CHANGES IN RATES OF UNSCHEDULED HOSPITAL READMISSIONS AND CHANGES IN EFFICIENCY FOLLOWING THE INTRODUCTION OF THE MEDICARE PROSPECTIVE PAYMENT SYSTEM

An Analysis Using Risk-Adjusted Data

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The purpose of this study was to analyze changes in rates of unscheduled readmissions and changes in technical efficiency following the introduction of the Medicare Prospective Payment System (PPS). We developed the Risk-Adjusted Readmissions Index (RARI), which allowed us to make comparisons in rates of unanticipated readmissions across hospitals and over time. Data envelopment analysis (DEA), a linear programming technique, was used to measure changes in technical efficiency by comparing the inputs used and the outputs produced across a cohort of hospitals, while adjusting for changes over time in case mix and case complexity. Rates of unscheduled readmissions and efficiency scores were computed for a sample of 245 hospitals for each year. Although both readmission rates and efficiency scores increased for most hospitals, there was no evidence that those hospitals that experienced the greatest increases in efficiency had the largest increases in their rates of unscheduled readmissions.

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Following the introduction of the Medicare Prospective Payment System (PPS), individual hospitals may have used a variety of strategies to improve efficiency in order to lower their costs per case. Some of these strategies are desirable, whereas others are not. If increases in efficiency occur while quality deteriorates, such actions are clearly undesirable; however, if the same quality of health care is produced using fewer resources, then the results would be positive.

In the first year after PPS was introduced, many dramatic changes were observed in the patterns of hospital care, both for Medicare and non-Medicare patients. Hospital admission rates, which had been rising from 1980 to 1983 for Medicare patients, decreased significantly in 1984 (DesHarnais et al., 1987). The average length of stay, which had been decreasing from 1980 to 1983 for Medicare patients, was significantly shorter in 1984 than what would have been projected on the basis of past trends (DesHarnais et al., 1987). Fewer ancillary services were used per Medicare admission, compared to earlier years (Long et al., 1987). Medicare discharge locations shifted (Long et al., 1987); and hospital readmissions, which had been increasing for Medicare patients in the years prior to the introduction of PPS, continued to increase in 1984 in a manner that was consistent with past trends (DesHarnais et al., 1987). Some similar changes occurred for non-Medicare cases, although the effects were not as pronounced (DesHarnais et al., 1987).

The trend of increasing readmission rates could be viewed as evidence that the quality of inpatient care deteriorated after 1983; however, other explanations are also possible. Perhaps the increase in readmissions occurred because hospitals were (more appropriately) discharging certain patients, and then readmitting them, rather than allowing them to remain in the hospital without any active therapy or diagnostic testing occurring; for example, patients waiting in the hospital for several days for an elective CT scan. The rising readmission rate does need to be monitored, because it can be financially beneficial to a hospital to treat a patient using two relatively short admissions rather than one long admission. If some hospitals chose to "game" PPS, then the savings that the Medicare program could achieve because of increased efficiency would be offset by the cost of these increased readmissions.

This potential problem was recognized at the time that PPS was introduced, and the peer review organizations (PROs) were given the task of monitoring hospital readmissions. This PRO readmission review activity, however, had not yet begun in most areas during the first year of the PPS. Therefore, it is not clear whether hospitals reacted to the financial incentives of PPS with strategies that increased their income, but resulted in increased readmissions, and thus increased costs to the Medicare program.

In this study we sought to determine whether there is evidence that hospitals made tradeoffs between quality and efficiency in the first year following the introduction of PPS. In particular, we wanted to see if those hospitals that had the greatest increases in *technical efficiency* in that year also experienced the greatest increases in rates of unscheduled readmissions. Technical efficiency refers to the relationship between the amount of resources used (inputs) and the level of services provided (outputs). We examined changes in rates of unscheduled readmissions in relationship to changes in technical efficiency for a national sample of 245 hospitals, comparing figures for the year before PPS was introduced (1983) to the figures for the following year. Our model, methods, and findings are presented in this article.

MODEL

The relationships among efficiency, costs, use, and quality have been explored in the literature, although most of the discussion has been in theoretical terms. Do higher expenditures result in better care, or is it possible to provide better care for lower levels of expenditures? Vuori (1980) distinguished between measuring hospital care in terms of its scientific and technical quality versus measuring whether the health services, "achieve their objectives with the least possible production costs." This issue has also been discussed in similar terms by Donabedian, Wheeler, and Wyszewianski (1982).

