A multidimensional approach to case mix for home health services

by Kenneth G. Manton and Tony Hausner

Developing a case-mix methodology for home health services is more difficult than developing one for hospitalization and acute health services, because the determinants of need for home health care are more complex and because of the difficulty in defining episodes of care. To evaluate home health service case mix, a multivariate grouping methodology was applied to records from the 1982 National Long-Term Care Survey linked to Medicare records on home health reimbursements. Using this method, six distinct health and functional status dimensions were identified. These dimensions, combined with factors describing informal care resources and local market conditions, were used to explain significant proportions of the variance (r^2 = .45) of individual differences in Medicare home health reimbursements and numbers of visits. Though the data were not collected for that purpose, the high level of prediction strongly suggests the feasibility of developing case-mix strategies for home health services.

Introduction

The growth in the demand for various types of long-term care (LTC) community and institutionally based services resulting from population aging in the United States has been well documented (e.g., Manton and Liu, 1984). In large part, this demand is driven by the rapid growth of the oldest of the elderly population (those 85 years of age or over) the group that has the highest per capita levels of need for a variety of LTC services (Soldo and Manton, 1985). Furthermore, the medical and functional characteristics of different subpopulations in the community based (Soldo and Manton, 1985) and institutional (Manton, Liu, and Cornelius, 1985) LTC populations have been described using data from the 1982 National Long-Term Care Survey (NLTCS) and the 1977 National Nursing Home Survey (NNHS) (Manton and Yashin, 1986). That information can be used to project the probable future aggregate demand for specific types of LTC services.

Given the well-documented growth in the need for LTC services of different types, the question arises of how to provide those services in an efficient and cost-effective manner. One proposal is to provide such services through a prospective payment system that will foster competitiveness among providers in the private market and still maintain cost discipline. Prospective payment systems have proven effective in controlling acute hospital care costs for Medicare. Under these systems, a fixed amount specific to each of 467 diagnosis-related groups (DRG's) is paid to providers as reimbursement for all services required for the treatment of that patient. An alternative type of prospective payment is capitation, where a contract is let to provide all appropriate medical services for a fixed period of time, rather than for a specific disease episode. This is the basis of the Medicare risk option for health maintenance organizations that uses the adjusted average per capita costs formula (Kunkel and Powell, 1981) to set capitation rates.

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Though prospective payment has proven effective in controlling acute care hospital costs, there are additional technical difficulties that have to be overcome before a prospective payment system can be constructed for LTC services. These technical difficulties arise from the need to develop a case-mix measure to insure that incentives exist to provide services to the more seriously ill and debilitated patients. Without a case-mix measure that matches reimbursement to the level of services needed by a particular patient, perverse incentives can emerge for the provider to selectively treat healthier patients to minimize costs while maximizing revenue.

The following are reasons why the development of a case-mix measure is more difficult for community-based LTC services:

- The determinants of service need are more complex, involving several dimensions (e.g., cognitive and physical) of functional disability as well as the medical condition of the patient.
- A practical system for reimbursing LTC services must preserve incentives to continue informal care assistance; thus living arrangements, family structure, and economic resources are relevant concerns in an LTC case-mix measure.
- It is difficult to define a community-based LTC service episode. Thus, a case-mix measure for community-based LTC services is intrinsically more complex than that for acute care because it must describe a multidimensional system of health, functional, and social needs evolving over a potentially long time span.

In this article, we explore a strategy for developing a case-mix measure for a particular type of community-based LTC service—the home health services reimbursable under Medicare. A study of Medicare home health reimbursement is particularly important becasue of the following:

- The recent rapid growth of Medicare expenditures for the home health benefit.
- The wide variation in home health service prices in different areas of the country (because of large differences in the availability of services and the newness of such services in the market place).

- The relative lack of prior empirical research (and literature) on this topic.
- The perceived merits of this type of service (in contrast to institutionalization) for preserving the autonomy and quality of life of elderly persons.

This proposed case-mix strategy is based on a classification procedure that is not only multivariate and multidimensional but that also represents individual heterogeneity by using continuous scores or weights. We applied this strategy to data on medical problems and functional limitations for persons receiving Medicare home health benefits who were interviewed for the 1982 NLTCS (Macken, 1984). With case-mix measures developed from the 1982 survey data, we examined variation in home health reimbursements and number of visits as reported in the Medicare Part A files. We examined the case-mix system in terms of the clinical distinctiveness of the case-mix categories, differentials in mean levels of service use among case-mix groups, and the ability to predict individual levels of home health benefit use by using case-mix measures.

Data

Two basic types of data were required for our evaluation: data to form the case-mix measure; and data on home health care costs or service use.

Data to construct the case-mix measures were taken from the 1982 NLTCS (Macken, 1984), a household survey of noninstitutionalized persons 65 years of age or over who reported (or expected) an activity of daily living (ADL) or an instrumental activity of daily living (IADL) limitation of 3-months duration or longer. To identify cases for the household survey, a sample of roughly 36,000 persons was drawn from the health insurance master file. From these cases, 6,393 persons were identified in the telephone screen as chronically disabled; and 6,088 were eventually contacted for the household survey. Of the 6,088, 5,583 persons fully completed the household interview, which covered a wide range of topics such as health status, functional limitations, informal care, and service use.

Data on home health reimbursement for all 36,000 persons drawn from the health insurance master file were available from Part A Medicare records, which contained information on reimbursements for hospital stays, home health use, and skilled nursing facility (SNF) use as well as data on home health use reimbursed under Part B Medicare. This yielded a total of 113,500 Part A bills of all types and 3,500 Part B home health bills for the period 1978 through the first quarter of 1985. Of the 117,000 total bills, about 24 percent were for home health reimbursement. The focus of these analyses is on home health service use in the interval 1982 to 1985.

By linking the Part A Medicare bills for the period 1978 to 1985 for individuals, it was possible to define different episodes of care with periods of service linked according to certain rules and fixed intervals of different lengths in which all service for a person is counted. After the episode or fixed-interval service use measures were created, they were combined with the data on health and functional status from the 1982 survey. These combined files were used for the two stages of our analysis—i.e., for construction of the case-mix index from the survey data and the analysis of the association of the case-mix index with different measures of service use.

Different service-use measures are required to model and analyze different types of reimbursement systems. The episode definition is required for reimbursement of all services associated with a specific health event or condition, and the fixed-interval model for assessing costs is necessary to evaluate capitation reimbursement. Because we had Medicare Part A service data back to 1978, we could also examine the effects of prior hospitalization and SNF use on the different episode and capitation home health service measures.

In defining the measure of service for either episodes or the capitation periods, several factors were considered. One was the amount of time over which home health service use is cumulated. Because the survey was not administered at the beginning of the service episode (or the capitation period), one has to restrict the period of time around the survey date over which service use is linked so that the service use is not too temporally distant from the health and functional conditions recorded in the survey. Clearly, the longer the time interval, the less likely are the health and functional characteristics reported in the survey to represent the characteristics of persons when they receive services. Given that the person was required (or expected) to have a chronic disability of at least 3-months duration, time intervals of 6 and 12 months were investigated.

The second factor involved the rules for linking services. The capitation model required taking all services delivered in a fixed period of time. For episodes, which can be of varying lengths, rules had to be made to link different types of services—e.g., an episode might be defined by a hopsitalization beginning in a period of up to 90 days before or after the survey date that leads to home health use and might include all services until no service was delivered for at least 60 days. In Table 1, we present the number of disabled elderly submitting bills for home health visits.

We conducted analyses for the seven different types of episodes and intervals. For three types, analyses were conducted of both Part A and Part B home health bills; and for four types, only Part A bills were analyzed. Because Part B use was relatively rare, the analyses of combined Part A and B use were similar to those for Part A use only. Consequently, the analyses presented describe only the more inclusive definition for two situations—for 1,316 persons with episodes beginning within 6 months of the survey date and for 1,286 persons with home health Part A or Part B bills beginning in 1982.

Of the 1,286 persons in the capitation model, 691 were determined to be chronically disabled according to the criteria used during the telephone screen, and they were included in the household interview. Also, 644 of the 1,286 completed most of the interview and were used in the multivariate analyses. The remaining 642 persons were included in the analysis, but there was limited information for them. In the episode analysis of 1,316 cases, 672 people completed the interview; and there was full health and functional status information for them. As in the capitation analyses, only limited demographic and service-use information was available for the remaining 644 cases. In addition to the data on hospitalization and SNF use in Part A records, we know that 604 of the 1,316 passed the telephone screen, and they did not report chronic disabilities.

Construction of case-mix measures

Methods

The dimensions to be used in our case methodology were identified using the Grade-of-Membership (GOM) procedure (Woodbury and Manton, 1982), a multivariate classification methodology. GOM has two components. The first component is a description of the relation of each case-mix dimension to each of the variables selected for analysis. By the GOM procedure, a prespecified number (say K) of dimensions can be identified by using the available information. The second component is a grade or weight for each person representing how much each person is described by the characteristics associated with a given case-mix dimension. A person can be represented by more than one case-mix dimension and have different degrees or grade of membership for each.

