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DO COMMUNITY-BASED, LONG-TERM-CARE SERVICES REDUCE NURSING HOME USE? A TRANSITION PROBABILITY ANALYSIS

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FOREWORD

As health care absorbs an increasing share of national income, the growing U.S. elderly population poses special challenges to the health-care system. Rising demand for nursing home facilities and commensurate growth in long-term-care expenditures stimulates the search for cost-effective alternatives to institutional care for the frail elderly. Community-based care is one alternative that showed early promise as a substitute for nursing home care. A community-based care system provides a variety of services, including skilled medical care, to elderly residing in the community. Despite the promise of this approach, however, government-sponsored demonstration programs and other research indicates that community services have little effect on nursing-home utilization and suggests that these services cannot reduce total long-term-care expenditures.

This study by Greene, Lovely, and Ondrich presents new evidence casting doubt on the conclusion that community-based care does not reduce nursing-home use. With data from the National Long Term Care (Channeling) Demonstration, the authors estimate the effect of personal and environmental characteristics on transitions between the community and institutional care. They find that the community-based services of nurses, home-health aides, and social support workers significantly reduce entry into nursing homes and promote transitions from nursing homes back to the community. Of the services considered, they find that nursing services have the most powerful effect in promoting community residence. Greene, Lovely, and Ondrich argue for a reconsideration of the role that community-based services can play in the long-term health care system.

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ABSTRACT

Community-based, long-term-care (CBLTC) service programs provide assistance to the frail elderly with the intent of reducing nursing home risk. Based on a random utility model of the choice of living arrangements, we use data from the National Long-Term Care (Channeling) Demonstration to estimate the effect of CBLTC service provision on the probability of returning to the community from a nursing home and the probability of entering a nursing home from the community. We find that home nursing services, home-health aide services, and personal care/homemaker services are significant inducements to nursing home exit and significant deterrents to nursing home entry. Of the three services, nursing services are the most powerful in encouraging discharge and discouraging entry.

DO COMMUNITY-BASED, LONG-TERM-CARE SERVICES REDUCE NURSING HOME USE? A TRANSITION PROBABILITY ANALYSIS

Introduction

As the U.S. elderly population grows, the demand for nursing home beds and public expenditures on long-term care are expected to increase commensurately. One hope for controlling the growth in long-term-care expenditures is the provision of services to frail elderly in the community, with the intent of reducing their need for nursing-home services. Beyond cost reduction, many observers believe that there are nonmonetary benefits for an elder and her family when she remains in the community. To this end, federal, state, and local agencies offer a variety of community-based, long-term-care (CBLTC) services. The exact nature of the services offered varies by locality, but most programs involve some combination of home nursing, home-health aidees, personal care aides, homemakers, physical therapy, meals, and transportation.

Even as CBLTC expenditures grow, however, evidence mounts suggesting that these services do not reduce nursing home use enough to offset costs associated with community service provision. Much of this evidence comes from the evaluation of CBLTC demonstration projects, the largest and most recent of which is the National Long Term Care Demonstration (NLTCD), also known as the Channeling Demonstration. The conclusion of the NLTCD evaluation was that while the demonstration resulted in benefits for its elderly clients, nursing home cost savings alone were insufficient to claim that such intervention is self-financing (Kemper, 1988). Moreover, the evaluation found limited evidence that receipt of lower-skilled services, such as personal care aides, reduces the probability of nursing home admission but found no effect for high-skilled services such as nursing

(Brown and Phillips, 1986). These findings, if confirmed, would suggest that public expenditure on CBLTC services must be justified more by the quality-of-life improvements they promote than by their effect on nursing home use.

This study offers new evidence on the effectiveness of CBLTC services in reducing nursing home risk. Using the NLTCD data and transition probability analysis, we find that both skilled and semi-skilled CBLTC services have a significant effect on nursing home use. Specifically, we find that the receipt of nursing services, home-health aides, and social support services (personal care and homemaker services) have a significant deterrent effect on transitions from the community into a nursing home and a significant promoting effect on transitions from a nursing home back to the community. Further, we find that an hour of nursing services has a larger effect on the probability of changing living arrangements than either of the other two lower-skilled services.

In the next section, we review previous research on CBLTC service effectiveness and on the factors influencing nursing home use. A following section describes our theoretical approach, which is based on a random utility model, and contains the derivation of two likelihood functions. Using NLTCD data, we estimate two transition probability models, one for transitions from a nursing home to the community and another for transitions from the community into a nursing home, the results of which are presented in a fourth section. In a concluding section, we summarize the effect of CBLTC services on nursing home use and discuss the implications of this research for long-term-care planning.

Previous Research

Previous research on the effectiveness of CBLTC services has been stimulated by the question of whether these services can be a cost-effective substitute for institutionalization. The primary source of evidence for addressing this issue is the evaluation of government-sponsored community care demonstrations. Applebaum, Harrigan, and Kemper (1986) review these demonstrations, some of which involve random assignment of eligible applicants to program services. The packages of services and the characteristics of the program-eligible populations differ widely among these demonstrations, making generalizations difficult (Palmer, 1982a). However, with the exception of a demonstration integrated with nursing home preadmission screening, demonstration evaluations have found insufficient nursing home cost savings to offset the costs associated with the demonstrations (Kemper, Applebaum, and Harrigan, 1987). This finding is confirmed by the results of the National Long-Term Care Demonstration.

Despite the uniformity of the findings from these demonstrations, what is known about the effect of CBLTC services on the probability of institutionalization is limited. The primary shortcoming of this record of evidence is that all of the demonstrations evaluated were service additions to an existing network of home care. In the case of the NLTCD, Kemper (1988) notes that the demonstration "tested the effect of adding comprehensive case management and expanded community care to service systems that already provided such services to some of the frail elderly." Thus, to the extent that the marginal effectiveness of CBLTC services in deterring nursing home use diminishes as the amount of CBLTC services

increases, demonstrations that supplement existing services offer incomplete measures of CBLTC service effectiveness.