The model of hospital behavior presented in this article was derived primarily from the work of Donabedian and his colleagues and con-

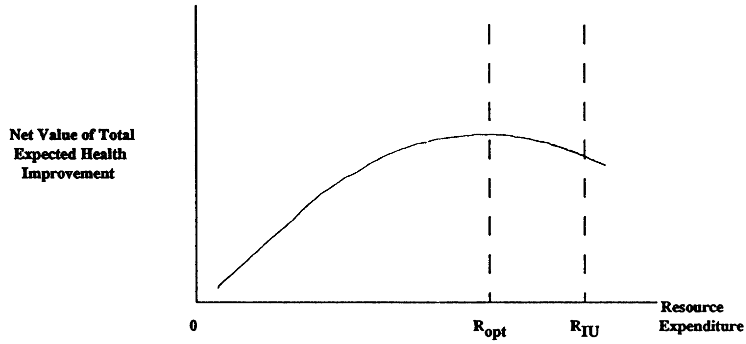

Figure 1: Effect of Employing Optimal Strategy on Net Value of Total Expected Health Improvements
SOURCE: Donabedian, Wheeler, and Wyszewianski (1982). Reprinted with permission.

siders the relationship between the resources used to treat a case and the health outcome of the patient treated. Donabedian presented a model illustrating the effect of employing an optimal strategy of resource use relative to total expected health improvements.

In Figure 1, Donabedian and his colleagues show the effect of employing the optimal level of resources (R_{opt}) on the net value of total health improvement. In any area to the right of R_{opt}, such as point R_{IU}, the net value of total expected health improvement is less than the value of the resources that would be employed to produce that improvement. It is not worthwhile to undertake the additional expenditure to reach R_{IU}, because the same "product," that is, patient discharge from the hospital with a given level of health improvement, is produced more efficiently (using fewer resources) at R_{opt} than at R_{IU}.

The model implies that one can make separate but simultaneous measurements of changes in cost and quality, then examine the relationship between these measures. This approach allows us to examine relationships between cost and quality and to evaluate the effects in terms of public policy objectives. This inverted-U model was used to develop the conceptual model for this study. If we assume that prior to the PPS, most hospitals were operating in a very efficient manner (at R_{opt}), then any decrease in the resources used per case would result in reduced quality of care. If, however, most hospitals were operating in an inefficient manner prior to the introduction of the PPS (either in the interior portion of the curve or to the right of R_{opt}), then it is possible that improvements in efficiency could have been achieved under PPS without compromising quality, given the proper financial incentives. If the reasons for excessive use prior to PPS were related to the incentives of the insurance system, which did not reward cost-effective decision making, then PPS could have resulted in improved efficiency without having any impact on the quality of care.

In our analysis we focused on the relationship between changes in the amount of resources used and changes in rates of unanticipated readmissions. We modified the Donabedian model to explain the relationship between the resources used and the risk of a subsequent readmission, taking into account various constraints on hospitals, such as the risk of malpractice litigation (see Figure 2).

In our revised model, the upper curve represents the relationship between resources used and health outcomes, similar to the Donabedian model. The lower curve represents the relationship between resources used and the probability of adverse outcomes, that is, increased readmissions, increased mortality, increased complications, and increased malpractice risk. Although it would be preferable to measure changes in the quality of hospital care directly (by assessing changes in patient outcomes following treatment), there is no practical way to obtain data on patient health status before and after treatment for a large national sample of hospitals in 1983 and 1984. Instead, we measured changes over time in the rates of certain adverse events (unscheduled readmissions), under the assumption that those hospitals with lower rates of adverse events are providing better patient care, that is, better outcomes. Thus the rate of unscheduled readmissions is used as a proxy for a positive measure of outcome. Hospital readmissions have been used in this manner by many investigators, including Zook, Savickis, and Moore (1980); Anderson and Steinberg (1984, 1985); Smith, Norton, and McDonald (1985); Gooding and Jette (1985); Roos, Cageorge, Austen, and Lohr (1985); Fethke, Smith, and Johnson (1986); Roos, Cageorge, Roos, and Danzinger (1986); Riley and Lubitz (1986); Halloway and Thomas (1989); and Halloway, Thomas, and Shapiro (1988).