The GOM model can be compared with another frequently used type of multivariate analysis, i.e., factor (or principal-component) analysis. As in GOM, factor analysis is used to extract the smallest number of basic factors or of latent variables that explain the nonrandom variation of the original measures. To do this, two types of coefficients are produced. First, factor loadings are produced that are the correlations between the original measurements and the analytically determined factors. The pattern of correlations is used to describe the latent variables in terms of their relation to the original measurements. Factor loadings are similar to the first type of GOM coefficient except that the GOM model is applied to discrete response data so that the GOM coefficients are probabilities rather than correlations. The second type of coefficient produced in a factor analysis are factor scores. These are calculated after the factor loadings, and they represent how much a person has a given factor. The GOM scores are logically similar to factor scores except that, because we are describing subpopulations using discrete response data, the GOM scores are restricted to the range 0 to 1.0 and they must add to 1.0 for each person over the full set of case-mix dimensions identified. This means that, in GOM, the observed characteristics of any person are explained as a simple weighted sum of the characteristics of some number of the K case-mix dimensions. In factor analysis, these scores range from plus to minus infinity, therefore, the constraint does not apply. The constraints on the weights for individuals are what make GOM useful for generating the case-mix descriptions; because factor analysis, which does not have this constraint, is not appropriate for developing the case-mix measures.

In the GOM procedure, a person may be described by more than one continuously varying case-mix dimension. Because of this, GOM is distinct from the classification methodology used to identify the DRG categories for hospital reimbursement by which homogeneous discrete groups are defined in terms of the variation of a single criterion (i.e., charges or length of stay) except where clinical judgment was used to modify the statistically defined groups; and each case is assigned to exactly one group and thus does not represent individual heterogeneity in the classification.

We can describe the GOM model with a single equation. The equation indicates that each person's score on the *jth* observed variables (x_{ijt}) is composed of the sum of the product of that person's weights for each of the dimensions (g_{ik}'s) times the scores of the

Table 1

Number of disabled elderly persons submitting bills for home health visits, by time interval and rule for bill inclusion

Rules for bill inclusion	Time interval of visit: 6 months before or after survey date 2/82-3/83	3 months before or after survey date 5/82-11/83	Within 12 months of survey date 8/82-8/83	Within 12 months of 1982
Capitation interval				
Any part of bill within interval	1,548	X	[1]1,593	X
At least 50 percent of bill within interval	[1]1,482	[1]931	X	X
Any bill with admission date in interval	X	X		[2]1,286
Episode				
All bills in episodes beginning in interval without a service break of 60 days	[2]1,316	X	[1]1,426	X

[1] Restricted to Part A home health use.
[2] Service intervals analyzed in sections B and C.

SOURCE: Health Care Financing Administration and the Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from Medicare Statistical System.

dimension on the *jth* variable ($\lambda_{kj\ell}$). Verbally this can be written

$$\begin{bmatrix}\text{person's score}\\ \text{on variable}\end{bmatrix} = \text{the sum of} \quad \begin{matrix}\text{person's weight}\\ \text{on dimension}\end{matrix}$$

$$\times \begin{bmatrix}\text{dimension's score}\\ \text{on variable}\end{bmatrix}$$

Using mathematical symbols the equation is

$$\hat{x}_{ij\ell} = \sum_{K} g_{ik} \lambda_{kj\ell}, \quad (1)$$

where

$x_{ij\ell}$ = the individual's score on the *jth* variable or attribute predicted by the model,
g_{ik} = an individual's weight on the *Kth* pure type (or group),
$\lambda_{kj\ell}$ = a dimension's score on the *jth* variable or attribute,
K = number of dimensions, and
j = number of variables (and ℓ is the number of different types of responses to the variable).

Each of the values defined in the model can be given a substantive interpretation. The score $\hat{x}_{ij\ell}$ represents the probability predicted by the model that the *ith* person has a particular attribute. The values of g_{ik} and $\lambda_{kj\ell}$ are selected so that the $x_{ij\ell}$ (the observed binary indicator values) and $\hat{x}_{ij\ell}$ (the predicted probability of each indicator) are as close as possible for a given number of case-mix dimensions, i.e., for a given value of K.

The product in (1) involves two types of coefficients. The first type are the scores $\lambda_{kj\ell}$. These are the probabilities that persons on the *Kth* dimension have response level ℓ for variable j. The set of these coefficients describes the substantive nature of each of the K analytically defined dimensions just as the set of factor loadings in a factor analysis describes the nature of the analytically determined factors. Thus, to describe the clinical characteristics of each of the K dimensions identified by the procedure, we need to determine if the attributes identified by the procedure as fitting a dimension are reasonably associated with one another.

A similar criterion (i.e., that the analytically defined groups be clinically meaningful) was employed in the creation of the DRG categories by using the expert judgment of physician panels. In the GOM analysis, the health and functional status variables are used directly in the statistical procedure to identify the case-mix dimensions. Of course, the GOM results could also be reviewed and modified by expert panels by one of the following:

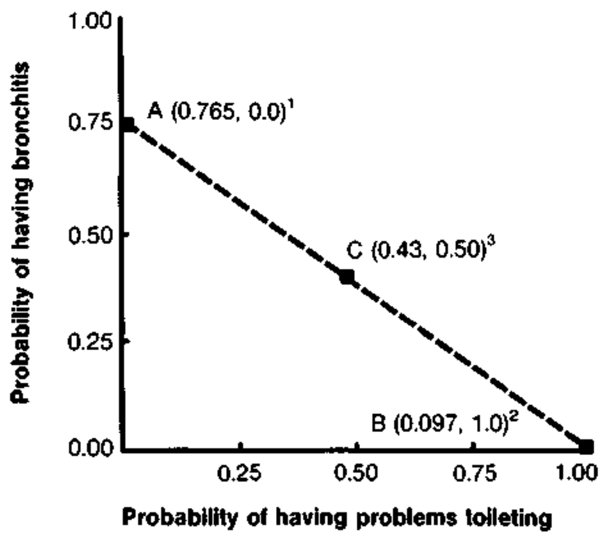
- Changing the distribution of the g_{ik}'s or altering the $\lambda_{kj\ell}$'s.
- Adding in additional variables to the GOM analysis to help objectively redefine the case-mix dimensions by increasing the scope of measures used in their definition.

The second type of coefficient or score are the g_{ik}'s. These scores describe how close the observed attributes of individual cases are to the profile of attributes (i.e., the pattern of $\lambda_{kj\ell}$'s) for each of the K case-mix dimensions. This score has the property that it must be between 0 and 1.0; and it must sum to 1.0 over the K dimensions for each case. As such, they can be used as linear weights to reproduce the observed attributes of each person as a composite of parts of the attributes associated with each of the K analytically determined profiles. These scores are the basis of our reimbursement formula.

Figure 1 is an illustration of how the two types of case-mix dimensions relate to 2 of 56 observed variables used in our analyses. (Table 3.) The vertical axis corresponds to the probability of having bronchitis, and the horizontal axis refers to the probability of having trouble toileting. Point A describes how the case-mix dimension characterized by multiple chronic problems relates to the two variables. Specifically, this dimension has a high probability of bronchitis (0.765) and a low probability of problems toileting (0.0). Point B refers to a second case-mix dimension, characterized by neurological problems, that has a high probability of problems toileting (1.0) and a modest probability of bronchitis (0.097). Point C refers to the probabilities predicted by the model for a specific person who has g_{ik}'s of 0.5 on both

Figure 1

The relation of case-mix dimensions to two observed variables



[1]A = Position of case-mix dimension characterized by chronic health problems relative to two observed variables.

[2]B = Position of case-mix dimension characterized by neurological impairments relative to two observed variables.

[3]C = Position of hypothetical patient with g_{ik} scores of 0.5 on each of the two case-mix dimensions relative to two observed variables. The values 0.43 and 0.50 refer to the probabilities of having either bronchitis or problems toileting predicted by the model.

dimensions. The predicted probabilities for each patient is a product of the weights (i.e, the g_{ik}'s) and the probabilities of each variable on each case-mix dimension.

An important parameter in the analysis is the number of case-mix dimensions (i.e., K). Because the coefficients are estimated using maximum likelihood procedures (Woodbury and Manton, 1982), the procedure provides a statistical criterion for selecting the best value of K. This criterion is a χ^2 value (calculated as twice the change in the log-likelihood function) describing the statistical significance of the $K+1$ dimension, i.e., whether the $\hat{x}_{ij\ell}$'s are closer to the $x_{ij\ell}$'s than could be expected by chance when the $K+1$ group is added. One continues to add dimensions until the $K+1$ dimension is no longer significant according to the χ^2 criterion.

