Determinants of Hospital Casemix Complexity

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Using the Commission on Professional and Hospital Activities' Resource Need Index as a measure of casemix complexity, this paper examines the relative contributions of teaching commitment and other hospital characteristics, hospital service and insurer distributions, and area characteristics to variations in casemix complexity. The empirical estimates indicate that all three types of independent variables have a substantial influence. These results are discussed in light of recent casemix research as well as current policy implications.

Developments in hospital casemix measurement are currently taking place in several research centers in the United States; in fact, the frontiers of health services research are advancing rapidly in this area. Casemix measures have several important applications: they can be used in managerial decision-making by administrators and health planners; they are extremely useful in research on hospital performance; and they are essential to the successful implementation of reforms in hospital reimbursement that attempt to relate hospital payment to outputs produced rather than to costs of inputs consumed.

The need for reimbursement reform is the primary impetus for the development and refinement of hospital casemix measures. The inflationary consequences of cost-plus hospital reimbursement are well documented and have led to several programs designed to impede cost increases by

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devising reimbursement constraints that recognize variations in innate expensiveness of different hospital product combinations. At the federal level, Section 223 of P.L. 92-603 (the 1972 Social Security Act Amendments) has established limits on reimbursement for routine hospital services delivered to Medicare patients. These limits incorporate a simple system of classifying hospitals by bedsize and urban/rural location which is partially based on evidence that hospitals in different bedsize-location groups vary systematically in the complexity of illnesses treated [1]. More sophisticated systems that explicitly recognize differences in individual hospital casemixes, such as those being used in New Jersey, New York, Maryland, and Georgia, are currently in the experimental stage but are expected to be fully implemented in some areas in the near future [2].

Casemix measurement is a means to an end. Most hospital payment systems implicitly regard casemix as exogenous in reimbursement formulas. Consequently, there had been very little analysis of factors that underlie variations in casemix complexity among hospitals. Our investigation postulates that if casemix measures are to be used in reimbursement systems and in other applications, it is essential to understand what accounts for variations in casemix complexity. Identification of complexity determinants can assist in the development of reasonable proxy measures in situations where detailed casemix measurement is infeasible. In addition, it is important to distinguish factors affecting casemix complexity that are beyond the control of the hospital from factors that may be viewed as decision variables. Such information would be useful for predicting potential behavioral responses to certain reimbursement reforms.

This study attempts to determine the relative contributions of hospital, patient, and area characteristics to variations in casemix complexity. It is part of conventional wisdom that teaching hospitals attract complex cases, on average, but the degree to which casemix complexity in such hospitals accounts for their relatively high level of average costs per case is a topic of controversy. Patient groups covered by major types of health insurance tend to vary in type and severity of illness—an obvious example is that of Medicare patients who suffer from diseases common to elderly populations. For the most part, however, reimbursement systems are insensitive to such differences. Our empirical analysis embraces these and other policy issues.

Recent developments in casemix measurement and applications are briefly discussed in the first section. There we describe the Resource Need Index, our measure of hospital casemix complexity, which was developed by the Commission on Professional and Hospital Activities (CPHA). Conceptual considerations on which the empirical analysis is based are discussed at the end of this section. In the second section we specify and estimate a model of casemix complexity based on data from CPHA's Professional Activity Survey. Conclusions and policy implications are discussed in the final section.

BACKGROUND AND APPROACH

TRENDS IN CASEMIX MEASUREMENT

The history and current state of hospital casemix measurement are admirably summarized in recent articles by Ament and others [3], Bentley and Butler [2], and Watts and Klastorin [4]. Briefly, casemix measures fall into two broad groups: indirect measures and direct patient-related measures. Indirect, or proxy, measures have been widely used in health services research. Such measures include hospital bedsize [5], assets per bed [6], number of facilities and services offered [7-9], and other hospital characteristics presumed to be associated with casemix complexity [10-12]. Direct casemix measures, typically based on diagnostic classifications of hospitalized patients, have been used more sparingly [13-18].

The diversity of proxy variables used to represent casemix variations in research attests to the fact that no single variable or set of variables has been found to be superior. In fact, Lave and Lave [19] show that although a number of proxy variables—bed size, number of facilities and services, and hospital teaching status—are correlated with casemix, they explain a relatively small proportion (less than one-half) of variation in such direct casemix measures as diagnostic distributions, surgical complexity, and extent of surgery performed. Nevertheless, the major virtue of proxy variables, relative to direct measures, is that the former are cheap; that is, the data required to construct proxy variables are readily available in many existing hospital data bases. Most of the research on hospitals that has used direct casemix measures is based on relatively small, localized hospital samples, whereas research using proxy variables more often is based on large national samples of hospitals.

