.048	1.7	2.1	.125
	90	4.3	4.7	.135	1.4	1.6	.082	1.2	1.3	.052	1.5	1.9	.158
High Education	70	15.2	16.0	.237	11.3	12.0	.237	2.2	2.4	.074	1.4	1.7	.097
	80	8.9	9.7	.227	5.3	6.0	.235	1.8	2.0	.082	1.4	3.8	.702
	90	4.5	5.4	.239	1.8	2.3	.194	1.1	1.4	.103	1.3	1.7	.140

Table 6. Coefficient of Variation: Life Expectancy by Status,Sex, Race, and Education at Age 70

Population Group	TLE	ULE	MLE	SLE
Males	1.12	1.89	3.80	8.80
Nonwhite	5.41	5.04	7.94	15.07
White	1.26	1.97	5.07	7.00
Low Education	2.44	3.40	7.07	4.75
High Education	1.51	2.58	5.86	12.13
Females	1.28	1.68	1.72	2.47
Nonwhite	2.20	2.86	8.61	9.48
White	1.28	1.76	1.88	3.71
Low Education	1.69	2.37	4.50	6.00
High Education	1.51	2.10	3.08	6.06

Table 7. Uncertainty in Average Length (in months) of Functional Status Spells, by Sex, Race, and Education

	Unimpaired			Moderately Impaired			Severely Impaired		
Population Group	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**	**Min**	**Max**	**SD**
Males	69.4	76.1	2.05	15.1	17.3	.636	17.4	22.7	1.48
Nonwhite	52.3	61.8	3.28	9.5	12.6	.100	16.8	22.5	2.24
White	70.9	77.8	2.34	16.0	18.4	.716	17.3	22.7	1.42
Low Education	57.5	64.5	2.68	16.4	18.8	.651	18.2	22.4	1.42
High Education	79.3	8.9	3.47	15.7	18.3	.875	15.2	24.2	2.33
Females	77.7	86.7	2.82	17.7	20.1	.788	23.7	26.7	1.02
Nonwhite	54.1	65.6	4.00	19.6	24.4	1.63	20.4	27.2	2.19
White	79.6	88.8	2.91	17.4	19.6	.727	23.9	27.1	1.15
Low Education	60.8	78.2	4.86	17.4	19.4	.745	25.8	28.4	.871
High Education	84.0	95.0	3.48	17.2	19.8	.852	22.2	27.8	1.82

Table A- 1. Parameters of Functional Status Transition Model: Males

Origin State	Destination State	Variable							
		Constant		Age		Nonwhite		Low Education	
		$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$
U	M	-5.4745 (0.1147)*	-5.4457 [0.0744]	0.0580 (0.0084)*	0.0549 [0.0010]	0.3603 (0.1082)*	0.3754 [0.1247]	0.3177 (0.0784)*	0.3392 [0.0739]
U	S	(-6.0575 (0.0851)*	-6.0555 [0.0455]	-0.9392 (0.0802)*	-0.9137 [0.0841]	-0.1205 (0.0184)*	-0.1116 [0.0130]	3.5002 (0.1204)*	3.5111 [0.0694]
U	D	-6.2744 (0.1030)*	-6.3125 [0.1188]	0.0801 (0.0085)*	0.0849 [0.0086]	-0.3152 (0.2013)	-0.3976 [0.1833]	0.2087 (0.0913)*	0.1539 [0.0838]
M	M	3.5153 (0.1827)*	3.4596 [0.1079]	0.0218 (0.0128)	0.0279 [0.0096]	-0.5033 (0.1122)*	-0.5682 [0.0810]	-0.0543 (0.0855)	-0.0562 [0.0342]
M	S	-1.0807 (0.2761)*	-1.1199 [0.2467]	0.1009 (0.0172)*	0.1039 [0.0148]	-0.0187 (0.1733)	-0.0495 [0.1079]	-0.0842 (0.1091)	-0.0543 [0.1070]
M	D	-1.2628 (0.2808)*	-1.1394 [0.2002]	0.0339 (0.0189)	0.0252 [0.0128]	-0.4746 (0.2092)*	-0.4352 [0.1222]	-0.0733 (0.1784)	-0.1588 [0.1415]
S	M	-2.5098 (0.0842)*	-2.4775 [0.0690]	0.2324 (0.0334)*	0.2225 [0.0313]	0.3625 (0.2372)	0.3707 [0.1452]	1.7010 (0.0679)*	1.6838 [0.0469]
S	S	3.0798 (0.1081)*	3.0826 [0.0640]	0.1666 (0.0293)*	0.1617 [0.0268]	-0.1467 (0.2550)	-0.1270 [0.1348]	1.1006 (0.0785)*	1.0849 [0.2012]
S	D	-0.8306 (0.0963)*	-0.8725 [0.0641]	0.2067 (0.0296)*	0.2048 [0.0277]	-0.4746 (0.2092)	-0.4352 [0.1222]	1.0967 (0.1042)*	1.1337 [0.0660]