Results

The first step in the identification of the case-mix dimension is the selection of the J variable on which we wish to differentiate cases and the estimation of the $\lambda_{kj\ell}$'s and g_{ik}'s. Because the case-mix measure is used to control differentials in need for services, we used data from the survey on both medical condition and functional status. From the survey, we selected 29 diagnosis-based measures of both longstanding conditions and medical events occurring in the past 12 months and 27 functional status measures (9 ADL's; 10 IADL's; and 8 measures of physical performance, sometimes referred to as IADL2 measures). GOM analyses were conducted with 29, 38, 48, and 56 health and functional status measures (Table 3) by adding in first the diagnostic variables and then successively the ADL, IADL, and IADL2 variables. The 56-variable GOM analysis produced case-mix measures that were best in terms of their ability to predict home health expenditures and numbers of visits. Extending the set of 56 variables by including such variables as scores on the Mini-Mental Status test, measures of behavioral problems, and selected demographic and economic factors did not improve the case-mix measures in terms of their power to predict home health reimbursements and visits. Thus, we used the set of 56 variables to define the functional and health status of persons relevant to home health use and used likelihood ratio tests to determine the value of K which satisfactorily explained the variation in those variables. We also added in the home health reimbursement and number of visits occurring during 1982 in an expanded 58-variable analysis. The results of the tests of the number of dimensions (K) needed to describe the systematic variation of the 56 variables are presented in Table 2.

In this table, we present several statistics. The first is the value of the log-likelihood function, which is the criterion that the model tries to maximize in fitting coefficients to explain the variation of the data. The importance of a dimension is tested by seeing how much the log-likelihood value changes when one additional dimension is added (column 3). Twice the change in the log-likelihood value is an χ^2 variable. For ease of interpretation, we present the value of the Fisher transform (i.e., $\sqrt{2\chi^2 - 1} - \sqrt{2d.f. - 1}$), which may be viewed as a normal variate for large degrees of freedom. Hence, a value of 1.96 for this statistic represents the 0.05-criterion level.

Table 2

Log-likelihood function, change in log-likelihood function, χ^2, and t-value for the 56 health and functional status variables, by dimension

Dimension	Log-likelihood function	Change in log-likelihood function	χ^2	t-value
5	5,357.7	0	0	0
6	5,824.8	467.1	934.2	2.9
7	6,182.8	358.0	716.0	−2.5

SOURCE: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from Medicare Statistical System.

We can see that six dimensions are necessary and sufficient to explain the variation in the health and functional status measures (i.e., $Z=2.9 > 1.96$). The seventh dimension does not contribute a statistically significant amount to the prediction. Similar results were found for 58 variables. This means that all the variation in the 56 (or 58) variables that is not the result of correlations among the measures or sampling variability is summarized in the g_{ik}'s for the six dimension solution. As a consequence, coefficients estimated for the regressions predicting service use should be better defined (i.e., not unstable because of the high collinearity among the original measures) and more likely to replicate in independent samples (because multiple measures are used to define a more reliable health-status index) than coefficients in regressions using the original 56 health and functional measures. In addition, the structure of the GOM model can represent nonlinear relations that could not be described in a linear regression with the original variables.

Beyond the statistical advantages of the GOM scores used as LTC case-mix indexes, each of the scores is associated with a dimension of clinical characteristics. These dimensions can be evaluated by persons with clinical training and experience to determine if the set of health and functional status measures found in a given dimension either tend to occur with one another in patient populations or represent classes of conditions with similar levels of functional impairment.

Given that six is the statistically correct number of dimensions (i.e., satisfactorily explains the variation of the medical and functional measures), we need to examine the clinical characteristics asociated with each profile. Thus, we examined the $\lambda_{kj\ell}$'s in Table 3 to determine which attributes best categorize each dimension.

Table 3

Percent of disabled elderly persons with home health use, responding to the National Long-Term Care Survey (NLTCS), and in each of six analytically defined dimensions, by health and functional status

Health and functional status	With home health use	Responding to NLTCS[1]	Dimension 1	Dimension 2	Dimension 3	Dimension 4	Dimension 5	Dimension 6
Health status			Percent of persons					
Chronic conditions								
Neurological:								
Parkinson's disease	4.12	2.63	0.0	0.0	9.01	10.99	0.0	5.03
Multiple sclerosis	0.95	0.59	0.0	1.86	0.0	0.03	0.0	4.15
Cerebral palsy	0.79	0.46	0.87	0.0	0.0	0.0	0.0	4.07
Epilepsy	0.63	0.79	0.0	0.0	0.0	1.72	0.0	2.55
Paralysis	16.96	9.33	0.0	17.73	0.0	0.0	0.0	100.0
Permanent numbness	27.26	24.41	0.0	25.20	0.0	0.0	100.0	66.17
Complications (i.e., have numerous effects):								
Rheumatism and arthritis	66.72	73.26	30.22	100.0	7.78	68.89	100.0	85.97
Diabetes	24.72	16.66	14.26	13.37	0.0	39.93	69.87	42.82
Frequent constipation	38.35	33.48	9.83	35.41	0.0	22.15	100.0	72.45
Frequent insomnia	46.28	42.05	16.70	44.55	0.0	41.77	100.0	64.92
Obesity	15.37	23.52	7.15	24.33	0.0	7.33	68.77	0.0
Mental retardation	3.49	1.84	0.0	0.0	0.0	0.0	0.0	26.33
Senility	14.42	9.20	0.0	0.0	0.0	0.0	0.0	100.0
Miscellaneous:								
Cancer	11.89	6.41	17.63	0.0	37.21	0.0	0.0	5.73
Glaucoma	9.51	8.64	0.0	0.0	0.0	45.49	0.0	16.62
Arteriosclerosis	38.03	31.44	11.48	0.0	0.0	53.61	100.0	100.0
Conditions experienced in last 12 months								
Stroke	16.96	6.60	0.0	0.0	0.0	0.0	0.0	100.0
Circulatory, heart:								
Heart attack	12.84	6.24	0.0	0.0	0.0	0.0	79.55	0.0
Other heart	35.82	29.07	12.27	0.0	0.0	47.11	100.0	41.06
Hypertension	47.07	47.11	23.55	49.93	0.0	43.95	100.0	74.03
Circulatory trouble in arms and legs	56.42	52.43	18.13	54.28	0.0	51.88	100.0	100.0
Respiratory:								
Acute								
Pneumonia	8.87	5.68	3.42	0.0	0.0	0.0	41.51	15.88
Influenza	11.09	16.98	2.27	8.83	0.0	0.0	56.91	10.13
Long term								
Bronchitis	11.09	12.88	0.0	0.0	0.0	0.0	76.51	9.72
Emphysema	11.41	9.86	12.55	0.0	8.86	0.0	50.49	0.0
Asthma	5.71	7.88	0.0	0.0	0.0	0.0	42.49	5.57
Fractures								
Broken hip	7.61	2.30	0.0	30.48	6.34	0.0	0.0	9.21
Other broken bones	9.19	5.55	0.0	31.50	17.17	0.0	0.0	3.43
Functional status[1]								
Activity of daily living								
Bathing	69.89	42.54	0.0	100.0	100.0	100.0	100.0	100.0
Dressing	44.06	21.02	0.0	0.0	100.0	0.0	0.0	100.0
Getting to or using toilet	42.63	19.71	0.0	41.60	100.0	0.0	0.0	100.0
Eating	15.85	6.31	0.0	0.0	0.0	0.0	0.0	100.0
Instrumental activity of daily living								
Doing heavy work	88.27	76.15	29.39	100.0	100.0	100.0	100.0	100.0
Grocery shopping	80.98	63.29	0.0	100.0	100.0	100.0	100.0	100.0
Laundry	70.21	46.42	7.89	48.97	100.0	98.10	100.0	100.0
Preparing meals	59.11	33.77	0.0	0.0	100.0	100.0	100.0	100.0
Doing light work	47.54	29.93	0.0	0.0	100.0	0.0	0.0	100.0
Taking medicine	47.39	25.16	0.0	0.0	100.0	100.0	0.0	100.0
Managing money	46.59	28.75	0.0	0.0	84.70	100.0	0.0	100.0
Making telephone calls	29.00	19.05	0.0	0.0	0.0	62.69	0.0	100.0

See footnotes at end of table.

Table 3—Continued

Percent of disabled elderly persons with home health use, responding to the National Long-Term Care Survey (NLTCS), and in each of six analytically defined dimensions, by health and functional status