Researchers frequently lament the unavailability of detailed direct measures because lack of adequate control for casemix variations may be a source of bias in estimating the influence of other factors on hospital performance. But most research is intended to gauge aggregate tendencies, and some imprecision in variable measurement is tolerable. Put another way, the lack of detailed patient-related casemix variables in past research on hospitals reflects a tacit consensus that the costs of acquiring the necessary data were likely to have exceeded the value of the marginal contribution to precision in estimation. If there were no reason for casemix measurement other than health services research, it is unlikely that casemix measurement would have progressed as far as it has to date.

In contrast to research applications, imprecision in casemix measurement in reimbursement systems may have serious consequences. In this context, individual hospitals' revenues are at stake, not just aggregate tendencies, and imprecision may result in serious reimbursement inequities. Thus, if variations in routine hospital costs are associated with variations in casemix, then reimbursement systems that classify hospitals on the basis of proxy variables, such as the Section 223 per diem routine cost limits, may be justifiably criticized for creating winners and losers in the reimbursement game.

The most advanced method of defining hospital casemix on the basis of diagnosis is the Diagnosis Related Group (DRG) system developed at Yale University. Descriptions of DRGs and current applications are readily available elsewhere [2, 20, 21]. DRGs were initially developed to examine hospital utilization patterns, but they are currently being used in several reimbursement systems. The 383 terminal DRGs classify patients into exhaustive, nonoverlapping groups that are, in theory, individually homogeneous with respect to resources required for patient treatment. DRGs per se do not constitute a measure of casemix complexity. Weights must be assigned to each group and a weighted average taken to arrive at a single measure of casemix complexity for a hospital. Pettengill and Vertrees [17] constructed a DRG case complexity index for 4,113 hospitals and found that the index was an important determinant of variations in Medicare cost per case.

DRGs are not necessarily an ideal measure of hospital casemix, nor are they the only measure based on patient diagnosis. Other systems, based on differing methods of grouping patients, are described in the literature [2, 22-25]. The Resource Need Index (RNI), which was developed by the Commission on Professional and Hospital Activities (CPHA), is a single-value index of hospital casemix complexity based on charges associated with treatment of different illnesses. The RNI is the casemix measure employed in the empirical section of this paper.

THE RESOURCE NEED INDEX

The RNI is based on a matrix of 349 broad disease categories broken down by five age groups and whether or not the patient had surgical treatment. For each of the resulting 3,490 cells CPHA has developed a charge-based weight. The weight represents the average charge per case for each cell calculated from a sample of over 2 million patient records from hospitals that participated in CPHA's Survey of Patient Charges from 1971 to 1976. Before calculating the charge weights, CPHA has adjusted actual charge data to correct for inflation in hospital charges over the period that patient data were collected and for the degree to which individual hospitals' case-type-specific charges tend to be relatively high or low compared to the entire base-data hospital sample. Each hospital's charges were raised or lowered by a constant factor depending on how its charges for each case type, aggregated across all case types, compared to those of all hospitals in the charge survey. The charge weights were converted to index values by dividing by the mean charge for all patients in the sample [3].

In contrast to the research and reimbursement applications of casemix measures, the RNI was originally developed as a managerial tool for subscribers to CPHA's information service. With the case-weight matrix in hand, however, an RNI can be calculated for any hospital (or any subset of its patients) provided the distribution of patient cases is supplied. To build the RNI for a hospital, each patient is assigned the index value from the cell corresponding to the patient's age-diagnosis-surgery status. The sum of these index values divided by the number of patients yields the RNI for the hospital [3].

Like all existing casemix measures, the RNI is subject to criticism. The charge weights and individual hospital RNIs must be recomputed periodically to account for technological and other changes, although Lave and Lave [19] have shown that hospital casemixes tend to remain stable for a period of years. Despite the fact that the RNI is based on a large number of patient records, only about 50 self-selected hospitals were represented in the base data survey, which may be a source of inaccuracy in the RNI as a tool for measuring hospital case complexity nationwide. In addition, because the RNI is a single-value index, it may not be able to capture the richness of diversity in hospital casemix [4].

All of these criticisms are certainly valid and shared by several other measures of case complexity. Inaccuracies implied by these criticisms do not lead to systematic bias in the RNI, but errors-in-variables in the index values will bias measured relationships between the RNI and its correlates toward zero. As shall be shown in the empirical section, however, the levels and statistical significance of associations between the RNI and its hypothesized determinants are quite high by conventional standards. The most serious criticism of the RNI is that because it is based on charges rather than costs it is not a true measure of resource requirements for treating illness in hospitals. Because this criticism implies that a form of systematic bias may arise from basing the RNI on charges, this potential problem requires extra attention.

