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Paula Diehr, *University of Washington*

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Probabilities of transition among health states for older adults*

Paula Diehr[1,2] & Donald L. Patrick[2]
[1]*Department of Biostatistics;* [2]*Department of Health Services, University of Washington, Box 357232, Seattle, Washington D.C., USA*

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Abstract

Goal: To estimate the probabilities of transition among self-rated health states for older adults, and examine how they vary by age and sex. *Methods*: We used self-rated health (excellent, very good, good, fair, poor, dead) collected in two longitudinal studies of older adults (mean age 75) to estimate the probability of transition in 2 years. We used the estimates to project future health for selected cohorts. *Findings*: These older adults were most likely to be in the same health state 2 years later, but a substantial proportion changed in both directions. Transition probabilities varied by initial health state, age and sex. Men were more likely than women to transition to excellent or dead. Women were more likely than men to transition to good or fair health. Although women aged 70 will have more years of life and more years of healthy life than men, they also have more years of unhealthy life, and the proportion of remaining life that is healthy is slightly higher for men. When observed and predicted years of healthy life (YHL) were compared in various subgroups, the YHL of persons with less favorable baseline characteristics was lower than predicted, and vice-versa. Differences, however, were small (about 5%). *Conclusions*: These transition probability estimates can be used to predict the future health of individuals or groups as a function of current age, sex, and self-rated health.

Key words: Aged, Clinical trials, Cost-benefit, Discounting, Healthy life expectancy, Health status, QALY, Survival

Introduction

In health research and planning, investigators often need to predict the health of persons at some future time. The goal might be to plan a clinical trial, to create a health index, to estimate the need for services in the future, to estimate quality-adjusted life-years for a cost-effectiveness analysis, to create simulated data sets for the evaluation of new statistical procedures, to estimate future health for persons at the end of a short clinical trial, or to predict a person's change in health over time to study the effect of different determinants. Policy makers dealing with the size of the future elderly population must also consider the future distribution of health when planning relevant health services [1].

A major challenge is the lack of published information on the probability that a person with certain characteristics will move from one health state to another, especially for older adults. Here we used data from two longitudinal studies of older adults to estimate the probabilities of transitions among self-rated health states, and to examine features of these transition probabilities. For example, we estimated the probability that a person in excellent health would be in poor health two years later, and examined how this probability varied as a function of age and sex. We then used the probability estimates to illustrate trajectories of change in health.

*See Appendix for details.

Methods

Health state

We used data on self-rated health (is your health excellent, very good, good, fair, or poor?) (EVGFP). EVGFP is a simple but well-known measure which has been studied in detail [2, 3]. It has been found to be predictive of future health events in many studies, as shown in a recent review [4]. Because we are examining health status over time, we added a sixth health state, dead.

Data

Data for estimating transition probabilities were taken from two large prospective studies of older adults (aged 65–100). The first data set was generated in the A Healthy Future study (AHF) [5]. Approximately 5000 randomly chosen Medicare enrollees in an HMO were offered participation in the randomized study of health promotion services, with about a 50% response [6]. The 2524 participants were randomized to either treatment or control and followed for 4 years, with health status ascertained at years 0.0, 2.0, and 4.0, using mailed surveys. Since the treatment and control groups were almost identical over time on EVGFP, data from both groups are used for this exercise. The AHF dataset provides only about 7% of the data used in this paper; we retained it to increase our data for persons near age 65.

The second and larger data set came from the Cardiovascular Health Study (CHS), a population-based longitudinal study of 5888 adults 65 years of age and older designed to identify factors related to the occurrence of coronary heart disease and stroke [7]. CHS subjects were recruited from a random sample of the Medicare eligibility lists in four communities in the United States [8]. Persons who were institutionalized, were not expected to remain in the area for the next 3 years, used wheelchairs at home, or were receiving treatment for cancer at baseline were excluded. About 70% of those invited participated in the study [9]. Vital status is known for all subjects 9 years after baseline for the initial cohort and 6 years after baseline for a second cohort of African Americans. Subjects were asked to rate their health at baseline and every 6 months thereafter.

To avoid bias from missing data, we interpolated values for missing observations whenever there was a valid measurement before and after the missing observation, about 4% of all the data (that is, we replaced the missing value with the mean of the closest measures before and after, weighted by their time from the missing value). Since death is one of the health states, data were thus complete for all people who died. Mundahl [10] found this imputation method to be less biased and to have lower mean square error than other methods examined, although values were somewhat underdispersed. For this reason, after interpolation, we added a small amount of random error and rounded to the nearest living health category. Missing data in CHS is discussed in more detail elsewhere [11].

Estimating transition probabilities

We first estimated the probability of transition from one health state to another, 2 years in the future, separately by initial age, sex, and health status. For example, we estimated the percentage of men aged 65 and in excellent health who were in excellent health 2 years later.

