This PDF is a selection from an out-of-print volume from the National Bureau of Economic Research

Volume Title: Issues in the Economics of Aging

Volume Author/Editor: David A. Wise, editor

Volume Publisher: University of Chicago Press, 1990

Volume ISBN: 0-226-90297-8

Volume URL: http://www.nber.org/books/wise90-1

Conference Date: May 19-21, 1988

Publication Date: January 1990

Chapter Title: Predicting Nursing Home Utilization among the High-Risk Elderly

Chapter Author: Alan M. Garber, Thomas E. MaCurdy

Chapter URL: http://www.nber.org/chapters/c7117

Chapter pages in book: (p. 173 - 204)

6 Predicting Nursing Home Utilization among the High-Risk Elderly

Alan M. Garber and Thomas MaCurdy

How likely is nursing home admission for an elderly person? How long does institutionalization last? These questions concern the elderly and their families, private insurers, and government agencies. The dearth of affordable, comprehensive insurance coverage makes long-term care (LTC) the leading cause of catastrophic health costs among the elderly. Private insurance rarely covers the costs of care received in nursing homes, which accounts for about 90 percent of LTC expenditures. Medicare and private insurance pay for only 1.7 percent and 1 percent, respectively, of all U.S. nursing home expenditures (Lazenby, Levit, and Waldo 1986), and Medicaid is available only to those who have become impoverished. The remaining burden falls on the elderly, their friends, and their families, who often provide "informal" care as well as financial assistance. Even unpaid care can have severe financial consequences; taking care of an impaired elderly relative frequently means reducing or abandoning paid employment (Muurinen 1986). Private LTC insurance, government LTC programs, and novel mechanisms for insuring and financing LTC have been proposed to alleviate these problems (Meiners 1983; U.S. Department of Health and Human Services 1986; Blumenthal et al. 1986). Insurers are becoming interested in offering comprehensive LTC insurance, and many of the elderly seem willing to consider the purchase of such plans. Whether the funds for LTC come from insurance payments, direct private

Alan M. Garber is assistant professor in the Department of Medicine at Stanford University School of Medicine, a staff physician at Palo Alto Veterans Administration Medical Center, and a research associate at the National Bureau of Economic Research. Thomas MaCurdy is both a professor in the Department of Economics and a senior fellow of the Hoover Institution at Stanford University as well as a research associate at the National Bureau of Economic Research.

This research was supported by a FIRST Award from the National Institute on Aging (1 R29 AG07651-01), a grant from the Veterans Administration (HSR&D Project IIR no. 86-118G), National Science Foundation Grant SE 85-13455, and grant 12761 from the Robert Wood Johnson Foundation. Bart Hamilton and Holly Prigerson provided valuable research assistance.

savings, or public coffers, financing can improve only if accurate projections of future LTC utilization become available. Inadequate information about expected nursing home utilization of the elderly impedes the development of these alternatives.

Demographic trends heighten the need to develop accurate predictions of nursing home utilization. Between 1980 and 2030, the number of Americans aged 65 and over is projected to increase from 24,927,000 to 55,024,000, as their fraction of the total U.S. population reaches 18.3 percent (Doty, Liu, and Wiener 1985). The number of Americans aged 85 and over—who are apt to be disabled, to live alone, to require frequent hospitalization, and to be found in nursing homes (Rosenwaike 1985)—is expected to quadruple in the same period (Taeuber 1983).

Although many authors have attempted to predict the risk of institutionalization, their estimates are often based on geographically limited populations of the elderly. Their data sources have sometimes been unsatisfactory, and many of these studies have used methods that do not lend themselves to forecasting. We report below the results of a new investigation of predictors of utilization, based on a national longitudinal sample of elderly persons at high risk of entering nursing homes. Our analysis of data from the National Long-Term Care Demonstration (Channeling) addresses the following questions. What is the probability of nursing home admission, and the expected number of annual nursing home days, for an elderly individual living in the community who possesses high-risk health characteristics? What is the distribution of lengths of stay in the nursing home for these individuals? How do these aspects of utilization vary with other personal characteristics?

Our answers to these questions are based on an analysis of data obtained in the early 1980s. These data reflect the current health care environment, which may change dramatically in the coming years. Current policy initiatives suggest that, in the future, nursing homes, home health care, and LTC insurance will be very different than they are today. We do not attempt to model the effects of these changes directly. We do not estimate, for example, the effects of moral hazard or adverse selection on future utilization. We emphasize instead the correlates of current nursing home utilization, an essential first step in any attempt to forecast future demand for LTC.

Our analysis proceeds as follows. First, we describe previous studies of nursing home utilization, identifying some of the issues that they have been unable to address. We then describe the data used for our study of nursing home utilization. The third and fourth sections explain the empirical approach and the estimation procedure, respectively. Since limitations in the data set make standard longitudinal models inappropriate, the methods applied in this study have unusual features. Results of the statistical analysis are described in section 6.5, along with simulations that show distributions of nursing home utilization for various categories of individuals.

6.1 Previous Studies of Nursing Home Utilization

6.1.1 The Likelihood of Nursing Home Admission

While few studies have fully investigated the determinants of nursing home length of stay, several have examined the likelihood of institutionalization (for a review, see Wingard, Jones, and Kaplan 1987). Insofar as they do not examine duration, these studies are of limited value for analyzing nursing home utilization; insurers and others concerned with the financial risks tied to LTC need to be able to distinguish very short nursing home admissions from stays that last for years. From their point of view, the several studies of the lifetime risk of nursing home admission are least useful since they neither predict the risk in specific age intervals nor distinguish short posthospital discharge stays, which Medicare usually reimburses, from prolonged institutionalization.

The studies of lifetime risk of nursing home admission have shown, however, that many of the elderly—25 percent–50 percent—will eventually be admitted to a nursing home (Palmore 1976; Vicente, Wiley, and Carrington 1979; McConnel 1984).

Several studies of the likelihood of admission in fixed intervals assess the effect of age, demographic characteristics, health status, and other variables. Logistic regression has been used to assess the probability of admission to nursing homes from the community (Branch and Jette 1982; Nocks et al. 1986; Cohen, Tell, and Wallack 1986a) and from hospitals (Kane and Matthias 1984) during fixed time intervals. Several other studies have used life-table methods or Markov models to predict the likelihood of nursing home admission (Manton, Woodbury, and Liu 1984; Liu and Manton 1984; Shapiro and Webster 1984; McConnel 1984; Lane et al. 1985; Manheim and Hughes 1986; Cohen, Tell, and Wallack 1986b). Several of these (Cohen, Tell, and Wallack 1986a; Lane et al. 1985; Manheim and Hughes 1986; McConnel 1984) do not control for individual characteristics. Generalizations based on studies that do not control for individual characteristics are particularly speculative; if health status, income, or other population characteristics change over time, the utilization patterns observed in the studies may no longer apply. Furthermore, the first-order Markov assumption is unlikely to be satisfied in a heterogeneous population unless there is an adjustment for determinants of institutionalization.

6.1.2 Duration of Nursing Home Admissions

Much of the previous literature on the duration of nursing home admission is based on demonstration projects. Several demonstrations have tested whether intensive community services could forestall nursing home admission or hasten discharge. Most studies of duration employ case-control methods to assess the effect of the community care interventions on nursing home utilization (e.g., Yordi and Waldman 1985; Branch and Stuart 1984; Hughes, Cordray, and Spiker 1984; Gaumer et al. 1986). For most of these investigations, the determinants of nursing home utilization are of less interest than the effectiveness of the intervention. The results of these studies seldom generalize to other areas since they are based either on single communities or on small areas that may offer community services not available elsewhere. Furthermore, the study populations differ greatly; rates of institutionalization in the control groups of the eight community-based LTC interventions reviewed by Weissert (1985) varied tenfold. Hence, this literature does not provide a basis for predicting either the likelihood or the duration of institutionalization that can be confidently applied elsewhere.

These and other studies of the duration of institutionalization have made it clear that there are at least two distinct groups of nursing home patients: those who are admitted for a short stay, either for convalescence from hospitalization or to die; and those who will become long-term residents of nursing homes because they are severely, chronically disabled but not dying (Keeler, Kane, and Solomon 1981). Liu and Manton (1984) found that 50 percent of a cohort of nursing home admissions were discharged within ninety days of entry, while 14 percent were institutionalized for over three years. Liu and Manton presented results for certain subgroups such as patients with particular diagnoses and disabilities. However, like most other studies of duration, their paper did not report a multivariate analysis that would enable the reader to infer the independent effects of personal characteristics.

6.1.3 Who Is at Risk of Institutionalization?

Despite their varied methods and data sources, published studies show remarkable agreement about the factors that are important determinants of institutionalization. These factors fall into four categories.

