Patterns of Self-Rated Health in Older Adults Before and After Sentinel Health Events

Paula Diehr, PhD,*‡ Jeff Williamson, MD,‡ Donald L. Patrick, PhD, MSPH,† Diane E. Bild, MD,§ and Gregory L. Burke, MD‡

OBJECTIVES: To describe and compare patterns of change in self-rated health for older adults before death and before and after stroke, myocardial infarction, congestive heart failure, cardiac procedure, hospital admission for cancer, and hip fracture.

DESIGN: “Event cohort,” measuring time in months before and after the event.

SETTING: Four U.S. communities.

PARTICIPANTS: 5888 participants in the Cardiovascular Health Study (CHS), sampled from Medicare rolls and followed up to 8 years. Mean age at baseline was 73.

MEASUREMENTS: Self-rated health, including a category for death, assessed at 6-month intervals, and ascertainment of events.

METHODS: We examined the percentage that was healthy each month in the 5 years before death and in the 2 years before and after the other events, and compared the patterns to a “no event” group and to one another, using graphs and linear regression.

RESULTS: For people who died, health status declined slowly until about 9 months before death, when it dropped steeply. Comparing persons equally far from death, health was unrelated to age, but men and whites were healthier than women and blacks. Health for other events declined before the event, dropped steeply at the event, showed some recovery, and then declined further after the event. About 65% to 80% of the subjects were healthy 2 years before their event, but only 35% to 65% were healthy two years afterwards. Patterns were similar although less extreme for the “no event” group.

CONCLUSION: Visualizing trajectories of health helps us understand how serious health events changes health. Conclusions about change must be drawn with care because of a variety of possible biases. We have described the trajectories in detail. Work is now needed to explain, predict, and possibly prevent such changes in health.


Key words: aged; clinical trials; cohort; health status; healthy life expectancy; QALY; self-rated health; sentinel events; survival

Little information is available about trajectories of health for older adults, particularly around the time of serious health events. Such information may allow for the prediction and prevention of future morbid events and may permit a better understanding of the loss of well-being associated with these events. This information is also needed for the evaluation of interventions such as screening programs.

We used data from a longitudinal cohort of older adults, where participants rated their health every 6 months and were followed extensively for health events. Since the timing of the health ratings was relatively independent of the occurrence of the event, measures of health that were made, say, 2 months before an event can be considered as a random sample of the health of all people 2 months before having such an event. We used these data to describe patterns of change in health status before and after the onset of seven important health events: death, stroke, congestive heart failure (CHF), myocardial infarction (MI), hip fracture, cardiac procedure (coronary artery bypass graft [CABG] or percutaneous transluminal coronary angioplasty [PTCA]), first hospitalization for cancer, and a “random” event (related to normal aging) defined below.

We plotted health over time and tested whether changes in health were significantly different from zero and among event types. We discuss some methodological insights into studies of change in health.

METHODS

Since the data and the analysis are somewhat unusual, we have provided a detailed methods appendix at the end of the paper. An overview of the methods is given here.

Data

The Cardiovascular Health Study (CHS) is a population-based longitudinal study of 5888 adults 65 years and older.
designed to identify factors related to the occurrence of coronary heart disease and stroke.\textsuperscript{1,2} CHS subjects were recruited from a random sample of the Medicare eligibility lists in four communities in the United States. Persons who were institutionalized at baseline; who used wheelchairs at home; or who were receiving hospice treatment, radiation therapy, or chemotherapy for cancer at baseline were ineligible. The original cohort had about 8 years of follow-up (N = 5201) and a second (all African-American, N = 687) had about 4.5 years of follow-up. Subjects rated their health at baseline and every 6 months thereafter.

**Health Outcome Measure**

We analyzed self-rated health: “Would you say that your health is excellent, very good, good, fair, or poor?” (EVGFP). Since data were collected over time, we added a sixth health state for death. People with missing data are usually sicker than those with more-complete data; excluding those people or their missing measurements biases the average health upward. We interpolated missing values of health status linearly (then added random noise and rounded to the nearest living value) whenever the person had a valid value before and after the missing value. Data were 92\% complete before interpolation and 97\% after.