The 2-year interval was chosen in part because data were collected every 2 years in the AHF study, and also because some change in health could be expected in 2 years. For example, in the AHF study, 65-year-old men had health measures at ages 65, 67, and 69. We used their health state transitions from age 65 to age 67, and also their transitions from age 67 to age 69. In CHS, health status was measured at 6-month intervals, allowing, for example, use of data at year 1.5 to predict health at year 3.5. Each AHF person thus contributed about two transitions, and each CHS person contributed up to 15. A total of 74,946 transitions were available for analysis. Even with this large number there were some transitions that were observed rarely. To provide better estimates for these transition probabilities we fit a model to predict the probability of transition as a function of age, log age, sex, and initial health status, and used the model to estimate probabilities for the smaller cells. These methods are discussed in more detail in an earlier paper which used the transition probabilities to calculate years of healthy life

(YHL) [12]. That paper was based on less data and did not present the transition probabilities.

We calculated the probabilities in 2-year age categories, but combined some age groups for this presentation. Detailed probability estimates by 2-year age groups are available in a technical report [13].

Analysis

Based on exploratory analyses we decided to present tables of the transition probabilities in four subgroups: men and women over and under age 80. We also calculated and plotted the trajectory of health for persons initially aged 69–70, separately by sex and initial health state. For example, for women in excellent health at age 70, we used the probabilities to estimate the proportion who would be in each state 2 years later at age 72, then estimated the proportion expected in each state at age 74, and so on (see Appendix). From these estimates we plotted the estimated percentage who would be healthy (in excellent, very good, or good health) over time, by sex and initial health state. We examined the validity of the estimates by comparing observed to expected years of healthy life.

Finally, we calculated trajectories of health for a group initially age 70, and with the following initial distribution of health states: excellent 15.3%, very good 20.3%, good 31.1%, fair 21.3%, and poor 11.9%. These percentages were taken from the long-term supplement on aging (LSOA), and represent the US distribution for people aged 70 and older [14]. We plotted the estimated percentage healthy and the percentage alive over time, for men and women with the same initial health distribution, and calculated the areas under these curves.

Findings

Table 1 shows the distribution of the 74,946 transitions by initial age, by sex and by initial health state (which we call time T_0). For example, we had data on 916 transitions made by women aged 65–66, and on 43 transitions made by persons (men or women) initially in poor health and age 65–66. The numbers are generally large, but they

Table 1. Number of transitions by age, sex, and health at T_0

Age	Gender		Health at T_0					
	Women	Men	Poor	Fair	Good	Very good	Excellent	N
65–66	916	493	43	219	537	387	223	1409
67–68	3253	1868	116	768	1954	1590	693	5121
69–70	5374	3303	258	1306	3367	2744	1002	8677
71–72	6688	4381	313	1780	4509	3463	1004	11,069
73–74	6519	4564	357	2002	4656	3230	838	11,083
75–76	5454	3996	361	1797	3941	2656	695	9450
77–78	4457	3242	364	1525	3318	2006	486	7699
79–80	3649	2624	339	1382	2619	1560	373	6273
81–82	2797	2128	290	1198	2011	1138	288	4925
83–84	1984	1559	259	918	1387	793	186	3543
85–86	1314	1050	185	615	893	517	154	2364
87–88	788	663	152	399	510	319	71	1451
89–90	468	398	90	234	292	189	61	866
91–92	249	252	54	138	142	121	46	501
93–94	125	129	36	71	77	37	33	254
95–96	52	73	16	34	34	28	13	125
97–98	34	30	12	12	23	12	5	64
99–100	25	12	7	4	16	7	3	37
101–102	15	8	4	5	8	4	2	23
103–104	7	5	4	2	2	2	2	12
Total	44,168	30,778	3260	14,409	30,296	20,803	6178	74,946

are smaller for ages 65–66 and over 90, and for poor and excellent health.

Table 2 shows the estimated transition probabilities for men and women aged 65–79 at T_0 (mean age 73). For example, of the 2827 transitions for women initially in excellent health, 35.64% remained in excellent health 2 years later (which we call time T_1); only 0.99% were dead 2 years later. Persons dead at T_0 have, of course, 100% chance of being dead at T_1. Table 3 presents similar information for persons aged 80 or more at T_0. The probabilities of dying are, as expected, larger than those in Table 2. There are two discrepancies in Table 3; both men and women in excellent health are more likely to die than those in very good health. This is most likely due to the small number of transitions available for people over 80 and in excellent health (shown in Table 1). The practical effect of this discrepancy is small, since there are not many people in this group. We point it out to remind the reader that these are only estimated probabilities.

Individuals were most likely to be in the same health state at both T_0 and T_1, but there was substantial variability. For every T_0 health state, many had improved by T_1. Even in the worst case,

Table 2. Transition probabilities (%) [age 65–79 (mean = 73)]

Sex	Health at T_0	Health at T_1 (%)						
		Excellent	Very good	Good	Fair	Poor	Dead	N
Women	Excellent	35.64	38.68	20.33	3.56	0.80	0.99	2827
	Very good	6.14	47.08	37.19	6.72	1.37	1.49	10,131
	Good	1.86	17.05	58.29	17.66	2.22	2.91	15,364
	Fair	0.55	5.71	28.40	49.09	8.95	7.29	6754
	Poor	0.37	2.81	12.63	28.85	28.02	27.31	1234
	Dead	0	0	0	0	0	100.00	
Men	Excellent	35.47	40.18	17.82	3.55	0.94	2.04	2487
	Very good	7.23	46.82	34.44	6.42	1.29	3.80	7505
	Good	2.82	18.87	52.51	17.38	2.52	5.91	9537
	Fair	0.93	6.16	27.03	41.55	10.47	13.85	4025
	Poor	0.88	2.74	9.54	21.17	25.89	39.78	917
	Dead	0	0	0	0	0	100.00	

Rows sum to 100%.