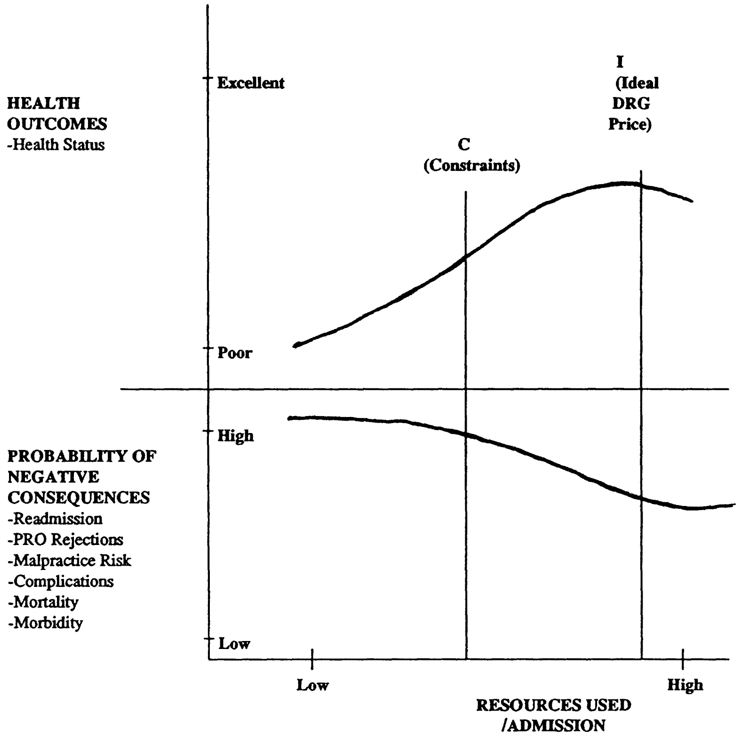

Figure 2: Cost-Quality Tradeoffs

Our model is based on the assumption that initially the more resources used per case, the better the outcome will be, and the lower the probability of negative consequences. We have drawn line C to represent the constraints that hospitals would face when reducing the amount of resources to be used per case. A hospital cannot operate to the left of line C without experiencing an unacceptable risk of various negative consequences. Line C can be equated with the PRO that helps to establish a "quality floor." Between line C and line I there is an area where some discretion can occur in deciding how many resources will be used for a case. Beyond line I, however, there are no additional benefits arising from the use of more resources. As additional resources are used per case beyond line I, patient outcomes may actually become worse. For example, a hospitalized patient who is kept too long may be exposed to increased risk of iatrogenic disease.

Note that we have drawn the vertical line I, labeled *Ideal DRG Price,* at the maximum point of the top curve. If the price paid by the Medicare program is close to this line, then hospitals would have incentives to provide the correct amount of resources, and outcomes would be optimal. There would be no need for hospitals to make tradeoffs between quality and efficiency unless hospitals chose to make such tradeoffs in order to increase their profits. Such a choice, however, would be constrained by the fear of negative consequences, which might offset the increased profits. If, however, many hospitals were operating prior to PPS by using amounts of resources past point I, then hospitals could become more efficient without the risk of increased negative consequences. We used this conceptual model to develop our hypotheses.

The hospital is the unit of analysis in this study. Both the risk-adjusted readmission rates and the efficiency scores were calculated over the Medicare and non-Medicare cases treated in each of the hospitals in our sample. Although the direct effects of PPS would have been on the Medicare cases, indirect effects would have affected the non-Medicare cases as well. Because many of the changes that hospitals made in adapting to the financial incentives of PPS could not be contained to the Medicare patients, we expected that all patients would be affected by PPS. If, for example, a hospital became more efficient by improving purchasing practices, reducing staff, or improving discharge planning, then such activities would have affected all patients treated in that hospital to some extent. Therefore we looked at changes in efficiency and changes in readmission rates by including both Medicare and non-Medicare patients in our analysis.

HYPOTHESES

The following hypotheses were tested:

Hypothesis 1: Rates of unanticipated readmissions increased after PPS was introduced.

Rationale: Under PPS the financial incentives encouraged earlier discharges; as the average length of stay decreased, the probability of an unanticipated readmission occurring would increase.

Hypothesis 2: Hospitals increased their technical efficiency under PPS.

Rationale: Because PPS is based on per case payments, hospitals had incentives to use fewer resources per case under PPS.

Hypothesis 3: Those hospitals that were the most technically efficient in 1983 were not the ones with the highest rates of unanticipated readmissions.

Rationale: If most hospitals were using excessive resources per case before PPS was introduced, then there would be little relationship between the amount of resources used and the rates of unanticipated readmissions. This corresponds to our assumption that most hospitals were operating either on the interior portion of the curves shown in Figure 2, or on the portion of the curve to the right of point I. If such "slack" existed, we would not expect those hospitals that were most efficient to have the highest rates of unanticipated readmissions. If such slack existed, then any tradeoffs that occurred (as fewer resources were used per case) would not have a negative effect on the quality of care.

Hypothesis 4: Those hospitals with the largest increases in technical efficiency in 1984 were not the ones with the greatest increases in their rates of unanticipated readmissions.

Rationale: If most hospitals were using excessive resources per case before PPS was introduced, then it would be possible for them to use fewer resources per case without causing systematic increases in the rates of unanticipated readmissions. This corresponds to our assumption that most hospitals were operating either on the interior portion of the curves shown in Figure 2, or on the portion of the curve beyond the point I. If such slack existed prior to the PPS, we would not expect those hospitals with the greatest increases in efficiency in

1984 to have the greatest increases in their rates of unanticipated readmissions after the PPS was introduced.

METHOD

OVERVIEW

We used existing data sources to test these hypotheses: Commission on Professional and Hospital Activities (CPHA) hospital abstracts, along with surveys done by the American Hospital Association. We developed the Risk-Adjusted Readmissions Index (RARI, see below), which allows for comparisons among hospitals and comparisons of each hospital's performance over time. Changes in technical efficiency were measured for the same sample of hospitals over the same time period using data envelopment analysis (DEA, see below), a linear programming technique. Using DEA, it was possible to compare inputs to outputs across hospitals, adjusting for changes over time in case mix and case complexity. Finally, the relationships between changes in rates of unanticipated readmissions and changes in efficiency were evaluated for the same cohort of hospitals.