We summarized the health data in two ways. For graphs, we plotted over time the percentage who were “healthy,” which we define as being in excellent, very good, or good health (as opposed to fair, poor, or death). This is simple and interpretable, but does not make some important distinctions, such as that between fair health and death. For more quantitative comparisons we gave each of the six health states a value, as suggested elsewhere:\textsuperscript{3} excellent = 96, very good = 93, good = 76, fair = 35, poor = 19, and death = 0. These values are the percentage probability that a person in this health state will complete before interpolation and 97\% after.

We first show how health changed in the 5 years before and after the event; and decline (or possible recovery) from semester 5 to semester 8.

**Analysis**

Our goal was to describe changes in health over time and to test whether events had different patterns. We plotted stacked bar graphs to show how proportions in the different health categories changed over time. We also plotted the percentage healthy (excellent, very good, or good) against time from the event so that we could show monthly detail and more easily compare the trends for several events on the same graph.

Since some curves were fairly noisy, we also created smoothed estimates by regressing health before the event on the logarithm of the number of months before the event. We regressed health after the event on both log time and time inverse to allow for short-term recovery. The predicted values for different events were then plotted on the same graph, to make comparisons easier. For deaths only, we examined the effects of age, sex, and race and their interactions on health over time, using stepwise multiple regression.

We also adjusted all the health measures (6-value coding) to the age/sex/race distribution of the random group (see Appendix). An event type that differed in health from the randoms only because it had a different age or sex distribution would have health values more similar to the randoms after this adjustment. We used analysis of variance to test for significant differences in mean-adjusted health and health changes among all of the event types, with and without a Bonferroni correction for multiple comparisons.

**RESULTS**

We first show how health changed in the 5 years before death. We then illustrate changes in health in the 2 years before and after each of the other events. Finally, we present age/sex/race-adjusted estimates of the four profile elements defined above and formally test for significant differences among the event types for the four profile elements.

Table 1 shows summary information about the events. There were 1464 deaths, 5478 randoms (people who survived at least until their random date), and 232 to 632 people with the other events. Mean age at the time of the event...
varied from 75 for cardiac procedures to 81 for hip fractures. The sex distribution was different among events, with 69% of the cardiac procedures but only 24% of the hip fractures occurring in men. The percentage who were white varied from 84% for randoms to 95% for hip fracture. Individuals had from 1 to 10 measures. People whose events occurred close to the beginning or the end of the follow-up caused low numbers. Most of the events were nonfatal, in that the person was still alive 30 days after the event.

Death
We analyzed death in the most detail, since it was the most frequent event (n = 1464). Figure 1 shows a stacked bar graph of health by quarter (3-month interval) in the 5 years before death. The number of health values per quarter varied from 394 to 670. Since health was measured about every 6 months, a typical individual should show up in alternate bars. Health declined gradually until about a year before death, when the percent in poor health began to increase; more than half were in poor health in the quarter before death. The pattern of change omitting the interpolated missing data (not shown) was similar, but health was better near to death, because people with missing data were sicker than the others.

To show monthly detail and to facilitate later comparisons, Figure 2 shows a plot of the percentage of people who were healthy (excellent, very good, or good health) each month in the 5 years before death. Each month includes approximately one-sixth of the people who died, with people repeating about every 6 months. There were from 118 to 261 values per month. About 70% were healthy 5 years before death. As in Figure 1, health declined slowly until about 2 years before death, when it began to decline more steeply, especially in the 9 months before death. This drop is less steep if we exclude the interpolated data (not shown), because some of the sickest people are then excluded.