Table 3. Transition probabilities (%) [age 80–100 (mean 85)]

Sex	Health at T_0	Health at T_1 (%)						
		Excellent	Very good	Good	Fair	Poor	Dead	N
Women	Excellent	23.48	27.69	19.75	7.46	2.56	19.05	431
	Very good	5.35	33.90	33.10	11.31	4.07	12.27	1716
	Good	2.39	13.03	44.64	22.39	4.91	12.64	2998
	Fair	0.84	4.99	21.19	41.36	10.35	21.25	2098
	Poor	0.11	2.84	9.04	22.97	23.37	41.66	615
	Dead	0	0	0	0	0	100.00	
Men	Excellent	19.48	25.28	18.01	6.23	2.12	28.86	433
	Very good	4.86	32.92	27.54	10.30	3.73	20.63	1451
	Good	2.91	12.48	38.98	19.75	5.58	20.29	2397
	Fair	0.93	4.88	18.39	34.53	12.03	29.23	1532
	Poor	0.39	2.12	6.08	15.94	18.79	56.66	494
	Dead	0	0	0	0	0	100.00	

Rows sum to 100%.

for men over 80 in poor health at T_0, 24.6% had improved by T_1 (Table 3, second line from the bottom, shows that 57% died, 19% remained in poor health, and the remainder improved). Presumably some of the people in poor health at T_0 suffered from an acute problem which had abated by T_1.

Some differences by sex can be seen in Tables 2 and 3. For every T_0 health state, men were more likely than women to die by T_1. Women under 80 were less likely than men to transition to excellent health, and were more likely than men to transition to good or fair health. Gender patterns for those over 80 are less clear (Table 3), but men were more likely than women to die and women more likely than men to transition into good or fair health.

As an example of the use of these probabilities, we estimated the trajectory of health for women initially aged 69–70, as a function of their initial health status. The calculation methods are shown in the Appendix. As a summary measure we plotted the estimated percentage of women in excellent, very good, or good health ('Healthy') (dead is considered not healthy). Figure 1 shows the estimated percentage healthy for women, starting at age 69–70. The five lines represent the five initial health states. By definition, 100% of the women in excellent, very good, or good health at T_0 were initially healthy, and none of those in fair or poor health were healthy.

Of women in excellent health at age 69–70, 100% were healthy at age 69–70, which dropped to about 55% by age 79–80 and about 12% by age 89–90. None of the women in poor health at age 69–70 were initially healthy (by definition). Table 2 shows that in 2 years we would expect 0.37% of these

