Methods

The Hospital Multistay Rate as an Indicator of Quality of Care

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Objectives. To evaluate the hospital multistay rate to determine if it has the attributes necessary for a performance indicator that can be applied to administrative databases.
Data Sources/Study Setting. The fiscal year 1994 Veterans Affairs Patient Treatment File (PTF), which contains discharge data on all VA inpatients.
Study Design. Using a retrospective study design, we assessed cross-hospital variation in (a) the multistay rate and (b) the standardized multistay ratio. A hospital's multistay rate is the observed average number of hospitalizations for patients with one or more hospital stays. A hospital's standardized multistay ratio is the ratio of the geometric mean of the observed number of hospitalizations per patient to the geometric mean of the expected number of hospitalizations per patient, conditional on the types of patients admitted to that hospital.
Data Collection/Extraction Methods. Discharge data were extracted for the 135,434 VA patients who had one or more admissions in one of seven disease groups.
Principal Findings. We found that 17.3 percent (28,300) of the admissions in the seven disease categories were readmissions. The average number of stays per person (multistay rate) for an average of seven months of follow-up ranged from 1.15 to 1.45 across the disease categories. The maximum standardized multistay ratio ranged from 1.12 to 1.39.
Conclusions. This study has shown that the hospital multistay rate offers sufficient ease of measurement, frequency, and variation to potentially serve as a performance indicator.

Key Words. Hospital multistay rate, performance indicator, repetitive admission

Hospital use in the United States and in other developed nations is concentrated in the small proportion of the population that is repeatedly hospitalized in any given year. The 1990 U.S. National Health Interview Survey (NHIS) showed that whereas 7.9 percent of the population was hospitalized in 1990, the 1.5 percent who were hospitalized more than once that year accounted for 44.7 percent of all hospital days (U.S. Department of Health and Human

Services 1991). The NHIS has documented this pattern over the past 25 years, and numerous studies have confirmed it.

The multistay rate is the number of hospital stays per hospital user within a given time period. These rates have been increasing over the past two or three decades in the U.S. private and public sectors, and in the United Kingdom as well. Between 1967 and 1977, the multistay rate for Medicare beneficiaries increased by 7 percent from 1.38 to 1.48 (Gornick 1982). In the U.S. Department of Veterans Affairs medical care system, the multistay rate increased from 1.54 to 1.71 between 1980 and 1990 (Ashton, Weiss, Petersen, et al. 1994). In the area of Britain covered by the Oxford Record Linkage Study during the period from 1968 to 1986, the overall multistay rate increased from 1.31 to 1.55 among men and from 1.32 to 1.58 among women (Goldacre and Ferguson 1995). An increase in the multistay rate was observed in 13 of 58 diagnoses studied (Ashton, Ferguson, and Goldacre 1995).

It is not known whether the increase in intensity of hospital use seen throughout the 1980s was related to the shifting of some care to the outpatient sector so that only the sickest patients were using hospitals, to hospital reimbursement mechanisms such as diagnosis-related groups (DRGs) that rewarded repetitive hospital use, to a combination of both, or to other changes in practice style. As the prevalence of capitated care has increased, one would expect the propensity to admit (and thus the propensity to readmit) to be reduced. However, if only the sickest were admitted, they would in general be more likely to be readmitted. The overall effect that these counteracting tendencies have had on multistay rates in the 1990s has not been investigated.

Although little attention has been paid to repetitive hospitalization patterns, there are substantial financial reasons under a capitated system of reimbursement to evaluate this very costly pattern of care. Because patients who

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have more than one hospital stay in a given time period are the costliest of all healthcare consumers (Zook and Moore 1980), we suggest that the multistay rate may be a particularly valuable indicator to administrators and clinicians as they strive to identify sources of inefficiency and avoidable costs. For some patients, repetitive admissions may be an indication of terminal disease that has been marginally responsive to medical management. Under these circumstances other options for care might better meet the patient's preferences. Additionally, for some patients, repetitive admissions may be indicative of the breakdown in the overall coordination of care. This breakdown may result from the failure to identify patients' post-discharge needs, to communicate those needs to outpatient providers, and to educate patients about medication regimens (Ashton and Wray 1996). Thus, we evaluated the multistay rate to determine if this measure possesses some of the attributes—namely, ease of measurement, great enough frequency to be of clinical and financial importance, and substantial cross-hospital variation unexplained by differences in case mix as measured using administrative data—necessary for a performance indicator that can be applied to administrative databases.