OPERATIONAL DEFINITION OF RATES OF UNSCHEDULED READMISSIONS

As noted earlier, readmissions have been used as a measure of adverse outcomes of hospital care in many previous studies; nevertheless, there are several practical problems that must be confronted directly when developing an operational definition of readmission rates. These problems are

- what time period to use when counting readmissions
- how to handle subsequent readmissions to another hospital
- what kinds of cases to exclude (left against medical advice, etc.)
- whether to distinguish scheduled from unscheduled readmissions
- whether to distinguish between related and unrelated readmissions
- how to adjust for differences in case mix and case complexity when making comparisons across hospitals or over time

- how to account for factors that are outside the hospital's control (differences in patient compliance; family and community resources; patient and physician preferences, etc.)

In our study we have defined readmissions to include only those that occurred to the same hospital within 30 days of hospital discharge. This was a practical decision, because our data source only included events that occurred within the same hospital. Although it is difficult to get national statistics, it appears that more than 75% of readmissions return to the same hospital (Younger, MacDonald, Morradan, & St. John, 1989).

When the first admission resulted in a transfer, death, or discharge against medical advice, the case was excluded from RARI, because readmissions under these circumstances are difficult to interpret. Newborns were excluded because the risk factors for such readmissions are different and are not recorded in sufficient detail in the abstracts.

It is important to distinguish those readmissions that are planned or scheduled from those readmissions that are unanticipated if one wishes to use readmissions as a proxy measure of quality. In some circumstances the appropriate method of treatment can involve repeated admissions. This may occur when planning a course of chemotherapy or when planning bilateral surgical procedures, where it is best to allow the patient to recover from the first procedure before undergoing the second procedure. Because we were interested in using the RARI as a measure of hospital performance, we excluded those types of readmissions that would ordinarily be either scheduled (bilateral elective surgery; chemotherapy; diagnostic admission followed by surgical admission) or unavoidable (multiple admissions for AIDS patients, cancer patients, etc.). A list of such pairs of admissions was compiled and is available upon request.[1]

We decided not to attempt to distinguish related from unrelated readmissions. Distinctions between related and unrelated problems are difficult even when complete medical records are available. Although some of the previous studies that focused on a limited number of clinical conditions have attempted to identify certain diagnoses that they consider related on a readmission, it was not possible to do that for this study, because we were looking at patterns of readmissions for virtually all types of patients who were hospitalized.

We did adjust our data to reflect the fact that the case mix and case complexity of hospitalized patients changed at the time that PPS was introduced, as the volume of hospital admissions dropped significantly from 1983 to 1984. Because patients who were hospitalized in 1984 appear to be, on the average, sicker than those hospitalized in 1983, it was necessary to account for these differences in order to make valid comparisons of readmission rates in 1983 and 1984. The method of risk adjustment used for comparing readmission rates over time is described in the following section.

THE RISK-ADJUSTED READMISSIONS INDEX

In order to account for differences over time in case mix and case complexity, we developed the RARI, which is a method of adjusting for differences in case mix and case complexity. Risk factors were calculated by means of indirect standardization to a large national data base.

This data base contained cases from the 776 U.S. short-term general hospitals that submitted their data to CPHA in 1983. This group of hospitals represented approximately 14% of all U.S. short-term hospitals at that time and was generally representative of all U.S. hospitals in terms of bed size, teaching status, region, and ownership, except that for-profit hospitals and southern hospitals were somewhat underrepresented, whereas major teaching hospitals were overrepresented. It should be noted that we (and others) have used the CPHA data base in previous research studies, in which we compared hospitalization patterns in the CPHA hospitals to those in the universe of all U.S. short-term general hospitals (DesHarnais et al., 1987). No differences in treatment patterns or outcomes were apparent in these comparisons, other than the fact that certain types of hospitals are underrepresented or overrepresented, as noted above. Even though there were some biases in hospital representativeness, these variations should not have presented a serious problem when performing indirect standardization, because it is the pool of all discharges (rather than the individual hospitals) that is of interest when performing the indirect standardization.

Of these 776 hospitals in the CPHA data base, approximately one half used unit record numbering systems, which allowed us to link admissions to subsequent readmissions of the same patient to the same hospital. Thus approximately 3 million discharges were pooled to model the risk factors related to readmissions.

The risk model was based on those clinical factors recorded in the CPHA abstract data that were found to be predictive of readmissions in several of the earlier studies (Anderson & Steinberg, 1985; Holloway et al., 1988; Roos et al., 1986): the reason for admission (principal diagnosis), the patient's age, and whether there were comorbidities or complications during the initial hospital stay.

The first step in constructing the risk model was to aggregate the various diagnosis-related groups (DRGs) into clusters, which contained all of those DRGs with the same clinical condition. For example, DRGs 89, 90, and 91 are all simple pneumonia and pleurisy but differed according to the patient's age and by the presence or absence of comorbidities and complications. Once these 316 clusters were formed, we modeled the risk of readmissions separately within each cluster.