Standard errors for estimated parameters in parentheses; standard deviation for sampled parameters in brackets. $^*t>2.0$.

Table A-2. Parameters of Functional Status Transition Model: Females

Origin State	Destination State	Variable: Constant		Age		Nonwhite		Low Education	
		$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$	$\hat{\beta}$	$\bar{\beta}^*$
U	M	-5.6982 (0.0852)*	-5.7424 [0.0616]	0.0778 (0.0059)*	0.0810 [0.0053]	0.3217 (0.0693)*	0.3232 [0.0968]	0.3050 (0.0776)*	0.3173 [0.0605]
U	S	-8.7519 (0.2455)*	-8.7054 [0.3116]	0.0965 (0.0198)*	0.0840 [0.0217]	1.3599 (0.1964)*	1.4136 [0.2288]	0.4320 (0.4279)	0.4527 [0.5543]
U	D	-7.0568 (0.1369)*	-7.0697 [0.1464]	0.0934 (0.0089)*	0.0955 [0.0107]	-0.3098 (0.1764)	-0.2088 [0.1865]	-0.1381 (0.1442)	-0.1417 [0.0579]
M	M	3.4784 (0.1051)*	3.4965 [0.1133]	0.0180 (0.0073)*	0.0176 [0.0091]	0.3044 (0.0906)*	0.3448 [0.0816]	-0.0754 (0.0968)	-0.0964 [0.0978]
M	S	1.0128 (0.1244)*	-0.9784 [0.0901]	0.0671 (0.0079)*	0.0688 [0.0090]	0.1736 (0.0664)*	0.1972 [0.0816]	-0.0269 (0.1358)	-0.0865 [0.1522]
M	D	-1.7235 (0.2054)*	-1.5845 [0.1791]	0.0277 (0.0124)	0.0231 [0.0106]	0.4910 (0.1947)*	0.4505 [0.2115]	0.0517 (0.1383)	0.0004 [0.1269]
S	M	4.1521 (0.1596)*	4.2427 [0.1231]	-0.0841 (0.0331)*	-0.0990 [0.0183]	-2.8218 (0.1532)*	-2.7807 [0.1117]	1.1409 (0.1653)*	1.1170 [0.1621]
S	S	7.6911 (0.0872)*	7.6551 [0.0881]	-0.0475 (0.0290)	-0.0534 [0.0246]	-2.5912 (0.0802)*	-2.6081 [0.0825]	1.2296 (0.1694)*	1.2809 [0.2185]
S	D	2.9145 (0.1335)*	2.8354 [0.1236]	0.0096 (0.0293)	0.0062 [0.0258]	-2.5404 (0.1048)*	-2.5604 [0.0586]	1.2948 (0.1832)*	1.3550 [0.2469]

Standard errors for estimated parameters in parentheses; standard deviation for sampled parameters in brackets. *t>2.0.

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