Health and functional status	With home health use	Responding to NLTCS[1]	Dimension 1	2	3	4	5	6
			Percent of persons					
Mobility								
Getting around outside	82.25	62.48	0.0	100.0	100.0	100.0	100.0	100.0
Going places outside of walking distance	79.56	60.74	0.0	100.0	100.0	100.0	100.0	100.0
Getting around indoors	65.77	50.11	0.0	100.0	100.0	0.0	100.0	100.0
Getting in or out of bed	53.25	25.85	0.0	100.0	100.0	0.0	100.0	100.0
Wheelchair fast	9.51	3.32	0.0	0.0	0.0	0.0	0.0	57.22
Does not get around inside at all	5.07	1.45	0.0	0.0	0.0	0.0	0.0	37.45
Bedfast	3.65	0.82	0.11	0.0	0.0	0.0	0.0	25.66
Detailed functional status								
Mobility:								
Difficulty climbing stairs								
No difficulty	6.42	16.65	27.88	0.0	0.0	0.0	0.0	0.0
Some difficulty	21.70	27.25	72.12	0.0	0.0	30.25	0.0	0.0
Very Difficult	30.94	34.52	0.0	69.48	0.0	66.94	51.15	0.0
Unable to at all	40.94	21.58	0.0	30.52	100.0	2.81	48.85	100.0
Physical:								
Difficulty lifting and holding a 10-lb. package								
No difficulty	11.76	26.63	52.20	0.0	0.0	0.0	0.0	0.0
Some difficulty	12.44	17.77	36.11	27.74	0.0	0.0	0.0	0.0
Very difficult	13.95	17.56	11.69	34.75	0.0	47.09	0.0	0.0
Unable to at all	61.85	38.04	0.0	37.51	100.0	52.91	100.0	100.0
Difficulty reaching above head								
No difficulty	41.69	52.30	100.0	100.0	0.0	0.0	0.0	0.0
Some difficulty	22.52	22.66	0.0	0.0	59.43	100.0	0.0	0.0
Very difficult	19.49	15.08	0.0	0.0	40.57	0.0	80.41	16.50
Unable to at all	16.29	9.96	0.0	0.0	0.0	0.0	19.59	83.50
Difficulty grasping and handling small objects								
No difficulty	57.39	65.38	100.0	90.87	75.26	47.89	6.68	0.0
Some difficulty	21.78	20.09	0.0	9.13	24.74	52.11	29.97	21.43
Very difficult	13.83	10.79	0.0	0.0	0.0	0.0	63.35	34.39
Unable to at all	7.00	3.75	0.0	0.0	0.0	0.0	0.0	44.18
Can see well enough to read newsprint with glasses	62.60	73.49	100.0	100.0	100.0	0.0	62.98	0.0
Activity of daily living:								
Difficulty bending for socks								
No difficulty	27.05	40.86	100.0	0.0	0.0	0.0	0.0	0.0
Some difficulty	23.21	28.59	0.0	75.07	0.0	100.0	0.0	0.0
Very difficult	23.37	20.18	0.0	24.93	12.88	0.0	100.0	0.0
Unable to at all	26.38	10.37	0.0	0.0	87.12	0.0	0.0	100.0
Difficulty brushing or combing hair								
No difficulty	52.23	68.86	100.0	100.0	0.0	37.58	0.0	0.0
Some difficulty	19.75	17.63	0.0	0.0	39.01	62.42	53.19	0.0
Very difficult	12.26	7.74	0.0	0.0	60.99	0.0	46.81	0.0
Unable to at all	15.76	5.77	0.0	0.0	0.0	0.0	0.0	100.0
Difficulty washing hair								
No difficulty	29.41	52.84	100.0	77.68	0.0	0.0	0.0	0.0
Some difficulty	14.15	16.53	0.0	22.32	0.0	71.83	0.0	0.0
Very difficult	11.13	9.64	0.0	0.0	0.0	0.0	100.0	0.0
Unable to at all	45.31	20.99	0.0	0.0	100.0	28.17	0.0	100.0

[1] Based on the Long-Term Minimum Data Set, National Center for Health Statistics.

NOTE: Based on a 50-percent random sample of respondents.

SOURCE: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from Medicare Statistical System.

In the table, descriptions of the variables are presented in the first column on the left. Contained in the second column are the percent of the disabled elderly with home health use that have the specified attribute. In the third are the percent of the total elderly disabled population that responded to the NLTCS who had the attribute. We see that persons with home health reimbursements are generally sicker and frailer (e.g., 3.65 percent of the home health group are bedfast compared with only 0.82 percent of the total surveyed population). The next six columns contain the probability of having each medical and functional attribute for each of the six dimensions (i.e., the $\lambda_{kj\ell}$'s). The six dimensions can be characterized as follows:

- Dimension 1 includes people with limited and uncomplicated medical problems (e.g., above average amounts of cancer, average amounts of emphysema, below average amounts of diabetes and heart trouble) but little chronic disability.
- Dimension 2 includes people affected by musculoskeletal problems. People in this dimension have the highest proportion of hip and other fractures. In addition, they have serious problems with arthritic and other degenerative joint problems. These people also have IADL mobility limitations—though probably of short duration. No cognitive problems are indicated.
- Dimension 3 includes people with acute, serious medical problems. The most distinctive characteristic of people in this dimension is their high likelihood of cancer. There is some risk of Parkinson's disease and some hip fractures. The dimension has people with serious ADL, IADL, and IADL2 restrictions. There are problems with managing money and medication but not with using the telephone, suggesting that these limitations are not because of cognitive impairments.
- Dimension 4 includes people with primarily chronic medical conditions (though few acute, serious problems) and IADL problems, including those involving cognitive tasks but with few ADL problems.
- Dimension 5 includes people with a combination of chronic and acute circulatory and respiratory problems. The collection of conditions suggests that it represents persons at different stages of circulatory degeneration involving chronic risk factors (e.g., diabetes, hypertension), acute circulatory events (e.g., heart attack), and associated respiratory complications. Though persons scoring high on the dimension are quite ill with several ADL limitations and IADL limitations, none imply cognitive impairment.
- Dimension 6 includes people who are neurologically impaired and chronically morbid. People in this dimension, like those in dimension 4, have a high prevelance of specific medical problems, but they seem to be most distinguished by a high prevalence of dementia and stroke as well as less common forms of neurological impairment. They also have the greatest level of functional impairments, including limitations suggesting cognitive impairment (e.g., managing money and telephoning), as well as the only significant probabilities of being bedfast, wheelchair-fast, and not getting around inside at all.

Several of the dimensions (e.g., 4, 5, and 6) are strongly characterized by multiple conditions and impairments. These conditions are grouped together either because of their tendency to occur with one another or because they produce similar levels of impairment. As a consequence, these case-mix measures can describe the increased service needs of a patient with multiple interacting medical problems—a type of geriatric patient that case-mix measures based upon discrete groups will generally have difficulty describing. The GOM dimensions do not represent all or nothing assignments to specific clinical categories. Thus, the fact that a large number of medical conditions are associated with a given dimension does not mean that we would expect any individual strongly characterized by that profile to have all of those conditions. The g_{ik}'s produced in the GOM solution allow a person to be described by some combination of, say, the attributes in dimension 1 (i.e., the dimension with limited and uncomplicated medical problems and with few chronic functional limitations) and dimension 4. Thus, the g_{ik}'s provide the flexibility to describe the complex but varying patterns of morbid conditions that emerge in very elderly patients. Reflecting the mixed clinical picture, the reimbursement would be a weighted combination of the reimbursement for these two dimensions.

In including both functional status and medical conditions in forming the dimensions, we include variables that determine both the intensity and chronicity of need for services. For example, the functional status of the person may better predict the intensity of need for certain types of services; and the medical conditions may be more predictive of the amount of time the service may be required, the likelihood of rehabilitation (e.g., hip fracture vs. cancer), and the likely future course of change in functional and health status. Thus, in a sense, the description of the state of the individual represented by these case-mix measures implies something about the change in the mix of service needs of a chronic care patient, possibly with multiple medical problems, over a significant period of time.

The six dimensions were reviewed by several physicians at Duke University Medical Center and were found to be clinically meaningful, though no formal evaluation by a physician panel has been conducted yet. We can also examine how those dimensions are associated with variables that were not used to define the dimensions. The probabilities that a given dimension is characterized by a particular variable are presented in Table 4.

The clinical nature of the dimensions seems consistent with these independent variables. Persons in dimensions 4 (with multiple chronic conditions and serious IADL's) and 6 (neurologically impaired with multiple acute medical problems and profound

Table 4

Percent of disabled elderly persons with home health use and percent in each of six dimensions, by demographic characteristics