If hospital charges were always equal to costs, or if they differed from costs by a constant factor for all illnesses, RNI case weights would not be affected at all. In addition, the fact that some hospitals typically have higher charge-cost ratios than others is not a source of systematic bias. CPHA's adjustments to charges correct for such tendencies, which would only be a source of nonsystematic measurement inaccuracy in any case. Two conditions are necessary for charges to introduce systematic bias into the RNI. First, some illnesses (or, more specifically, some diagnosis-age-surgery groups) must systematically have higher charge-cost ratios than others. One can readily anticipate that this is likely to be the case for illnesses that typically require heavy use of ancillary services, both diagnostic and therapeutic. Second, hospitals must systematically specialize in treating illnesses with either relatively high or low charge-cost ratios. For example, if proprietary hospitals tend to be "cream-skimmers," their RNIs may overstate true resource costs relative to those of other hospitals. It is important to recognize that the second condition is necessary for systematic bias. If only the first condition holds true (or is important), it will introduce "noise" of the sort discussed above into computation of the RNI but not systematic bias.

Although many analysts would prefer casemix measures to be based on costs rather than charges [16], computation of cost-based measures is not without problems. Even if the necessary cost data were readily available, the joint cost allocation problem and wide variation in cost accounting techniques employed by hospitals are important sources of measurement error. In any case, the conditions for systematic bias in the RNI are stringent and, more to the point, only charge data were available for computation of the index.

Fortunately, some comparisons between the RNI and other casemix measures have been conducted. Ament and others [3] found great similarity between the DRG case classifications and those on which the RNI is based. In a comparative study of case complexity measures pertaining to a sample of 316 short-term hospitals, Watts and Klastorin [4] found that the RNI correlated highly ($r = 0.97$) with a DRG index based on case weights developed from New Jersey hospitals. The DRG index was based on costs rather than charges; therefore, the charge foundation of the RNI is unlikely to be a source of substantial systematic bias. In general, there was considerable similarity among all case complexity measures based on diagnostic groupings, suggesting that an empirical examination of variations in case complexity should be relatively insensitive to the specific measure used.

CONCEPTUAL CONSIDERATIONS

The system that governs the distribution of patient cases among hospitals is undoubtedly very complex, and a complete model of such a system would necessarily encompass a long time period and all components of the health sector. Factors that determine the distribution of illness in the population would need to be depicted, as would the interactions between health care delivery and illness and the influence of social, environmental, and technological change. It is beyond our scope and resources to specify and estimate a model of this sort. Nevertheless, we are able to specify a much simpler model to investigate cross-sectional variations in hospital case complexity. Our approach implicitly assumes that even when the distribution of illness and other factors are held constant (as in a cross section), there is considerable play in the system. Factors that may influence cross-sectional hospital case complexity variations include the extent to which illnesses are diagnosed and treated, whether treatment occurs in hospitals or in other health care settings, and modes of hospital treatment (e.g., surgical versus nonsurgical). In addition, the distribution of cases among hospitals may be influenced by intercommunity patient border-crossing and by the extent and type of competing hospitals and other health care providers within communities.

We assume that hospitals differ systematically in their preferred output combinations and that these differences influence patient mix. Several of the variables in our specification are intended to determine the relative influences of specific hospital characteristics on case complexity. We further assume that certain characteristics of a hospital's patient population are associated with average complexity of illness. In particular, type of insurance coverage may influence case complexity both through the demographic correlates of health insurance and illness and through an association between coverage and the propensity to seek care in hospitals.

We expect the composition of the hospital's medical staff to influence case complexity. In our data base we do not have direct information on medical staff characteristics; instead, this factor is represented by the distribution of patients with respect to basic case types—surgical, pediatric, and so forth. In addition to their value as proxies for medical staff composition, such variables allow us to gauge complexity levels associated with fundamental categories of medical treatment.

Various characteristics of the hospital's locale may influence the extent to which community illnesses are treated in community hospitals. Our specification contains several area variables to capture the effects of characteristics of the hospital's county, including its health care resources. In sum, our behavioral model is based on the assumption that cross-sectional variations in hospital casemix complexity are a function of characteristics of hospitals, patients, and the communities in which hospitals are located. Specific variables, hypotheses, and the empirical estimates are presented and discussed in the next section.

Empirical Findings

DATA AND DESCRIPTIVE STATISTICS

The sample consists of 397 hospitals, each of which gave permission to allow PAS data for 1974 to be used for research purposes. In addition to the

RNI for the hospital, data on expected payment sources and service distributions were obtained from the PAS data set. Additional hospital-specific data were obtained from the American Hospital Association's Annual Survey for 1974 and Survey of Medical Staff Organization conducted in 1973. These data were merged with readily available information on counties in which sample hospitals are located to construct a complete data set for examination of casemix complexity determinants.