METHODS

Data were extracted from the fiscal year 1994 Veterans Affairs Patient Treatment File (PTF), an administrative database containing discharge data on patients treated at all 158 hospitals maintained by the Department of Veterans Affairs.

The multistay rate during time period t for hospital h can be defined as the average number of hospitalizations per hospitalized patient during time period t after an indexed stay at VA hospital h. The original admission is classified by disease X, where $X = X_1, X_2, X_3, \ldots$. Readmissions are counted for any diagnosis Y, where $Y = Y_1, Y_2, Y_3, \ldots$, at any one or more VA hospitals Z, where $Z = Z_1, Z_2, Z_3, \ldots$. The multistay rate is denoted: $MR(t, h, X, Y, Z)$. The expected rate at VA hospital h is conditional on the characteristics of the patients at VA hospital h relative to the characteristics of the patients at all VA hospitals. The standardized multistay ratio for time period t for VA hospital h, given X, Y, and Z, is the quotient of the observed multistay rate to the expected multistay rate at VA hospital h, denoted:

$$SMR(t, h, X, Y, Z) = MR(t, h, X, Y, Z)/E[MR(t, h, X, Y, Z) \mid \text{patient characteristics at } h]$$

To determine the multistay rate for diagnosis X_1 at hospital h during time t requires first the specification of the diagnosis of interest for study and then the assignment of patients with one or more discharges during the time period of interest to a single diagnostic cohort and the identification of the index stay for the members of this cohort. For our study this was done in the following manner. DRGs that differed only with respect to age and/or presence of comorbidities or complications were combined to form adjacent DRGs (ADRGs). We selected 29 ADRGs that were prevalent within the VA healthcare system and that had outcomes sufficiently prevalent for stable estimates to be obtained. Patients were classified into one of the 29 ADRGs based on their principal diagnosis at the time of discharge. Any individual patient was assigned to only one of our 29 ADRGs, regardless of whether or not the patient had multiple discharges. If a patient had more than one discharge within our 29 ADRGs, we randomly selected one of these discharges. We then identified the patient's first discharge in the fiscal year in that ADRG (i.e., the index stay) as the "defining discharge." The defining discharge was the source of descriptive information about each patient, and it established the beginning date for patient follow-up.

The outcome of interest was the number of hospitalizations during the period between the date of the defining discharge and the end of the federal fiscal year, regardless of diagnosis. Thus, in the definition of the multistay rate, $MR(t, h, X, Y, Z)$, Y could take any clinical diagnosis. All subsequent hospitalizations were counted. Thus, Z took on the value of any VA hospital. To prevent the counting of transfers, hospital readmissions to a different VA hospital within 24 hours of a discharge were not counted as rehospitalizations.

We chose a fixed 12-month period of data (the federal fiscal year) with individuals having variable periods of follow-up, rather than using a single cohort of individuals, each with a fixed period of follow-up. Hospital-level comparisons of the multistay rate would be biased if the length of time patients were followed was different across the facilities. We examined the mean follow-up time and found that the average of seven months did not differ among the hospitals. As a result, we did not include adjustments for follow-up time in our analyses.

To estimate a patient's risk of repetitive admission, a risk-adjustment model was created for each of the 29 ADRGs. The Wray-Petersen method of risk adjustment was used (Wray, Petersen, Souchek, et al. 1997; Wray 1993). The risk-adjustment model employed demographic variables to account for differences in physiologic reserve and social support, and diagnostic variables to account for differences in severity of illness. Risk adjustment covariates were extracted from the defining discharge abstract for all patients.

The demographic covariates were age, sex, race, and marital status. Age was used as a continuous variable. Race and marital status were missing from the discharge abstract for a small percentage (less than 2 percent) of patients. For most of these cases, separate dummy variables were used for the missing data. When the number of missing data elements was too small to warrant assigning a missing value indicator variable, the mode was entered.