Demographic characteristic	With home health use	Dimension 1	2	3	4	5	6
	Percent of persons						
Sex							
Male	32.33	49.68	10.08	44.96	28.73	0.0	45.08
Female	67.67	50.32	89.92	55.04	71.27	100.00	54.92
Age							
65-69 years	15.21	8.23	7.86	30.79	8.33	24.80	9.86
70-74 years	18.54	26.97	18.91	17.23	0.0	25.31	18.06
75-79 years	23.14	30.56	21.63	23.93	5.36	43.55	7.80
80-84 years	22.35	22.73	27.41	15.70	37.01	6.35	28.08
85-89 years	14.26	11.51	19.24	1.85	34.40	0.0	24.64
90 years or over	6.50	0.0	4.95	10.51	14.90	0.0	11.56
Mean age of group	0.00	77.6	79.8	76.1	84.2	74.1	81.2
Marital status							
Married	41.52	44.91	17.37	60.44	28.29	52.28	42.16
Not married	58.48	55.09	82.63	39.56	71.71	47.72	57.84
Education							
None	6.34	1.65	3.08	5.44	7.88	3.90	18.15
Grade school	18.07	12.24	8.07	7.52	38.15	25.81	25.75
Junior high	32.01	27.52	38.42	26.40	29.39	49.89	24.42
Senior high	29.48	45.32	28.41	43.99	9.24	18.79	18.51
College	12.84	13.03	19.41	16.65	15.34	1.61	8.19
Graduate school	1.27	0.24	2.61	0.0	0.0	0.0	4.97
Income							
Less than $5,000	15.06	18.71	20.18	0.0	10.21	32.14	14.89
$5,000-$6,999	12.68	13.10	23.33	2.58	15.58	18.24	8.37
$7,000-$9,999	18.07	9.51	19.27	18.82	9.29	27.75	25.42
$10,000-$14,999	16.96	21.04	9.31	29.16	5.65	7.01	19.23
$15,000-$29,999	10.46	8.84	3.00	14.84	14.80	0.43	19.98
$30,000 or more	5.55	5.33	4.11	6.86	12.81	0.0	4.92
Refused to answer	6.81	5.97	12.56	4.61	11.51	6.25	2.04
Don't know	14.42	17.51	8.24	23.14	20.15	8.17	5.15
Works 30 hours per week							
Yes	0.16	0.01	0.40	0.34	0.91	0.22	0.06
No	99.84	99.99	99.60	99.66	99.09	99.78	99.94
Has been hospitalized							
Yes	69.89	57.02	74.15	70.73	55.15	96.35	71.90
No	30.11	42.98	25.85	29.27	44.85	3.65	28.10
Hospital reimbursement							
None	16.01	7.82	22.07	10.79	22.32	5.08	28.84
Less than $3,071	20.44	28.07	17.91	10.74	23.04	35.09	13.12
$3,071-$5,750	20.60	23.06	22.48	25.03	17.47	8.87	21.03
$5,751-$10,110	19.18	23.19	13.67	24.54	13.25	26.07	13.67
$10,111-$19,820	17.12	13.63	21.06	12.63	23.92	22.78	12.08
$19,821 or more	6.66	4.22	2.80	16.27	0.0	2.10	11.26
Number of informal caregivers							
None	11.73	39.41	13.86	2.67	0.0	10.40	0.0
1	46.43	43.41	40.82	47.12	44.67	57.91	48.22
2	24.56	15.94	28.21	25.25	17.34	29.06	23.66
3	9.83	1.23	10.21	11.46	15.56	0.0	19.98
4 or more	7.45	0.0	6.90	13.50	12.43	2.63	8.18
Number of home health visits							
Less than 5	19.33	26.84	31.16	20.59	15.81	12.18	2.67
6-15	24.88	38.43	17.36	24.75	37.66	21.11	5.03
16-30	19.97	20.46	19.22	8.70	23.85	33.51	19.86
31-65	16.16	8.04	21.11	23.74	14.79	15.40	12.27
66 or more	19.65	6.23	11.15	22.22	7.90	17.80	60.17

SOURCE: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey.

impairment) are the oldest (i.e., mean age 84.2 years and 81.2 years, respectively). Those in dimension 5 (multiple circulatory and respiratory problems) are relatively young (mean age 74.1 years), probably reflecting poor survival, but consistent with a lower level of ADL impairment. Persons in dimensions 3 and 6 have the largest number of informal caregivers, and those in dimension 3 (with the highest cancer risk) have high hospital expenditures. Thus, the pattern of conditions represented by the dimensions seems reasonably associated in terms of medical diagnoses, functional status, and in terms of these external criteria.

We also conducted a GOM analysis where we used home health reimbursement and the total number of home health visits in addition to the 56 health and functional status measures to define the six groups. Though the six sets of coefficients ($\lambda_{kjl's}$) for the 56 health and functional status variables were generally similar in the two analyses, there were a few significant differences. The most significant was for the fourth and fifth dimensions. The health profile of persons in dimension 4 was altered most with the emergence of a strong association with stroke (43.5 percent) and dementia (39 percent) along with more atherosclerosis, less glaucoma, and more epilepsy, obesity, constipation, and insomnia. This dimension, which has more persons with neurological impairments and less with acute medical problems than in the analyses of only the health and functional measures, also turns out to have persons with much lower levels of home health reimbursement. Because dementia and long-term stroke effects are unlikely to be reversed or significantly diminished in a very elderly population, it seems reasonable that the home health benefits for such a population should be low if that population does not have many serious acute medical problems. Thus, the introduction of the cost measures in the GOM analysis helped clarify the health and functional status profile of a dimension, and it provides a guide for further development of case-mix measures. The fifth dimension was modified primarily in terms of a reduction in certain ADL measures that made it more purely an acute medical problem dimension (e.g., the mean age of people in this dimension was even lower, 73.9 years).

Estimation of reimbursement levels

Methods

Once the case-mix dimensions are formed using the GOM methodology, the reimbursement level for each is estimated. This is done by regressing the g_{ik}'s (and other relevant covariates) on the level of reimbursement for the *ith* case. Symbolically this may be represented as,

$$\text{Costs or visits} = \left[\text{Rate for a given case-mix dimension} \times \text{Score on case-mix dimension}\right] + \left[\text{Reimbursement adjustment for a covariate} \times \text{Covariates (e.g., hospital use, demographics, State of residence)}\right] \quad (2)$$

or,

$$\text{Reimb}_i = B_l g_{ik} + \beta_c X_{ic} + e_i.$$

Where the g_{ik} are the K scores or weights obtained obtained for the *ith* person in the GOM analysis, e_i's are errors in prediction, and the X_{ic}'s are the individual values (when included) on the relevant covariates. The regression coefficients, B_k's represent the amount that should be reimbursed for a person exactly described by the *Kth* dimension, i.e., for a person who has a $g_{ik} = 1.0$ for that dimension. Because a person can belong, potentially, to more than a single dimension, reimbursement can vary continuously between the bounds established by the B_k, i.e., a person can have a reimbursement that is a weighted combination of two or more B_k's where the g_{ik}'s are the weights. Although the g_{ik}'s are constrained to be less than 1.0, a reimbursement can never be higher than the B_k for the most expensive case-mix dimension. The coefficient β_c represents how much reimbursement should be changed for certain characteristics represented by geographic and other health-service use covariates.

Determining reimbursements in this way has several useful properties. First, the reimbursable amount can be continuously adjusted, through the g_{ik}, to represent differences on all the variables summarized in the definition of the K dimensions.

A second important property of the GOM approach is that the dimensions are designed to explain individual differences in clinical and functional characteristics. In the DRG system, because groups are defined on their ability to predict costs (or lengths of stay), group definitions are dependent on the historical pattern of charges or service use. A reliance on historical charges was a necessary limitation of the data in calculating case-mix weights for acute hospital care. It is potentially a greater problem for LTC reimbursement, where such charges are less well established and often confounded with local market conditions and State regulations.

In our initial analyses, service use was not used to define the dimensions. Thus, the first set of case-mix dimensions was defined only on medical and functional needs. Therefore, if reimbursements have not appropriately been made, this will not confound the definition of the dimensions though individual costs will be difficult to predict from the case-mix scores. If the dimensons are clinically meaningful, the appropriateness of the current reimbursements can be evaluated by the level of predictability of costs. Furthermore, because changing reimbursement levels would not change the case-mix definitions, the case-mix scores could be used to analyze different reimbursement structures and levels.

In the current analysis, we also wished to compare the price levels for case-mix dimensions defined solely on health and functional status with case-mix dimensions where service-use measures have been added in. To do this, in GOM, we included service-use measures in the definition of the K dimensions by adding them to the set of J variables used to define the dimensions. In this way, reimbursement and service variables were objectively combined with the health and functional status measures used to represent the interaction between the health and service variables. Including the reimbursement measures in the definition of the case-mix dimensions, however, makes them functionally related to the outcome measures. Analyses of such augmented sets of composite health measures can be useful to identify the effects of currently unmeasured variables. This is accomplished by examining how the profile of health and functional measures for each case-mix dimension was altered when service use measures were introduced. The changes in the dimensions were described earlier.

In addition to the medical and functional need variables summarized in the g_{ik}'s, one can also add adjustment factors to equation (2) in order to represent nonmedical dimensions (i.e., the X_{ic}). For example, a variable representing metropolitan versus nonmetropolitan residence could be used as a proxy measure for cost differentials between the two types of areas. This can be done either additively (i.e., simply include a dummy variable in the regression for metropolitan residence) or interactively (i.e., enter in the product of metropolitan residence with each g_{ik} to represent the fact that delivering certain packages of services is more expensive in certain areas). In this way, we can determine how much of the cost variation is the result of nonmedical factors (i.e., examine the coefficients for the nonmedical factors) and how much that nonmedical cost variation affected the differentials between the dimensions (i.e., examine the increase or decrease in the B_k after adding the nonmedical factors to the equation).

One final use of this procedure is to make comparisons across populations. For example, given that the g_{ik} estimates are from a national population, they should be representative of the distribution of characteristics determining the use of home health services. In addition, data may be available from demonstration projects that relate more detailed service use measures to the same basic health and functional status measures used to generate the g_{ik}'s from the national sample. In this case, the g_{ik}'s can be estimated for the demonstration populations using the $\lambda_{kj\ell}$'s estimated from the national study. We can then regress these constructed g_{ik}'s on local service-use measures and determine a new set of case-mix rates (B_k's). These rates can be applied to the distribution of the g_{ik}'s in the national survey data. Because the scores (g_{ik}'s) from the demonstration and national samples are related to the same case-mix dimensions (because the $\lambda_{kj\ell}$'s are the same), the blending of the rates (B_k's) with the g_{ik} statistically controls for all of the health and functional measures used to calculate the g_{ik}'s. In a similar way, we can examine the level of use among persons currently receiving a benefit and extrapolate that use to the nonbeneficiary population. This provides estimates of the resources required if the benefits were used more generally by persons with comparable health and functional problems.