Sample hospitals were not randomly selected since participation in PAS is voluntary. However, 46 states (including Washington, D.C.) are represented and sample hospitals account for approximately 13 percent of hospital beds, admissions, and births in all nonfederal short-term general hospitals in the United States. Comparing sample hospitals to the universe, the former are larger on average (274 beds versus 150 beds), less costly on a per admission basis ($916/admission versus $992/admission), and have slightly fewer personnel per bed (2.43/bed versus 2.46/bed).

For sample hospitals, the average RNI is 0.97, slightly below 1.00, the average for all hospitals in the cohort that generated the charge weights on which the RNI is based. Table 1 gives breakdowns of the RNI for sample hospitals along common hospital characteristics. These breakdowns indicate that the RNI is higher for nongovernment hospitals, it increases with bedsize and level of teaching commitment, and it is highest in the eastern and western regions of the country and in urban areas. RNI differences displayed in Table 1 do not appear large, but the RNI is tightly distributed—its coefficient of variation is 0.11.[1] All of the RNI differences shown in the table are statistically significant at the 0.01 level.

In examining sources of variation in casemix complexity, we cannot be satisfied with bivariate statistics. We use regression analysis, with all variables entered in linear or binary form, to estimate the contribution of independent variables to variations in the casemix complexity index. Variable descriptions and hypotheses are integrated with the discussion of empirical results. In addition to the estimates presented below, we have also estimated a predictive model, based solely on data available from American Hospital Association Annual Surveys, to generate a casemix complexity instrument for use as an independent variable in other research on hospitals. Parameter estimates from this equation are available from the authors on request.

REGRESSION RESULTS

Variable definitions, means, standard deviations, and parameter estimates pertaining to the RNI regression are presented in Table 2. On the whole, we are able to explain a considerable amount of variation in casemix complexity with a linear specification that includes variables describing hospi-

Table 1. RNI by Selected Hospital Characteristics

Variable	*RNI*	*(N)*	*Variable Name*	*RNI*	*N*
Ownership*			Bed size		
Nongovernment	0.981	(530)	< 100	0.903	(67)
Government	0.939	(76)	100-249	0.955	(144)
			250-399	0.996	(109)
			≥400	1.028	(86)
Location			Teaching Commitment‡		
Rural	0.933	(149)	NONE	0.943	(275)
Urban	0.996	(257)	RES	1.006	(26)
			MEDSCH	1.024	(56)
Region†			COTH	1.063	(49)
EAST	1.012	(82)			
NCENTRAL	0.956	(165)			
SOUTH	0.954	(97)			
WEST	1.027	(62)			

*Federal, for-profit, and specialty hospitals are excluded from the comparison.
†EAST—ME, NH, VT, MA, RI, CT, NY, NJ, PA;
NCENTRAL—OH, IN, IL, MI, WI, MN, IA, MO, ND, SD, NE, KS;
SOUTH—DE, MD, DC, VA, WV, NC, SC, GA, FL, KY, TN, AL MS, AR, LA, OK, TX;
WEST—MT, ID, WY, CO, NM, AZ, UT, NV, WA, OR, CA.
‡NONE—no teaching program; RES—approved residency program; MEDSCH—medical school affiliation; COTH—member of Council of Teaching Hospitals. Hospitals are defined according to their highest level of commitment.

tal characteristics, distributions of clinical service and insurance coverage proportions, and community characteristics. The adjusted R^2 for the RNI regression is 0.77, and the equation is significant at the 0.01 level. Because the dependent variable is an index, elasticities have little meaning; however, the parameter estimates permit us to gauge the direction and relative magnitudes of effects of the exogenous variables on casemix complexity. Relative contributions of the independent variables are indicated by the beta coefficients in Table 2.[2]

Hospital Characteristics

The hospital's teaching status is defined by three binary variables: T1, T2, and T3. T1 equals one if the hospital has at least one approved residency program but no medical school affiliation; T2 is one if the hospital has a medical school affiliation without membership in the Council of Teaching