A second limitation of demonstration evaluations as measures of CBLTC effectiveness is that most of the evaluations do not attempt to distinguish the effect of individual services.[1] The evaluations are designed to measure the effect of an intervention taken as a whole. They provide little evidence on the relative effectiveness of the various CBLTC services individually and, therefore, they offer few instructions on how service packages may be adjusted to improve effects.

An alternative to demonstration results as measures of CBLTC service effectiveness is the direct estimation of the determinants of nursing home risk. A large number of studies use multivariate methods to assess the risk of nursing home admission, but few include as regressors the level of CBLTC services received. Garber and MaCurdy (1989) review the literature and find substantial agreement among published studies regarding the important determinants of institutionalization. They identify four categories of factors associated with nursing home admission, none of which includes CBLTC services: demographic factors, health and functional status, financial status, and informal supports.

In these studies the exact set of factors used to explain nursing home risk is constrained by data availability. Besides CBLTC service delivery, the standard sources of information (e.g., the Panel Study on Income Dynamics) lack detailed information on the health status of individuals included in the sample. For example, in a study using U.S. Census data, Chiswick (1975) lacks the information to control for the health status of the sample population.

In contrast, studies based on data collected from a limited geographic area specifically for research on long-term-care issues usually draw upon an array of health information. Among this group is Branch and Jette (1982), which uses data on the Massachusetts elderly, Nocks et al. (1986), which uses the South Carolina Community Long Term Care Project data, Boersch-Supan, et al. (1988), which also uses data on Massachusetts elderly, and Garber and MaCurdy (1989), which uses data from the NLTCD. Boersch-Supan, et al. (1988) examine the importance of controlling for health status when estimating the probability of institutionalization.

Just as health status is an important control variable, it is our hypothesis that the receipt of CBLTC services by frail elders is also a significant determinant of the choice of living arrangements. Previous studies of nursing home risk that include CBLTC services as regressors provide conflicting evidence of their relationship to the choice of living arrangement. In his evaluation of California's In-Home Supportive Services (IHSS), Miller (1987) finds that IHSS service hours have a positive, significant effect on days of community residency. Brown and Phillips (1986) use data from the NLTCD and find some evidence that receipt of semi-skilled services (home-health or personal-care assistance and housekeeping) reduces institutional use. They find no evidence, however, that receipt of skilled services (nursing or physical therapy) affects the choice of living arrangements.

Our study contributes to the discussion about CBLTC services by measuring the individual effect of three services--nursing, home-health aide, and homemaker/personal care services--on the probability of nursing home admission and on the probability of returning from a nursing home to

the community. The study extends the literature in several ways. First, we use data from the NLTCD to create an event history of transitions into and out of a nursing home. Longitudinal analysis is necessary in examining nursing home use as nursing homes are often used for short-term recuperation care. That many nursing home residents enter the facility more than once confounds cross-sectional analysis. Second, unlike previous longitudinal analysis, including Garber and MaCurdy (1989) and Boersch-Supan, et al. (1988), we control for the level of CBLTC services received by sample members. Thus, we are able to examine the effect of these services on the probability of institutionalization in a longitudinal context. Finally, because the NLTCD data set includes information on the total amount of each CBLTC service received by each client, we are able to examine for each service its total and marginal effect on transitions between the community and the nursing home. This analysis sheds light on the demonstration findings and may be useful to long-term-care planners in their design of service packages.

A Random Utility Model of Nursing Home Entry and Exit

Theoretical Basis for Choice Probabilities

We model the decision to enter or leave a nursing home as a repeatable decision made by the client herself or by someone who correctly perceives the preferences of the client and acts on her behalf.[2] Each period the elder decides whether living in the community or in a nursing home is preferable, given her personal characteristics, including her current living arrangement, and the nature of her environment. We assume that an

elder living in state s, in time period t, associates with each of the two alternatives j a utility index, U_{sjt}, and that she chooses the living arrangement alternative with the highest utility index of the choices available to her.

We assume that the utility index consists of a deterministic component, V_{sjt}, and a disturbance, ε_{sjt}, taking the form

$$U_{sjt} = V_{sjt} + \varepsilon_{sjt} \quad . \tag{1}$$

Each elder in each time period associates an index of this form with each of two alternative living arrangements for the following period--living in the community or in a nursing home.

The deterministic component of the index is taken to be linear and an additively separable function of a set of nonstochastic attributes, given the elder's current living arrangement. The deterministic component of the utility index is

$$V_{sjt} = A_t' \beta_{sj} \tag{2}$$

where:

A_t = vector of attributes of an elder and her environment at time t,

β_{sj} = vector of weights for the utility index for choice j if the elder is living in state s at time t.

The disturbance term, ε_{sjt}, accounts for random influences on the utility index, which cannot be explained by reference to the attributes in the vector, A_t. This stochastic component is assumed to be independent and identically distributed across individuals and time periods.[3] It is drawn

from a two-dimensional joint distribution, characterized by the cumulative density function, $F(\varepsilon)$.