Contingency table models were used to distinguish six risk categories within each of the DRG clusters, based on three age groups and the presence of comorbidities or complications. Within the DRG clusters there were large differences in the probability of readmission across these six cells. Using this approach, we derived risk factors empirically for each cell within each cluster, using our large data base.

The resulting readmission risk score assigned to each patient is similar in some respects to Disease Staging (Gonnella, Hornbrook, & Louis, 1984), because severity scores are based on the interaction between the patient's principal diagnosis and certain secondary diagnoses that increase the risk of negative consequences. Staging, however, was derived in part through consultation with panels of physicians and was not developed to predict the risk of readmissions. Our approach is an empirical method of assigning the probability of readmission to each cell in each cluster strictly by means of indirect standardization to a large national data base.

There are some limitations and some advantages to using an empirical approach to measuring patient severity or complexity in relationship to the risk of readmission. Although it might have been desirable to use a severity measurement that included physiological measures recorded during the hospital stay, such as Acute Physiology and Chronic Health Evaluation (APACHE) II scores (Knaus et al., 1981); MedisGroups scores (Brewster, Jacobs, & Bradbury, 1984); or the Patient Severity Index (Horn et al., 1986), we did not have access to either the medical records or the detailed clinical information needed for these scoring systems. More important, none of these severity measures was developed to predict the risk of readmission, so there is no reason to believe that they would be useful for this purpose. Similarly, we chose not to use patient management categories (Young, Swinkola, & Zorn, 1982), because that system groups patients according to their use of resources, not severity in the sense of risk of readmission. Although it might have been useful to incorporate information on patient attitudes or self-rated health status (Holloway & Thomas, 1989), such information was not available for 1983 and 1984 for a nationally representative cohort of hospitals.

In our model we were not able to account for certain factors that are outside a hospital's control but might influence its readmission rate. Differences in patient compliance, family socioeconomic background, and patient or physician preferences could affect hospital readmission rates. Our data set did not contain information on these factors, but we assume that between 1983 and 1984 these factors did not vary greatly for the group of hospitals that we studied. It is possible that more community resources for home health became available in 1984. If anything, this change in supply might have lessened the need for readmissions in 1984.

In order to validate our model, we selected a sample cohort of 300 hospitals for 1983 and 1984. This cohort was chosen to be representative of all U.S. hospitals in terms of bed size, teaching status, and region of the country, and represented approximately 5% of all U.S. short-term general hospitals. Of the 300 hospitals originally selected, we determined that 245 had unit record numbering systems, which allowed us to link patient records to determine whether a readmission had occurred. The loss of 55 hospitals may have resulted in some bias in representativeness, because the vast majority of the hospitals that we lost were small (<100 beds), southern, nonteaching, and for-profit hospitals. Table 1 shows the characteristics of the 245 hospitals in the sample, in relationship to all U.S. short-term general hospitals.

We processed these patient records from the 245 hospitals through the RARI model and calculated the probability of an unanticipated

TABLE 1
Characteristics of the Sample Hospitals

	Commission on Professional and Hospital Activities Sample Hospitals	*All U.S. Hospitals in 1983*	*Sample as a % of All U.S. Hospitals*
Total	245	5,663	4.3
Region			
Northeast	38	813	4.7
North Central	86	1,674	5.1
South	66	2,125	3.1
West	55	1,051	5.2
Teaching status			
Nonteaching	199	4,796	4.1
Teaching	46	868	5.3
Ownership			
Governmental	44	1,686	4.1
Not-for-profit	184	3,220	5.7
For profit	17	757	2.2
Bed size			
<100	109	2,771	3.9
100-199	45	1,209	3.7
200-500	80	1,369	5.8
>500	11	314	3.5

SOURCE: Hospital characteristics were given on the tape of the American Hospital Association's Annual Survey of Hospitals, 1983.

readmission for each of these cases. We then accumulated the predicted number of unanticipated readmissions that would have occurred in each hospital had this group of patients been given "average" care (i.e., standardized to the almost 3 million observations we used to derive the risks for RARI). Next, we calculated the actual number of unanticipated readmissions for these hospitals and compared them to the predicted number. This procedure allowed us to identify changes in patterns of unanticipated readmissions, both over time and across hospitals.

In order to estimate the goodness of fit of the model, we calculated the correlation between the predicted and actual readmission rates across the 245 hospitals in our sample. Our results were $r^2 = .42$ in 1983, and $r^2 = .48$ in 1984, so almost one half of the variation in readmission rates across hospitals is explained by the variables in the model. The model thus makes a significant improvement over using "raw" or "unadjusted" readmission rates when measuring hospital performance. When comparing the raw predictions to the adjusted predictions, there is a substantial improvement in goodness of fit. The average error in the number of readmissions predicted per cluster per hospital, compared with the number of readmissions actually observed per cluster per hospital dropped from 2.23 cases using unadjusted data to 1.38 cases when using the adjustment. This demonstrates that the adjustment methodology gives much better predictions and is thus useful when attempting to adjust for differences in case mix and case complexity.