Table 2. Variables, Means, Standard Deviations, and Regression Results

Variable§	*Mean*	*Standard Deviation*	*Regression Coefficient*	*Standard Error*	*Beta*
RNI	0.97	(0.11)	—	—	—
T1‖	0.063	—	0.046*	(0.011)	0.10
T2‖	0.14	—	0.057*	(0.0086)	0.18
T3‖	0.12	—	0.096*	(0.011)	0.29
RESRCH‖	0.12	—	0.034*	(0.010)	0.10
GOVT‖	0.19	—	0.0031	(0.0071)	0.011
OCC	0.77	(0.10)	0.11*	(0.031)	0.10
OUTPAT	0.73	(0.45)	0.016*	(0.0063)	0.068
MCARE	0.20	(0.07)	0.68*	(0.062)	0.43
MCAID	0.068	(0.071)	0.082‡	(0.043)	0.055
BLUE	0.26	(0.14)	-0.063†	(0.026)	-0.084
OTHINS	0.086	(0.16)	0.11*	(0.024)	0.17
NOINS	0.080	(0.068)	-0.062	(0.048)	-0.039
MED	0.27	(0.068)	-0.13‡	(0.067)	-0.083
PED	0.042	(0.027)	-1.02*	(0.11)	-0.25
OBG	0.18	(0.057)	-0.75*	(0.074)	-0.40
OTH	0.10	(0.036)	-0.32*	(0.11)	-0.11
URBAN‖	0.63	—	0.010	(0.0074)	0.047
PCY	4.46	(6.36)	0.017*	(0.0048)	0.10
BEDPOP	4.90	(2.20)	0.0009	(0.0014)	0.018
GPPROP	0.25	(0.19)	-0.073*	(0.021)	-0.13
CONSTANT	—	—	0.90	—	—

R^2 (C) = 0.77
F (20, 377) = 67.7*

*Significant at the 0.01 level (two-tailed test).
†Significant at the 0.05 level (two-tailed test).
‡Significant at the 0.10 level (two-tailed test).
§Variable definitions: RNI—resource need index; T1—hospital with an approved residency program; T2—hospital with a medical school affiliation; T3—hospital is a member of the Council of Teaching Hospitals; RESRCH—hospital with funded research; GOVT—hospital is nonfederal government-owned; OCC—occupany proportion; OUTPAT—outpatient visits per admission; MCARE—proportion of patients covered by Medicare; MCAID—proportion of patients covered by Medicaid; BLUE—proportion of patients covered by Blue Cross; OTHINS—proportion of patients with other (noncommercial) types of insurance coverage; NOINS—proportion of patients not covered by insurance; MED—proportion of medical patients; PED—proportion of pediatric patients; OBG—proportion of obstetric-gynecological patients; OTH—proportion of unclassified patients; URBAN—hospital is located in a Standard Metropolitan Statistical Area; PCY—county per capita income (in 1,000s) adjusted for variations in cost of living; BEDPOP—county short-term general hospital beds per 1,000 population; GPPROP—proportion of county patient-care M.D.'s who are general practitioners.
‖Indicates binary (0, 1) variables.

Hospitals (COTH); and T3 is one if the hospital is a member of COTH. This construction expresses teaching in terms of the level of teaching commitment, moving from T1 to T3. Hospitals without approved teaching programs comprise the reference category. Because complex cases provide teaching material and teaching hospitals have the staff and resources to treat complex illnesses, we expect casemix complexity to be positively influenced by the degree of teaching commitment. Thus, the coefficient of T3 should be larger than T2 and T2 larger than T1.

The regression results confirm these hypotheses; teaching has an important effect on casemix complexity and this effect increases with the level of teaching commitment.[5] Closely associated with the teaching is the hospital's propensity to engage in research activities. The variable RESRCH equals one if any medical staff members are engaged in a funded research project. Like teaching, we expect a research orientation to have a positive impact on casemix complexity; indeed, in many instances research activities focus on diagnostic and therapeutic problems associated with complex illnesses. The regression results support this hypothesis—the parameter estimate on RESRCH is positive and statistically significant at the 0.01 level.

We include a binary variable identifying nonfederal government ownership, GOVT, in the specification with the expectation that if government hospitals tend to have liberal policies regarding acceptance of low-income, possibly "unprofitable" cases, or if they are the victims of patient "dumping," these tendencies might be reflected by a positive impact on case complexity. This hypothesis is not supported by the results. We are unable to test the effect of for-profit hospital ownership because there are too few proprietary hospitals in our sample.

Two variables that characterize the hospital's patient flow are OCC and OUTPAT, which measure occupancy rate and the ratio of outpatient visits to inpatient days, respectively. Our hypothesis on the effect of occupancy rate derives from Rafferty's investigation of the association between occupancy and diagnosis mix [26]. Rafferty concluded that when occupancy is low hospitals are more inclined to admit discretionary, nonurgent cases. This implies that hospitals with low occupancy should have relatively low levels of casemix complexity, *ceteris paribus*, at least in the short run. Our expectation with regard to the effect of outpatient activity is similar. Hospitals with large outpatient departments are better able to provide continuous care to patients with complex illnesses who require extensive follow-up after discharge. We therefore hypothesize a positive effect of OUTPAT on casemix complexity.

Both hypotheses regarding the effects of occupancy rate and outpatient activity are supported by the regression results. Parameter estimates on

OCC and OUTPAT are positive and statistically significant at the 0.01 level, and the beta weights are of the same order of magnitude. The effect of these variables is, however, not as great as that of teaching.