Consider an elder who resides in a nursing home at time t. She maximizes utility if she prefers to return to the community (choice "c") next period rather than remain in the nursing home (choice "n") if and only if

$$U_{nct} > U_{nnt} \quad , \tag{3}$$

or, equivalently,

$$A_t'\beta_{nc} + \varepsilon_{nct} > A_t'\beta_{nn} + \varepsilon_{nnt} \quad .$$

Because of the disturbance component, these utility indices are stochastic. Hence, the probability that the elder, who is characterized by the deterministic utility components $V_{nt} = (V_{nnt}, V_{nct})$, will return to the community is

$$P_{nc}(V_{nt}) = \int_{\varepsilon_{nn}=-\infty}^{\infty} \int_{\{\varepsilon_{nc} | \varepsilon_{nc} > \varepsilon_{nn} + A_t'(\beta_{nn} - \beta_{nc})\}} dF(\varepsilon). \tag{4}$$

Similarly, the probability that an elder living in the community at time t, who is characterized by the deterministic component, $V_{ct} = (V_{cnt}, V_{cct})$, will enter a nursing home next period is

$$P_{cn}(V_{ct}) = \int_{\varepsilon_{cc}=-\infty}^{\infty} \int_{\{\varepsilon_{cn} | \varepsilon_{cn} > \varepsilon_{cc} + A_t'(\beta_{cc}-\beta_{cn})\}} dF(\varepsilon). \tag{5}$$

Derivation of Likelihood Function

To estimate the sensitivity of the choice probabilities to the explanatory variables, we must identify a distribution for the disturbance

component of the utility index. We assume that the distribution of the ε_j is the extreme-value distribution and, hence, $(\varepsilon_{nn} - \varepsilon_{nc})$ and $(\varepsilon_{cc} - \varepsilon_{cn})$ are logistically distributed. The logistic distribution yields the familiar logit choice probabilities and equation (4) can be written

$$P_{nc}(V_{nt}) = \frac{1}{1+\exp\{A_t'(\beta_{nn} - \beta_{nc})\}} = \frac{1}{1+\exp\{A_t'\beta_n\}} \tag{6}$$

Similarly, equation (5) can be written

$$P_{cn}(V_{ct}) = \frac{1}{1+\exp\{A_t'(\beta_{cc} - \beta_{cn})\}} = \frac{1}{1+\exp\{A_t'\beta_c\}} \tag{7}$$

To estimate the coefficient vectors β_n and β_c, we define a likelihood function for the sample. As described in the next section, the data are organized to record transitions made by individuals from one month to the next between the nursing home and the community. Because the desires of individuals who die before they are fulfilled cannot be observed, the probabilities we estimate are conditioned on individual survival.

The independence assumptions imply that the likelihood contribution of the individual can be written as the product of the probabilities of the observed monthly events for that individual and that the likelihood of the sample is the product of the likelihood of the observed transitions for each individual. To represent the probability of the observed monthly event generally, let the variable, Y_{it}, equal unity if individual i moves from one living arrangement to another at the end of the month t and equal zero otherwise. The variable δ_{it} is unity if the individual begins month t in a nursing home and zero if in the community. Denoting the number of

individuals in the sample by I and the number of time periods by T, the likelihood of the sample is

$$L = \prod_{i=1}^{I} \prod_{t=1}^{T} \{(P_{nc}(V_{int}))^{Y_{it}}(1-P_{nc}(V_{int}))^{(1-Y_{it})}\}^{\delta_{it}}$$

$$\cdot \{(P_{cn}(V_{ict}))^{Y_{it}}(1-P_{cn}(V_{ict}))^{(1-Y_{it})}\}^{(1-\delta_{it})} . \qquad (8)$$

This likelihood function can be simplified by noting that

$$L = L_n \cdot L_c \qquad (9)$$

where

$$L_n = \prod_{i=1}^{I} \prod_{t=1}^{T} (P_{nc}(V_{int}))^{Y_{it}}(1-P_{nc}(V_{int}))^{(1-Y_{it})}, \quad \delta_{it} = 1$$

$$L_c = \prod_{i=1}^{I} \prod_{t=1}^{T} (P_{cn}(V_{ict}))^{Y_{it}}(1-P_{cn}(V_{ict}))^{(1-Y_{it})}, \quad \delta_{it} = 0.$$

Both L_n and L_c represent logistic likelihoods, so estimates of β_n and β_c can be obtained separately by binomial logit procedures.

Data Source and Measures

Data Source and Construction of Transition Histories

We estimate (9) with data from the public-use files compiled from the NLTCD. The NLTCD study population is drawn from 10 sites representing considerable geographic diversity. The demonstration gathered data from control and treatment groups at each site, all of whom were screened to be of age 65 or older, substantially impaired in functional capacity, and to have some degree of unmet need in important functional areas. Individuals residing in the community and in nursing homes were included in the sample,

but those enrolled while in a nursing home were required to be deemed a good prospect for discharge within 90 days. Details of eligibility criteria and a comparison of sample characteristics with those from a simulated national probability sample can be found in Applebaum (1988). Because the NLTCD sample is not representative of the general public of age 65 or older, our results apply to high-risk populations such as those enrolled in the demonstration.

The data contain 12-month nursing home use histories and information on personal, medical, and CBLTC services at six-month intervals for 4,593 individuals. From this group, we eliminated all individuals for whom there was missing data for any variable in our models, reducing the sample size to 3,293.

Estimating equation (9) requires the data to be organized in terms of person-months rather than individuals. The public-use files contain a set of variables that indicate whether or not each individual was in a nursing home during each month. From these data, we constructed a transition history for each individual, charting movements between nursing home and community residence, which is defined as any survival status other than nursing home care including being in the hospital. Because the data source used does not indicate the exact timing of transitions within any given month, sample members were taken to be in a nursing home throughout any month in which they spent time in a nursing home. The transition data were used to organize two person-month data sets; one for months spent in a nursing home and used in estimating the NC transition function, the other for months spent in the community and used in estimating the CN transition

function. A total of 2132 person-month observations comprise the nursing-home data set and 32899 person-months comprise the community data set.

Independent Variables

Four groups of independent variables are included as regressors in the estimation of the NC and CN transition functions. These groups are: formal CBLTC services, personal and environmental characteristics, medical and functional disability measures, and finally, NLTCD-related control variables. Table 1 provides descriptions of these variables and our expectations for parameter signs.

We include three measures of CBLTC services as regressors in both transition functions. The first of these service measures is hours of home nursing care. Home nursing can provide skilled care that otherwise only would be provided within an institutional setting. The second service measure included is hours of service provided by a home-health aide. Home-health aides provide medical services of a less-skilled nature than those provided by a nurse. The third service measure included is hours of nonprofessional services, comprised of homemaker and personal care assistance. These services provide assistance with the daily activities of independent living, such as bathing, housekeeping and preparing meals. We expect a priori that availability of all three services promotes the return of nursing home clients to the community and encourages elders in the community to remain there.