To quantify these results, we used multiple regression to predict being healthy from the logarithm of the number of months before death (not including the month of death). We then added terms for age, sex, and race and their interactions, using forward selection. The resulting regression equation based on 5 years before death is: % Healthy = 22.9 + 24.0*Log_{10}(Months) + 5.9*Male, meaning that health was better further from death and better for men than for women. Surprisingly, age did not significantly improve the equation. An equation including race, using only data from the 2 years before death because of shorter follow-up in the African-American cohort, yielded the following equation: % Healthy = 17.5 + 23.2*Log_{10}(Months) + 6.2*Male + 6.8*White, meaning that male and white subjects reported better health than females and blacks at

### Table 1. Demographics of Different Events

<table>
<thead>
<tr>
<th>Event</th>
<th>Number of People</th>
<th>Mean Age</th>
<th>Percent Male</th>
<th>Percent White</th>
<th>Mean Number of Health Values</th>
<th>Percent Nonfatal*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Death</td>
<td>1464</td>
<td>80.5</td>
<td>56</td>
<td>88</td>
<td>7.9†</td>
<td>0.0</td>
</tr>
<tr>
<td>Stroke</td>
<td>397</td>
<td>78.2</td>
<td>47</td>
<td>88</td>
<td>7.4</td>
<td>84.1</td>
</tr>
<tr>
<td>CHF</td>
<td>652</td>
<td>78.6</td>
<td>55</td>
<td>87</td>
<td>7.3</td>
<td>95.6</td>
</tr>
<tr>
<td>Cancer</td>
<td>480</td>
<td>76.1</td>
<td>52</td>
<td>88</td>
<td>6.8</td>
<td>90.2</td>
</tr>
<tr>
<td>MI</td>
<td>352</td>
<td>77.2</td>
<td>60</td>
<td>90</td>
<td>7.3</td>
<td>87.7</td>
</tr>
<tr>
<td>Hip fracture</td>
<td>232</td>
<td>81.2</td>
<td>24</td>
<td>95</td>
<td>7.2</td>
<td>93.5</td>
</tr>
<tr>
<td>Procedure</td>
<td>337</td>
<td>75.0</td>
<td>69</td>
<td>93</td>
<td>7.5</td>
<td>94.7</td>
</tr>
<tr>
<td>Random</td>
<td>5478</td>
<td>75.6</td>
<td>41</td>
<td>84</td>
<td>7.9</td>
<td>99.8</td>
</tr>
</tbody>
</table>

* Person lived at least 30 days after the event.
† Number of measures in 5 years before death.
CHF = congestive heart failure.
MI = myocardial infarction.

---

Figure 1. Distribution of health states by time from death.

Figure 2. Percent healthy by number of months from death.
comparable times before death. Age did not significantly improve the equation.

Other Events
We considered the other events in less detail because the number of subjects was smaller. As an example of our approach for these events, Figure 3 shows a bar graph of health for people who had an MI. It is different from Figure 1 in that Figure 3 covers the 2 years before and after the MI, and there is an additional category: death. The pattern is not as smooth as Figure 1 because there were only 325 MIs. Each person had provided health data every 6 months, even after death, and so a particular person is present in alternating quarters. There are fewer deaths in quarter 8 than in 7 because the estimate is based on different people. There is a gradual decline in health until the MI and a large drop at the time of the MI. Part of that drop is due to the deaths. Although the percentage dead increased over time, the percentage who were in excellent, very good, or good health (the lowest three categories combined) also increased somewhat. This indicates that on average people got better after their MI, even when the deaths were counted.

To make it easier to compare the events, Figure 4 plots the percentage healthy by month, in the 2 years before and after each of the nondeath events. The dashed vertical line shows the time when the events occurred. The plot for MI has the features noted in Figure 3 (gradual decline, steep drop, some improvement).

Consider the random event at the far right. The percentage healthy decreased gradually over the four years. There is no large drop at the time of the event. There is low variability from month to month because nearly 6000 people were followed, with about 1000 observations per month. All of the remaining events have noisier curves, since they are based on fewer subjects. Even so, we can see that all had a decline in health before the event and a large drop at the time of the event, and some had further decline after the event.

We plotted regression fits to these curves to make it easier to compare events, with separate regressions before and after the event. Figure 5 shows the estimated percentage healthy over time, for all eight events. The randoms (line number 8) had the best health at all times, which declined from about 80% to 70% healthy. There was a small jog at the time of the event, caused by our having fit the before and after curves separately. Thus, this big a jog can be expected even without an event. The deaths (line 1) had the worst health of any group. Excluding the randoms and the deaths, about 65% to 80% were healthy 2 years before the event, but only 35% to 65% were healthy 2 years after the event.