Three parameters were used to adjust for severity of illness: (1) the principal diagnosis, (2) the count of significant comorbidities, and (3) the organ systems affected by selected comorbidities. A four-step hierarchical rule was used for grouping the principal diagnoses that occurred within each ADRG to form dummy variables. First, any single 3-, 4-, or 5-digit ICD-9 code that contained 3 percent or more of the individuals in an ADRG was coded as a separate variable. Second, any 4- or 5-digit codes in a 3-digit ICD-9 unit that remained after step 1 were combined. Third, any 3-digit units for which the sum of the frequencies of the composite 4- or 5-digit codes was 3 percent or more were coded separately. Fourth, all remaining codes were combined into a single dummy variable representing all other diagnoses. In 21 of the 29 ADRGs, fewer than 10 percent of the patients were in the all other diagnoses category. The ICD-9 code containing the largest number of patients in the ADRG was used as the reference group against which other codes in the ADRG were compared. The number of principal diagnosis variables created for the ADRGs ranged from two to nine.

We used the following algorithm to determine the count of each patient's important comorbidities. First, we wished to exclude conditions that were relatively clinically insignificant because inclusion of such conditions would tend to dilute the mean of this parameter. To accomplish this, we chose to use the complications and comorbidities designated by the DRG system as our list of important conditions since this contains only those conditions judged by clinicians to increase the length of stay by at least one day in 75 percent of hospitalized patients (Averill et al. 1986). The second step in the algorithm was to assess which of the conditions on this list were most likely to have been comorbidities (present at the time of admission) rather than complications that occurred during the hospital stay. This step was necessary because risk adjustment must account for case mix at admission, not at discharge. Hence, failure to exclude likely complications of care will bias estimates of case mix at admission. The second step was performed by a panel of three board-certified internists (NPW, CMA, JMG) who reviewed the DRG complications and comorbidities list for each of the ADRGs to determine whether each condition on the list should be classified as a comorbidity or a complication. The three internists used two criteria in their determination. First, any acute condition was classified as a complication. Second, any diagnosis that was judged unlikely, from a clinical standpoint, to have been present at admission was classified as a complication. The internists classified the conditions independently, and any disputes were resolved through discussion. All conditions that the panel classified as complications were excluded from the comorbidity count. The maximum comorbidity count was nine because the PTF has up to nine secondary diagnosis codes for each discharge. Most patients had considerably fewer comorbidities than the maximum.

Finally, we employed a risk adjustment parameter, developed at the Institute for Health Policy Studies (IHPS) of the University of California, San Francisco, which classifies patients by whether they have a significant comorbidity in each of eight organ systems: endocrine, hematological, neurological, circulatory, respiratory, digestive, genitourinary, and musculoskeletal (Luft, Garnick, Mark, et al. 1989, 1990). Each of the eight variables was coded 0 or 1 for each patient. This approach allows for comorbidities that are more serious than the average comorbidity included in the count variable to enter the model and to develop their own additional weights. The other advantage of this risk adjustment method is that its organization according to body system is a sound approach from a clinical standpoint. The codes included within each body system category are limited to those that represent significant disease states and that are likely to influence utilization.

Multiple linear regression was used to model the relationship between the log of the number of discharges and the risk-adjustment variables. A separate linear regression was done for each ADRG. Because the data were skewed to the right, we used the log transformation of the number of discharges for each patient as the dependent variable in the regression model. The F-statistic was used to assess whether the variables in each model explained a significant proportion of the variation in the data. The R^2-value represents the proportion of total variation in the dependent variable due to the independent variables. These risk adjustment models provided the expected value of the logarithm of the multistay rate for each individual patient. For each ADRG, a hospital-level observed multistay rate was calculated as the geometric mean of the patient-level multistay rates.