Information on formally supplied services in the NLTCD data set is drawn from surveys administered prior to, at the sixth month, and at the twelfth month of the demonstration. The survey instrument uses retrospective questioning that required participants to recall the total

TABLE 1

VARIABLE DESCRIPTIONS AND EXPECTATIONS
FOR PARAMETER SIGNS

Variable Name	Variable Description	Expected Sign NC Model	Expected Sign CN Model
Nursing Hours	Total hours of professional nursing per month.	+	-
HH Aide Hours	Total hours of service provided by a professional home health aide per month.	+	-
PC/Homemaker Hours	Total hours of service provided by a personal care assistant or homemaker per month,	+	-
African-American	Binary variable: 1 = African-American, 0 = otherwise.	+	-
Hispanic	Binary variable: 1 = Hispanic, 0 = otherwise.	+	-
Monthly Income	Total reported monthly income in thousands of dollars.	+	-
Gender	Binary variable: 1 = male, 0 = female.	?	?
Age	Age in years.	-	+
Education	Years of formal education.	+	-
Homeowner	Binary variable: 1 = homeowner, 0 = otherwise	+	-
Married	Binary variable: 1 = married, 0 = otherwise.	+	-
Live Alone	Binary variable: 1 = lives alone, 0 = otherwise.	-	+
Informal Care Hours	Total hours of care per week provided informally by family and friends, at baseline.	+	-
Unmet Needs	Binary variables: 1 = client has more than three unmet needs in functional areas, 0 = otherwise.	-	+
Rural	Binary variable: 1 = lives in Eastern Kentucky or Southern Maine NLTCD sites, 0 = otherwise.	-	+

TABLE 1 (CONT.)

Variable Name	Variable Description	Expected Sign NC Model	Expected Sign CN Model
Bed Supply	Nursing home beds per 1000 persons over 65 years of age within site area.	-	+
IADL	Binary variable: 1 = client has severe or very severe IADL index, 0 = otherwise.	-	+
Cognitive Impairment	Binary variable: 1 = client has severe or very severe cognitive impairment, 0 = otherwise.	-	+
Bed Days	Days spent in bed during two months preceding survey, as reported retrospectively by client.	-	+
Physician Visits	Number of visits to a physician during two months preceding survey.	-	+
IV Tube	Binary variable: 1 = client requires use of an intravenous tube, 0 = otherwise.	-	+
Catheter/Colostomy	Binary variable: 1 = client requires use of a catheter or colostomy bag, 0 = otherwise.	-	+
Smoker	Binary variable: 1 = smoker, 0 = nonsmoker.	-	+
Self-Rated Health	Health as rated by client on a scale from 1 (poor) to 4 (excellent).	+	-
Life Satisfaction	Binary variable: 1 = client reports she is "moderately" or "very" satisfied with life, 0 = otherwise.	+	-
Treatment Group	Binary variable: 1 = member of NLTCD treatment group, 0 = otherwise.	+	-
Financial Model	Binary variable: 1 = reside in a location where the NLTCD used a financial control model, 0 = otherwise.	+	-

hours of services, by type, received in the previous week of community residence from all sources. Because of the retrospective nature of the questioning, we assume that service hours reported at the time of the six-month survey are representative of the actual hours received in months 1 through 6. Similarly, information reported at the twelve-month survey is imputed to months 7-12.

Individuals residing in a nursing home at the time they were surveyed were asked to recall the CBLTC services they received in the week prior to their admission. We assume that the service hours reported in this manner are the service hours that the client expects to receive if she returns to the community.

A concern in estimation of the parameters associated with services is that these services may be endogenous. CBLTC services may affect the decision to remain or return to the community by providing the means for independent living. It is also, possible, however, that the risk of moving into or out of a nursing home influences service levels. Such endogeneity of service levels would occur if decision makers controlling service allocations explicitly considered the risk of institutionalization in assigning services or if random factors affecting the risk of institutionalization also affected service assignments. If services are endogenous, inconsistent parameter estimates will result. We explored using an instrumental variables procedure to correct this potential problem.

Unfortunately, few previous studies address the question of how CBLTC services are determined. As Palmer (1982b, p. 355) notes, many observers have found that clients with similar personal and health characteristics

receive quite different assignments of services from public sources. This diversity in prescription may explain some of the difficulty previous researchers have had in accounting for the endogeneity of service assignments. In his study of California's IHSS program, Miller (1987) uses a two-stage linear procedure but explains less than one-quarter of the variation in assignments. In their evaluation of the NLTCD, Brown and Phillips (1986) also use a two-stage linear procedure to handle endogeneity of services. The resulting instruments are considered of poor quality, as the first-stage regressions left between 80 and 95 percent of observed variation in services unexplained.

We attempted to handle service endogeneity by using a tobit specification for the service regressions. The choice of a tobit specification is based on the observation that most individuals in the sample received no services in one or more service categories. It was our hypothesis that use of a linear regression model by Miller and Brown and Phillips may be a partial explanation for their poor results. Like those of previous researchers, however, our attempts to account for potential endogeneity of service assignments did not result in useful instruments. Despite the nonlinear specifications, we were able to explain only a small portion of the variation in services. We consider our instruments to be of poor quality because they lead to few predictions of nonnegative service levels, particularly for individuals residing in a nursing home. Consequently, the results reported below were obtained using actual CBLTC service levels as regressors.

The second type of regressor used in estimating the transition function controls for personal and environmental characteristics. Within

this category of regressors are sets of variables indicating a client's race, socio-economic characteristics, social supports in the community, and indicating nursing home bed availability.