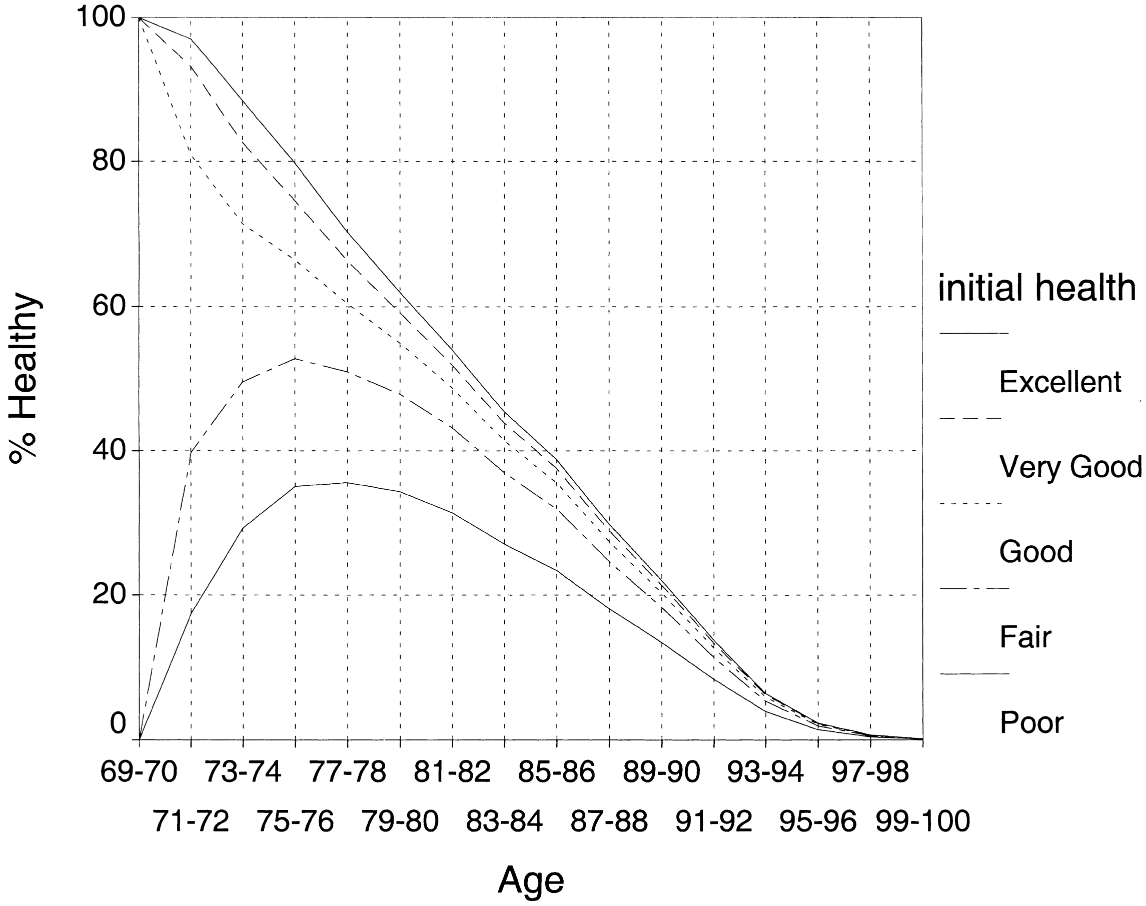

Figure 1. Percentage healthy by age and initial health for women.

women to be in excellent health, 2.81% in very good health, and 12.63% in good health, yielding an estimate that 15.81% would be healthy 2 years later, at age 71–72. This improvement is evident in the bottom line of Figure 1 (we used the 2-year probabilities rather than those in Table 2 to create this figure, which accounts for the small discrepancy between the figure and the calculation). Since the curves represent the percentage healthy rather than the percentage alive, some of those at age 95 are still alive but not healthy. This is a type of 'floor effect' for the summary measure.

The percentage healthy for the three healthiest initial states is similar, but the lines are separate and correctly ordered over time. The decline over time is almost linear for these initial states. For women in fair or poor health at age 70, the percent healthy increases until about age 75 and then decreases. Figure 2 provides similar estimates for men. The shapes of the two figures are quite similar, but at every age the percentage healthy for women is higher than that for men. This finding is primarily due to the higher death rate for men. The area under each curve can be interpreted as the average YHL for a person in the denoted initial health state, which has been tabulated elsewhere [12]. We re-estimated future YHL using the new larger data set, and found virtually identical estimates to the published numbers (not shown).

Figure 3 shows health trajectories for cohorts of men and women, with the initial distribution of health states taken from the LSOA (the same for men and women). The top line shows the percentage of women predicted to remain alive at