A multiple regression analysis was used to test for bias in the model, using hospital characteristics as the independent variables. The results showed that RARI is not biased by region, type of hospital ownership, or teaching status of the hospital. The only hospital characteristics that were associated with the RARI scores were the range of services (p = .02, with a value of –.0004), and rural status (p = .001, with a value of –.0083). This means that rural hospitals and those with more types of services had higher scores (significantly more readmissions), even after adjustments for case mix and case complexity, but the actual differences are very small, and of little practical significance.

MEASURING CHANGES IN EFFICIENCY

We also examined the impact of the Medicare PPS on changes in technical efficiency. Technical efficiency refers to the relationship between the resources used by hospitals, such as staff, beds and supplies, and the outputs they produce, such as hospital discharges, outpatient visits, and trainees. The technical efficiency with which hospitals provide services was evaluated based on 20 input and 31 output measurements using DEA.

DEA is based upon the pioneering work of Farrell (1957) and involves the use of linear programming techniques to calculate an "envelope" of frontier efficiency. This envelope is based upon the best use of technology observed in the sample, which becomes the standard against which the other observations are indexed. Charnes and Cooper (1962) have developed the theory behind this technique and applied it to other types of organizations. Sexton, Silkman, and Hogan (1987) extended the DEA methodology to include the measurement of average cross-efficiency.

Given a fixed DRG payment, hospitals can generate excess revenues by

1. increasing the level of services provided (outputs) without increasing the resources used (inputs); and
2. decreasing the resources used (inputs) without decreasing the level of services provided (outputs).

These two strategies describe what is commonly called technical efficiency. They address the relationship of the quantity of inputs required to produce a quantity of outputs. Simple examples of technical efficiency measures are miles per gallon (automotive technical efficiency), bushels per acre (agricultural technical efficiency), or tons per employee (technical efficiency of mineral extraction). An example from the health care industry is occupancy rate.

In this study we used DEA to compare the technical efficiency among our original sample of 300 hospitals with observations of each hospital in 1983 and 1984.

There are three major steps in performing DEA:

1. Select inputs and outputs to be used.
2. Derive optimal input/output weights.
3. Calculate average efficiency scores for each hospital.

We will now review each step in detail.

Select Inputs and Outputs to Be Used

The first step is to select those variables that will be used to measure inputs and outputs. For example, inputs may be measured in terms of number of beds, number of nurses, number of physicians, or amount of heating fuel, whereas outputs could be measured in terms of number of discharges in various specialties, number of residents and interns trained, number of long-term care patient days, or number of emergency room visits.

The efficiency scores produced by DEA are global, in that they characterize the operation of the entire hospital. To characterize accurately the operation of the entire hospital, it is necessary to include all of the resources (inputs) used to produce all of the services (outputs). We used essentially all of the inputs listed in the American Hospital Association Annual Survey. It was convenient to consolidate some inputs, for example, physicians, dentists, nurse practitioners, physician assistants, into a single category to lessen the computational burden of solving the model. Similarly, for outputs, all inpatient DRG categories were used, in addition to outpatient, long-term care, and education services. Again, some aggregation of variables was necessary to lessen the computational expense of performing the DEA.

The following inputs were used:

Physical plant
  General acute beds, pediatric beds, obstetric beds, psychiatric beds, subacute/long-term care beds, intensive care/other special beds, bassinets, surgical operating rooms, and birthing rooms.

Labor (FTE)
  Registered nurses, licensed practical nurses, nursing aides, health professionals (MDs, DDSs, nurse practitioners, physician assistants and others), ancillary technicians, other health-related personnel, and support personnel (administrative, clerical, and other).

Other
  Depreciation, interest, and fees; energy expense.

Financial
  Employee benefits and all other supplies.

All of the inpatient hospital outputs were derived from the CPHA discharge abstracts, which contain information on each hospital discharge for all of the hospitals in our cohort. Each abstract record contains information on the patient's principal diagnosis, secondary diagnoses, surgical procedures, age, and other aspects of treatment. Using this information, each case can be classified according to type of service (medical, surgical, obstetric, psychiatric) and patient's age (adult, pediatric) and according to whether any comorbidities or complications were present. The definition of comorbidities and complications is taken from the Health Care Financing Administration's list of such conditions, as promulgated in the PPS regulations issued in 1983. Each discharge was weighted by its corresponding DRG case-mix weight (as given in the original PPS regulations in 1983), and then aggregated into the following categories:

- Pediatric
  - No comorbidities or complications
  - 1+ comorbidities or complications
- Adult medical
  - No comorbidities or complications, 18-64 years
  - No comorbidities or complications, 65+ years
  - 1 comorbidity or complication, 18-64 years
  - 1 comorbidity or complication, 65+ years
  - 2+ comorbidities or complications, 18-64 years
- Adult surgical
  - No comorbidities or complications, 18-64 years
  - No comorbidities or complications, 65+ years
  - 1 comorbidity or complication, 18-64 years
  - 1 comorbidity or complication, 65+ years
  - 2+ comorbidities or complications, 18-64 years
  - 2+ comorbidities and/or complications, 65+ years
- Obstetrics
  - Normal delivery 18-39 years
  - Normal delivery <18 or >39 years
  - C-section 18-39 years
  - C-section <18 or >39 years
  - Other obstetric 18-39 years, no comorbidities or complications
  - Other obstetric <18 or >39 years, no comorbidities or complications
  - Other obstetric 18-39 years, with 1+ comorbidities or complications
  - Other obstetric <18 or >39 years, with 1+ comorbidities or complications
- Psychiatric/Substance Abuse
  - <18 years
  - 18-64 years
  - 65+ years
- Newborn
  - Normal
  - Abnormal

