

Utilization and case-mix impacts of per case payment in Maryland

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Maryland has simultaneously operated per case and per service hospital payment systems since 1976 with varying levels of stringency in setting per case rates. Regression analyses of this experience are used to compare the impacts of these systems on admissions, length of stay, and case-mix costliness from July 1,

1976 to June 30, 1981. Our results indicate a positive effect on admissions and negative effects on case mix and length of stay for the per case payment approach relative to the per service approach. More stringent levels of per case payment are associated with stronger utilization responses.

Introduction

Although cost containment is a primary objective of prospective hospital payment systems, it is widely recognized that these systems may also impact on utilization (Kinzer and Warner, 1983). These utilization impacts may be fully consistent with the cost-containment goal; an example is reductions in length of stay to eliminate days of inpatient care having little or no health benefit. On the other hand, these impacts could take the form of increases in utilization and thus could undercut cost-containment efforts.

Concern has recently been expressed about perverse utilization impacts of per diem and per service payment systems in which hospitals receive additional revenues for each additional day or specific service (e.g., lab test). This concern is supported by empirical evidence of positive impacts on length of stay (Worthington and Piro, 1982) and use of ancillary services (Lewis, 1985). To correct this deficiency of per diem or per service payment systems, per case payment systems have been developed (Seidman and Frank, 1985; Atkinson and Cook, 1981; Hellinger, 1985). The Maryland Guaranteed Inpatient Revenue (GIR) program, the first of these per case systems, was introduced in 1976. New Jersey introduced a diagnosis-related group based system in 1980 and Medicare's prospective payment system (PPS) was enacted in 1983. A number of other States and private insurers have subsequently moved to adopt their own per case payment program (Hellinger, 1985).

This article is an empirical analysis of the experience under the Maryland GIR program from 1976 to 1981. This program is of interest for several reasons. First, it has been in effect the longest and has presumably dealt with any operational problems in its startup phase. Second, the program allowed us to compare two different approaches to per case payments, as well as a per service payment scheme, because all three systems were in operation in Maryland during our study period. Comparisons among these systems in terms of impacts on admissions, length of stay, and case mix are presented.

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Payment systems and incentive structures

The Maryland Health Services Cost Review Commission began setting per service rates for all hospitals in Maryland on July 1, 1974. Selected hospitals were first placed by the Commission on per case rates (GIR) in late 1976; during the 5 years of our study (from July 1, 1976 to June 30, 1981), 22 of the 46 acute care hospitals in our study had experience with per case payments. When Medicare and Medicaid waivers took effect on July 1, 1977, all patients in the State were paid for according to rates set by the Commission.

Per service rates were set for all hospitals on the basis of budgeted volumes and costs in routine care, special care, and ancillary patient service centers. When actual revenues in a year exceeded budgeted revenues because service volumes exceeded projections, hospitals were allowed to retain 60 percent of the excess revenues for routine services and 40 percent of the excess for ancillary services. (The 60 percent figure increased to 70 or 80 percent for especially large volume increases.) When actual revenues fell short of projections because of volume shortfalls, the hospital was allowed to recoup 80 percent of the revenue shortfall in its next year's rates. A smaller percentage of revenue was recouped if the volume shortfall was larger than 5 percent (Maryland Health Services Cost Review Commission, n.d.). The asymmetry between upward and downward revenue adjustments because of volume fluctuations was intended to encourage reductions in unnecessary utilization (Maryland Health Services Cost Review Commission, 1982).

For hospitals on the GIR program, per service rates set in the manner just described were the basis for generating bills to patients or third-party payers; however, the GIR program superimposed on this process a projected case-mix-adjusted revenue cap per case. If a GIR hospital realized an actual revenue per case below (above) its cap, it received additional (reduced) revenues via higher (lower) rates in the following year, equal to the relevant variable cost factor times the number of discharges times the difference between the cap and actual revenue per case. For example, suppose a hospital's actual revenue exceeded projected revenue and its overall variable

cost factor was approximately .5. If its case-mix-adjusted average revenue per case was \$500 below its GIR level and it had 5,000 discharges, it received $\$500 \times 5,000 \times .5$ or \$1,250,000 in additional allowable revenue in next year's rates.