Because some hospitals had small numbers of patients readmitted in certain ADRGs, data on the observed and expected multistay rates from the 29 ADRGs were combined into seven disease categories. The following disease categories were created: (1) chronic obstructive pulmonary disease (COPD); (2) other pulmonary (simple pneumonia and pleurisy; bronchitis and asthma); (3) congestive heart failure (CHF); (4) other cardiology (angina pectoris; cardiac arrhythmia and conduction disorders; acute myocardial infarction; atherosclerosis); (5) general medicine (diabetes; cellulitis; kidney and urinary infections; transient ischemic attacks; hypertension; urinary stones; cirrhosis and alcoholic hepatitis; red blood cell disorders; gastrointestinal obstruction); (6) solid tumors (digestive malignancies; kidney and urinary tract neoplasms; malignancy of the female or male reproductive systems); and (7) lymphoma/leukemia (lymphoma and non-acute leukemia; acute leukemia without a major operating room procedure; other myeloproliferative disease or poorly differentiated neoplasms).

The residual was the difference between the observed and predicted log of the number of discharges for each patient. An analysis of variance was performed to test whether residuals differed among hospitals. We set the overall significance level for the tests at .20 and tested each of the 158 hospitals at the .0014 level. The probability of incorrectly designating any of the facilities as an outlier was less than .20 and the probability of more than one error was less than .02. A facility was defined as a high outlier if the p-value was significant and the observed number of admissions per patient exceeded the expected number.

The standardized multistay ratio was also calculated for each facility. This is the ratio of the geometric mean of the observed number of hospitalizations per patient to the geometric mean of the expected number of hospitalizations per patient, based on the model.[1] The standardized multistay ratio evaluates the degree to which a hospital's observed multistay rate is not explained by the types of patients for whom the hospital provided care. To the degree to which the hospital's standardized multistay ratio exceeds one, the hospital's observed multistay rate is higher than is explained by differences in case mix, as measured by the case-mix adjustments employed in this study.

RESULTS

Table 1 gives the number of veterans with one or more stays, the total number of stays, the average number of stays per inpatient, and the range of the number of stays per patient for each of our seven disease cohorts. The average number of discharges per inpatient ranged from 1.15 for the general medicine and other pulmonary cohorts to a high of 1.45 discharges per patient for

Table 1: Number of VA Inpatients and Stays, 1994

Disease Group	*Number of Veterans with One or More Stays*	*Total Number of Stays*	*Average Number of Stays per Inpatient*	*Range of the Number of Stays per Inpatient*
COPD	14,287	18,465	1.29	1–14
Other pulmonary	14,501	16,704	1.15	1–10
CHF	12,947	16,761	1.29	1–08
Other cardiology	30,966	36,672	1.18	1–22
General medicine	41,041	47,105	1.15	1–24
Solid tumors	17,790	22,355	1.26	1–18
Lymphoma/Leukemia	3,902	5,672	1.45	1–78

members of the lymphoma/leukemia cohort. There was a striking difference in the range of the number of stays per patient. The range of the number of discharges per patient varied from one to eight for the congestive heart failure cohort to 1 to 78 for the lymphoma/leukemia cohort.

Hospital-level data are provided in Table 2. Although there are 158 Department of Veterans Affairs acute care hospitals, we included only those facilities in our hospital-level analysis that had at least ten patients in the respective cohort. The number of hospitals evaluated varied from a low of 110 for the lymphoma/leukemia cohort to a high of 158 for the other cardiology, other pulmonary, and general medicine cohorts. Thus we evaluated at least 150 of the 158 acute care facilities for six of our seven cohorts. Table 2 contains, for each cohort, the geometric grand mean of the observed number of hospitalizations per person, the ranges of the geometric means of the observed and expected multistay rates per hospital, and the ratio of the observed to the expected multistay rate, that is, the standardized multistay ratio. As noted under Methods, both the expected and the observed multistay rates are the geometric means of the patient-level data. This explains why, for each cohort, the observed multistay rate across all hospitals in Table 2 is lower than the average number of stays per person found in Table 1. The maximum observed multistay rate varied greatly across the cohorts. The congestive heart failure cohort and the lymphoma/leukemia cohort had the highest maximum observed multistay rates; there was a hospital with a rate of 1.49 for congestive heart failure and a hospital with a rate of 1.77 for lymphoma/leukemia.