In addition, we extracted information on several outputs from the American Hospital Association Annual Survey. The following outputs are measured as simple counts:

subacute/long-term patients
trainees (FTE)
emergency room visits
outpatient visits
outpatient surgical procedures

In all, the DEA model was formulated with 31 outputs and 20 inputs for the 300 hospitals in our original sample for 2 years.

Derive Optimal Input/Output Weights

A hospital produces many outputs (a variety of inpatient services, outpatient and emergency room visits, and skilled nursing care) and uses a host of resources to produce these services (clinical and nonclinical labor, supplies, physical plant, and equipment). Having selected the variables for the DEA model, we used a mathematical technique called linear programming to search for the set of input and output weights that would, when applied to the outputs and inputs of the first hospital, produce the highest possible efficiency score. We repeated this process for each successive hospital until we had a unique set of weights for each hospital. When we applied the unique set of weights to that hospital's inputs and outputs, a hospital-specific global efficiency score was calculated. The global efficiency score can be represented symbolically as

$$\text{Efficiency} = \frac{\text{Outputs} \times \text{Output Weights}}{\text{Inputs} \times \text{Input Weights}}$$

Calculate Average Efficiency Scores

With the set of input and output weights determined for each hospital, we proceeded to calculate the efficiency scores for the hospitals. When the set of input and output weights selected by a hospital was applied to the actual data on the resources used and the services produced by the hospital, a self-rated efficiency score was produced. Because the input and output weights were selected specifically to maximize this self-rated efficiency, this score was often close to 1.0 (the maximum possible score). When the weights selected by one hospital were applied to the input and output data of another hospital, a cross-efficiency score was produced. The cross-efficiency scores vary in value resulting in a score that was usually below 1.0.

For each hospital, then, there is one self-rated efficiency score and a set of cross-efficiency scores derived from the weights of each of the other hospitals. For example, if there are 300 hospitals in a peer group, there will be 300 sets of unique input/output weights and 300 sets of inputs and outputs. When every set of weights is applied to every set of inputs and outputs, then 300 × 300 = 90,000 efficiency scores are calculated. The average cross-efficiency score for a hospital N is calculated by taking the simple average of the efficiency scores produced by applying the 300 sets of weights to the inputs and outputs of hospital N. The average cross-efficiency score is a measure of how well a hospital can transform resources into services in the aggregate.

RESULTS

The DEA was calculated for our sample cohort of 300 hospitals for 1983 and 1984; however, 51 of the hospitals in the original sample did not use unit record numbering systems, and thus readmission rates could not be calculated. These hospitals were thus eliminated from the quality/efficiency analysis, in which we looked at changes in rates of unscheduled readmissions in relationship to changes in efficiency for the same cohort of 245 hospitals for 1983 and 1984.

Hypotheses 1 and 2 were tested by examining changes in the rates of unanticipated readmissions and changes in efficiency that occurred between 1983 and 1984 for our cohort of 245 hospitals. Table 2 summarizes these changes. Note that these measures have already been adjusted (as described above) to reflect the differences in case mix and case complexity that occurred between 1983 and 1984.

We found that the rate of unanticipated readmissions increased by about 6% overall between 1983 and 1984. The increase for Medicare

TABLE 2
Changes in Efficiency and Unanticipated Readmissions: Pre- and Post-PPS

Measure	*1983*	*1984*	*Change*
Efficiency score	0.222	0.241	+10.3%
Index of risk-adjusted unanticipated readmissions	1.00 (base year)	1.06	+6%
Medicare	1.00	1.06	+6%
Non-Medicare	1.00	1.05	+5%

patients was slightly greater than for non-Medicare patients. The results are consistent with Hypothesis 1. It is evident that a substantial improvement in efficiency occurred between 1983 and 1984 when PPS was introduced. The improvement in technical efficiency averaged more than 10% in the hospitals in our sample. These findings are not surprising, given the financial incentives of PPS. Because hospitals are paid per case, there are incentives to use fewer resources per case, thus reducing cost, usually by shortening the average length of stay. Our findings are thus consistent with Hypothesis 2.

Next, we tested Hypothesis 3 by examining whether those hospitals that were the most efficient were the ones with the highest readmission rates in either 1983 or 1984. Each hospital was ranked according to its relative scoring on the efficiency measure and its relative scoring on the readmission measures. Then a Spearman rank order correlation coefficient was calculated to determine whether hospitals' rankings on one measure were related to their rankings on the other measure. Our results showed no significant rank correlation in either year (correlation of .04; not significant at .05). Those hospitals with the highest efficiency scores were not the ones with the highest readmission rates. This finding was consistent with Hypothesis 3.