Demographic Factors

Virtually every study that controls for age has found that advancing age is associated with a rising risk of institutionalization; the prevalence of institutionalization rises with age, in univariate analyses, and it has a smaller but still significant effect in multivariate analyses. Sex also seems to be an important factor; univariate analyses find that elderly women are more likely than elderly men to enter a nursing home (Greenberg and Ginn 1979; Vicente, Wiley, and Carrington 1979). Since women are far more likely than men to survive their spouse, the effect of living alone may be confounded with the sex effect.

Health and Functional Status

Other studies have found that certain health conditions, such as cancer and dementia, raise the risk of institutionalization. Also important is functional status. Existing measures of functional status have important drawbacks: most have not been validated; they are coarse measures, insensitive to large changes in physical functioning; they are not usually cardinal scales, though they have been used that way (Spitzer 1987; Feinstein, Josephy, and Wells 1986). These flaws should weaken the ability of functional status measures to predict health events. Nevertheless, the most widely used measures are clearly associated with the risk of institutionalization.

Two measures are widely used to assess chronic disability in the elderly. The first of these, "activities of daily living" (ADL), describes the ability to perform basic functions such as dressing, eating, and walking without assistance. Functional status evaluation using this measure dates to the late 1950s (Katz et al. 1963). The second measure is based on limitations in "instrumental activities of daily living" (IADL). The IADLs measure the ability to perform more complex tasks without assistance, such as shopping, handling finances, and cooking. Most nursing home residents suffer from at least one ADL impairment, and nearly all have an IADL impairment. Previous investigations have found that ADL and, to a lesser extent, IADL limitations predict subsequent nursing home admission rates well.

Financial Status

Few studies have examined whether wealth or income affects nursing home utilization. Vicente, Wiley, and Carrington (1979) found that individuals whose family income was "inadequate" were more than twice as likely to be admitted to a nursing home as individuals of "very adequate" means. Greenberg and Ginn (1979) found that the coefficient of a binary variable for poverty was of borderline statistical significance in a multiple logistic regression predicting the probability of nursing home admission. Increased utilization of home health services may explain why wealthier people are less likely to enter institutions.

Living Arrangement, Marital Status, and Informal Supports

Being married is associated with a lower likelihood of nursing home admission (Cohen, Tell, and Wallack 1988), while living alone is associated with an increased risk of institutionalization (Kovar 1988). A spouse often provides substantial aid for a disabled person. The elderly who live alone have fewer disabilities than others of the same age who live with a spouse or other family members (Feller 1983), suggesting that they cannot continue to live independently in the face of severe disability. The National Long-Term Care Survey revealed that the likelihood that a disabled elderly individual who lives alone will be in a nursing home two years later is more than half again as great as for a similarly disabled person living with a spouse (Kovar 1988).

Collectively, these studies show that the elderly are likely to be admitted to a nursing home at some time, though the risk of prolonged institutionalization is distributed unequally. Studies that forecast utilization need to analyze duration as well as the probability of admission. It is important to explore the sources of the heterogeneity in nursing home utilization. We next describe a data set particularly suited for this purpose, the National Long-Term Care Demonstration.

6.2 The Channeling Data

Our analysis of the determinants of nursing home utilization is based on data from a sample of very frail elderly Americans. The data were collected as part of the evaluation of the National Long-Term Care (Channeling) Demonstration. This project, which was organized by the Department of Health and Human Services in 1980, was designed to demonstrate and evaluate the efficacy of "case management" in improving the LTC of the elderly. The advocates of case management hoped that it would control the costs of LTC while providing valuable services to the frail elderly. Channeling incorporated a total of ten study sites throughout the country. Within these sites, patients were randomized to usual care or assigned to a case manager. Case management could take one of two forms. At five sites, the case manager assumed responsibility for evaluating the elderly and planning and obtaining specific services. At five other sites, the case manager was also responsible for LTC expenditures on behalf of the enrollee. Other differences between the two forms that channeling took are detailed in Kemper et al. (1986) and Carcagno et al. (1986).

Like most large studies of community care interventions, Channeling enrolled individuals at high risk for institutionalization. Had the investigators studied a random sample of elderly individuals, either a much longer follow-up or a substantially larger sample would have been required to obtain reliable statistical estimates. Furthermore, as detailed in table 6.1, the criteria for enrollment in the Channeling demonstration were specified clearly. Other demonstration projects enrolled individuals who applied for particular services or who met other criteria of uncertain generalizability. Finally, unlike most other demonstration projects Channeling was performed at geographically diverse sites.

Table 6.1 Eligibility Criteria for Channeling Demonstration

Age	65 or over.
Functional disability	Two moderate ADL limitations or three severe IADL limitations or two severe IADL limitations and one severe ADL limitation.
"Unmet needs"	Must need help with at least two categories of service affected by functional disabilities or impairments for six months (such as meals or personal care), or informal supports may no longer be able to provide needed care.
Residence	Must be living in community or, if in nursing home, certified to be likely to be discharged within three months.
Medicare coverage	Must be eligible for Medicare Part A.

Source: Adapted from Kemper et al. (1986, 36).

We did not examine the effect of the Channeling intervention as part of this study. Previous studies have reported that the intervention had negligible effects on nursing home utilization and health outcomes (Kemper 1988). Our interest focuses instead on the utilization of nursing home services by the entire enrolled population. Data in the Channeling study were collected by surveying the participants and family members. These data were augmented by Medicare and Medicaid records, death certificate data, and data from providers. The baseline and followup data included the following:

- *Baseline* (September 1982–July 1983). Information about level of function (ADL and IADL impairments), health status, health service use, availability of informal care, basic demographic information, financial resources, health insurance (sample size 5,626);
- *Six-month follow-up* (September 1982–February 1984). Insurance coverage, health status, housing conditions, expenditures, health service use, community service use, nursing home admissions, income and assets, disability (sample size 4,593);
- *Twelve-month follow-up* (March 1983–July 1984). Same as six-month (sample size 4,752);
- *Eighteen-month follow-up* (September 1983–July 1984). Same as six-month (sample size 2,248).

To be included in this follow-up, a sample member had to be in the cohort of individuals enrolled in the first half of the demonstration and to have completed both the six- and the twelve-month follow-ups.

Summary statistics for the baseline characteristics of the sample, displayed in table 6.2, reveal that the average age of the Channeling participant was 80 years and that nearly 72 percent were female. Both physical and mental disability were common; nearly half the participants had moderate or severe cognitive impairments (dementia), and most had multiple and severe functional limitations. Although 42 percent owned their homes, 55 percent had very low (< \$500) monthly incomes, and only 10 percent reported monthly incomes that exceeded \$999.

The population included in the Channeling Demonstration was not selected randomly. Their uniqueness is evident in the outcomes during the first year of the study; in that period, 26 percent of the participants died, and about 16 percent entered nursing homes. The results presented below characterize utilization for this high-risk segment of the population. Because this group is so unusual, one should draw only limited conclusions about utilization in the general population from this set of data.

Despite limited generalizability, analysis of the Channeling data can lead to several insights. These insights depend on the application of suitable statistical models to a data set with unusual characteristics. In the next section, we describe a method for obtaining more precise estimates of mortality and of nursing home utilization for various subgroups of the Channeling population.

Table 6.2 Baseline Characteristics

Variable	Mean	Standard Deviation	Min	Max
Age	79.5797	7.6981	64.0	103.0
Male	.2850	.4514	.0	1.0
Married	.3186	.4660	.0	1.0
Living alone	.3717	.4833	.0	1.0
Has living children	.6569	.4748	.0	1.0
Education	8.2552	4.0670	.0	18.0
Nonwhite	.2641	.4409	.0	1.0
Severe cognitive impairment	.1532	.3603	.0	1.0
Moderate cognitive impairment	.3193	.4662	.0	1.0
Mild or no cognitive impairment	.4697	.4991	.0	1.0
No ADLs and some IADLs	.1177	.3222	.0	1.0
No severe ADLs	.2083	.4061	.0	1.0
1 severe ADL	.2236	.4167	.0	1.0
2 or more severe ADLs	.5808	.4935	.0	1.0
Weighted number of ADL impairments	5.4801	3.8841	.0	12.0
Weighted number of IADL impairments	5.0815	3.6926	.0	14.0
No assets	.5524	.4973	.0	1.0
Assets $1–$5,000	.2442	.4296	.0	1.0
Assets $5,001–$10,000	.0826	.2754	.0	1.0
Assets > $10,000	.1208	.3259	.0	1.0
Income < $500 per month	.5508	.4975	.0	1.0
Income $500–$999 per month	.3508	.4773	.0	1.0
Income > $999 per month	.0984	.2979	.0	1.0
Own a home	.4206	.4937	.0	1.0
Receive Medicaid	.2277	.4194	.0	1.0
Receive private insurance	.5902	.4918	.0	1.0
In nursing home at baseline	.0407	.1976	.0	1.0
Any nursing home stays six months prior to baseline	.0847	.2784	.0	1.0
Dead at end of six months	.1545	.3614	.0	1.0
Dead at end of twelve months	.2608	.4391	.0	1.0
Dead at end of eighteen months	.3514	.4775	.0	1.0
N = 5,625				

Note: Number of observations for dead at end of eighteen months = 2,820.