The events have somewhat different patterns of change in health status. Some events, such as death (line 1) and cancer (4), had steep declines in health before the event, while stroke (2) had almost no change. All events had a large drop at the time of the event, and many had further decline. MI (5) and cardiac procedure (7) show some improvement after the event. (The group could not improve...
months before the stroke; standard error with stroke was 68.1 points in semester 1 (19 to 24 each profile statistic. For example, the mean health of people to decline in health. Patterns for nonfatal events (not noted above (ranging from excellent to dead = 0). The shapes of the curves before the event were fairly similar to those in Figure 5, but the shapes after the event differed somewhat; there was more decline over time for stroke, CHF, cancer, and MI than in Figure 5. To take advantage of this additional detail, we used the 6-value coding to calculate the health profiles.

**Health Profiles**

To assess the statistical significance of differences between events, we used the age/sex/race-adjusted health data for the four profile variables, defined in the methods section. Table 2 shows the adjusted means and standard errors for each profile statistic. For example, the mean health of people with stroke was 68.1 points in semester 1 (19 to 24 months before the stroke; standard error = 1.4); health dropped 5.7 points between semester 1 and semester 4; it dropped 22.1 more points at the time of the stroke (semester 4 to semester 5); and dropped another 4.1 points from semester 5 to semester 8. (The final number for deaths is negative because the deaths declined less than “expected” based on age, sex, and race.)

We estimated the proportion of the drop at the time of the event that was caused by people who died. For example, for MI, the mean adjusted drop was 17.5 points; the drop for persons still alive in the 6 months after the MI was 11.4. The proportion of the drop attributable to the deaths is thus 1 - 11.4/17.5 = 0.35. The percentages of the drop due to deaths are as follows: death, 100%; stroke, 34%; CHF, 29%; cancer, 36%; MI, 35%; hip fracture, 33%; cardiac procedure, 40%; and random, 21%. Only about 60% of the persons with procedures were healthy after their event (Figure 5). If we had not counted the deaths, the procedures would have looked much more favorable.

We also estimated the proportion of individuals who did not recover; that is, whose health was worse in semester 6 (6 to 12 months after the event) than in semester 4 (1 to 6 months before the event). Those percentages were: death, 100%; stroke, 61%; CHF 57%; cancer 55%; MI 55%; hip fracture, 50%; procedure, 42%; and random, 36%. The numbers are sobering, but the results for the randoms suggest that much of this decline would have occurred even without an event.

We used analysis of variance to test whether the average values of the four profile variables were significantly different from zero. All but two of the profile items in Table 2 were significant; only the post-event declines for MI and cardiac procedures were not significantly different from zero.

We also tested whether the mean profile statistics were significantly different by event type. The results of this large number of significance tests are summarized in Table 3. Upper-case letters represent significant differences between the row and column events after correction for multiple comparisons, and lower case letters represent significance without this correction. For example, after correction for multiple comparisons, strokes are significantly different from deaths in all four profile elements, indicated by the “ABCD.” Strokes are significantly different from cancer in health 2 years before the event and in the drop at the time of the event, but these differences are not significant after adjustment for multiple comparisons (denoted by the lower-case letters “a” and “c”). Each event type may be compared with others using information from this table. We next discuss each profile element.

Most events differ significantly from the randoms and the deaths, and sometimes from one another. As denoted by a or A in Table 3, 2 years before the event the deaths were significantly less healthy than all the other event types and the randoms were significantly healthier than all but cancer. CHF was significantly lower than cancer, MI, and procedure, and stroke was significantly lower than cancer.

It is of interest whether the person experienced some type of prodrome or premonition before an event, defined here as a pre-event decline in perceived health status significantly greater than the decline in the randoms. The mean drop from semester 1 to semester 4 (denoted by b or B in Table 3) is significantly larger than the drop for the randoms for every event but cardiac procedure. Most often, there was a premonition. Except for death and random, the event types did not differ significantly.