Previous research (Eribes and Bradley-Rawls, 1978) indicates that minority elderly are less likely than others to use nursing home services, although there is debate as to whether this propensity reflects characteristics specific to minority ethnic status or is simply a reflection of socioeconomic status. In our estimation procedure, we use separate binary variables for African American and Hispanic American (mainly Cuban American and Puerto Rican) ethnicity. As shown in Table 1, we expect that minority status will be positively associated with the probability of leaving the nursing home and negatively associated with the probability of entering one.

Boersch-Supan, et al. (1988) find that the probability of institutionalization declines as income rises. Moreover, they find that the estimated effect of income is lower when health status is controlled for properly. Accordingly, we control for income level and both health status and CBLTC services.

Although some early studies found gender to be a significant determinant of nursing home risk, most recent studies do not confirm this. Controlling for age, income, and marital status, Boersch-Supan, et al. (1988) and Garber and MaCurdy (1989) find that gender has no significant effect on institutionalization. While we make no prediction for the direction of effect, we include gender as a regressor to test whether it has a significant effect when CBTLC services are included as regressors.

The literature provides inconsistent evidence on the effect of age on the probability of transition to and from a nursing home. Boersch-Supan, et al. (1988) find that age has an insignificant effect on the probability of institutionalization once health status is considered. In contrast, Garber and MaCurdy (1989) control for health status and find that the likelihood of transition to a nursing home increases with age. We expect age to be positively related to the risk of institutionalization and negatively related to the risk of leaving a nursing home.

Garber and MaCurdy (1989) do not find a significant relationship between education level and the risk of institutionalization. Nevertheless, to control for correlations between education and other regressors, we include it in both equations. We hypothesize that a higher education level leads to an enhanced ability to manipulate one's environment and thus we expect education to be negatively related to institutionalization risk.

Garber and MaCurdy (1989) find that homeownership is negatively related to nursing home use. Homeownership may indicate a strong psychological and social attachment to the community and, hence, resistance to institutionalization. Moreover, as bequeathable wealth, a home may influence an elder's decision by giving potential heirs an incentive to provide support that prevents a potential bequest from being eroded by nursing home costs. Thus, we expect that owning a home deters nursing home use and facilitates exit.

Although Garber (1988) and Kotlikoff and Morris (1987) emphasize the importance of family relationships, especially the existence of children, in analyzing the risk of institutionalization, we choose instead to measure

the level of social support available to an elder in the community. Our measures of social support are marital status, whether or not the elder lives alone, informal service hours received by the elder, and a measure of unmet needs.

Living alone and being unmarried have been found to be associated with greater risk of nursing home use. Individuals living with others may be less prone to nursing home use in that they have access to an environment maintained by others and perhaps direct caregiving available from them. Closely related to this consideration is marital status in that a living spouse is not only a potential caregiver in the same household, but is also likely to be a highly motivated one.

We also control for the amount of service supplied by family or friends. The measure of informal service hours is drawn from retrospective questioning contained in the baseline survey. For respondents in nursing homes at the start of the NLTCD, informal service hours reported refers to the period prior to entry. We also include a measure of unmet needs, which is a binary variable indicating that the individual has more than three unmet needs in important functional areas. We expect that informal services hours reduce while unmet needs enhance a client's perceptions of the benefits of nursing home care.

Finally, we control for several characteristics of the elder's environment. As Greene (1984) suggests that elderly living in rural areas are at greater risk of nursing home use, we include a binary variable indicating whether a client lives at a rural site. We also include a measure of bed supply, nursing home beds per 1000 persons over 65. Nyman (1988), using data from Wisconsin, finds that excess demand for nursing

home care inhibits quality competition among providers and eliminates an important quality signal for consumers. Our measure of bed supply is a crude proxy for bed availability, but we expect that a larger bed supply is correlated with availability and we hypothesize that a larger bed supply, all else equal, promotes institutionalization by reducing consumer uncertainty about quality.

Previous research has indicated that our fourth category of regressors, medical and functional disability measures, are factors that influence nursing home use. As a measure of functional impairment, we use a binary variable indicating whether the individual was categorized as having either severe or very severe impairment based on the Instrumental Activities of Daily Living (IADL) index. The IADL measures the ability to perform daily tasks, such as shopping and cooking, without assistance. As a measure of cognitive deficit, we again use a binary variable indicating whether the individual was considered to have severe or very severe difficulties in cognitive functioning. Also included are measures of bed days and frequency of visits to a physician in the two months preceding the survey, the use of an IV tube or catheter and whether or not an elder is a smoker. Generally, we hypothesize that impairment, poor health, and the need for frequent medical intervention increase the risk of institutionalization.

Although Boersch-Supan, et al. (1983) finds that self-assessments of health and well-being are poor predictors of nursing home use, we include two measures in our equations. First, we include a measure of health as rated by the client herself on a scale from poor to excellent. Second, to

assess the possible effects of morale and attitudes toward life, a binary indicator of positive life satisfaction is also included in the model.

Finally, the last group of regressors contains variables associated with the NLTCD. Even though the NLTCD evaluation study (Kemper, et al., 1986) found the intervention to have had negligible impact on nursing home risk, we include the treatment group binary variable for the NLTCD to control for any effects, especially from enhanced case management services, that might be due to the intervention. We control also for whether an individual was at a financial control model or basic model intervention site in the demonstration. The basic model emphasized case management, providing only a limited amount of discretionary funding to fill service gaps. In contrast, the financial control model added to case management expanded service coverage, a funds pool, and cost control measures.[4] The financial control model tended to be established in communities with a great variety of service options independent of the NLTCD. This richer environment may promote community residence. Thus, we expect both the treatment group and financial model indicators to be negatively related to institutionalization risk.

Transition Probability Estimates

Table 2 provides descriptive information about the sample used to estimate the transition probabilities. The first column of data is a vector of mean values for the independent variables that appear in the two functions, calculated for all individuals in the sample. The next two columns present means calculated over the person-months of transition risk, classified by origin state.