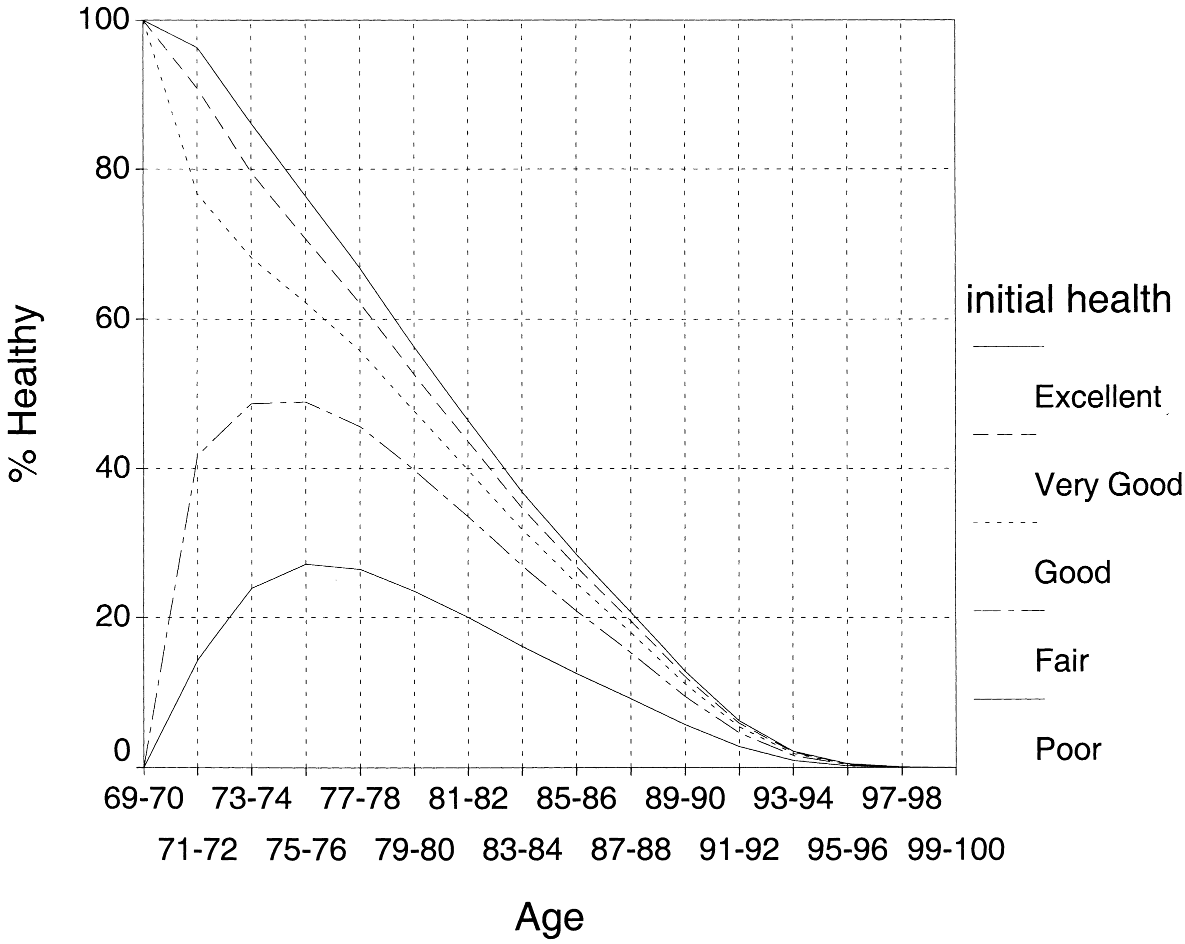

Figure 2. Percentage healthy by age and initial health for men.

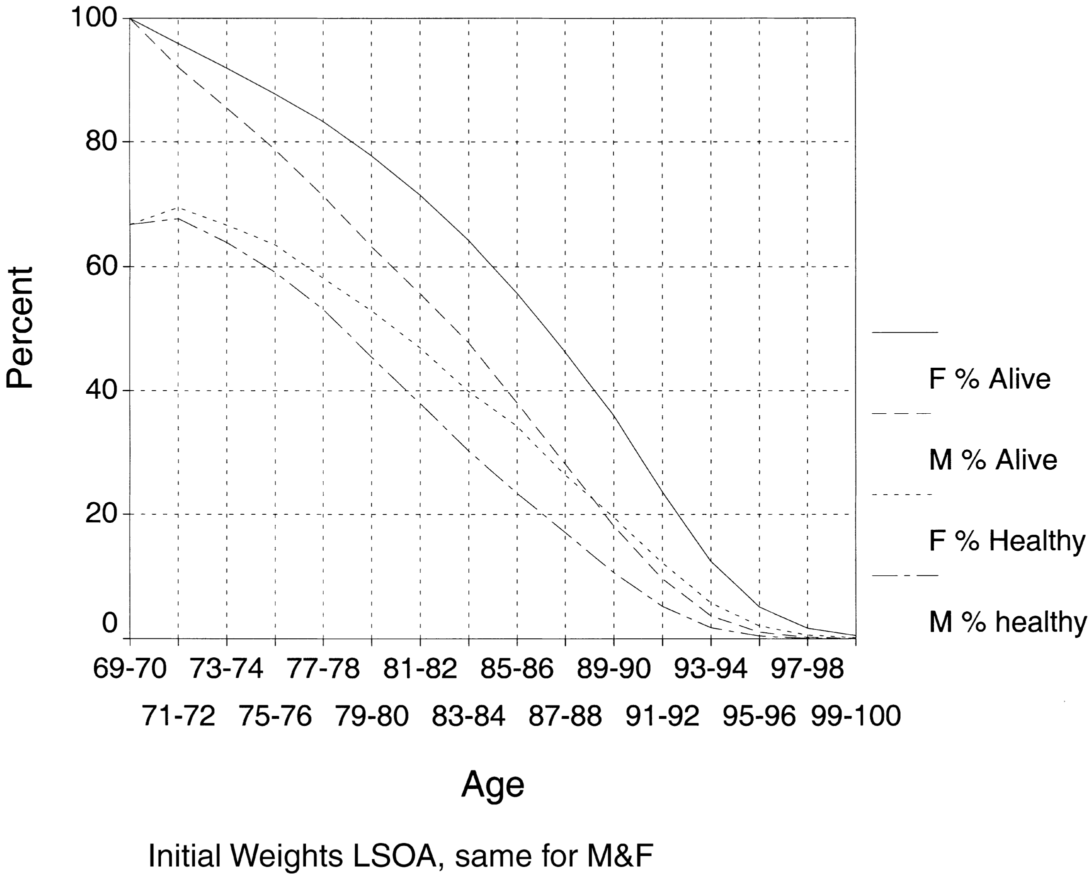

Figure 3. Percentage alive and percentage healthy by age.

various ages; the second line is the same, but for men; the third is the percentage of women predicted to be healthy; and the fourth is for men.

The areas under these curves are the years of life or YHL, respectively. Expected years of life in the 30 years from age 70 to 100 are about 12.7 for men and 16.1 for women; YHL are about 9.0 for men and 10.9 for women; years of unhealthy life (the difference) are 3.7 for men and 5.15 for women. Women thus have more years of life, more YHL, and more years of unhealthy life than men. The percentage of life after age 70 projected to be healthy was 71% for men and 68% for women. We also used a different summary measure, where the six health categories were coded 95, 90, 80, 30, 15, and 0 for death as suggested elsewhere [15]. The plot of the average recoded variable was very similar to the plot for the percentage healthy, and is not shown here.