The effect of the actual event (change from semester 4 to 5) varied considerably, with the effect of cardiac procedure and hip fracture on health significantly smaller than that of the other events, and the effect of death and stroke significantly larger.
Recovery after the event (denoted by d or D in Table 3, as compared with death which had no change in semesters 5 to 8) is also of interest. All events showed significant further decline, except for MI and cardiac procedure, where decline was not significantly different from zero. Thus, the MI and cardiac procedures can be said to have recovered somewhat, while after the other events people declined at about the same rate as the randoms (although with much worse absolute health).

Except in the random group, the pre-event decline was always larger than the post-event decline, but the semester just following the event included some recovery from the event. To estimate the decline independent of the event we compared the decline from semester 1 to 3 with the decline from semester 6 to 8 (thus excluding the 6 months before and after the event). Measured this way, all the post-event declines were larger than the pre-event declines. Changes near the time of the event may thus bias estimates of longer-term change.

**DISCUSSION**

These findings describe the trajectory of health near the time of death, and changes in health before and after other sentinel health events. Others have addressed these topics, but our data are unusually detailed and our analytic approach is somewhat different. This research yielded some substantive and some methodologic insights. We also have further support for the ability of EVGFP to track changes in population health.

Many papers in the literature deal with the relation of events to health. Most of these studies, however, are based on small numbers of people, with at most a few measurements before or after the event. Because the CHS data were measured frequently and we could relate the date of the measurement to the date of the event, we have been able to show a detailed pattern of changes in health, month by month, before and after each event. This allows us to separate changes that occurred before the event from those that were associated directly with the event.

A second novel feature of this study is that it accounts specifically for death. Most analyses of change in health are restricted to persons who survived to provide follow-up data. Such analyses underestimate the full cost of the event to the group experiencing the event, and are generalizable only to a favorable subgroup. We noted that from 21% to 40% of the drop at the time of the event is due to people who died in the first 6 months after the event, which is missed if deaths are not included.

We also accounted for missing data, which avoids the positive bias probably existing in other studies. We were able to do this because measurements were made frequently. Our decision to interpolate from the closest value before and after the missing data guaranteed that the estimated data are within the range of the person’s observed data near that time.

We have identified one study that examined health both before and after unplanned events, but that study did not explicitly consider mortality or missing values. Another study based on the Long Term Study on Aging, which compared 368 persons with hip fracture to persons without hip fracture. Mortality effects were assessed by choosing a random event date for the controls (who had no hip fracture), and subtle effects in the mortality pattern near the time of the event were detected. Health was measured by activities of daily living (ADL) and intermediate activities of daily living (IADL) at year 0 and year 4 of the study, without reference to how far the measurement was from the event, and was examined only for people who provided data at both times. This approach was necessary because the health data were collected infrequently. Our data permitted us to examine subtle patterns for health as well as for mortality. Wolinsky and colleagues have used longitudinal data to assess the effect of MI, stroke, and CHF on future mortality and readmissions. They also provide a detailed analysis of change in five functional states over time, and found that longitudinal analyses of multiple waves of data could provide insights not available from simple change-score analyses.

**Substantive Results**

Our findings for death were the most detailed. One goal of successful aging in the population has been expressed as