TABLE 2

DESCRIPTIVE STATISTICS OF SAMPLE, BY INDIVIDUALS AND BY PERSON-MONTHS

	Mean of Sample Individuals	Mean of Person Months in Nursing Home	Mean of Person Months in Community
Nursing Hours			
monthly average		0.13	0.88
at six months	0.77		
at twelve months	0.82		
HH Aide Hours			
monthly average		1.42	5.06
at six months	5.40		
at twelve months	3.55		
PC/Homemaker Hours			
monthly average		9.00	33.60
at six months	31.48		
at twelve months	29.88		
African-American	0.22	0.13	0.23
Hispanic	0.05	0.02	0.05
Monthly Income	0.52	0.50	0.52
Gender	0.27	0.25	0.26
Age	79.65	81.31	79.43
Education	8.17	8.35	8.15
Homeowner	0.43	0.37	0.43
Married	0.31	0.26	0.32
Live Alone	0.38	0.44	0.38
Informal Care Hours	11.72	14.75	11.57
Unmet Needs	0.30	0.36	0.29
Rural	0.16	0.19	0.16
Bed Supply	45.59	48.27	45.49
IADL	0.34	0.46	0.33
Cognitive Impairment	0.44	0.60	0.42
Bed Days	17.59	19.51	17.40
Physician Visits	1.79	1.53	1.81
IV Tube	0.01	0.03	0.01
Catheter/Colostomy	0.08	0.12	0.08
Smoker	0.13	0.13	0.13
Self-Rated Health	3.29	3.24	3.30
Life Satisfaction	0.42	0.39	0.43
Treatment Group	0.60	0.58	0.61
Financial Model	0.53	0.53	0.53
Number of Observations	3293	2132	32899

NC Transition Probability Results

Table 3 provides estimation results for the NC transition probability function. The first and second columns of data contain parameter estimates and t-statistics for the model including CBLTC services. The final two columns of Table 3 contain the parameter estimates and t-statistics for the model without CBTLC services.

A likelihood ratio test indicates that, taken together, the CBLTC service variables add significantly to the explanatory power of the equation. Individually, each parameter estimate has the expected negative sign and is statistically significant. Availability of nursing care, home-health aide service, and personal care/homemaker service each promote return to the community from a nursing home.

The magnitude of the coefficients suggests that nursing hours are more effective in reducing nursing home use than the other services measured. When evaluated at the mean, an additional hour per month of expected home nursing services produces an increase in the probability of leaving a nursing home of .0134.[5] In comparison, an additional hour of expected home-health aide assistance increases the probability of exit by .0017 and an additional hour of expected personal care/homemaker services by .0005. Thus, on average an additional hour of nursing has over seven times the effect of home-health services and 26 times the effect of personal care/homemaker services in promoting nursing home exits.

The two binary variables controlling for ethnicity are not statistically significant at the 5 percent significance level. For an Hispanic, the odds of leaving a nursing home in a given month, all else equal, are 2.1 times the odds faced by non-Hispanics. In contrast, the

TABLE 3

MAXIMUM LIKELIHOOD ESTIMATION OF NC
TRANSITION PROBABILITY MODEL

	With CBLTC Services		Without CBLTC Services	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Nursing Hours	0.178**	3.09		
HH Aide Hours	0.024**	4.71		
PC/Homemaker Hours	0.007**	4.64		
African-American	-0.509	1.66	-0.715*	2.38
Hispanic	0.762	1.55	0.777	1.64
Monthly Income	0.106	0.34	0.075	0.25
Gender	-0.087	0.43	-0.086	0.45
Age	-0.016	1.48	-0.022*	2.22
Education	-0.018	0.81	-0.033	1.58
Homeowner	0.239	1.35	0.313	1.84
Married	0.281	1.08	0.352	1.42
Live Alone	-0.113	0.51	-0.041	0.19
Informal Care Hours	-0.010*	2.28	-0.008*	2.13
Unmet Needs	-0.035	0.19	0.068	0.39
Rural	-0.160	0.59	-0.194	0.74
Bed Supply	-0.003	0.46	-0.000	0.16
IADL	-0.502*	2.42	-0.434*	2.20
Cognitive Impairment	-0.548**	3.16	-0.654**	3.94
Bed Days	0.001	0.27	0.000	0.06
Physician Visits	-0.023	0.57	-0.035	0.88
IV Tube	0.621	1.33	0.678	1.49
Catheter/Colostomy	-0.252	0.90	-0.311	1.12
Smoker	0.106	0.43	0.081	0.35
Self-Rated Health	0.176	1.68	0.250	2.47
Life Satisfaction	-0.042	0.22	-0.042	0.23
Treatment Group	0.066	0.38	0.171	1.05
Financial Model	0.285	1.39	0.360	1.84
Constant	-1.166	1.01	-0.747	0.68
Log Likelihood	-585.4		-622.0	
χ^2	147.4		74.2	
Number of Observations	2132		2132	

NOTES: Absolute value of t-statistic reported. Significance determined using a two-tailed test.

χ^2 = likelihood ratio test statistic versus H_o.

*0.5 significance level, **.01 significance level.

sign of the estimated African-American coefficient is unexpectedly negative. For an African-American, the odds of leaving a nursing home are only 60 percent of the odds faced by others.[6]

Among the remaining personal characteristics used as controls in the NC function, only age, homeownership and marital status have t-statistics greater than one in absolute value. Increased age reduces the probability of returning to the community. Evaluated at the mean, the partial derivative of exit risk with respect to age is -0.0012. In contrast, homeownership increases the probability that an elder will return to the community. All else equal, the odds of a homeowner leaving a nursing home are 127 percent of the odds of a nonhomeowner exiting. Being married also increases an elder's chances of returning to the community. All else equal, the odds of a married person leaving a nursing home are 132 percent of the odds faced by an unmarried person.