In addition to the 56 variables presented in Table 3 used to define health and functional status in the GOM analysis, we used the 15 other measures described in Table 5 with the case-mix measures in our regressions.

These variables control for factors such as informal care days delivered per week and use of nonhome health services (e.g., out-of-pocket payments, SNF use). Some service-use variables (e.g., hospital reimbursement) also serve as proxies of the intensity of medical need for people who were not chronically disabled and, consequently, did not respond to the survey. Finally, we also used dummy variables to represent State differences in home health service use and reimbursement.

In addition to the standard measures of service use, we also employed interaction variables. These variables were designed to determine whether a person with a given set of health or functional problems consumed different amounts of home-health services depending on the amount of hospitalization or institutional care he received. Thus, hospital costs (from Medicare Part A) multiplied by the score (g_{ik}) for health-status dimension 2 (e.g., in Table 4, this represents a hip fracture dimension) describe the effect on home health expenses of increases in hospital costs for persons with a certain level (i.e., value of g_{i2}) of impairments and health problems of the second dimension. Actually, interactions with all six of the health and functional status dimensions were evaluated, but only those with significant effects were included in our analyses.

Table 5

Summary list of service-use measures and socioeconomic variables used in the regressions on service use

Acute and long-term care service-use measures (1982-1983)
Skilled nursing facility bills
Hospital costs
Number informal caregiver days
Out-of-pocket payment
Unmet instrumental activities of daily living service needs
Unmet activities of daily living service needs
Interaction of health and functional status indexes with service use
Hospital costs × score for Type 2
Hospital costs × score for Set 2
Skilled nursing facility bills × score for Type 5
Skilled nursing facility bills × score for Type 4
Socioeconomic measures
Age
Marital status
Sex
Race
Income
State of residence
Dummy variables representing all States

Results: Capitation

In this section, we analyze the use of home health services for 1,286 persons with either Part A or B bills who had an admission date in 1982. For persons who were not in the household survey, we did not have g_{ik} estimates. Because such persons failed to pass the telephone screen for disability, we know that they did not report disabilities of 90 days duration or more. We, however, do not have direct information on their medical status except for their use of hospitals and SNF's (from the Part A records). To include them in our reimbursement analyses, we treated them as a homogeneous seventh dimension with all of their g_{ik}'s for that seventh dimension set equal to 1.0 (given the GOM model logic, they must have zeros for all other g_{ik}'s). This is identical to including them in the regression with a dummy variable to indicate that they were in their own subgroup. Clearly, our R^2 will be lower than it would be if we had g_{ik} estimates for these people. We also defined a separate eighth group of 47 persons who used home health services and were identified as disabled on the screen but for whom g_{ik}'s could not be calculated because of missing survey data.

The regression for the logarithm of home health costs and visits are presented in Table 6.

In these regressions, we truncated the distribution of the measures of service use at two standard deviations from the predicted reimbursement to simulate the risk limiting effect of the special day and cost outlier payments made in the DRG prospective reimbursement system. Technically, this was done in two stages where a regression was run to determine the two-standard deviation bound around the regression line, and a second regression was run with cases that fell beyond this bound adjusted back to the value of the two-standard deviation limit at that point on the predicted regression line. Depending on the spread of the distribution, this improved the R^2's moderately (the effect is moderate because the logarithmic transform also served to reduce the variation due to extreme outliers). Moreover, this truncation procedure produced R^2 estimates that more accurately reflect the risk to home health providers (i.e., outlier reimbursement means that costs beyond the two standard deviation limits will involve special payments) and eliminates variation resulting from statistically deviant cases (i.e., the usual reason for adjusting outlier cases in statistical analyses). The rationale for such a truncation is that the lower weighted amounts can be paid, and the savings in paying those lower amounts can be held in a reserve account to distribute to agencies for cases that go beyond the two-standard deviation values or reimbursements. As an incentive for cost containment on outlier payments, the agency might be reimbursed, say, only 80 percent of the outlier costs to reflect possibly cheaper chronic care visits. An exact payment mechanism would be based on more detailed studies of the nature and costs of different types of home health visits, the nature of visits used by different case-mix groups, and whether the mix of visits for a given type of patient changes over time.

The first step in evaluating these equations is to examine the differences in the B_k between the eight different health status measures. Because we used the logarithm of the costs and visits variables, we provide both the unlogged coefficient that represents the reimbursement amount for persons exactly in a group and the coefficient from the logarithmic equation (in parentheses). These coefficients should be examined to determine if the reimbursement differentials are large enough to provide incentives to respond appropriately to the groups with high service needs and if the level of service is adequate for the needs manifest by persons in different groups.

In Table 6, we see that the cost differences between the dimensions are large—over 6 to 1 between the lowest ($751, dimension 4) and highest ($4,637, dimension 6) use dimensions for total reimbursement and 5½ to 1 for the number of visits. We also see that the reimbursement levels for dimensions 1, 2, and 4 for those without disabilities (set 2) are similar in terms of total reimbursement ($900, $900, $751, and $782) and visits (22.5, 28.8, 20.9, and 21.6). The relatively low cost of the hip fracture dimension ($900) probably reflects rapid rehabilitation. The cancer dimension is highly debilitated, and more expensive ($1,544) than the fifth, cardiovascular, dimension ($1,454), which has few ADL problems. The sixth dimension has the greatest reimbursement level ($4,637). This is probably because these persons qualify for the home-health benefit as a result of an acute medical episode, but they have longer chronic care needs because of their comorbid conditions and cognitive impairment. The 47 persons who passed the disability screen but who did not complete the interview have fairly high expenditures ($1,121), reflecting the likelihood that they probably did not complete the interview because of health problems. Thus, the reimbursement levels for the eight categories of home health beneficiaries seem to be reasonable in terms of their medical and functional characteristics, and they reflect significant differentials in reimbursement for persons in very different functional and health states.

It should be noted that the R^2's for the equations without covariates (16.8 and 14.8 percent) are highly significant. The R^2 values are calculated from the correlation of the predicted value from the regression function, after it has been unlogged, with the observed value of the dependent variable in its original metric. Thus, it reflects the ability of the regression equation to describe variations in the original service use measure. Furthermore, the differences between the B_k's for different dimensions are highly significant, and the equations are predicting individual costs that are much more difficult to predict than the aggregate reimbursement of a home health agency would be. It should also be remembered that we are predicting costs over a long period of time and not for specific episodes, and that we have only partial information on many of the home health

Table 6

Expected home health agency reimbursement costs and number of home health visits for different case-mix dimensions with and without covariates, by selected variables

Variable	HHA[1] reimbursements: Without covariates	HHA[1] reimbursements: With covariates	HHA[1] visits: Without covariates	HHA[1] visits: With covariates
R^2	16.8	25.3	14.8	25.0
Case-mix dimensions (g_{ik}'s)				
Type 1, Acute problem	$900	$781	22.5	28.5
	(6.16)	(6.13)	(2.47)	(2.82)
Type 2, Hip and other fracture	900	750	28.8	33.8
	(6.16)	(6.09)	(2.72)	(2.99)
Type 3, Cancer	1,544	1,738	41.8	68.8
	(6.70)	(6.93)	(3.09)	(3.70)
Type 4, Chronic medical problem	751	750	20.9	28.8
	(5.98)	(6.09)	(2.40)	(2.83)
Type 5, Acute medical problem	1,454	964	47.6	40.5
	(6.64)	(6.34)	(3.22)	(3.17)
Type 6, Multiple problems and neurological	4,637	4,585	114.6	167.4
impairment	(7.80)	(7.90)	(4.10)	(4.59)
Set 1, Incomplete survey	1,121	1,154	31.6	45.6
	(6.38)	(6.52)	(2.81)	(3.29)
Set 2, Not chronically disabled	782	773	21.6	30.0
	(6.02)	(6.12)	(2.43)	(2.87)
Service use (percent change in price)				
SNF[2] bills	—	-2.8	—	-6.3
SNF[2] bills × Type 5	—	1.5	—	16.0
SNF[2] bills × Type 4	—	-17.4	—	-25.0
Hospital costs (per $1,000)	—	1.9	—	1.9
Hospital costs × pure Type 2 (per $1,000)	—	2.5	—	1.4
Hospital costs × Set 2 (per $1,000)	—	-0.1	—	-0.3
Number of informal caregiver days	—	-1.8	—	-1.9
Out-of-pocket payment for long-term care (per $1,000 per year)	—	-1.4	—	-1.3
Unmet activity of daily living	—	-3.8	—	-33.9
Unmet instrumental activity of daily living	—	6.2	—	8.9
Sociodemographic				
Age	—	0.4	—	0.4
Marital status	—	4.4	4.0	—
Male	—	10.4	—	10.1
Income per $1,000	—	-0.4	—	-0.5
Black	—	2.5	—	19.5
State of residence controls	—	(3)	—	(3)
$\bar{x}$	1,133.6	1,127.0	31.5	31.6
Range:				
Predicted	410.2 to	133.1 to	11.0 to	2.6 to
	2,485.2	4,481.3	62.9	108.9
Observed	34.7 to	27.5 to	1.0 to	1.0 to
	17,827.6	15,737.0	356.0	315.0

[1]Home health agency.
[2]Skilled nursing facility.
[3]Numbers and coefficients not presented.