Insurance and Service Distributions

Several studies have established an association between health insurance and hospital costs, but the association between insurance distribution and casemix complexity has received relatively little attention. Rafferty [27], in an analysis of elderly and nonelderly patient mixes before and after introduction of Medicare, concluded that insurance coverage differences among hospitals have a substantial effect on output mix which, in turn, has an effect on costs independent of variations in population health status. Goodisman and Trompeter [16], in analyzing data pertaining to Blue Cross and Medicare patient use of hospital services in the New York City area, found differences in the underlying diagnostic distributions of the two types of patients. They concluded that differences in hospital use between Blue Cross and Medicare patients may reflect both variations in casemix and differences in restrictiveness of coverage and reimbursement controls.

In the present specification, five variables define the hospital's coverage distribution.[4] The variables MCARE and MCAID represent the proportions of patients covered by Medicare and Medicaid, respectively. The variables BLUE and OTHINS represent proportions of patients covered by Blue Cross and other (noncommercial) health insurance, respectively, and the variable NOINS identifies the proportion of self-paying patients. The reference category in the regression is the proportion with commercial insurance coverage. These variables are defined such that the sum of the included variables and the commercial proportion equals 1.00.

Because the commercial insurance proportion is the omitted category, predicted effects of the included variables must be expressed in terms of anticipated effects relative to that of commercial coverage. For the most part, there is little information available on the illness correlates of insurance coverage. Because of the association with age, however, we do expect a positive effect of the Medicare proportion (MCARE) on casemix complexity, but no other a priori predictions are offered.

The empirical results show that the Medicare proportion has a substantial positive effect on casemix complexity relative to commercial coverage. Proportions of Medicaid patients and patients with other coverage have a much less pronounced positive effect on the RNI. The parameter estimate on the Blue Cross proportion is negative and statistically significant at the 0.01 level, indicating that patients with Blue Cross coverage tend to have the least complex illnesses of all insurance groups.

Similar to the insurance coverage variables, each hospital's patient distribution is described with respect to the service that corresponds to the primary diagnosis. That is, on the basis of diagnosis, each case is classified as surgical, medical, pediatric, obstetrical, or other service. The variables MED, PED, OBG, and OTH identify proportions in the latter four categories, and the surgical proportion constitutes the reference category.

Because surgical cases tend to be complex, on average, negative parameter estimates on the included variables are expected, but relative magnitudes are uncertain. We do, in fact, find that all parameters of the included variables are negative and statistically significant. (The variable MED is significant only at the 0.10 level, but all others are significant at the 0.01 level.) Based on these estimates, the ranking of the services, in order of most complex to least, is surgical, medical, other, pediatric, and obstetrical.

Community Characteristics

Four variables describe characteristics of the counties in which sample hospitals are located: URBAN is a binary variable which equals one if the hospital is located in a Standard Metropolitan Statistical Area (SMSA); PCY is county per-capita income adjusted for interarea variations in cost of living;[5] BEDPOP is the number of short-term nonfederal hospital beds per 1,000 county population; and GPPROP is the proportion of county patient-care M.D.'s who are general practitioners.

As stated earlier, the Section 223 limits on routine hospital costs reimbursable by Medicare are based, in part, on evidence that such costs are systematically higher in urban hospitals than in rural hospitals. Many factors, including input cost differences, may account for the routine cost differential, but if casemix is one of these factors, this should be reflected by a positive parameter estimate of URBAN in the RNI regression. The coefficient of URBAN is, in fact, positive, but it is small in absolute value and does not attain statistical significance at the 0.10 level. This suggests that urban/rural location does not have much independent impact on casemix complexity in hospitals. However, the simple correlation between the variable URBAN and RNI is +0.28 ($p < 0.001$), indicating that inclusion of the other exogenous variables in the RNI regression tends to reduce the impact of urban location. The relevance of this finding to the Section 223 limits is reduced to some extent by the fact that the limits apply only to routine hospital costs, whereas the RNI pertains to all resources used in patient treatment.

Several alternative hypotheses are plausible with regard to the effect of per capita income on casemix complexity. If affluent communities demand more discretionary care for (on average) less severe illnesses, the coefficient of PCY should be negative. In addition, if the demographic correlates of affluence reflect a lower incidence of severe illness in the community, this would also suggest a negative effect. However, if community affluence is associated with hospital ability to purchase and staff relatively sophisticated equipment and facilities, and these in turn attract complex cases, this implies a positive sign on PCY in the RNI regression. In fact, the coefficient of PCY is positive and statistically significant, suggesting that the latter hypothesis has more validity than the other two. In addition, since many elective services are surgical, it may be incorrect to assume that discretionary care tends to be low in complexity.