6.3 An Empirical Framework

This section develops a statistical model that enables us to predict nursing home utilization over a wide range of ages. The measure of utilization predicted in this analysis is the number of weeks spent in a nursing home by subgroups of the elderly, classified by demographic and other characteristics. A transition probability model (TPM), of the sort found in the analysis of Markov chains,[1] serves as the statistical foundation for this model. The absence of information on spell lengths significantly complicates estimating a

TPM using the Channeling data (with the public-use files currently available). This data source provides information on the total days an individual resides in nursing homes during each month, and it is possible to infer the number of admissions during this month, but the duration of individual admissions is unknown. Consequently, standard duration models cannot be applied to estimate a TPM with the Channeling data available. The following discussion proposes an alternative estimation procedure that can be implemented using the available information.

6.3.1 Transition Probabilities

A TPM to describe nursing home utilization must specify the probabilities that an elderly man or woman occupies particular "states of the world" and the transition probabilities for moving from one of these states to another. In our formulation, an individual may occupy any one of three states in a given week: if an elderly person resides in a nursing home for any part of a week, we classify him or her as being in state n; we assign this individual to occupancy in state c if he or she lives in the community (i.e., outside a nursing home); finally, we assign persons who have died to state d. Occupancy in state c captures a wide variety of circumstances, including hospitalization.

To characterize the stochastic process governing the transitions between states, let $\delta(t)$ and $y(t)$ denote two discrete random variables that can take the values of either zero or one in each week t. An individual is alive in week t if $y(t) = 1$ and is dead if $y(t) = 0$. Given $y(t) = 1$, an elderly person resides in a nursing home in week t if $\delta(t) = 1$ and lives in the community if $\delta(t) = 0$. Specifying the intertemporal stochastic properties of $\delta(t)$ and $y(t)$ determines the probabilities relevant to our TPM.

To introduce these probabilities, let $Z(t)$ represent the attributes of an individual that are deemed to influence the distributions of $\delta(t)$ and $y(t)$. Define

$$(1) \quad P[n \rightarrow c \mid Z(t)] = \text{prob}[\delta(t) = 0 \mid \delta(t-1) = 1, y(t) = 1, Z(t)],$$

$$(2) \quad P[c \rightarrow n \mid Z(t)] = \text{prob}[\delta(t) = 1 \mid \delta(t-1) = 0, y(t) = 1, Z(t)],$$

and

$$(3) \quad P[(n, c) \rightarrow d \mid Z(t)] = \text{prob}[y(t) = 0 \mid y(t-1) = 1, Z(t)].$$

Expression (1) gives the probability that an elder moves from state n in period $t-1$ to state c in period t given $Z(t)$ and survival until period t. Expression (2) provides an analogous relation for moving from state c to state n, and (3) shows the probability that an elderly person dies in week t. Because there is no return from state d (i.e., death is an absorbing state),

$$(4) \quad \text{prob}\,[y(t) = 1 \mid y(t-1) = 0, Z(t)] = 0,$$

which simply indicates that y cannot return to one after it equals zero. Note that the relations given by (1)–(3) are not conventional transition probabilities. Expressions (1) and (2) condition on not being in state d in period t, and (3) provides the joint probability of moving from either state n or state c to state d. One can interpret this formulation as a nested two-state TPM. At the first level, the value of $y(t)$ determines whether state d or states (n, c) obtain. At the second level, $\delta(t)$ allocates individuals who are not in state d between the states n and c.

Our empirical analysis incorporates two categories of variables in $Z(t)$. The time-varying category contains only a single variable representing a person's age in week t, which we denote by $A(t)$ with $A(t) = A$ for all weeks in which an individual is A years old (i.e., a person between 70 and 71 is assigned $A = 70$ until he or she actually turns 71). The second category includes attributes of individuals reflecting their functional status, living arrangements, the presence of certain chronic conditions, and financial status, which are interpreted to be characteristics that do not change over time. Grouping this latter set of variables into the quantity X, we have $Z(t) = [A(t), X] = (A, X)$. The lack of data on spells limits the variables that can be included in $Z(t)$. Because we do not have data on spell lengths, we cannot allow for elaborate forms of duration dependence. Models of these forms of duration dependence require the inclusion of measures of spell durations in $Z(t)$.

This choice of Z effectively introduces three assumptions concerning the stochastic processes generating the discrete variables $\delta(t)$ and $y(t)$. The first is that these processes satisfy a Markov property; the second is that past values of $\delta(t)$ do not influence the value of $y(t)$;[2] and the third is that transition probabilities are constant over the period of time during which an individual is at a given age. With i and j denoting arbitrary states, this last assumption allows us to introduce the shorthand notation

$$P[i \rightarrow j \mid Z(t)] = P_A(i \rightarrow j \mid X) \equiv P_A(i \rightarrow j) \quad (5)$$

for all t such that $A(t) = A$. This property amounts to assuming that weekly exit rates are stationary over any T-week period (with $T \leq 52$) in which a person's age does not change. While these assumptions imply that the discrete variable $y(t)$ follows a Markov process given a person's age, it does not imply this property in broader context because A is included as one of the characteristics determining probabilities. This admits a form of duration dependence in the distribution generating y that permits the likelihood of death to increase with age.

6.3.2 Predicting Nursing Home Utilization

Knowledge of the transition probabilities provides sufficient information to infer the distribution of the total time spent in nursing homes by a group of elderly persons over any age range and period. Given $P_A(n \rightarrow c)$, $P_A(c \rightarrow n)$,

$P_A[(n, c) \rightarrow d]$, and a set of characteristics X and starting values for δ and y, one can simulate a large number of sample paths for the variables $\delta(t)$ and $y(t)$ over time and, in doing so, can estimate the distributions of quantities that are averages of these variables such as the total weeks spent in nursing homes occurring in an age range.

The simulations for a person with a given set of characteristics proceed as follows. First, calculate the predicted values of the transition probabilities corresponding to the set of characteristics. Second, generate a random variable whose value determines that transition occurs; the probability of generating a random number that will yield a particular transition is equal to the transition probability. For example, if the probability of survival is .90 and only the transition to death is being considered, a uniformly distributed random number between zero and one might be drawn, and a transition to death would occur only if the number exceeded .9. After the simulated individual is assigned to a state for the next period, another random number is drawn to determine the following transition. This process is repeated until the simulated individual dies. At that point, the process begins again with a new person. By repeating this process (the results described here are based on five thousand repetitions), it is possible to generate the distributions of survival and of nursing home utilization.

6.4 An Estimation Procedure

In this section, we describe the procedure for estimating the transition probabilities that are used in the simulation. We first describe an approach for estimating $P_A(n \rightarrow c)$ and $P_A(c \rightarrow n)$ using the type of information provided by the Channeling data. We then describe a procedure for estimating $P_A[(n, c) \rightarrow d]$.

6.4.1 Specifying the Distribution of Accumulative Utilization

Over a fixed period of time (say, six months), the Channeling data offer sufficient information to infer the following three aspects of an individual's nursing home utilization: whether this person begins the period in or out of a nursing home; the total number of weeks of residence in a nursing home; and the total number of admissions. To use this information to estimate the probabilities associated with transitions between the states n and c, we require a formulation for the likelihood function describing these data.

Other measures of utilization can be constructed using the Channeling data. Consider a population of elderly individuals who are at the same age, over a period of observation of T weeks, who possess a common set of characteristics X, and who are alive for the entire period. Let S_n denote the number of distinct nursing home admissions experienced by an individual from this population during the weeks 1 to T; let S_c represent the number of distinct spells not in a nursing home; and let L denote the total number of weeks spent in a nursing home over this period. The variable S_n (or S_c) is incremented by one if a person is in a nursing home (not in a nursing home) in week 1 and each time thereafter that she transits from state c to state n (from n to c). Thus, S_n represents the number of nursing home admissions, and S_c represents the number of noninstitutional spells. The variables S_n and S_c need not be equal because spells may be interrupted either at the start or at the end of the sample period (i.e., there may be either left or right censoring). From the three informational items provided by the Channeling data listed above, one can construct observations for the variables $\delta(1)$ (i.e., whether an individual starts the period in a nursing home or not), L, S_n, and S_c.