Researchers can use the probabilities to estimate the health trajectory for any group of interest, by specifying the number of persons in each initial age/sex/health grouping. They could also choose different summary measures, such as the percentage in excellent health or the percentage in fair or better health.

Validation

Since there are no other published transition probabilities, it is difficult to test the validity of these estimates directly. In the earlier paper, based on less data, we calculated observed and predicted 4-year YHL for every person with available data. We found that the observed and expected agreed very well for the AHF data, for the CHS data, and for an African American subset of the data which was not used in estimating the transition proba-

Table 4. Observed and predicted YHL, by baseline factors

		YHL, 6 years		Observed–expected	
		Observed*	Predicted		N
	All	4.13	3.98	0.15	5276
Gender	Women	4.23	4.10	0.13	3025
	Men	4.00	3.83	0.17	2251
Age	65–69	4.61	4.57	0.04	1809
	70–74	4.31	4.16	0.15	1675
	75–79	3.74	3.57	0.17	1086
	80–84	3.27	3.01	0.26	505
	85+	2.60	1.90	0.70	201
Health	Poor	0.61	0.92	−0.31	144
	Fair	1.86	1.89	−0.02	1001
	Good	4.42	4.32	0.10	2233
	Very good	5.21	4.88	0.33	1536
	Excellent	5.47	5.15	0.32	362
Race	White	4.25	4.04	0.21	4784
	Black	2.95	3.42	−0.47	459
Education	<High school	3.43	3.51	−0.08	1492
	HS grad	4.28	4.11	0.17	1935
	College grad	4.55	4.24	0.31	1832
Income	<$16k	3.60	3.66	−0.05	1980
	$16–35k	4.34	4.12	0.22	1756
	>$35k	4.75	4.36	0.39	1195
Marital status	Married	4.28	4.08	0.20	3591
	Widowed	3.78	3.72	0.06	1238
	Div/separated	3.70	3.91	−0.21	227
	Never married	4.13	3.92	0.21	215
Smoking	Never	4.21	3.95	0.26	2452
	Former	4.17	4.01	0.15	2215
	Current	3.68	4.00	−0.32	606
Arthritis	No	4.46	4.20	0.26	2525
	Yes	3.83	3.79	0.04	2687
Stroke	No	4.21	4.03	0.18	5014
	Yes	2.70	3.13	−0.43	262
CHF	No	4.19	4.01	0.17	5141
	Yes	2.13	2.86	−0.73	135
Angina	No	4.35	4.11	0.24	4281
	Yes	3.21	3.44	−0.23	995
MI	No	4.28	4.08	0.20	4492
	Yes	3.29	3.45	−0.16	784
Cancer (ever)	No	4.16	4.01	0.15	4495
	Yes	3.99	3.85	0.14	773

* Calculated from year 1 to year 7.

bilities. We extended that indirect validation approach here, by calculating and comparing observed and predicted 6-year YHL (years spent in excellent, very good, or good health). We calculated YHL from 1 year after baseline to 7 years after baseline, hoping to decrease the influence of the probable volunteer bias at baseline.

Table 4 shows comparisons for a subset of the variables known at baseline. Line 1 shows that the 5276 persons in CHS with complete data averaged 4.13 YHL (of a possible 6), compared to 3.98 YHL expected, a difference of 0.15 years (about 2%). The bias does not vary by sex, but is 0.70 years for persons 85 and older at baseline. This could be because of the relative sparseness of the data for persons over age 85 shown in Table 1, or because the persons who enrolled in CHS at age 85 or more were exceptionally healthy.

The bias is shown for a variety of subgroups. In general, the YHL of persons with less favorable demographic and health characteristics was over-estimated, and the YHL of those with more favorable characteristics was under-estimated. The bias is generally small, on the order of 0.3 years (5%). The largest estimated biases, for persons over age 85 or with CHF, were based on fewer than 200 persons, and may not be well estimated.

We also regressed observed YHL on expected YHL, and then added the variables in Table 4 and other baseline variables using forward selection. The first variable to enter was a measure of depressive symptoms; the final model had 21 variables. Expected YHL explained 40% of the variation in observed YHL, and the remaining 20 variables increased the percentage explained to only 48%. Expected YHL is thus a very strong predictor of observed YHL. We consider the agreement between observed and expected YHL to be remarkably good.

Discussion

Our goal was to provide estimates of the transition probabilities, and to illustrate how they varied by age and sex. It is clear that age and sex are related strongly to transition probabilities for older adults; a person's future health is not uniquely defined by her T_0 health value. It is important to consider age and sex along with EVGFP in analyses, and perhaps to consider interactions between the three variables as well.

We used the data in Tables 2 and 3 to create health trajectories for people of a particular age, sex, and initial health state, and also for cohorts with a given initial distribution of health states. This method can of course be used to create other summary measures for a cohort with a different distribution of initial states. One might, for example, use people's health state at the end of a brief clinical trial to predict the percentage whose health would be fair or better 10 years in the future.