The degree to which the relationship between a hospital's observed and expected multistay rate varied by disease cohort is given in Table 2 by the standardized multistay ratio. The cohorts with the highest maximum

Table 2: Ranges of the Geometric Means of the Observed and Expected Multistay Rates and of the Standardized Multistay Ratios Across Hospitals, Based on Counts of Discharges

Disease	*Number of Hospitals with 10+ Patients*	*Geometric Mean of Observed MSR* Across All Hospitals*			*Geometric Mean of Expected MSR* Across All Hospitals*		*Standardized Multistay Ratio*	
		Mean†	*Minimum*	*Maximum*	*Minimum*	*Maximum*	*Minimum*	*Maximum*
COPD	157	1.18	1.00	1.38	1.16	1.20	0.84	1.16
Other pulmonary	158	1.10	1.00	1.26	1.07	1.13	0.90	1.14
CHF	157	1.19	1.05	1.49	1.16	1.21	0.89	1.26
Other cardiology	158	1.12	1.00	1.25	1.09	1.15	0.87	1.12
General medicine	158	1.09	1.03	1.29	1.06	1.12	0.95	1.17
Solid tumors	152	1.18	1.03	1.38	1.13	1.19	0.91	1.19
Lymphoma/Leukemia	110	1.26	1.00	1.77	1.18	1.35	0.78	1.39

*MSR: multistay rate.

†This is the weighted geometric mean of the geometric mean MSR of each hospital, which results from transforming the arithmetic grand mean of the log of the number of hospitalizations per person back to the original scale.

Table 3: Number of Hospitals Moving One or More Deciles of Rank Between Observed Multistay Rate and Standardized Multistay Ratio

Disease	*Number of Hospitals with 10+ Readmitted Patients*	*Number of Hospitals Moving 1+ Deciles*	*Percent of Hospitals Moving 1+ Deciles*
COPD	157	36	22.9
Other pulmonary	158	69	43.7
CHF	157	52	33.1
Other cardiology	158	83	52.5
General medicine	158	92	58.2
Solid tumors	152	50	32.9
Lymphoma/Leukemia	110	65	59.1

standardized multistay ratios were lymphoma/leukemia (1.39) and congestive heart failure (1.26).

Our methodology for adjusting for differences in the multistay rates due to the variation in the types of patients who received care at individual hospitals had an effect on the rank-order of the hospitals by their multistay rate. As shown in Table 3, from 22.9 percent of hospitals in the COPD cohort to 59.1 percent of the hospitals in the lymphoma/leukemia cohort moved at least one decile in rank-order when their ranking by unadjusted multistay rate is compared to their ranking by standardized multistay ratio. These data emphasize the importance of limiting any assessment of hospital performance to data adjusted for the variation related to patient differences.

DISCUSSION

The findings of this study suggest that the hospital multistay rate would be a valuable addition to the collection of performance indicators that are customarily used for large-scale comparisons of performance across providers or systems of care. The multistay rate would be a useful complement to the more frequently used indicators, such as 30-day mortality and 30-day readmission, because it measures a different aspect of performance. Primarily, the multistay rate evaluates the ongoing longitudinal coordination of care.

The study was designed to determine if the multistay rate possessed some of the attributes necessary for a performance indicator that can be applied to administrative databases: namely, ease of measurement, great enough frequency to be of clinical and financial importance, and substantial cross-hospital variation unexplained by differences in case mix, as measured using administrative data. This study shows that the multistay rate possesses all of these characteristics.

The first requirement for a performance indicator to be used with administrative databases is ease of measurement. The fulfillment of that requirement depends on the ability to link patient-specific data over time. This can be readily done in any administrative database that has a patient-specific identifier. However, because of concerns regarding confidentiality, some states that are collecting statewide discharge data are not including a patient-specific identifier on their public release tapes (National Association of Health Data Organizations 1993). This issue is important not just for the multistay rate but also for many other indicators, such as early readmission. Thus, if these databases are to be of maximum value in evaluating performance, a mechanism for linking all of a patient's data over time must be available.

Two examples of databases that contain record linkage identifiers are the hospital discharge database maintained by the State of California and the Medicare hospital discharge database. The Medicare database would be particularly well suited for future comparisons of multistay rates because (a) the Medicare beneficiaries' data can be linked, (b) all reimbursable discharges for Medicare beneficiaries are contained in the database, and (c) Medicare fee-for-service providers have a financial incentive to unbundle hospitalizations and thus to increase the multistay rate.