NOTE: Figures in parentheses are log values.

SOURCES: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from the Medicare Statistical System.

beneficiaries. Even with these limitations and without including service measures in the case-mix definition, our ability to predict home health service use at the individual level is significantly better than the ability of DRG's to predict individual hospital costs for medical (e.g., from 6 to 9 percent) and psychiatric (e.g., from 5 to 10 percent) problems in some studies (e.g., Morrison et al., 1985).

In establishing the reimbursement mechanisms for DRG's, adjustments were made for economic and other factors (e.g., State of residence) that could impact costs. The analyses with additional sets of nonhealth and economic status variables are also included in Table 6.

We see that the addition of these additional variables greatly increased the R^2 (to 25.3 and 25.0 percent). The introduction of the covariates affected the reimbursement for dimension 5 most strongly, reducing it by almost one-third. Reimbursement for the third dimension (cancer) increased moderately, and the first two dimensions decreased. The rates for the other dimensions were relatively unaffected by the introduction of the covariates. In interpreting the regression coefficients for the other covariates, we must remember that we are dealing with a logarithmic dependent variable. Consequently, these coefficients represent the percent change in the reimbursement level that change in the covariate would cause. For example, the fact of the visit to a SNF would reduce the reimbursement level by 2.8 percent—probably because of a shortening of the period of home health use by a visit to a SNF. The interaction variables (i.e., SNF x dimension 5 and SNF x dimension 4) show that a SNF visit has a much different effect on home health service use for people strongly characterized by these two types of health problems. In particular, persons in dimension 4 (chronic medical conditions) who have a SNF visit have a 17.4- percent lower home health reimbursement. This is probably because persons in this dimension have a greater likelihood of remaining in a SNF because of the chronic nature of their medical problems.

We see that hospital reimbursement, which can be viewed as a proxy measure for the severity of the medical problem, increases home health expenses 1.9 percent for each $1,000 of expenses in the hospital. This reimbursement effect is much larger for persons with hip fractures (i.e., dimension 2) producing a 4.4-percent increase per $1,000 (i.e., $1.9 + 2.5 = 4.4$ percent) for persons in dimension 2. Having greater amounts of LTC (i.e., number of informal caregiver days and out-of-pocket payments) decreases home health reimbursements as does unmet ADL limitations—possibly reflecting situations where home health is an inadequate service option. In contrast, unmet IADL needs increase home health reimbursement 6.2 percent. Of the social and demographic variables, marital status and sex are most important.

In the equations for the total number of home health visits, we see that certain of the covariates have a larger effect than in the cost equation. Specifically, the effect of SNF use has a greater effect on visits than costs (especially for dimension 5). This probably occurs because the different types of home health visits are differently affected by SNF use—in particular it appears that the more expensive home health visits (for more acute medical problems) are more likely to be reduced by SNF use. For visits we also see a much larger effect of current ADL's (-33.9 percent versus -3.8 percent) and being black ($+19.5$ percent versus 2.5 percent) than in the cost equation.

On the bottom of Table 6, we also presented the minimum and maximum levels of reimbursement—both as observed for these cases and as calculated from the function in the table (i.e., the simulated reimbursement payment). The amount actually paid ranged from $34.70 to $17,827.60. The amount the function suggested to pay ranged from $410.20 to $2,485.20.

In Table 7, the same sets of coefficients are presented as in Table 6 except that the g_{ik}'s for the six dimensions are calculated with 58 variables, i.e, the 56 health and functional variables and home health costs and visits.

The new g_{ik}'s greatly increased the R^2 for both equations with only the health status scores—to 40.7 percent and 37.6 percent. Most striking of the changes in the coefficients are for dimensions 2, 4, and 6. Dimension 4 now has a nearly no service use. Apparently, the introduction of the service measures in the definition of the groups redefined dimension 4 as a demented and neurologically impaired dimension with few acute medical problems. The low service use of this dimension seems consistent with the intent of the home health benefit, because these persons would have little likelihood of improving their cognitive status; and there were few coexistent physical problems that could be benefited by home health service. The increase in reimbursement for dimensons 6 and 2 reflect the effect of introducing the interaction of service use with health status. Thus, there are factors (e.g., early mortality for highly morbid persons, high potential for rehabilitation) affecting these two dimensions that drive up costs that are not reflected in the original 56 health and functional status measures.

The introduction of covariates into the cost equations shows effects similar in sign but generally larger than in Table 6. For example, SNF use for dimension 4 reduces the home health reimbursement 86.3 percent, and hospital bills increase home health reimbursement 10 percent per $1,000 of hospital costs. The effect of unmet needs increases as does the effect of being black. The sign of the sex coefficient reversed.

The coefficients for the total number of visits equation are generally consistent with the pattern of increases and decreases for the cost equation.

At the bottom of the table, we see that the range of reimbursements predicted by the equations is much greater (i.e., 153.20 to 7986.70) reflecting the higher predictability of costs.

Results: Episodes

In Table 8, we present an analysis of constructed episodes orginating in a 12-month interval centered on the midpoint of the survey.

The R^2's (30.4 and 30.7) for episodes using the g_{ik}'s from the 58 variable GOM analyses are not as high as for the capitation model. In this case, however, the covariates increase R^2's to 43.2 and 42.3 percent—values as high as for the capitation results.

The prices for the case-mix dimensions are similar to those in Table 7 except for dimensions 5 and 6. Dimension 5 shows a large increase in reimbursement (to $1,738). Dimension 6 experienced a decrease to $6,841 in the episode model. The effects of SNF use for the episode model are much greater than for capitation, and the effects of hospital reimbursements are smaller.

Table 7

Expected home health agency reimbursement costs and percent of home health agency visits, with and without covariates, by selected variables

Variable	HHA[1] reimbursements: Without covariates	HHA[1] reimbursements: With covariates	HHA[1] visits: Without covariates	HHA[1] visits: With covariates
R^2	40.7	44.8	37.6	41.7
Case-mix dimensions (g_{ik}'s)				
Type 1, Acute problem	$954	$750	24.3	27.1
	(6.86)	(6.62)	(3.19)	(3.30)
Type 2, Hip and other fracture	1,940	1,108	61.6	49.9
	(7.57)	(7.01)	(4.12)	(3.91)
Type 3, Cancer	1,557	1,541	42.5	60.3
	(7.35)	(7.34)	(3.75)	(4.10)
Type 4, Chronic medical problem	41	37	1.0	1.5
	(3.71)	(3.66)	(0.07)	(0.42)
Type 5, Acute medical problem	1,301	880	42.1	36.3
	(7.17)	(6.78)	(3.74)	(3.59)
Type 6, Multiple problems and neurological impairment	8,783	6,905	221.5	257.2
	(9.08)	(8.84)	(5.40)	(5.55)
Set 1, Incomplete survey	1,013	934	28.2	37.3
	(6.92)	(6.84)	(3.34)	(3.62)
Set 2, Not chronically disabled	700	578	19.3	22.4
	(6.55)	(6.36)	(2.96)	(3.11)
Service use (percent change in price)				
SNF[2] bills	—	-3.4	—	-7.3
SNF[2] bills × Type 5	—	6.3	—	28.0
SNF[2] bills × Type 4	—	-86.3	—	-90.8
Hospital costs (per $1,000)	—	10.0	—	1.1
Hospital costs × pure Type 2 (per $1,000)	—	5.9	—	4.4
Hospital costs × Set 2 (per $1,000)	—	0.8	—	1.0
Number of informal caregiver days	—	-1.3	—	-1.4
Out-of-pocket payment for long-term care (per $1,000 per year)	—	-1.8	—	-1.7
Unmet activity of daily living	—	-36.3	—	-33.2
Unmet instrumental activity of daily living	—	18.3	—	21.0
Sociodemographic				
Age	—	0.5	—	0.5
Marital status	—	4.2	—	4.2
Male	—	-9.7	—	-9.5
Income per $1,000	—	-0.1	—	-0.8
Black	—	27.3	—	20.9
State of residence controls	—	([3])	—	([3])
$\bar{x}$	1,135.6	1,132.2	31.5	31.8
Range:				
Predicted	153.2 to 7,986.7	90.5 to 11,124.2	4.1 to 200.9	2.2 to 293.2
Observed	28.5 to 18,327.6	27.5 to 18,327.6	1.0 to 356.0	1.0 to 356.0

[1]Home health agency.
[2]Skilled nursing facility.
[3]Numbers and coefficients not presented.

NOTE: Figures in parentheses are log values.

SOURCES: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from the Medicare Statistical System.

Discussion

We have demonstrated that a multivariate classification strategy could be used to generate a case-mix index for Medicare home health benefits based on dimensions that were clinically distinct, that had significant differences in reimbursement that were consistent with the clinical nature of the dimensions, and that predicted both individual costs and visits over a long period of time very well.