The probabilities could be used to create a fictitious cohort with specified baseline characteristics that could be used to evaluate new statistical methods. One could modify the probabilities somewhat, say increasing the probability of transition to poor while decreasing the probability of transition to dead, to see what the effect of an intervention that had such properties would have on the long-term distribution of health states.

It is common to combine some of the health states for ease of reporting. Tables 2 and 3 demonstrate that there are systematic difference in transition probabilities among all of the T_0 states. Thus, information is lost by combining those categories. However, Table 1 indicates that in this general population the number of older persons in poor or excellent health is relatively small, and it may be advisable to combine categories for that reason.

Others have written about transitions among health states. Chiang provided a theoretical basis for using a discrete-state, continuous-time Markov model of health states and state transition probabilities to create a general health index, but did not apply the method to data [16]. It is unusual to have sufficient longitudinal data to estimate the transition probabilities. Rogers et al. [17] estimated active life expectancy based on only 1300 transitions.

Hisanick studied transitions of US veterans among health states defined by the number of disabilities in activities of daily living (ADL) and death [18]. He found that many characteristics other than initial ADL status affected the transition probability. We also found that other demographic and health characteristics helped to predict the transition probability, but that the percentage of variation that they explained over the expected value was small. We retained this simple model so that the probabilities can be applied to any data set that includes initial age, sex, and EVGFP.

Biritwum and Odoom estimated probabilities of transition among two states (sick and well) for 1152 children in Uganda up to the age of 18 months [19]. After the first few months of life the dependence on age seemed to 'wear off', leading to a time-homogeneous Markov Chain, which attained a steady state distribution at about 12 months. In contrast, our data on the end of life are time-inhomogeneous, and steady state will be reached only when all are dead.

Two studies based on the Established Populations for Epidemiologic Studies of the Elderly used multiple waves of data to estimate Markov transition models for physical function [20], to study the risk of becoming disabled and of recovering [21]. These studies did not publish the transition probabilities.

Some measures of quality-adjusted survival, such as the Q-Twist, make the assumption that people's health does not improve [22]. Although this assumption may hold approximately for seriously ill persons, we found that a meaningful proportion of older adults improved over time, even men over 80 and in poor health. Methods that require this assumption, or that ignore age, may be less appropriate for a general population of older adults.

There are several ways of calculating active life expectancy. Rogers et al. [1] describe single-decrement life-table analysis which assumes that health does not improve. They also present results from a multi-state model which assumes time-homogeneous Markov chains; that is, that the probabilities do not change with age. Our results show that these assumptions of no improvement or of probabilities constant with age do not strictly hold for these older adults.

Similar to our results, Crimmins et al. found that women had more years of active life than men, but that the proportion of life that was active was smaller for women [23]. Manton and Stallard also found that females had higher active life expectancy at age 65, but that men had higher amounts at 85 [24].

Crimmins et al. also used health transition rates in a five-state multi-state life table analysis to examine the relative effects of improving mortality and improving morbidity [25]. She found that improving mortality alone implies increases in both the years and the proportion of dependent life, while improving morbidity alone reduces both the years and the proportion of dependent life. It would be possible to calculate similar estimates by varying our transition probabilities. For example, if we lowered the probability of dying while increasing the probability of transition to poor health, this would affect mortality but would have little effect on the percentage who are healthy.

Limitations

We defined health states using only a simple measure of health status, EVGFP. Since this measure is routinely collected in national surveys, and is also one of the items on the SF-36 health status instrument [26], other investigators should be able to use these probabilities. Transitions among differently defined health states should also be investigated.

Both of the data sets from which the probabilities were estimated had some positive selection bias, due to exclusions in CHS and the healthy volunteer effect among these HMO enrollees of AHF, but this is not necessarily a problem. The CHS and AHF studies probably have 'too few' sick people at baseline, but the analyses for this paper require only that people in poor health be similar to other people in poor health. Further, the bulk of the transition data come from later in the CHS study, when the selection effects should have attenuated. The earlier paper reported good validation results with national data and for an independent cohort. Here we found that 6-year YHL was predicted well in most subsets of the population, which also suggests that these probabilities are applicable to other populations [12].

It is possible that these transition probabilities would be biased if applied to an earlier time period. There were probably fewer older adults in excellent health at earlier times, but this need not imply that the transition probabilities are different. It would be interesting to test for these differences using data collected at different times.

These estimates can be improved and extended to other age groups if there are other data sets with longitudinal measures of health status, few losses to follow-up and complete ascertainment of deaths. Unfortunately, the NCHS LSOA does not measure EVGFP over time, and the NIA epidemiological follow-up data set uses a non-standard version of self-rated health.

Conclusions

We have estimated health state transition probabilities for older adults, and found them to be sensitive to age, sex, and initial health status. Although on average health declines with age, many people improve in health status in any 2-year period. The tables presented here should be useful to other investigators.

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Appendix

The method for projecting the distribution of future health states given current health states involves setting an initial state distribution, and then using the probabilities to estimate the percentage in each state 2 years later, 4 years later, etc.