**Table 3. Profile Comparisons**

<table>
<thead>
<tr>
<th>Event Type</th>
<th>Death</th>
<th>Stroke</th>
<th>CHF</th>
<th>Cancer</th>
<th>MI</th>
<th>Hip Fracture</th>
<th>Procedure</th>
<th>Random</th>
</tr>
</thead>
<tbody>
<tr>
<td>Death</td>
<td>—</td>
<td>ABCD</td>
<td>aBCD</td>
<td>ABCD</td>
<td>ABC</td>
<td>ABC</td>
<td>ABC</td>
<td>ABCD</td>
</tr>
<tr>
<td>Stroke</td>
<td>ABCD</td>
<td>—</td>
<td>C</td>
<td>—</td>
<td>d</td>
<td>C</td>
<td>ABC</td>
<td>ABCD</td>
</tr>
<tr>
<td>CHF</td>
<td>aBCD</td>
<td>C</td>
<td>—</td>
<td>A</td>
<td>a</td>
<td>—</td>
<td>C</td>
<td>ABC</td>
</tr>
<tr>
<td>Cancer</td>
<td>ABCD</td>
<td>ac</td>
<td>A</td>
<td>—</td>
<td>D</td>
<td>C</td>
<td>CD</td>
<td>BC</td>
</tr>
<tr>
<td>MI</td>
<td>ABC</td>
<td>d</td>
<td>a</td>
<td>D</td>
<td>—</td>
<td>C</td>
<td>C</td>
<td>C</td>
</tr>
<tr>
<td>Hip fracture</td>
<td>ABCD</td>
<td>C</td>
<td>c</td>
<td>C</td>
<td>Cd</td>
<td>—</td>
<td>d</td>
<td>ABC</td>
</tr>
<tr>
<td>Procedure</td>
<td>ABC</td>
<td>Cd</td>
<td>acd</td>
<td>CD</td>
<td>C</td>
<td>d</td>
<td>—</td>
<td>ACD</td>
</tr>
<tr>
<td>Random</td>
<td>ABCD</td>
<td>AbC</td>
<td>ABC</td>
<td>BC</td>
<td>aBCD</td>
<td>aBCD</td>
<td>ACD</td>
<td>—</td>
</tr>
</tbody>
</table>

After adjustment for age, sex, and race, the row and column event types differ significantly (P < .05, 2-tailed) in:

- a,A: Health in Semester 1 (19–24 months before event).
- b,B: Change from Semester 1 to Semester 4 (change before event).
- c,C: Change from Semester 4 to Semester 5 (change at event).
- d,D: Change from Semester 5 to Semester 8 (change after event). (Note: deaths have no change in this semester, so D in the column for death signifies that the decline in the other event is significantly different from zero). 

Upper-case letters denote significance after correction for multiple comparisons; lower-case letters denote significance with no correction.

CHF = congestive heart failure; MI = myocardial infarction.
the compression of morbidity to as late as possible in life with little decline until just before death,\textsuperscript{10} sometimes known as rectangularization of morbidity. We found such a terminal decline in the 9 months before death, but there was also a gradual decline in health in the 5 years preceding death. Decline in health thus has a gradual component followed by a steep component, which is a right-trapezoid rather than a rectangle. Other studies have had similar findings.\textsuperscript{11,12} Our important finding that health is fairly independent of age in persons the same distance from death has also been noted by others.\textsuperscript{13} This suggests that future advances in delaying mortality may result in additional years of healthy life, for people of all ages, rather than additional years of disability.

We also described and compared health status around nondeath events. Few other studies provide such information. One study of health status both before and after unplanned health events evaluated health status for 254 patients with stroke, MI, or hip fracture,\textsuperscript{4} based on one pre-event measure and interviews 6 weeks and 6 months afterwards.

A study of 368 persons with hip fracture\textsuperscript{5} found that the event increased the number of functional status dependencies and increased the mortality rate shortly after the event, compared with a random event date in a group of people without a hip fracture. This is consistent with our results, although we combined death and health into a single measure. The authors asked whether hip fracture was a sentinel event that initiates decline in health or merely a marker showing that a decline has begun. In our data, Figures 4 through 6 and Table 2 all demonstrate that there was a substantial decline in health before the hip fracture, suggesting that hip fracture may be primarily a marker. More detailed modeling of this and the other events, including relevant covariates, is needed.