In producing case-mix measures for different definitions of episodes and fixed intervals, insights were developed into the use of the home health benefit—and the implications of that use for case-mix strategies. First, the capitation and episode models predicted service use at the individual level equally well. The health composite variable was more strongly predictive in the capitation model, and the interaction of prior acute care service use with the health composite variable was more important for the

Table 8

Expected home health agency reimbursement costs and percent of home health agency visits, with and without covariates, by selected variables

Variable	HHA[1] reimbursements		HHA[1] visits	
	Without covariates	With covariates	Without covariates	With covariates
R^2	30.4	43.2	30.7	42.3
Case-mix dimensions				
Type 1, Acute problem	$926	$624	24.5	14.2
	(6.30)	(6.03)	(2.67)	(2.65)
Type 2, Hip and other fracture	2,102	859	63.5	35.4
	(7.12)	(6.35)	(3.62)	(3.16)
Type 3, Cancer	1,809	1,459	49.5	51.2
	(6.97)	(6.88)	(3.35)	(3.53)
Type 4, Chronic medical problem	42	47	1.1	1.7
	(3.20)	(3.45)	(−0.43)	(0.13)
Type 5, Acute medical problem	1,738	978	51.9	34.7
	(6.93)	(6.48)	(3.42)	(3.14)
Type 6, Multiple problems and neurological impairment	6,841	4,087	176.0	140.5
	(8.30)	(7.91)	(4.64)	(4.54)
Set 1, Incomplete survey	935	739	25.3	26.5
	(6.31)	(6.20)	(2.70)	(3.28)
Set 2, Not chronically disabled	821	516	22.2	18.1
	(6.71)	(5.84)	(2.57)	(2.90)
Service use (percent change in price)				
SNF[2] bills	—	17.7	—	−17.5
SNF[2] bills × Type 5	—	−364.1	—	−345.0
SNF[2] bills × Type 4	—	−126.6	—	−143.0
Hospital costs (per $1,000)	—	1.7	—	1.8
Hospital costs × pure Type 2 (per $1,000)	—	7.4	—	6.0
Hospital costs × Set 2 (per $1,000)	—	1.3	—	1.1
Number of informal caregiver days	—	−1.6	—	−1.5
Out-of-pocket payment for long-term care (per $1,000 per year)	—	−1.7	—	−1.9
Unmet activity of daily living	—	−26.6	—	−23.0
Unmet instrumental activity of daily living	—	54.2	—	56.2
Sociodemographic				
Age	—	0.9	—	0.8
Marital status	—	6.8	—	6.7
Male	—	−3.7	—	−3.7
Income per $1,000	—	−0.01	—	−0.1
Black	—	49.6	—	41.5
State of residence controls	—	([3])	—	([3])
$\bar{x}$	1,204.7	1,202.0	32.8	33.0
Range:				
Predicted	166.5 to 5,376.6	103.8 to 7,431.6	4.5 to 138.2	2.3 to 211.4
Observed	30.4 to 11,899.3	27.5 to 11,899.3	1.0 to 342.0	1.0 to 342.0

[1] Home health agency.
[2] Skilled nursing facility.
[3] Numbers and coefficients not presented.

NOTE: Figures in parentheses are log values.

SOURCES: Health Care Financing Administration and Office of the Assistant Secretary for Planning and Evaluation, Department of Health and Human Services: Data from the 1982 National Long-Term Care Survey; Health Care Financing Administration, Bureau of Data Management and Strategy: Data from the Medicare Statistical System.

episode definition. This seems reasonable given that the episode accumulation of home health reimbursement is driven by the medical acuity of the health problems involved. The capitation model seemed to be less time dependent and to function more like a purely long-term care benefit. This would seem to suggest the superiority of the capitation based case-mix measures. Second, the introduction of reimbursement and visits into the GOM analyses to produce augmented health composite measures produced two important insights. One insight was that, by employing service use measures in the definition of case mix in a similar fashion to the construction of discrete case-mix categories on charges or length of stay, the R^2 of the individual prediction was greatly increased. Additionally, the health content of the composite measures was altered by the introduction of the cost measures (and in ways that seemed clinically reasonable). These insights are useful in guiding subsequent research. Finally, we saw that the other service use measures included in the regressions had significant impact. Consequently, the use of the case-mix index has to take into account the informal care resources of the individual; the substitutability of institutional, hospital, and home health care; and the individual's own resources and payments out of pocket for formal care.

The analysis illustrated both the potential for developing a home health case-mix measure and the feasibility of developing case-mix measures for other types of community based LTC services. These analyses should be viewed, however, as demonstrating feasibility rather than as defining the precise reimbursement mechanisms because the analyses lacked precise cost and service data and we did not possess data identified by provider to determine the aggregate cost implications of different reimbursement strategies across home health agencies. Nonetheless, the results demonstrate the potential for prospectively reimbursing home health services to create incentive to care for frailer subpopulations but yet to preserve the overall budget neutrality of the benefit.

Summary

In the foregoing analyses, we used data from the 1982 NLTCS linked to reimbursement records for Medicare Part A and B to generate case-mix measures for home health service reimbursement. In the NLTCS, 6,393 people were identified as chronically disabled (>90 days impairment in an ADL or IADL) from 36,000 persons drawn from the health insurance master file. For these 6,393 persons, two types of rules were calculated for describing use of home health benefits. The first defined episodes of care for continuous periods of service use beginning within 6 months of the survey date—1,316 persons of the 36,000 had home health service use, with 712 of these disabled persons. The second defined a fixed interval or capitation period. In this case, we examined any bill that had a beginning date in 1982—1,286 of the 36,000 had some health bills in 1982, with 691 of these persons chronically disabled.

To generate a case-mix measure, a multivariate procedure was applied to health and functional status measures recorded in the survey. Included among these were 29 diagnostic indicators and 27 ADL, IADL, and IADL2 measures. The procedure identified the following six clinically meaningful dimensions:

- A relatively functionally intact dimension with limited medical problems.
- A dimension characterized by musculoskeletal problems with serious mobility limitations.
- A dimension with cancer and other acute medical problems.
- A dimension with multiple chronic health problems.
- A dimension with acute and chronic circulatory and respiratory problems.
- A neurologically impaired dimension with a wide range of functional problems.

Table 9

Percent of variance explained for different home health service regression models with different periods of service definitions, health measures, and levels of control for other covariates

Source	Variables used in constructing case-mix dimensions	Period type	Case-mix dimensions only	Case-mix dimensions and other covariates
			Percent of variance	
Table 6	Health, functional (56)	Capitation	16.8	25.3
Table 7	Health, functional, services (58)	Capitation	40.7	44.8
Table 8	Health, functional, services (58)	Episode	30.4	43.2

Individual scores on each of these dimensions were regressed on the logarithm of both home health total reimbursements and number of visits. The level of prediction using these health and functional status measures is provided in Table 9 along with the level of prediction achieved when additional service-use measures are included.

Up to 45 percent of the individual variation of home health reimbursements could be explained. This level of predictability can be compared with the level of prediction achieved by the DRG case-mix system for individual costs for Medicare hospital charges. For all DRG's in four States with available data in 1982 (i.e., Michigan, New Jersey, North Carolina, Washington), the level of predictability was from 17 to 30 percent, with three States being between 16 and 18 percent. Perhaps more importantly, the overall level of DRG prediction was higher because of high R^2's for surgical DRG's. The R^2's for medical and psychiatric DRG's, which would seem to be more comparable to predicting home health use, were much lower, i.e., from 6 to 9 percent for medical DRG's and from 5 to 10 percent for psychiatric DRG's (Morrison et al., 1985). Thus, though we did not use identically the same regression methodology for evaluating the level of fit as in those studies, it appears that the level of prediction achieved by the GOM groups in predicting individual costs is higher than that achieved for the DRG groups—especially for individual medical and psychiatric hospital costs. Because we did not have home health agency specific costs, we cannot compare the ability of the GOM groups to predict aggregate agency costs with the DRG ability to predict hospital level costs that had been cited as about 35 percent using case-mix index only and about 72 percent using case-mix and nonmedical variables (Pettingill and Vertrees, 1982).

The research reported in this article had two purposes: to assess the feasibility of developing case-mix indexes for home health service and to analyze the factors contributing to the use of the services. The results of the study suggest strongly that it is feasible to develop such case-mix indexes; but that, not surprisingly, they will be differently structured than case-mix indexes for acute care. Central to the differences between the two types of measures are the needs in the home health indexes to reflect the likely chronicity of service use, the effect of service substitution on the period of home health service use, and the impact of individual economic and family resources on home health use.

Naturally, before actually implementing a specific case-mix index, a significant amount of validating work and research is required. For example, one would need to apply any derived case-mix measure to more extensive sets of data to see how well the structure of the case-mix groups replicates. One should also evaluate the performance of the GOM methodology (and the blended rate pricing methodology) against other grouping procedures (e.g., Autogroup—the classification program used in the creation of the DRG categories). Finally, one should compare the performance and structure of the GOM dimensions with those derived for reimbursements in nursing homes (e.g., RUG's or resource utilization groups) and with those developed for acute care reimbursement (i.e., DRG's and some proposed modifications). Such a comparison could help us understand differences in market mechanisms and patient needs in each service area. This could help us to determine how the different case-mix systems might need to be coordinated and to better understand the impact on levels of services delivered under those systems. We are currently involved in the extension of these evaluations to the 1984 replication of the national LTC survey and to comparisons with other grouping methodologies.

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