Our hypothesis on the effect of BEDPOP on casemix complexity is similar in reasoning to the hypothesized effect of occupancy. Where hospital beds are abundant, we expect more discretionary cases to be admitted. This reasoning finds its rationale in "Roemer's Law," which states that the supply of hospital beds creates its own demand [28, 29]. Thus, a negative impact of BEDPOP on RNI is expected, but this hypothesis is not confirmed. The BEDPOP parameter estimate is positive and not significantly different from zero in the RNI regression.

The hypothesized effect of GPPROP on casemix complexity derives from the association between physician training and cases treated. Physicians are the "gatekeepers" to health services, including hospital care. Because general practitioners have less sophisticated medical training than specialists, we expect patients who are treated by GPs to have relatively noncomplex illnesses, and this should be reflected in the casemix complexity of area hospitals. The regression results confirm this hypothesis—the coefficient of GPPROP is negative and statistically significant at the 0.01 level. This finding is consistent with past research that has identified a negative effect of the general-practitioner proportion on average hospital costs per admission and patient day [6, 30, 31].

Conclusions and Implications

Casemix measurement has received a great deal of attention in recent years, but most would agree that there is still much to accomplish if such measures are to be widely used in reimbursement and other applications. In contrast to Diagnosis Related Groups, CPHA's Resource Need Index is unlikely to ever be employed as a casemix variable in reimbursement formulas because of the large number of cells required to generate the RNI for each hospital. This disadvantage for practical application, however, is an advantage for investigating sources of variation in the RNI because the multiple cells permit considerable variation. Because the RNI is highly correlated with other diagnosis-based indices of case complexity, the empirical results are not likely to be sensitive to the classification system or data used to construct case weights.

With a specification that includes variables describing teaching commitment and other hospital characteristics, hospital service and insurer distributions, and area characteristics, we are able to "explain" 77 percent of the variation in RNI in our sample of 397 PAS hospitals. The regression results indicate that all three types of independent variables have a substantial influence on casemix complexity. We have attempted to select and define the independent variables in such a way as to create a foundation for a useful policy discussion regarding external influences on hospital casemix. Our analysis and related discussion is based on the premise that policy debates in this area require not only refinements in casemix measurement, but also an understanding of underlying influences that bring about variations in casemix complexity.

A hospital's teaching status has a major influence on its average case complexity as measured by the RNI. We chose to define teaching in terms of degree of teaching "commitment," a property that we assumed would be reflected by an approved residency program, a medical school affiliation, and/or membership in the Council of Teaching Hospitals. We found that teaching has a substantial effect on casemix complexity and that this effect increases with the degree of commitment. When teaching is defined in this manner, it completely dominates the influence of hospital size on casemix complexity; that is, with the teaching variables in the specification, addition of hospital size variable(s) adds a negligible amount to explained variance in the RNI.

A crucial question is, To what extent does the higher casemix complexity of teaching hospitals account for their higher costs? Available evidence indicates that even when casemix complexity is controlled for, either by direct casemix variables [17] or by proxy variables [6], teaching still has a substantial effect on average cost per case. A precise answer to this question, however, will require additional research focused directly on the relationships between casemix, teaching, and hospital costs.

With regard to insurance coverage proportions, two findings are of interest. First is the pronounced influence of the Medicare proportion on casemix complexity; in fact, this was the most substantial influence in the RNI regression as gauged by the beta coefficients. A proposal to reduce the 8.5 percent per diem nursing cost differential in reimbursement for hospitalized Medicare patients was not implemented by the 96th Congress [32]. Our results suggest that the relationship between hospital costs and insurance mix should be closely examined before any such proposal is implemented. This finding is only suggestive, however, because the charge weights on which the RNI is based include ancillaries and other services that are not a part of the basic hospital per diem.

The other notable finding is that increases in the proportion of Blue Cross patients relative to those with commercial health insurance lead to substantial decreases in casemix complexity. The regression results imply that Blue Cross patients tend to have the least complex illnesses relative to the other major insurance groups. Again, it is necessary to be mindful of the fact that the RNI is not confined to complexity of purely basic hospital services, and the evidence is not conclusive that Blue Cross patients require less nursing and other basic care than other types of patients. Nevertheless, such information may be useful in rate negotiations between insurers and hospitals.