To develop the implied specification of the likelihood function associated with these variables, consider the distribution for that segment of the population that resides in a nursing home during week 1, i.e., for which $\delta(1) = 1$. Let $G_A[S_n, S_c, L \mid \delta(1) = 1, T]$ denote the probability that a randomly drawn individual from this subpopulation experiences S_n nursing home spells, S_c spells outside a nursing home, and L total weeks in the nursing home over the period 1 to T conditional on living until period T. Given the statistical model introduced above, the implied specification for this joint probability is

$$(6) \qquad G_A[S_n, S_c, L \mid \delta(1) = 1, T] = K_n P_A(n \rightarrow n)^{L-S_n} P_A(n \rightarrow c)^{S_c} P_A(c \rightarrow c)^{T-L-S_c} P_A(c \rightarrow n)^{S_n - 1},$$

where the quantity $K_n \equiv K_n(S_n, S_c, L, T)$ represents the number of unique ways in which the variables S_n, S_c, and L can occur in the T-week period. The quantity $P_A(n \rightarrow n) = 1 - P_A(n \rightarrow c)$ in this expression corresponds to the transition probability associated with staying in a nursing home from one week to the next, and, similarly, $P_A(c \rightarrow c) = 1 - P_A(c \rightarrow n)$ represents the probability of remaining in the community state. The probability function (6) determines the fraction of the elderly population who reside in nursing homes in week 1 who will eventually experience S_n and S_c spells and L weeks of occupancy.

Now consider the analogous distribution for the segment of the population that does not reside in a nursing home during week 1. Let $G_A[S_n, S_c, L \mid \delta(1) = 0, T]$ represent the probability of observing S_n, S_c, and L conditional on being in the community in week 1 and living until period T. This probability takes the form

$$(7) \qquad G_A[S_n, S_c, L \mid \delta(1) = 0, T] = K_c P_A(n \rightarrow n)^{L-S_n} P_A(n \rightarrow c)^{S_c - 1} P_A(c \rightarrow c)^{T-L-S_c} P_A(c \rightarrow n)^{S_n},$$

where $K_c = K_n(S_c, S_n, T - L, T)$. This expression determines the fraction of the elderly who reside in the community in week 1 who will eventually experience S_n and S_c spells and L total weeks of institutionalization during the T-week period.

Combining these probability functions associated with the two segments of the elderly population achieves the goal of formulating a likelihood function that links the three aspects of nursing home utilization provided by the Channeling data. The implied specification is

$$(8) \qquad \mathcal{L}[S_n, S_c, L \mid \delta(1), T, A, X] =$$
$$G_A[S_n, S_c, L \mid \delta(1) = 1, T]^{\delta(1)} G_A[S_n, S_c, L \mid \delta(1) = 0, T]^{1-\delta(1)}.$$

Maximum likelihood estimation using (8) yields estimates of the transition probabilities $P_A(n \rightarrow c)$ and $P_A(c \rightarrow n)$. One can infer how these probabilities vary as functions of the age variable A and the characteristics X by introducing explicit functional forms for $P_A(n \rightarrow c)$ and $P_A(c \rightarrow n)$ in this estimation procedure. We use a binary logit functional form for these probabilities.

6.4.2 Specifying the Distribution of the Length of Life

The third transition probability that we need to know determines the time of death. The Channeling study provides information on the week that an elderly person dies if he or she does not survive until the end of the observation period. This information can be used to estimate $P_A[(n, c) \rightarrow d]$.

To develop a specification for the likelihood function describing the time of death, consider a population of elders who are at the same age over a period of T^* weeks and who possess a common set of characteristics X. To be included in this population, a person must be alive in week 1, i.e., $y(1) = 1$. The probability that a member of this population survives exactly T weeks for $T < T^*$ is

$$(9) \quad \text{prob}[y(T) = 0, y(T-1) = 1, \ldots, y(2) = 1 \mid y(1) = 1, A, X]$$
$$= P_A[(n, c) \rightarrow (n, c)]^{T-1} P_A[(n, c) \rightarrow d],$$

where the quantity $P_A[(n, c) \rightarrow (n, c)] = 1 - P_A[(n, c) \rightarrow d]$ corresponds to the transition probability associated with remaining alive from one week to the next. The probability that a population member survives that entire $T = T^*$ weeks is

$$(10) \qquad \text{prob}[y(T) = 1, \ldots, y(2) = 1 \mid y(1), A, X]$$
$$= P_A[(n, c) \rightarrow (n, c)]^{T-1}.$$

The Channeling study includes information on T, the number of weeks that a sample member survives during an observation period of T^* weeks. According to (9) and (10), the likelihood function describing the distribution of T is given by

$$(11) \qquad \mathcal{L}[T \mid y(1) = 1, A, X]$$
$$= P_A[(n, c) \rightarrow (n, c)]^{T-1} P_A[(n, c) \rightarrow d]^{1-y(T^*)},$$

where $y(T^*) = 1$ if $T = T^*$ (i.e., if an individual survives the entire period). Applying maximum likelihood, using specification (11) enables one to estimate the transition probability $P_A[(n, c) \rightarrow d]$. With an explicit functional form for $P_A[(n, c) \rightarrow d]$ substituted into (11), one can further estimate the relation linking this probability to the age variable A and to the characteristics X. For the estimates we report below, we have used logit functions. To derive the predicted length of life, we employed simulation methods as described in the preceding section.

6.5 Empirical Analysis

The construction of the data sets for nursing home transitions and for transitions from living to dead is described in the appendix. The estimation procedure uses the maximum number of observations available for each follow-up period; that is, all individuals with complete information on the six-month follow-up are included, even though many were not included in the eighteen-month follow-up.

6.5.1 Estimating Transition Probabilities

The functional forms assumed for the transition probabilities are the following binary logistic equations:

$$(12) \qquad P_A(n \rightarrow c) = 1/\left[1 + \exp\left\{-\left(\sum_{i=0}^{5} A^i\beta_{11} + X\gamma_1\right)\right\}\right],$$

$$(13) \qquad P_A(c \rightarrow n) = 1/\left[1 + \exp\left\{-\left(\sum_{i=0}^{5} A^i\beta_{12} + X\gamma_2\right)\right\}\right],$$

$$(14) \qquad P_A[(n, c) \rightarrow d] = 1/\left[1 + \exp\left\{-\left(\sum_{i=0}^{5} A^i\beta_{13} + X\gamma_3\right)\right\}\right].$$

The results of the logit estimates appear in tables 6.3–6.5. Variables included are demographic characteristics (i.e., race and sex); health and functional status measures (ADL and IADL impairments, dementia, other measures of cognitive impairment); social supports (marital status, number of living children); Medicaid and supplemental insurance coverage; and measures of financial well-being (variable for income below \$500 per month, home ownership) and educational attainment. The specification allows for interactions between the severity and number of ADL impairments.

Table 6.3 presents estimates for the transition from community to nursing home. Notably, the factors that influence nursing home admission are largely distinct from those that are generally expected to influence health. Homeownership markedly diminishes the probability of nursing home entry. Having

Table 6.3 **Parameter Estimates for $P_A(c \rightarrow n)$**

Variable	Estimate
Constant	−4,229.9537
	(1,595.5759)
Age/10	2,570.5673
	(985.9692)
$Age^2/10^3$	−6,219.6365
	(2,426.4012)
$Age^3/10^5$	7,478.5185
	(2,972.6041)
$Age^4/10^7$	−4,468.4258
	(1,813.0247)
$Age^5/10^9$	1,061.3707
	(440.4258)
Education—9–11 years	−.079870
	(.076576)
Education—12 years	−.029645
	(.075007)
Education—over 12 years	−.043779
	(.092108)
Male	.105647
	(.061570)
Married	−.065005
	(.072989)
Living children	−.199735
	(.054644)
Nonwhite	−.887912
	(.073200)
Dementia	.520179
	(.098012)
ADL score	.137180
	(.062315)
Dementia • ADL score	−.014364
	(.014422)
1 severe ADL	.528313
	(.192858)
2 or more severe ADLs	.779851
	(.131734)
ADL • 1 severe ADL	−.218540
	(.087713)
ADL • 2 or more severe ADLs	−.131557
	(.063323)
Income less than $500 per month	.103728
	(.073897)
Own home	−.388055
	(.056903)
Medicaid	.581507
	(.064207)
Private insurance	.106319
	(.062844)

Note: Standard errors in parentheses. Total number of observations = 8,596.