Another concern, however, and one that applies to this study, is whether the databases being studied include discharge data from all hospitals from which a patient may be discharged. If the database includes information on only a subset of hospitals from which a patient may be discharged, then to the degree that a patient uses a variety of hospitals, some of which are not in the database, the patient's utilization pattern will be underestimated. For example, Fleming, Fisher, Chang, et al. (1992) found that 4.2 percent of VA patients in 11 surgical categories and one medical category had no VA readmission but had a Medicare readmission within six months.

Sufficient frequency is the second requirement for a performance indicator. As has been shown by others in previous studies of Medicare data, VA data, and international data, we show that repetitive hospitalization is still a common pattern of healthcare in these data. The average number of stays per person in this study ranged from 1.15 to 1.45. Across all of our cohorts, 17.3 percent (28,300) of the admissions were readmissions.

Substantial variation is the third requirement for a performance indicator. Marked variation in hospital use according to area has been found in numerous studies over the past 20 years (Gornick 1977; Wennberg et al.

1989). Factors contributing to this variation may include uncertainty about the indications for hospitalization (Wennberg, Barnes, and Zubkoff 1982), differences in supply (Knickman and Foltz 1985), differences in access (Weissman, Gatsonis, and Epstein 1992), and differences in HMO market penetration (Hillman, Pauly, and Kerstein 1989).

Substantial variation in hospital use was also found in this study. We demonstrated significant cross-hospital variation in multistay rates unexplained by differences in case mix. The ratio of the observed to expected multistay rate, the standardized multistay ratio, expresses the degree to which a hospital's multistay rate is not explained by differences in case mix as measured by the case-mix adjustment system used in this study. As noted earlier, the maximum standardized multistay ratio varied from 1.12 for the other cardiology cohort to 1.39 for the lymphoma/leukemia cohort. Cohorts with a greater range in the standardized multistay ratio have greater variability in readmission rates across the hospitals studied—a variability that is unexplained by the risk adjustment used in this study. We questioned whether the greater range in standardized multistay ratios was due to poorer-fitting risk adjustment models. However, the R^2-values of the models for the lymphoma/leukemia cohort (.1178) and the congestive heart failure cohort (.0077) were not substantially different from the R^2-values of our other risk adjustment models (range of .0038 to .0387). Thus, the wider variation in the standardized multistay ratios in these two cohorts might suggest a wider variation in care for patients in these cohorts.

This variation in hospital use comes at considerable cost. Across those hospitals whose standardized multistay ratio was greater than one, there were 2,146 more readmissions for all disease cohorts than would have occurred in equally ill patients if their care had been provided at hospitals whose standardized multistay ratio was not greater than one.[2]

Although we have shown that the multistay rate has some of the attributes necessary for a performance indicator that can be applied to administrative databases, these attributes are not sufficient. Further studies must be undertaken to show that hospital-specific standardized multistay ratios as calculated from administrative databases are valid indicators of performance. Based on primary data collection, one must determine the degree to which hospital-specific standardized multistay ratios, as calculated from administrative databases, are altered if important clinical variables that are not present in administrative data are added to the case-mix adjustment system. This will reveal to what degree hospital outlier status as assessed from administrative databases is simply due to unmeasured case-mix differences. If hospital-specific standardized multistay ratios that are based on a clinically enriched case-mix adjustment system continue to demonstrate significant cross-hospital variation, then primary data collection studies should be undertaken to ascertain the potential healthcare practice factors that might be causative in producing high readmission rates. Repetitive hospitalization is such a costly type of care that it will be worth the investment to study it further.

NOTES

1. When the difference between the arithmetic hospital means of the observed and expected number of hospitalizations per person is transformed back from the log scale to the original scale, it becomes the ratio of geometric means in the original scale.
2. For hospitals with a standardized multistay ratio greater than one, the number of excess admissions at each hospital was defined as the difference between the observed and expected number of admissions. Specifically, $x = n * (smsr - 1) * m$, where x is the number of excess admissions, n is the number of patients at a hospital, *smsr* is the standardized multistay ratio, and m is the geometric mean over all patients of the expected number of stays per patient.

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