The finding that case complexity varies significantly with proportions of patients in different service categories, and that surgical cases tend to be the most complex, is not startling. Pediatric and, especially, obstetrical cases tend to be substantially less complex than other types of cases. A hospital's service proportion mix is likely to be closely related to the specialty distribution of its medical staff. These results raise questions about potential hospital response to casemix-dependent reimbursement programs. In general, would such programs create an incentive for hospitals to alter their specialty distributions in order to change casemix configurations? If revenue margins on surgical cases tend to be relatively high, for example, would systems that explicitly recognize surgical/nonsurgical case differences (such as the DRG system) create an incentive for hospitals to attract a higher proportion of surgeons to their medical staffs? And would specialty-related casemix complexity differences that are not explicitly recognized create an incentive for hospitals to prefer specialties, at the margin, whose caseloads tend to require less intensive basic services? Questions of this nature will have to be addressed as the movement toward casemix-adjusted reimbursement systems progresses.

The influence of area characteristics (all of which are defined for the hospital's county in our specification) reveals a mixed pattern. The empirical results provide no support for the hypothesis that hospitals tend to admit less complex cases where community beds are relatively plentiful. This finding is consistent, however, with evidence that hospital costs per admission and per patient day do not systematically fall in response to an increase in community beds [6].

Despite the fact that a variety of reimbursement programs, most notably the Medicare Section 223 limits, rely on urban/rural location distinctions, we found that, other things being equal, urban location has no appreciable effect on casemix complexity. But the urban location variable is correlated with other independent variables in the RNI regression, particularly the county GPPROP (r = -0.52), which exerts a stronger independent effect on case complexity. Thus, urbanization is a proxy for a number of community attributes in simplistic hospital classification systems. While simplicity is certainly a worthwhile attribute in reimbursement systems, it is also desirable to recognize factors that directly influence casemix variations, when such factors can be readily measured, rather than rely on proxy measures. More equitable application of reimbursement criteria and constraints may require trading off simplicity for more thorough and direct adjustments for hospital case severity in different geographic areas.

Earlier we hypothesized offsetting effects of community affluence on casemix complexity, but we found that per capita income has a significant positive coefficient in the RNI regression. Because insurance variables were included in the specification, the effect of income is purged of the association betweeen income and insurance coverage. Why does high community income lead to relatively complex cases? We suspect that community affluence enables hospitals to purchase and staff sophisticated equipment and institute ancillary services that attract specialist physicians and patients with complex illnesses. The precise mechanism for this is uncertain—perhaps such hospitals are more successful in fund-raising efforts independent of third-party reimbursement. One implication of this finding is that analysts should take care to account for product differences in estimating the income elasticity of the demand for hospital care.

It is clear from the empirical estimate that hospital casemix determination is extremely complicated. A number of diverse factors have a substantial influence on casemix complexity, and it is unlikely that simple proxy measures can adequately capture this diversity. Hospitals are not passive recipients of their casemixes—they have multiple opportunities to alter casemix complexity through such decision variables as medical staff composition, level of teaching commitment, addition of facilities and services, and others. At present, several experiments with casemix-adjusted reimbursement are being conducted in different areas of the United States. We hope that these experiments will yield information on hospital behavioral response to casemix-adjusted reimbursement.

NOTES

1. The coefficient of variation is the standard deviation divided by the mean. In an evaluation of a case complexity index constructed from DRGs weighted by average cost per DRG, Pettengill and Vertrees [17] concluded that data errors (e.g., in recording diagnosis) tend to result in compression of the index range. The same is likely to be true for the RNI.
2. Beta coefficients are obtained from regressions in which all variables are standardized by subtracting variables' means and dividing by their respective standard deviations.

We have considered the extent to which the regression results may have been influenced by multicollinearity among the independent variables. In general, the simple correlations were acceptably low, the degrees of freedom sufficiently high, and the majority of coefficients statistically significant, all of which lead us to believe that multicollinearity is not a serious problem in our specification. In a preliminary regression, both teaching and hospital bedsize variables, which tend to be highly correlated, were entered. As indicated in Table 1, teaching and bedsize are both significantly associated with the RNI, but in the preliminary regression the parameter estimates of the size variables were not significantly different from zero. The size variables were therefore removed from the final specification, and we should recognize that to some extent the teaching variables may also measure the effect of hospital scale on casemix complexity.

3. Hospital teaching status may be measured in several alternate ways (e.g., number of residency programs offered or number of residents per bed), and results from preliminary regressions indicate that such measures are highly correlated. We prefer the specification adopted because of its hierarchical composition and ease in interpretation of results.
4. Insurance coverage distributions are derived from expected source of payment entries on patient abstract forms. In cases where patients have multiple coverage, the primary source of payment is recorded. Payers in the "other" coverage category include workmen's compensation, the Maternal and Child Health and Crippled Children programs, other government agencies, and voluntary charities.
5. The cost-of-living adjustment is accomplished by dividing per capita income by an index derived from Bureau of Labor Statistics data on city and regional relative living costs. See Sloan and Steinwald [6] for a more thorough description.

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