Among our measures of social supports, only the measure of informal care hours provided by family and friends is significant at the 5 percent level. Surprisingly, though, informal care hours are negatively related to the probability of leaving the nursing home. One possible explanation for this is caregiver burnout. More intense efforts by caregivers up to the time of admission may reflect the devotion of significant family resources to keeping an elderly relative or friend out of a nursing home, but a resulting disinclination to take up the struggle again.

Among medical and functional status variables, two are significantly related to exit risk. Having severe or very severe difficulties with IADL, all else equal, decreases the odds of returning to the community to 61 percent of the odds of exiting by those without severe difficulty.

Similarly, severe or very severe cognitive impairment reduces the odds of exiting to 58 percent of the odds experienced by those without impairment.

Whether or not the elder resides in a site chosen by NLTCD as a financial model is not significantly associated with exit risk. Furthermore, we note that participation in the NLTCD treatment group is not significantly associated with exit risk, a finding that confirms the conclusion of the demonstration evaluation.

When CBLTC services are omitted from the NC function, the magnitude of several coefficient estimates changes but conclusions regarding rejection of the null hypothesis at the 5 percent significance level do not change. As Boersch-Supan, et al. (1986) found when health status is omitted, omitting CBLTC service measures has a noticeable effect on the monthly-income parameter estimate. While still insignificant, the estimated effect of monthly income on returning to the community is smaller in magnitude without CBLTC service controls. In contrast, the effects of age, education, homeownership, and marital status are larger in absolute value. Among the controls for health status, the omission of CBLTC service measures causes the estimated coefficient for unmet needs to switch signs. Finally, we note that without controls for CBLTC services participation in an NLTCD treatment group appears to have a larger effect than it does otherwise.

CN Transition Probability Results

Turning to factors that influence the risk of entering a nursing home from the community, Table 4 provides estimation results from the CN transition function. A likelihood ratio test indicates that the service variables add significantly to the explanatory power of the equation.

TABLE 4

MAXIMUM LIKELIHOOD ESTIMATION OF CN
TRANSITION PROBABILITY MODEL

	With CBLTC Services		Without CBLTC Services	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Nursing Hours	-0.116**	2.96		
HH Aide Hours	-0.008**	2.58		
PC/Homemaker Hours	-0.021**	9.75		
African-American	-0.848**	5.69	-0.891**	6.01
Hispanic	-0.789**	2.76	-0.851**	2.98
Monthly Income	-0.114	0.64	-0.139	0.78
Gender	0.045	0.40	0.095	0.84
Age	0.014*	2.44	0.109	1.94
Education	0.008	0.66	-0.002	0.15
Homeowner	-0.319**	3.16	-0.348**	3.46
Married	0.138	0.95	0.179	1.22
Live Alone	0.487**	3.88	0.488**	3.89
Informal Care Hours	-0.000	0.17	-0.000	0.17
Unmet Needs	0.159	1.61	0.120	1.22
Rural	0.038	0.26	-0.058	0.40
Bed Supply	0.010**	3.10	0.006	1.86
IADL	0.694**	5.82	0.565**	4.78
Cognitive Impairment	0.370**	3.74	0.419**	4.25
Bed Days	0.001	0.60	0.000	0.30
Physician Visits	-0.041	1.67	-0.047	1.86
IV Tube	1.409**	4.52	1.520**	4.98
Catheter/Colostomy	-0.061	0.35	-0.138	0.81
Smoker	-0.031	0.21	0.013	0.08
Self-Rated Health	-0.009	0.15	-0.025	0.45
Life Satisfaction	-0.019	0.19	0.035	0.34
Treatment Group	0.190*	2.02	-0.064	0.69
Financial Model	0.228*	1.99	-0.066	0.60
Constant	-5.863**	9.83	-5.423**	9.28
Log Likelihood	-2420.1		-2517.5	
χ^2	372.0		177.4	
Number of Observations	32395		32395	

NOTES: Absolute value of t-statistic in parentheses. Significance determined using a two-tailed test.

χ^2 = likelihood ratio test statistic versus H_o.

* 0.5 significance level, ** .01 significance level.

Higher levels of CBLTC services lead to a lower risk of nursing home admission, as each service coefficient has a negative sign and is statistically significant. The absolute value of the nursing services derivative is .0017, smaller than its value of .0134 in the NC estimation, indicating that at the mean the effect of nursing services on the probability of nursing home admission is more modest than its effect on the probability of exit. Furthermore, the effects of the other two services are weaker as well. The absolute value of the home-health aide derivative is .0001, smaller than the .0017 value for NC equation, and the absolute value of the personal care/homemaker derivative is .0003, smaller than the .0005 value for the NC equation.

Relative to the other services, nursing services are clearly the most powerful in deterring admission. Its derivative is 17 times that of home-health aide and 5.7 times that of personal care, homemaker services. This finding is in contrast to the findings of Brown and Phillips (1986). Using NLTCD data, they find some evidence that lower-skilled services reduce the probability of nursing home admission but no evidence that nursing services do so.[7] This difference in findings may be attributed to differences in method. Brown and Philips use an ordinary least squares procedure to estimate the relationship between community services and whether an elder is admitted to a nursing home during a six-month period and between community services and the number of days spent in a nursing home during the period. In contrast, we organize the data into a record of monthly transitions.

The coefficients for the African-American and Hispanic indicator variables are both negative, of large magnitude and statistically

significant. Thus, controlling for education and income, we find minority ethnic status to be a powerful factor related to nursing home admission. Indeed, the odds of nursing home entry by African-American or Hispanic elders, all else equal, is less than half that for others. The reasons for this difference deserve further investigation.

Among the controls for personnel characteristics, age and homeownership are significant predictors of nursing home risk. The derivative of the probability of nursing home admission with respect to age is .0002, with advancing age increasing the risk of admission. Homeownership is a significant deterrent to nursing home entry. All else equal, homeowners had only 73 percent the odds of admission as did those who are not homeowners.