Table 6.4 **Parameter Estimates for $P_A(n \rightarrow c)$**

Variable	Estimate
Constant	3,363.6942
	(1,999.0484)
Age/10	−2,109.0280
	(1,227.8786)
$Age^2/10^3$	5,258.6005
	(3,003.3717)
$Age^3/10^5$	−6,523.2438
	(3,656.8733)
$Age^4/10^7$	4,026.0538
	(2,216.5447)
$Age^5/10^9$	−989.0995
	(535.0832)
Education—9–11 years	.036003
	(.109582)
Education—12 years	.054864
	(.097245)
Education—over 12 years	−.323784
	(.123172)
Male	−.011968
	(.087073)
Married	.316133
	(.096487)
Living children	.185329
	(.077202)
Nonwhite	−.034065
	(.104408)
Dementia	−.484524
	(.130421)
ADL score	−.091484
	(.068393)
Dementia • ADL score	.020004
	(.019351)
1 severe ADL	−.052812
	(.221783)
2 or more severe ADLs	−.098761
	(.180023)
ADL score • 1 severe ADL	.165044
	(.093898)
ADL score • 2 or more severe ADLs	.094215
	(.069748)
Income less than $500/month	−.115566
	(.091941)
Own home	.144524
	(.075214)
Medicaid	.008409
	(.085629)
Private insurance	.175246
	(.081411)

Note: Standard errors in parentheses. Total number of observations = 8,596.

Table 6.5 Parameter Estimates for $P_A[(n, c) \rightarrow d]$

Variable	Estimate
Constant	249.4911
	(1,586.1160)
Age/10	−184.9339
	(981.1263)
$Age^2/10^3$	524.4331
	(2,416.9041)
$Age^3/10^5$	−730.9426
	(2,963.8794)
$Age^4/10^7$	501.7803
	(1,809.4293)
$Age^5/10^9$	−135.8604
	(439.9563)
Education—9–11 years	.028640
	(.082634)
Education—12 years	.044137
	(.080369)
Education—over 12 years	.036470
	(.089636)
Male	.617575
	(.062476)
Married	−.062005
	(.074941)
Has living children	−.068667
	(.058975)
Nonwhite	−.034362
	(.066414)
Dementia	.050580
	(.114349)
ADL score	−.008919
	(.081203)
Dementia • ADL score	.008523
	(.014900)
1 severe ADL	−.115739
	(.199950)
2 or more severe ADLs	−.184681
	(.152688)
ADL score • 1 severe ADL	.124168
	(.098132)
ADL score • 2 or more severe ADLs	.123985
	(.081870)
Income less than $500 per month	.108454
	(.073513)
Owns home	−.054480
	(.058230)
Medicaid	−.189711
	(.078321)
Private insurance	−.042883
	(.064451)

Note: Standard errors in parentheses. Total number of observations = 10,722.

living children and being nonwhite are associated with decreased risk of nursing home admission. As might be expected, Medicaid participation is associated with a markedly increased likelihood of transition to the nursing home, as are advanced age, functional impairments, and dementia. Income does not appear to have a major independent association with institutionalization.

As table 6.4 shows, the factors that are associated with increased duration of admission are not necessarily the factors that indicate strong risk of admission. Being married and having living children are associated with an increased probability of leaving a nursing home, confirming the important role of social supports, but owning a house is no longer significant, and Medicaid coverage does not seem to matter once an individual is in a nursing home. Even though supplemental insurance does not usually provide significant nursing home coverage, individuals who have such insurance appear to leave nursing homes earlier, although this variable is only marginally significant. Dementia is associated with a diminished probability of discharge.

Table 6.5 presents results for the survival probabilities. Note the diminished roles of socioeconomic factors and social supports. Being male markedly diminishes the likelihood of surviving, while Medicaid coverage is associated with increased survival. Functional limitations do not seem to affect mortality. The age variables are jointly significant.

Several findings emerge from these estimates. First, since the factors that influence survival are so different from the variables associated with nursing home utilization, future changes in nursing home utilization are likely to be highly dependent on the effects of new medical technology. Life-prolonging technology, for example, may have no effect on age-adjusted disability from chronic illness. Dementia does not increase mortality, at least in this population, and dementia is likely to be more common in the future as long as old-age survival continues to improve. Because there are no effective preventive measures or treatments for the most common causes of dementia, life-prolonging health interventions are likely to increase the demand for nursing home care. Similarly, since functional impairment is not closely related to mortality, any increases in its prevalence are sure to lead to more nursing home use.

Numerous studies have documented the association between socioeconomic factors and health status. The most important socioeconomic factors have been education and, to a lesser extent, income, wealth, occupation, and race. The Channeling data are not ideal for measuring the effects of these factors, particularly because the population studied was predominantly low income and had limited education. Nevertheless, our analysis found no evidence that these factors were closely tied to nursing home utilization, with two exceptions. Advanced education was associated with longer stays, and nonwhite race was associated with a lower probability of nursing home admission. The latter finding could reflect poor access to nursing home care for nonwhites, but by many measures utilization of acute health services is higher for nonwhites (some authors argue that increased utilization may not reflect adequate access to health care since low-income, nonwhite, and less educated people may have a much greater need for health care). These findings emerge in an analysis that controls for Medicaid coverage, which is more common among nonwhites.

6.5.2 Predicting Accumulative Utilization

The effects of these variables on measures of utilization are not readily interpreted from the logit parameters. Being male, for example, increases the transition probability to death, and it also raises the likelihood of nursing home admission (although its logit parameter in the community to nursing home transition is not statistically significant at the 5 percent level). Is total nursing home utilization greater for men or women of a given age and set of functional limitations? Questions such as these are best answered by the results of the simulations that generate cumulative utilization figures (accumulative measures) for specific subgroups. These results are reported in tables 6.6–6.9. The simulations are based on the transition probabilities estimated from the logit equations above.

Simulation results for several sets of representative individuals are presented in tables 6.6–6.9. The simulations are performed as described in section 6.3.2. In each simulation, transition probabilities are updated as an individual ages, but other variables (the X's in eq. [12]–[14]) are held at fixed values over time. In these tables, the utilization figures are divided into age categories. Each now gives the distribution of nursing home utilization associated with the indicated age category experienced by an individual who starts in the simulation at age 65. The expected number of weeks in nursing homes at the older ages is very small because the probability of surviving to very old age in this high mortality population is low.

In each table, the first set of simulations is for an individual with Medicaid coverage, and the second is for an otherwise identical person without Medicaid. Findings for individuals who have private health insurance are not presented; private insurance had little effect on predicted nursing home utilization in the simulations, except at advanced ages. Very few individuals are expected to survive that long, so this disparity has little effect on predicted overall utilization.

Table 6.6 simulates the distribution of nursing home use for a very high-risk individual—a severely impaired, unmarried 65-year-old male on Medicaid who does not own his home. The chance that he will enter a nursing before the age of 70, if he is on Medicaid, exceeds 70 percent; if he did not have Medicaid, he would have had a 54 percent chance of entering a nursing home in the same interval. On entering the nursing home, the Medicaid patient is expected to stay longer than his uninsured counterpart; the length of stay for nursing home admissions is forty-six weeks for the men on Medicaid and thirty-three weeks for the uninsured men, between the ages of 65 and 70. In

Table 6.6 Distribution of Nursing Home Use

Description of population characteristics:
Demographic: Male, white, unmarried, living children, high school graduate
Health status: Cognitively impaired, 2 severe ADL impairments
Financial attributes: Income over $500 per month, does not own home, Medicaid/no Medicaid, no private insurance

Summary Statistics

	Probability of Not Entering a Nursing Home	Fraction Alive at Initial Age	Distribution of Nursing Home Utilization Given at Least One Admission: Mean Number of Weeks in Nursing Home	Quartiles for Number of Weeks: Q1	Q2	Q3
Medicaid:						
Age 65–70	.271	1	45.65	17	38	66
Age 70–75	.758	.289	50.82	20	42	74
Age 75–80	.940	.075	47.15	15	39	68
Age 80–85	.985	.019	51.45	22	44	76
Age 85–90	.996	.005	42.78	16	46	72
Age 90–95	.999	.001	43.50	7	80	80
Age 65–95	.265	1	61.44	20	47	94
No Medicaid:						
Age 65–70	.456	1	33.24	10	24	47
Age 70–75	.855	.212	36.00	11	27	53
Age 75–80	.976	.041	31.91	11	23	43
Age 80–85	.996	.006	34.43	8	29	38
Age 85–90	.999	.002	39.00	13	42	63
Age 90–95	1	0	. . .	. . .	. . .	. . .
Age 65–95	.443	1	42.99	11	29	62

every age category, both the likelihood and the duration of admission are longer for the Medicaid men.

At the older ages, the probability of nursing home admission is very low. This sample is not only at high risk of institutionalization but also dies at an increased rate. Fewer than 1 percent of the non-Medicaid men at age 65 are expected to live to age 80, so they are not likely to utilize nursing homes at advanced age, unless they are among the very few individuals who survive for more than a decade.