\textbf{Methods Results}

The trajectory over time for the randoms is surprisingly similar in shape to those of the other groups, even though the randoms had no event at their random time. Their early decline occurred in part because health in older adults declines over time. The apparent change in slope about a year before the event is an artifact, caused by the fact that everyone had to be alive before the “event” but could die afterward. Data missing just before the event were interpolated in part from values after the event, which might have included death. The decline is small and is noticeable only because the sample size is so large. Analysts must take care not to ascribe all observed changes to the event itself, because some of them would have happened without an event. A comparison group is important. The results also illustrate the importance of timing in studies of health following an event. Since there is some recovery, the estimated decline after the event will be fairly small if the first measure is taken close to the time of the event, when health is particularly low. When we looked at trajectories 6 months away from the event, we found that decline after the event was steeper than the decline before. Decline should be compared to the natural decline shown by the randoms. It is also important to compare the results for deaths with other event types. Figures 1 and 2 seem to show that health changed very little until the 9 months before death. Figure 5, however, shows that the deaths were much sicker than the other groups even 2 years before death, which changes the interpretation considerably.

There are many survival graphs in the literature, but few plots of changes in health. Health graphs are more complicated because people or groups of people can improve in health over time. These curves (or the regression equations in log time that created them) can be used to estimate the benefit of preventing different types of events. The area under the curves (AUC) in Figure 5 is a measure of years of healthy life\textsuperscript{14} or quality-adjusted life-years. It might be best to estimate the AUC after the event adjusted for the AUC before the event. For instance, the AUC after stroke and CHF are fairly similar, but the AUC before the event was higher for stroke than for CHF, showing that the loss in health due to stroke was greater.

\textbf{Performance of EVGFP}

EVGFP seems to have performed well, revealing some reasonable and subtle patterns of change. This measure is well known to predict mortality and morbidity.\textsuperscript{15,16} Our finding that the randoms had significantly less early decline than the other events also supports this predictive ability. This seems to suggest measuring EVGFP frequently on older persons and developing indexes to predict such events. It is unclear, however, that such predictors would be cost-effective, since factors related to a person’s decline in health, such as other events, might be well known to patients and their providers. A related question of interest is whether prior health patterns can predict recovery from the event. These important questions are outside the scope of this paper.

Investigators have tried to understand the ability of EVGFP to predict future events, testing whether it is a measure of current health or an evaluation of future health, and whether it influences health-related behaviors or reflects access to health-related resources.\textsuperscript{15} Another area for future research suggested by this paper is the meaning of the large drop in EVGFP at the time of the event, only about one-third of which is due to death. It is of interest to know whether people’s “objective health” actually dropped this far, or whether change can be explained in part as a response shift, in which people change the process by which they evaluate their health because of the event.\textsuperscript{17,18}

\textbf{Limitations}

There are some limitations involving the data and the generalizability of the results. Although the amount of missing data was small and the interpolation method we used is reasonable, we may have distorted the health values closest to death, but examination of results with and without the interpolated data yielded similar findings.

Other health measures that account for death, such as the Quality of Well-Being scale,\textsuperscript{19} might have detected more detailed patterns for individuals. Because we found strong and consistent trends, however, it is unlikely that we missed important population-level findings.

For cardiac procedures, cancer, and CHF, it is likely that patients were aware of their diagnoses before the hospitalization that provided the event dates used here, which could have caused some of their pre-event decline. Since all events had similar patterns of decline before the event, the effect of this advance knowledge may not be large.

Although the CHS population was somewhat healthier at baseline than the general population,\textsuperscript{20} related bias is
probably small, because ineligible people who might have died soon after enrollment would not have contributed much information to this analysis. Since we consider only the first event for a person, these results cannot necessarily be applied to repeat events.

We compressed a significant amount of information into graphs and tables, for the sake of brevity, and may have omitted important details. Profiles and hypothesis tests may not correspond directly to the graphs since they are calculated on 6-month semesters, and only for people who have the relevant data to calculate the profile elements. Additional information is available from the authors.

A final limitation is that brevity required that this paper be restricted in scope. We explained the data and the methods, described the curves, and compared the event types, but could not follow up on the many intriguing questions raised by these data.

CONCLUSION
We have described population-level changes in health status over time in relation to serious health events. These changes are substantial and persistent. Future research should address reasons for these changes as well as ways to predict and perhaps to prevent them.