Finally, we examined the simultaneous changes in the efficiency and readmission measures, to test Hypothesis 4. Each hospital was ranked according to the degree of change it experienced in efficiency; then it was ranked according to the degree of change it experienced in its rate of unanticipated readmissions. The Spearman rank order correlation coefficient was calculated to determine whether those hospitals that experienced the greatest increases in efficiency between

1983 and 1984 were also the ones that had the greatest increases in their readmission rates. Once again, the result was an insignificant Spearman rank order correlation coefficient. It is clear that tradeoffs between efficiency and rates of unanticipated readmissions did not occur in any systematic fashion. Those hospitals with the largest gains in efficiency were not the ones that demonstrated the largest increases in their readmission rates. These findings are consistent with our fourth hypothesis.

DISCUSSION

This project was designed to produce case-mix-adjusted measures of rates of unanticipated hospital readmissions and also measures of hospital efficiency, using existing data bases from the CPHA and from the American Hospital Association. These measures were then used to monitor changes over time for individual hospitals and for groups of hospitals. A sample cohort of hospitals was observed for 1983 and 1984. We found that (overall) technical efficiency improved during this time period, whereas the rates of unanticipated readmissions increased. We did not find that the most efficient hospitals had the highest rates of unanticipated readmissions; neither did we find that changes in hospital scores on the readmission index were correlated with changes in the efficiency scores.

Several limitations should be noted. Measurement of changes in readmissions and efficiency between 1983 and 1984 were undoubtedly affected by financial incentives of PPS to "upcode" comorbidities and complications. Such inconsistencies in coding practice could bias our results somewhat. If coding in 1984 was more inclusive of comorbidities and complications than in 1983, the case mix and case complexity in 1984 would appear higher than they actually were, relative to 1983. This bias would have caused us to underestimate slightly the increase in readmissions that occurred in 1984 and also to overestimate slightly the improvements in technical efficiency that we observed in 1984. Although we acknowledge this as a possible bias in our estimates of changes from 1983 to 1984, we do not believe that the bias is a serious problem in our analysis of tradeoffs.

Another caveat should also be noted. The fact that we did not find pronounced tradeoffs between readmissions and efficiency does not imply that such tradeoffs could not have occurred. Our unit of analysis was, of necessity, the hospital, because hospital cost statistics cannot be obtained broken down by hospital departments. If such figures eventually should become available, then we would be able to refine this analysis to the hospital department level, where tradeoffs may have occurred.

Our interpretation of these findings is that hospitals did not have to reduce the quality of care in order to increase efficiency during the first year of the PPS, because there was a great deal of slack (or inefficiency) in the hospitals prior to the introduction of the PPS. This interpretation is consistent with findings reported by other investigators. Guterman, Altman, and Young (1990) examined the PPS operating margin for hospitals in the years following the introduction of the PPS. The operating margin is described as the percentage of PPS payments remaining after PPS operating costs are accounted for. The PPS operating margin compares the payments received by the hospital under PPS with the operating costs to which those payments are intended to apply. This comparison provides a reasonable measure of PPS payments. Guterman and his colleagues reported that the aggregate PPS margin for all hospitals was very high (14.5%) in the early years of PPS, although it was less for rural hospitals (8.4%). In subsequent years, however, the margins had dropped considerably, and by the fifth year of the PPS, rural hospitals had a negative estimated aggregate PPS margin, which meant that PPS payments did not cover PPS operating costs for the group as a whole. These findings help to explain why the increases in technical efficiency that we observed in the first year of PPS did not appear to be related to increases in the rates of unanticipated readmissions. Studies by Feder, Hadley, and Zuckerman also support this interpretation. Hadley, Zuckerman, and Feder (1989) found that "hospitals responded immediately and strongly to the opportunity to earn a profit." They also found that "even without further reductions in length of stay and with increases in total spending, hospitals that did not face high fiscal pressure managed to increase their total margins in the second year [of PPS]" (Feder, Hadley, & Zuckerman, 1987). Apparently there was little danger of financial loss under PPS in the early years, so there was no need to reduce resource use to the point that quality of care was threatened. As the PPS margins dropped in subsequent years, however, it is clear that the tradeoffs could be quite different: Any increases in efficiency could pose serious threats to the quality of care. Such behavior should be monitored carefully.

From the policymaker's perspective, our study is important because it demonstrates that it is possible to use existing data sources to develop a monitoring system that accounts for differences across hospitals by using case-mix-adjusted measures. Such a system could be useful for monitoring the effects of various changes in reimbursement incentives. Also, such measures may be useful in developing incentives that allow for hospital reimbursement based on the quality of hospital performance, in addition to using a disease-and-treatment classification system. Before such aggregate measures are used by policymakers, however, one would need to evaluate the charts of patients from hospitals with high unexpected readmissions rates, to validate that the models can identify clinically important problem areas.

NOTE

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