Among our measures of informally supplied social supports, only the binary for living alone is a significant predictor. Those living alone have 1.63 times the odds of admission as those living with others. Unlike the NC equation, informal care hours in the CN equation has the expected sign but is insignificant. This result is surprising but may reflect the inability of unskilled family and friends to administer the type of care necessary to deter nursing home admission. Finally, the quantity of nursing home beds is also a significant predictor of admission, reflecting either lower supply constraints or lower quality uncertainty in areas with greater supply.

Three medical and functional status measures are significantly associated with the risk of admission. A person with severe or very severe problems with IADL has twice the odds of admission as those without these difficulties. Similarly, a person with severe or very severe cognitive

impairment has 145 percent the odds of admission as those without impairment. Finally, use of an IV tube increases the odds of admission 4 times.

Both of the control variables for the NLTCD are significant, but both are positive. Controlling for CBLTC services, participation in the NLTCD treatment group is associated with a greater probability of nursing home entry. In fact, those elders in the treatment group have 121 percent the odds of admission as those in the control group. As entry into the treatment group was randomly assigned during the demonstration, this finding must reflect some aspect of the treatment itself. One possible explanation is that the enhanced case management provided the treatment group facilitated the identification and admission of people who need nursing home care. Living in a location designated as a financial model site is also a significant predictor of admission risk. We suspect that this variable, like the treatment group binary, reflects a greater degree of professional involvement with the elders in the sample and, hence, greater assistance with admission.

Omitting CBLTC services from the CN equation raises the magnitude of several parameter estimates. Among the controls for personal characteristics, the omission increases the estimated coefficient of the ethnic binary variables, monthly income, gender, age, homeownership, and marital status. The estimated effect of age, in particular, appears to be much larger without CBLTC controls. Further, the parameter estimate for the rural location binary switches sign.

Several parameter estimates for the health-status control variables also change in magnitude when CBLTC services are omitted. Only the two

subjective health measures and the smoker binary appear to be substantially affected, however. The estimated effect of the self-rated health measure is larger while greater life satisfaction and being a smoker appear to promote nursing home entry without CBLTC service controls.

Finally, and most importantly, the omission of CBLTC services from the CN equation alters the sign and significance of the binary variables for both treatment-group participation and residence in a financial-model site. While the full model suggests that the NLTCD intervention, as distinct from CBLTC service provision, increases the probability that an elderly client enters a nursing home, this effect is obscured by failure to control for community service delivery. This result has two implications for long-term-care research and planning.

First, because the demonstration treatment consisted primarily of case management, it implies that case management has a complex association with nursing home risk, one which on balance facilitates admission. Brown and Phillips (1986) also report some evidence that case management increased nursing home use but express disbelief in the results.[8] Clearly, further investigation of this issue is warranted. The second implication of this result is that observation of the treatment effect from the NLTCD is a flawed guide to the effect of CBLTC services on nursing home use. The demonstration added a complex administrative structure to an existing service delivery system; its effect is not identical to the effect of CBLTC services alone.

Conclusion

The results of the transition probability analysis suggest that CBLTC

services do reduce nursing home use. Nursing services, home-health aides, and personal care/homemaker services are significant inducements to nursing home exit. Moreover, all three services are significant deterrents to nursing home entry. Of the three services, nursing services are the most powerful both in encouraging discharge and discouraging entry.

To summarize the total effect of CBLTC services on nursing home use, we consider the risk distributions implied by the transition probability functions both with and without community based services. As is clear from Table 4, existing services play a major role in reducing the risk of entry. The mean estimated probability of admission from the community rises from .015 with services to .024 without services, an increase of 60 percent.[9] Further, the mean probability of returning to the community from a nursing home falls from 0.169 with services to 0.110 without services, a decline of 35 percent. Thus, the existing system of CBLTC services appears to function as a major deterrent to nursing home use both through limiting admissions and through accelerating discharges.

Two implications of these results are relevant to long-term-care planning. First, these results provide new measures of the effectiveness of CBLTC services in reducing nursing home use. While these measures alone do not imply that CBLTC services are cost-effective, they do argue for reconsideration of the degree to which CBLTC services can be self-financing. Second, CBLTC service planners nationwide have responded to increases in the price of nursing care by substituting lower-skilled services for nursing. Our estimates of the relative effectiveness of higher and lower-skilled services suggest, however, that such substitution

should be carefully considered. The more highly skilled service may reduce nursing home risk enough to outweigh its higher relative price.

Our study is among the first to address the influence of individual CBLTC services on institutionalization. Clearly, further research is needed to improve upon and substantiate the results presented here. In particular, we are unable to correct for potential endogeneity in service assignments, a problem also experienced by the NLTCD evaluation effort. Progress in this area requires further understanding of how CBLTC services are assigned and the collection of data useful in estimating a model of service assignment.

Endnotes

[1]The NLTCD evaluation is an exception in that it included an attempt to examine the effect of skilled and semi-skilled services. See Brown and Phillips (1986).

[2]McFadden (1981) provides conditions under which discrete choice models can be treated as demand equations arising from utility maximization by a consumer. This section draws upon the general discussion of such treatment in Boersch-Supan (1987).

[3]Boersch-Supan, et al. (1988) analyze the choice of living arrangements without the assumption of time independence. They use a multinomial logit model to explain the more common choice sequences of living arrangements. This method is intractable with our data as we observe twelve decision periods and consider two choices.

[4]See Wooldridge and Shore (1986) for a description of the different intervention models.

[5]These derivatives are calculated as the mean over person-months of the instantaneous rate of change in the probability of transition in response to a change in the independent variable.

[6]The odds ratios reported for binary independent variables are the antilogs of their coefficients in the logits.

[7]See Brown and Phillips (1986), Table IV.4.

[8]See Brown and Phillips (1982), Tables IV.4 and IV.6 and the accompanying discussions.

[9]These estimated probabilities of admission are calculated as the mean probability of admission for all individuals in the data set.

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