Less-impaired men with better social and economic supports are represented in table 6.7. The 65-year-old men represented here are married, have only one severe ADL impairment, and own their homes. About 58 percent of Medicaid men with these characteristics will enter a nursing home by the age of 70, while their non-Medicaid counterparts have a 38 percent chance of entering a nurs-

Table 6.7 Distribution of Nursing Home Use

Description of population characteristics:

Demographic	Male, white, married, living children, high school graduate
Health status	Cognitively impaired, 1 severe ADL impairment
Financial attributes	Income over $500 per month, owns home, Medicaid/no Medicaid, no private insurance

Summary Statistics

			Distribution of Nursing Home Utilization Given at Least One Admission			
	Probability of Not Entering a Nursing Home	Fraction Alive at Initial Age	Mean Number of Weeks in Nursing Home	Quartiles for Number of Weeks		
				Q1	Q2	Q3
Medicaid:						
Age 65–70	.419	1	21.55	7	16	30
Age 70–75	.747	.397	22.40	8	17	32
Age 75–80	.914	.137	20.14	6	15	28
Age 80–85	.965	.052	22.80	8	18	34
Age 85–90	.988	.018	22.43	10	21	28
Age 90–95	.998	.004	25.42	6	13	20
Age 65–95	.377	1	33.69	10	23	47
No Medicaid:						
Age 65–70	.623	1	16.65	6	12	23
Age 70–75	.848	.329	18.77	6	14	26
Age 75–80	.962	.094	16.81	5	12	24
Age 80–85	.988	.025	18.02	7	15	25
Age 85–90	.996	.007	22.86	3	10	17
Age 90–95	.999	.001	16.67	2	4	44
Age 65–95	.560	1	22.98	7	16	31

ing home. For the men who are admitted to a nursing home, the distribution of length of stay is substantially shorter than for the men in table 6.6; both median and mean durations are roughly half as large.

The logit estimates suggest that women utilize nursing homes more heavily than men, but the size of this effect is not readily apparent. Women have significantly lower mortality rates, but sex seems to have no effect on duration of nursing home admission, independent of the other variables, and surviving men may have a higher risk of entering a nursing home. However, the coefficient of sex falls short of statistical significance at the 5 percent level of the logit regression predicting institutionalization. A comparison of table 6.6 and table 6.8, which gives predicted utilization for a high-risk woman who differs from the man in table 6.6 only in sex, clarifies the effects of sex on utilization in the severely impaired elderly. Medicaid coverage continues to be

Table 6.8 Distribution of Nursing Home Use

Description of population characteristics:

Demographic	Female, white, unmarried, living children, high school graduate
Health status	Cognitively impaired, 2 severe ADL impairments
Financial attributes	Income over $500 per month, does not own home, Medicaid/no Medicaid, no private insurance

Summary Statistics

	Probability of Not Entering a Nursing Home	Fraction Alive at Initial Age	Distribution of Nursing Home Utilization Given at Least One Admission			
			Mean Number of Weeks in Nursing Home	Quartiles for Number of Weeks		
				Q1	Q2	Q3
Medicaid:						
Age 65–70	.192	1	50.07	22	42	73
Age 70–75	.562	.498	56.16	25	50	82
Age 75–80	.799	.233	51.72	21	45	76
Age 80–85	.903	.111	56.60	24	50	78
Age 85–90	.953	.052	62.86	26	56	93
Age 90–95	.983	.019	55.78	15	49	93
Age 65–95	.181	1	75.75	29	75	146
No Medicaid:						
Age 65–70	.348	1	36.97	13	29	53
Age 70–75	.677	.432	39.00	14	31	57
Age 75–80	.874	.176	35.65	12	29	49
Age 80–85	.952	.067	43.17	16	36	61
Age 85–90	.978	.027	41.16	12	30	57
Age 90–95	.995	.008	46.54	19	28	74
Age 65–95	.311	1	59.90	20	46	91

associated with increased utilization. At any age, a woman is more likely to enter a nursing home than a comparable man. If she enters a nursing home, she will tend to stay longer than her male counterpart. Of course, elderly women are not comparable to elderly men. They are more likely to be unmarried (because they usually survive their spouses) and to have functional impairments, so their nursing home utilization tends to be even higher, relative to men, than these results suggest.

The "best-risk" case is examined in table 6.9. This is a woman who may have IADL impairments but has no ADL or cognitive impairments. She is married, has children, and owns her home. While her projected mortality greatly exceeds that of the general population, it is less than that of the other categories examined here. Compared to the other simulated cases, she has better chances of staying out of a nursing home and spends less time there if

Table 6.9 Distribution of Nursing Home Use

Description of population characteristics:
Demographic: Female, white, married, living children, high school graduate
Health status: No cognitive impairment, no ADL impairments
Financial attributes: Income over $500 per month, owns home, Medicaid/no Medicaid, no private insurance

Summary Statistics

	Probability of Not Entering a Nursing Home	Fraction Alive at Initial Age	Distribution of Nursing Home Utilization Given at Least One Admission: Mean Number of Weeks in Nursing Home	Quartiles for Number of Weeks: Q1	Q2	Q3
Medicaid:						
Age 65–70	.618	1	11.93	4	9	16
Age 70–75	.723	.647	12.78	4	9	17
Age 75–80	.834	.402	11.57	4	9	16
Age 80–85	.891	.250	12.52	4	9	17
Age 85–90	.929	.152	12.48	4	10	18
Age 90–95	.962	.086	13.49	4	10	20
Age 65–95	.417	1	21.92	7	16	31
No Medicaid:						
Age 65–70	.770	1	10.68	3	8	15
Age 70–75	.833	.600	10.91	4	8	15
Age 75–80	.904	.347	9.93	3	7	13
Age 80–85	.948	.195	11.45	4	8	16
Age 85–90	.967	.111	10.71	4	8	14
Age 90–95	.985	.050	10.84	4	9	15
Age 65–95	.594	1	15.66	5	11	22

she is admitted. While Medicaid coverage is associated with longer stays, the mean weeks in nursing home conditional on admission are never more than one week longer under Medicaid, over a five-year period, than for the non-Medicaid women. At any age, the probability of admission remains higher for Medicaid women.

These simulations demonstrate that a small number of characteristics distinguish groups of people with very different expected utilization patterns. Medicare partially covers nursing home stays that last one hundred days or less; this exceeds the median number of nursing home days in a five-year period for the "low-risk" women in table 6.9 who are admitted to nursing homes. They would be under the Medicare maximum even if all the days were incurred in a single admission. However, men like the individual in table 6.6 have a 70 percent chance of being admitted to a nursing home between the ages of 65 and 70; if they are admitted, they will spend nearly eleven months, on average, in a nursing home over that five-year period.

Although all the underlying characteristics (''X variables'') have been held constant in these simulations, it is straightforward to allow the variables to change with time. For example, the utilization figures could be recalculated for a man initially free of functional impairments who faces a 5 percent annual risk of developing a severe ADL limitation.

Only a limited number of patterns of underlying characteristics are represented in these simulations. A much wider variety is possible, of course, but simulation for low-risk individuals is hazardous since the logit estimates were obtained from a sample of elderly people who had very high risks of institutionalization and death.

6.6 Conclusions

The population included in the Channeling Demonstration is not representative of elderly Americans. Because the inclusion criteria were designed to select a population that would use nursing homes heavily, Channeling participants were relatively sickly, disabled, cognitively impaired, and lacking in social and financial supports. Our analysis reveals the hazards of targeting a population this way: although Channeling participants were at high risk of entering a nursing home, they were also very likely to die. During the first twelve months of follow-up, more of them died than entered a nursing home. Furthermore, those who entered institutions often had short admissions.

Is it possible to select a population that is likely to utilize nursing homes more heavily than the Channeling population? We believe that it is possible since the determinants of institutionalization appear to be distinct from the factors associated with earlier death. In the Channeling population, mortality rates varied with age but not with many of the important determinants of nursing home admission, such as functional impairment and social supports. While advancing age is associated with a rising risk of institutionalization in the general population, within this sample age did not have large effects on nursing home utilization when functional status and support measures were taken into account. By emphasizing the factors that are associated with institutionalization but not death, one can define a population that is likely to use nursing homes heavily.

In summary, we find that the most disabled, sickly elderly may not be the heaviest utilizers of nursing homes. Such individuals die early. When they are admitted to nursing homes, death cuts their stays short. Our analysis leads us to speculate that a properly selected population less disabled than the Channeling participants would spend more time in nursing homes as a consequence of their greater life expectancy.

Appendix
The Channeling Data and Its Arrangement

From the original sample of 6,326 individuals, 700 were dropped because they did not complete the baseline interview. One person was dropped because he or she did not provide age data. The remaining individuals formed the research sample. About half (2,820) were followed for eighteen months after the baseline interview, while the rest were followed for twelve months or until death. The overall data set included baseline and six-month follow-up data on 5,625 individuals; twelve-month follow-up on 4,756 individuals (869 individuals died during the six months after the baseline interview); and eighteen-month follow-up on 2,075 individuals (2,820 less the 745 who died during the first twelve months).