The GIR program was intended to create incentives to reduce length of stay and use of ancillary services and to be neutral for changes in the volume of admissions. It is possible, however, that it actually encouraged increased admissions. If a GIR hospital reduced its length of stay and ancillary revenues per case by 5 percent and simultaneously increased admissions by 5 percent (so that actual revenue was about equal to projected revenue), it would receive a GIR "bonus" equal to 3.1 percent of total revenues. Assuming that the hospital's revenues are evenly split between routine and ancillary departments, its variable cost factor for the first 2-percent increase in admissions would be 0.5; for the next 3-percent increase, its variable cost factor would be 0.7. The weighted average of these two factors is 0.62; applying it to the 5-percent difference between actual revenue and allowable revenue under the GIR yields a bonus of 3.1 percent. Moreover, if these simultaneous changes had little effect on total costs, the 3.1-percent GIR bonus would all be added net revenue. In comparison, a per service hospital in the same situation would receive no net revenue bonus at all.

Usually, the GIR level was derived from the hospital's own charges during a base period of its choosing. For this period, live discharges (excluding newborns) were grouped according to a case-mix scheme and average charge per case for each group was computed. Adjustment of these average charges for rate changes between the base and current periods yielded current average charges that were then applied to the current period frequency distribution of live discharges by group to determine the current period GIR level.

In three instances, hospitals were judged by the Commission to have excessively high per case costs and were placed on a per case revenue cap that was actually below projected levels based on inflation adjustments and their historical experience. For these three capped hospitals, the excess of average charge per case above the cap was deducted from next year's rates and savings below the cap were not added to next year's rates. Thus, the main effect of reducing length of stay or ancillary use was to reduce losses; bonus payments were not made for beating the cap. Reductions in case-mix costliness were also encouraged because the cap for these hospitals was not case-mix adjusted. Finally, as with the regular GIR, additional admissions could offset some of the negative impacts of reduced length of stay or ancillary use on total revenues.

Although the constraint on the capped hospitals was mandatory, the GIR program was phased in on a voluntary basis starting in late 1976. The Commission offered inducements for hospitals to go on the GIR, including an extra 1 percent inflation allowance and additional revenues for a hospital's administrative

expenses in monitoring its own performance. In some instances, the GIR was offered to hospitals as an alternative to a full review of rates, which the Commission felt would otherwise have been needed because of major service additions, expansions, or out-of-line cost performance.

The strength of these inducements resulted in fairly rapid implementation. Of the 46 non-Federal general acute care hospitals in the State in 1976, 6 went on the GIR in the latter part of 1976 (including 2 capped hospitals), 6 were added during 1977, 6 in 1978, 3 (including 1 capped hospital) in 1979, and 1 in 1980. Six hospitals dropped off the GIR program and returned to per service payment; these were smaller hospitals, generally lacking adequate management information systems. One of the two hospitals capped in 1976 switched to a regular GIR in 1981; the hospital capped in 1979 switched to the regular GIR in late 1980.

Objectives and methods

The objective of the study from which this article derives was to assess the impacts of the GIR per case payment system by comparing the experience of Maryland's general acute care hospitals under per case versus per service payment. Our analysis pertains to the fiscal years 1977-81 and the 46 hospitals operating throughout this period. We have previously reported on cost, charge, and efficiency impacts (Salkever, Steinwachs, and Rupp, 1986; Rupp, Steinwachs, and Salkever, 1984; Rupp, Steinwachs, and Salkever, 1985).

The regression models used for estimating these GIR impacts are based on a standard short-run model of hospital decisionmaking (Sloan, Feldman, and Steinwald, 1983). The hospital decisionmakers are presumed to choose variable input quantities so as to maximize an objective function based on output quantity, quality, and net revenue. The hospital is subject to constraints imposed by demand conditions, technology, input prices, fixed capital, and the rates set by the regulators. (The hospital can still vary its rate structure within classes of services.) The levels of admissions, length of stay, and case mix resulting from the hospital's choices can be related, via the first-order maximization conditions, to the exogenous factors that determine the constraints faced by the hospital. These factors, which appear as independent variables in our regression models, pertain to market demand conditions (e.g., income), input prices (e.g., wages), and the hospital's fixed capital stock. A measure of teaching activity is also included to control for differences in objectives between teaching and nonteaching institutions.