PARTICIPATING INSTITUTIONS AND PRINCIPAL STAFF

Forsyth County, NC
Bowman Gray School of Medicine of Wake Forest University: Gregory L. Burke, Sharon Jackson, Alan Elster, Walter H. Ettinger, Curt D. Furberg, Gerardo Heiss, Dalane Kitzman, Margie Lamb, David S. Lefkowitz, Mary F. Lyles, Cathy Nunn, Ward Riley, John Chen, and Beverly Tucker.

Bowman Gray School of Medicine-EKG Reading Center: Farida Rautaharju and Pentti Rautaharju.

Sacramento County, CA

Washington County, MD

NHLBI Project Office: Diane E. Bld, Robin Boone, Teri A. Manolio, Peter J. Savage, and Patricia Smith.

Coordinating Center

REFERENCES
METHODS APPENDIX

Missing Data and Deaths

The measure of health status was self-rated health: “Would you say that your health is excellent, very good, good, fair, or poor?” (EVGFP). It is important in longitudinal studies to deal specifically with deaths and missing data.

We added a sixth health state to account for deaths. For people who died, we created a dummy record for each time when they would, if still alive, have been scheduled for an interview (at 6-month intervals from baseline). That is, people who died were included in the calculations as being in the death state, as though they had continued to provide data on their original schedule.

People with missing data were usually sicker than those with more complete data; for example, about two-thirds of those with missing data just before death were in fair or poor health at their previously known measure. Excluding those people or their missing measurements would tend to bias the estimated average health upward. We interpolated missing values of health status linearly whenever the person had a valid value before and after the missing value. We then added a small amount of random error and rounded to the nearest nondeath value.

Health data were not collected in year 2, and all for that year were estimated. About 92% of the health data were complete before interpolation, increasing to about 97% after interpolation (not counting year 2). Since the overall amount of missing data is small, the only concern is data missing near the time of the event. Data missing just before the event would tend to have a low imputed value since it would be estimated in part from data after the event; conversely, data missing just after the event would tend to have a high value. This could cause the estimated drop at the time of the event to be underestimated. (Since the drops were generally large, this may not have been a problem.) Data that are missing because the event was close to the beginning or the end of data collection are “missing completely at random,” and their omission does not cause bias.

EVGFP

We summarized the health data in two ways. One is the percent who were healthy, which we define as being in excellent, very good, or good health (as opposed to fair or poor health or death). This is simple and interpretable, but does not make the important distinction between fair or poor health and death. For quantitative comparisons, we recoded the six health states into a continuous variable with a plausible value for death. Each health state was coded as the approximate percentage probability that a person in this health state will be healthy (in excellent, very good, or good health) 2 years in the future. Death then has a natural value of 0, since there is zero probability of being healthy in the future. The weights were developed elsewhere as excellent = 96, very good = 93, good = 76, fair = 35, and poor = 19.

A mean score of, say, 50 can be thought of simply as a score somewhere between fair (35) and good (76), or one could say that on average about half of the people with that score will be healthy 2 years later.

Randoms

The random group is not typical of natural aging before the event because they had to be alive until that time. In the entire CHS cohort, over a typical 4-year calendar period, mean health dropped about 13 to 16 points (not shown), while the random group dropped only about 9 points.

Regression Methods

We created smoothed estimates of health over time by regressing health before the event on the logarithm of the number of months until the event. We regressed health after the event as a function of both log time and time inverse to allow for short-term recovery. We compared the predicted and the observed values to be sure that the regression lines fit the data. Although we could have used logistic regression for some of these analyses, we used least squares throughout, to maintain our focus on average health. Since the proportion healthy was usually between 0.3 and 0.8, linear regression is appropriate.

We also adjusted the health measures to the age/sex/race distribution of the random group. Specifically, we used multiple regression of health on age, sex, race, and interactions for people in the random group. We then adjusted the observed health measurements for people in other groups as their observed health minus predicted health (from the regression equation) plus the grand mean for the randoms. An event type that differed in health from the randoms only because it had a different age or sex distribution would have health values more similar to the randoms after this adjustment. We used analysis of variance to test for significant differences in adjusted health among all the event types in health and health changes, with and without a Bonferroni correction for multiple comparisons.