To estimate the transition probabilities, we pooled data from each follow-up sample. This gave 12,456 observations of six-month periods. Observations were also deleted if they were missing data on key variables: education (840 dropped); functional limitations (466 dropped); income (287 dropped); home ownership (14 dropped); marital status (16 dropped); race (16 dropped); and Medicaid (95 dropped). The remaining 10,722 observations were used to estimate the transition probabilities to death. Because 2,126 observations lacked data on nursing home use, only 8,596 observations were included in the estimates of transitions between nursing home and community.

The following notes explain how the nursing home variables were constructed.

1. Skilled, intermediate, and other LTC facilities were included in the definition of nursing home stays.

2. Days in the nursing home were rounded to the nearest week.

3. The Channeling data did not report the dates of admission and discharge for each nursing home stay. The following assumptions were made to determine whether an individual was in a nursing home at the beginning of each period. The baseline survey recorded whether the individual was in a nursing home, so the initial status could be determined for the first six months of follow-up. For months 7–12, the individual was considered to be in a nursing home at the beginning of the interval if he or she was in the nursing home at the end of month 6 and was in a nursing home for any part of month 7. For months 13–18, the initial status was considered to be in nursing home if the individual was in a nursing home at the end of month 12 and was in a nursing home during months 13–18.

4. An individual who died during the first twelve months was considered to have died in a nursing home if he or she (*a*) was in a nursing home during the month of death or (*b*) was in a hospital during the month of death and had been in a nursing home the prior month.

5. An individual who died during months 13–18 was considered to have died in a nursing home if he or she (*a*) died in month 13 and was in a nursing

home during month 13 or (*b*) died during months 14–18 and spent more than half the days that he or she was alive during those months in a nursing home.

6. The number of community spells was assumed to equal the number of nursing home stays if the participant was in a nursing home at the beginning of the period but not at the end. If the participant was in a nursing home at both the beginning and the end of the period or died during the period, the number of community spells was assumed to equal the number of nursing home stays minus one. If the person was in the community at the beginning and the end of the period, the number of community spells was the number of nursing home stays plus one.

Notes

1. For further discussion of Markov chain models, see the textbooks by Bartholomew (1982) and Howard (1971).

2. Stated more precisely, $\delta(t)$ does not Granger-cause $y(t)$ so that

$$\text{prob}[y(t)|y(t-1), \delta(t-1), A(t), X] = \text{prob}[y(t)|y(t-1), A(t), X].$$

References

Bartholomew, D. J. 1982. *Stochastic models for social processes*. 3d ed. New York: Wiley.

Blumenthal, D., M. Schlesinger, P. B. Drumheller, and the Harvard Medicare Project. 1986. The future of Medicare. *New England Journal of Medicine* 314:722–28.

Branch, L. G., and A. M. Jette. 1982. A prospective study of long-term care institutionalization among the aged. *American Journal of Public Health* 72:1373–79.

Branch, L. G., and N. E. Stuart. 1984. A five-year history of targeting home care services to prevent institutionalization. *Gerontologist* 24:387–91.

Carcagno, G. J., R. Applebaum, J. Christianson, et al. 1986. *The evaluation of the national long-term care demonstration: The planning and operational experience of the Channeling projects*, vol. 1. Princeton, N.J.: Mathematica Policy Research.

Cohen, M. A., E. J. Tell, and S. S. Wallack. 1986a. Client-related risk factors of nursing home entry among elderly adults. *Journal of Gerontology* 41:785–92.

———. 1986b. The lifetime risks and costs of nursing home use among the elderly. *Medical Care* 24:1161–72.

———. 1988. The risk factors of nursing home entry among residents of six continuing care retirement communities. *Journal of Gerontology* 43:S15–S21.

Doty, P., K. Liu, and J. Wiener. 1985. An overview of long-term care. *Health Care Financing Review* 6:69–78.

Feinstein, A. R., B. R. Josephy, and C. K. Wells. 1986. Scientific and clinical problems in indexes of functional disability. *Annals of Internal Medicine* 105:413–20.

Feller, B. A. 1983. Need for care among the noninstitutionalized elderly. In *Health, United States, 1983*. Department of Health and Human Services Publication no. (PHS) 84-1232. Washington, D.C.: U.S. Government Printing Office.

Gaumer, G. L., H. Birnbaum, F. Pratter, et al. 1986. Impact of the New York long-term home health care program. *Medical Care* 24:641–53.

Greenberg, J. N., and A. Ginn. 1979. A multivariate analysis of the predictors of long-term care placement. *Home Health Care Services Quarterly* 1:75–99.

Howard, R. 1971. *Dynamic probabilistic systems*, vols. 1, 2. New York: Wiley.

Hughes, S. L., D. S. Cordray, and V. A. Spiker. 1984. Evaluation of a long-term home care program. *Medical Care* 22:460–75.

Kane, R., and R. Matthias. 1984. From hospital to nursing home: The long term care connection. *Gerontologist* 24:604–9.

Katz, S. K., A. B. Ford, R. W. Moskowitz, B. A. Jackson, and M. W. Jaffe. 1963. Studies of illness in the aged: The index of ADL: A standardized measure of biological and psychosocial function. *Journal of the American Medical Association* 185:914–19.

Keeler, E., R. Kane, and D. Solomon. 1981. Short- and long-term residents of nursing homes. *Medical Care* 11:363–69.

Kemper, P. 1988. The evaluation of the national long-term care demonstration: 10. Overview of the findings. *Health Services Research* 23:161–74.

Kemper, P., M. Harrigan, R. S. Brown, et al. 1986. *The evaluation of the national long-term care demonstration: Final report.* Princeton, N.J.: Mathematica Policy Research.

Kovar, M. G. 1988. Aging in the eighties, people living alone—two years later. In *Advance Data from Vital and Health Statistics*, no. 149. Department of Health and Human Services Publication no. (PHS) 88-1250. Hyattsville, Md.: Public Health Service.

Lane, D., D. Uyeno, A. Stark, E. Kliewer, and G. Gutman. 1985. Forecasting demand for long-term care services. *Health Services Research* 20:435–60.

Lazenby, H., K. R. Levit, and D. R. Waldo. 1986. *Health Care Financing Notes.* HCFA Publication no. 03232. Washington, D.C.: U.S. Government Printing Office, Office of the Actuary, Health Care Financing Administration.

Liu, K., and K. G. Manton. 1984. The characteristics and utilization pattern of an admission cohort of nursing home patients (II). *Gerontologist* 24:70–76.

Manheim, L. M., and S. L. Hughes. 1986. Use of nursing homes by a high-risk long-term care population. *Health Services Research* 21:161–76.

Manton, K. G., M. A. Woodbury, and K. Liu. 1984. Life table methods for assessing the dynamics of U.S. nursing home utilization: 1976–1977. *Journal of Gerontology* 39:79–87.

McConnel, C. E. 1984. A note on the lifetime risk of nursing home residency. *Gerontologist* 24:193–98.

Meiners, M. R. 1983. The case for long-term care insurance. *Health Affairs* 3:56–78.

Muurinen, J.-M. 1986. The economics of informal care: Labor market effects in the national hospice study. *Medical Care* 24:1007–17.

Nocks, B. C., R. M. Learner, D. Blackman, and T. E. Brown. 1986. The effects of a community-based long term care project on nursing home utilization. *Gerontologist* 26:150–57.

Palmore, E. 1976. Total chance of institutionalization among the aged. *Gerontologist* 16:504–7.

Rosenwaike, I. 1985. A demographic portrait of the oldest old. *Milbank Memorial Fund Quarterly* 63:187–205.

Shapiro, E., and L. M. Webster. 1984. Nursing home utilization patterns for all Manitoba admissions, 1974–1981. *Gerontologist* 24:610–15.

Spitzer, W. O. 1987. State of science, 1986: Quality of life and functional status as target variables for research. *Journal of Chronic Diseases* 40:465–71.
Taeuber, C. M. 1983. America in transition: An aging society. In *Current Population Reports,* ser. P-23, no. 128. Washington, D.C.: Census Bureau.
U.S. Department of Health and Human Services. 1986. *Report to the President: Catastrophic illness expenses.* Washington, D.C.: Department of Health and Human Services.
Vicente, L., J. A. Wiley, and R. A. Carrington. 1979. The risk of institutionalization before death. *Gerontologist* 19:361–67.
Weissert, W. G. 1985. Seven reasons why it is so difficult to make community-based long-term care cost-effective. *Health Services Research* 20:423–33.
Wingard, D. L., D. W. Jones, and R. M. Kaplan. 1987. Institutional care utilization by the elderly: A critical review. *Gerontologist* 27:156–63.
Yordi, C. L., and J. Waldman. 1985. A consolidated model of long-term care: Service utilization and cost impacts. *Gerontologist* 25:389–97.