As an example, let us project the future health of women in excellent health at age 70. The first column of Table A1 shows that 100% of the women are in excellent health at age 70 (by definition). To estimate the distribution of health states at age 72, we apply the transition probabilities for women in excellent health at T_0 (Table 2, line 1), which shows that 35.64% of these women will still be in excellent health at age 72, 0.80% in poor health, and 0.99% will be dead. These numbers are shown in the second column of Table A1.

We next use the probabilities to project the health distribution at age 74 for each health state at age 72. For example, the expected percentage of people who will be dead at age 74 is the 0.99% already dead at age 72 + 1.49% of the 0.80% previously in poor health (from line 4 column 6 of Table 2) + 2.91% of the 3.56% previously in fair health (from line 3 column 6 of Table 2) + 2.91% of the 20.33% previously in good health + 7.20% of the 38.68% previously in very good health + 27.31% of the 35.64% previously in excellent health, for a total of 2.99% expected to be dead by age 74. Probabilities for the other states are calculated in a similar manner. The process can be continued until age 80, at which point we would switch to the probabilities of Table 3. At age 80, only 4.37% would be in excellent health, and 13.12% would be dead.

Table A1 thus provides the expected health history for a hypothetical cohort of women in excellent health at age 70. These data can be summarized in various ways. In this paper we showed the percentage projected to be in excellent, very good, or good health (the sum of the first three rows in Table A1). Another example of calculations is available [12].

Table A1. Projected percentage of population in each health state over time for women in excellent health at age 70

State	Age					
	70	72	74	76	78	80
Excellent	100	35.64	15.48	8.41	5.62	4.37
Very good	0	38.68	35.69	29.28	24.67	21.7
Good	0	20.33	34.58	39.48	40.01	38.96
Fair	0	3.56	9.52	14.43	17.39	18.78
Poor	0	0.80	1.81	2.74	3.40	3.78
Dead	0	0.99	2.99	5.87	9.34	13.12

Participating institutions and principal staff

Forsyth County, NC – Wake Forest University School of Medicine: Gregory L. Burke, Sharon Jackson, Alan Elster, Curt D. Furberg, Gerardo Heiss, Dalane Kitzman, Margie Lamb, David S. Lefkowitz, Mary F. Lyles, Cathy Nunn, Ward Riley, John Chen, Beverly Tucker. Forsyth County, NC – Wake Forest University – ECG Reading Center: Farida Rautaharju, Pentti Rautaharju. Sacramento County, CA – University of California, Davis: William Bonekat, Charles Bernick, Michael Buonocore, Mary Haan, Calvin Hirsch, Lawrence Laslett, Marshall Lee, John Robbins, William Seavey, Richard White. Washington County, MD – The Johns Hopkins University: M. Jan Busby-Whitehead, Joyce Chabot, George W. Comstock, Adrian Dobs, Linda P. Fried, Joel G. Hill, Steven J. Kittner, Shiriki Kumanyika, David Levine, Joao A. Lima, Neil R. Powe, Thomas R. Price, Jeff Williamson, Moyses Szklo, Melvyn Tockman. Washington County, MD – The Johns Hopkins University – MRI Reading Center: Norman Beauchamp, R. Nick Bryan, Douglas Fellows, Melanie Hawkins, Patrice Holtz, Naiyer Iman, Michael Kraut, Cynthia Quinn, Grace Lee, Carolyn C. Meltzer, Larry Schertz, Earl P. Steinberg, Scott Wells, Linda Wilkins, Nancy C. Yue. Allegheny County, PA – University of Pittsburgh: Diane G. Ives, Charles A. Jungreis, Laurie Knepper, Lewis H. Kuller, Elaine Meilahn, Peg Meyer, Roberta Moyer, Anne Newman, Richard Schulz, Vivienne E. Smith, Sidney K. Wolfson. University of California, Irvine – Echocardiography Reading Center (baseline): Hoda Anton-Culver, Julius M. Gardin, Margaret Knoll, Tom Kurosaki, Nathan Wong. Georgetown Medical Center – Echocardiography Reading Center (follow-up): John Gottdiener, Eva Hausner, Stephen Kraus, Judy Gay, Sue Livengood, Mary Ann Yohe, Retha Webb. New England Medical Center, Boston – Ultrasound Reading Center: Daniel H. O'Leary, Joseph F. Polak, Laurie Funk. University of Vermont – Central Blood Analysis Laboratory: Elaine Cornell, Mary Cushman, Russell P. Tracy. University of Arizona, Tucson – Pulmonary Reading Center: Paul Enright. University of Washington, Seattle – Coordinating Center: Alice Arnold, Annette L. Fitzpatrick, Richard A. Kronmal, Bruce M. Psaty, David S. Siscovick, Will Longstreth, Patricia W. Wahl, David Yanez, Paula Diehr, Corrine Dulberg, Bonnie Lind, Thomas Lumley, Ellen O'Meara, Jennifer Nelson, Charles Spiekerman. NHLBI Project Office: Robin Boineau, Teri A. Manolio, Peter J. Savage, Patricia Smith.

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Address for correspondence: Paula Diehr, Department of Biostatistics, University of Washington, Box 357232, WA 98195-7232, Seattle, Washington D.C., USA
Phone: +206-543-8004; Fax: +206-523-3286
E-mail: pdiehr@U.washington.edu