Comment Joseph P. Newhouse

This paper is motivated by a desire to improve the ability to predict nursing home utilization among the elderly; its premise is that the primitive methods and results in the literature with respect to this issue have impeded the development of long-term care insurance.

The methodology used in this paper is an improvement over the existing literature in several regards, as pointed out by the authors. Many studies look only at admission and do not study duration. Those that do study duration do not control for detailed patient characteristics. Further, the results in the literature tend to be based on data from single areas, which naturally raises an issue of generalizability.

I wish to focus my comments on two issues: the degree to which these estimates are generalizable and then, even if the estimates are generalizable, whether a lack of such estimates has been a major impediment in developing long-term care insurance.

Suppose for the moment that we accept the argument that estimates of the transition probabilities such as those in this paper are important in developing long-term care insurance. Should we believe the estimates in the paper?

It is clear from the title of the paper, which includes the term "high-risk elderly," that the authors have a nonrepresentative sample of the elderly. The sample was limited to the high-risk elderly, as defined by the criteria in table 6.1, because, as the authors explain, with a random sample of the elderly either

Joseph P. Newhouse is the John D. and Catherine T. MacArthur Professor of Health Policy and Management at Harvard University and director of the Division of Health Policy Research and Education. He is also the founding editor of the *Journal of Health Economics.*

a longer follow-up or a larger sample would have been required to obtain reliable estimates of the effect of channeling, the purpose for which the data were collected. The advantages of this sample for estimating the effect of channeling, however, do not carry over for the authors' purposes.

The channeling sample is not a representative sample from the population that will be insured by long-term care insurance, and apparently these results cannot be reweighted to reflect the population that will be covered. Thus, I consider trying to use these estimates to predict the cost of a universal public long-term care insurance plan, and simply note that I think it would be even more difficult to apply them to a likely private insurance scenario, namely, an employer who provided long-term care insurance as a fringe benefit to employees and to retirees.

The main point is that suitably reweighted estimates are likely to be very different from the estimates here. For example, table 6.9 presents, among other things, the predicted likelihood of death for a cohort of white females who are high school graduates, who are married with living children, and who have an income over $500 per month and own their own home. Based on results for these covariates in table 6.5, which certainly accord with expectations, this subgroup of white females should have a more favorable mortality experience than the average for all white females. In 1980, the annual death rate for all white females 65–74 was .020666 (USDHHS 1985, table 10). Approximating cumulative mortality by treating the death rate as constant within the interval, 81 percent of an average white female cohort alive at age 65 should be alive at age 75. Using the same method to project to age 85 (and the 75–84 annual mortality rate of .054017), 47 percent of that white female cohort would be alive at age 85.

Yet the predicted fraction alive in this sample at age 75 is 37 percent, less than half as large as for an average cohort, and at age 85 is 11 percent, less than a quarter as large as the average. Thus, as the authors say in their conclusion, it seems likely that nursing home experience will be greater among a cohort of women with 47 percent alive at age 85 than among a cohort with 11 percent alive at age 85.[1]

Although the mortality differences between this sample and the general population make the point of unrepresentativeness, it is emphasized by other major differences between the sample and the over-65 population. For example, the percentage white among the elderly over 65 in 1980 exceeded 90 percent (USDOC 1986, 34), but in this sample it is only 74 percent. Only 12 percent of this sample had assets greater than $10,000, but median wealth among the over 75 in 1983 was $36,000 (USDOC 1986, 451). Over half the over 65 have no limitations attributable to health (USDHHS 1985, table 31), but in this sample (according to table 6.1) all the participants were to have a limitation in the activities of daily living (ADL) (though table 6.2 tells us that at least 12 percent in fact had no such limitation; the "at least" refers to the fact that 12 percent had no ADLs but some instrumental activities of daily living [IADL]).

Now I would like to turn to the broader issue of long-term care insurance. Suppose that in fact this study had been carried out on a large national probability sample rather than the sample from the Channeling Demonstration. Suppose further that duration data were available. If the methods used here (or rather the improved methods that would exploit the duration data) were applied to such data, how useful would the results be to a potential long-term care insurer? Instead of estimates of use, such an insurer needs estimates of cost, unless the insurance policy is of the form that the insurer pays a fixed number of dollars per day in the nursing home. Bringing cost into the picture, however, both complicates the data collection and means that it is cost rather than duration of stay that should be estimated.

But suppose one had collected cost data so that one could give an estimate in dollars rather than days. Is the lack of a reliable estimate of that sort why we do not observe private long-term care insurance? I doubt it, although I think it is well worth pondering why there is so little private insurance for long-term care. One explanation is misperception on the part of the elderly that Medicare covers long-term care (Task Force on Long Term Health Care Policies 1987). This explanation is hardly satisfying to an economist; among other things, it cannot explain why an insurer has not sought to educate the elderly. (Of course, for any one insurer there is a free-rider problem, but that is the case for advertising in any industry with several firms.) Another possibility is that the availability of Medicaid stifles the private market, but this should apply only to elderly with little wealth to protect from the Medicaid spendown rule. Pauly (1989, 1990) has cited other reasons: the elderly might not wish to transfer income to the sick state or may not want to make it too easy for children to substitute formal care for their own care.

My guess, though it is only a guess, is that the problem lies deeper than a lack of good cost estimates. It is likely that, if one sold individual long-term care insurance among the elderly, there would be a serious adverse selection problem, and there would probably be a moral hazard problem as well.

An alternative to individual insurance among the over 65 is to sell to groups under 65 (e.g., have an employer purchase such insurance as a fringe). But selling insurance to groups under 65 might pose two types of systematic risk that could lead to high loadings. Both risks arise because, unlike traditional group health insurance, the payout is several years downstream from the premium. The first risk concerns the relative price of nursing home services in the future. If the insurance company is to bear the risk of price changes (or, say, 80 percent of them through a coinsurance rate), the risk for the insurance company would be systematic across all policies. An insurer can avoid such risk by limiting payouts to $X per day, and, apparently, many policies now on the market in fact do this; that the policies do this suggests to me that this type of risk may be a problem. Of course, such a policy leaves the insured bearing the risk of incorrect estimates of future nursing home prices and may therefore be unattractive as insurance (i.e., there may not be much demand for such policies).

A second type of systematic risk in selling to the under 65 is a change in disease, for example, an increase in the incidence of Alzheimer's disease, or a marked change in mortality. The fragility of predicting is emphasized by the change in mortality rates; between 1980 and 1984 mortality for white males over 65 fell 6.25 percent, but for white females over 65 it fell only 1.7 percent; by contrast, between 1970 and 1980 the percentage reductions for each sex were virtually identical, a little over 16 percent for each (USDHHS 1985, table 10). Changes in mortality risk are a problem in life insurance as well, but payouts in long-term care insurance will be more sensitive to changes in mortality rates among the very old (e.g., over 85) because of the concentration of long-term care use there (see n. 1 above). Mortality rates among the very old are likely to be more variable than mortality rates across all age groups because of the low mortality rates among the under 65.

Another problem with private insurance is uncertainty about a future public program. Because so little is known about what such a program might look like, it would be difficult, one would think, to write a contingent contract.

In sum, good estimates of utilization of long-term care services are necessary for developing long-term care insurance but may not be the key obstacle to private long-term care insurance. This emphatically does not mean that we should not be working on estimates of demand for long-term care. I think we should especially want to know what the insurance elasticity of demand is for purposes of costing possible public programs, if nothing else. Toward that end, what I take away from this effort is that at a minimum we need a sample that is representative of a general population, and it would be even better if there were some exogenous variation in insurance in that sample.

Note

1. This claim relies on the fact that in the general population nursing home use rises sharply with age. The probability in 1977 of an average female's 65–74 being in a home is .016, for a female 75–84 it is .086, and for females 85 and over it is .252 (USDHHS 1985, table 56). Nonetheless, it is possible that utilization in this very sick cohort would be greater, especially if future utilization is discounted.

References

Pauly, Mark V. 1989. Optimal public subsidies of nursing home insurance in the United States. *Geneva Papers in Risk and Insurance* 14 (January):3–10.

______. 1990. The rational nonpurchase of long-term-care insurance. *Journal of Political Economy* 98, no. 1 (February):153–68.

Task Force on Long Term Health Care Policies. 1987. *Report to the Congress and the Secretary.* Washington, D.C.: U.S. Government Printing Office, 21 September.

U.S. Department of Commerce (USDOC). Bureau of the Census. 1986. *Statistical Abstract, 1987.* Washington, D.C.: U.S. Government Printing Office, December.

U.S. Department of Health and Human Service (USDHHS). 1985. *Health, United States, 1985.* Publication no. (PHS) 86-1232. Washington, D.C.: U.S. Government Printing Office.