Within the context of this conceptual framework, several different interpretations of the GIR impacts reported in our statistical analyses are possible. First, there may be evidence of supplier inducement in an imperfect agency relationship; this is analogous to the often studied inducement effects on the demand for physician services (Wilensky and Rossiter, 1981;

Pauly, 1980). For example, GIR hospitals may respond to their incentive structures by encouraging staff physicians to admit more patients and to reduce length of stay. This encouragement is translated into induced demand if it affects the staff physicians' recommendations to their patients. Effects of GIR incentives on case mix are less clear because the GIR level will increase as case-mix costliness increases. For some of the hospitals, however, the case-mix categories for calculating the GIR adjustment were fairly broad. Moreover, the capped hospitals did not have their per case payment limit tied to case mix. In these instances, per case payment may encourage admissions policies oriented toward a less costly case mix. It should also be noted that GIR impacts on case mix could be the indirect result of GIR impacts on admissions. For example, if per case payments encourage admissions but it is generally easier to shift the demand for admissions in the less costly case categories, a negative impact on case mix would be observed. In addition, there is the possibility of changes in coding practices if payments depend upon the hospital's case mix. Recent analysis of the Medicare prospective payment system (PPS) suggests that this program did encourage hospitals to code patient data more carefully with the result that patients tended to be classified into more costly diagnosis-related groups (DRG's) (Carter and Ginsburg, 1985).

A second interpretation of GIR impacts does not involve direct inducement or demand manipulation. If per case payment leads to improvements in efficiency that are translated into lower costs to patients, the number of admissions demanded would rise (though the price elasticity of demand is presumably small). Similarly, GIR-induced reductions in waiting time for elective admissions could increase the demand for admissions.

Dependent variable measures and trends

Data on numbers of hospital admissions were taken from the Medicare cost reports (MCR's) of the 46 study hospitals. The average length of stay variable was computed from tabulations of the discharge abstract data hospitals are required to submit to the Commission. Occasional missing data items were filled in from the American Hospital Association Annual Survey data and statistical reports of the Maryland Hospital Association.

The case-mix measure used in our study was developed for two purposes: To use as an explanatory variable in cost-function regressions, and to serve as a dependent variable in examining hospital responses to the financial incentives under Maryland's per case payment arrangements. Accordingly, we devised a measure that used data on charges for constructing weights for each case category. This approach, which has been used in many hospital cost studies, assumes there is at least a strong correlation between costs and charges for the various types of cases. Given this assumption, we refer to the index as a measure of

case-mix costliness. Because the Commission substantially restricted internal cross-subsidization in its rate-setting policies, the correlation between costs and charges for specific services should be much higher in Maryland than elsewhere during this period. This makes more tenable our assumption that our case-mix index based on charges in fact measures the costliness of the hospital's case mix.

Our case-mix costliness index is developed from data on the diagnostic classification and charges for all short-stay hospital discharges in Maryland provided by the Maryland Resource Center and the Commission. The computational method begins by defining a market basket set of diagnostic categories. The original DRG classification scheme with 383 DRG's is employed and the following 9 DRG's are included as the market basket set:

- 074—Diabetes without surgery without secondary diagnosis or with minor secondary diagnosis with age greater than 35.
- 075—Diabetes without surgery with major secondary diagnosis.
- 121—Disease of the heart, acute myocardial infarction.
- 132—Disease of the heart, failure (poor function) without surgery.
- 158—Hemorrhoids.
- 167—Pneumonia without surgery with secondary diagnosis with age greater than 30.
- 264—Disease of the female reproductive system with surgical procedure (dilatation and curettage, visualization, removal of fallopian tubes) without secondary diagnosis.
- 265—Disease of the female reproductive system with surgical procedure (dilatation and curettage, visualization, other) with secondary diagnosis.
- 266—Disease of the female reproductive system with surgery (removal of womb, repair of female reproductive organ, other major).

This set of categories was selected because it includes both surgical and nonsurgical cases and because all nine DRG's are common and were reported by all the study hospitals. (Note that obstetrical conditions are absent because several of the hospitals do not have obstetrical units.)

The next step in the computational procedure was to calculate the average charge in 1980 for each of the nine DRG's in each hospital to compute an overall market basket average charge for each study hospital. This figure was then divided into the actual charge figure for every discharge in every DRG in each of the study hospitals, so that all 1980 charge data for individual patients were expressed relative to the hospital market basket average.

For each of the 383 DRG's, these relative charge figures were averaged across patients within each hospital, and then these hospital-specific averages were averaged across all hospitals reporting at least one patient in that DRG. The result was a statewide average relative costliness figure for each of the 383 DRG's. Finally, these 383 figures were applied to the frequency distribution of discharges in each study year

in each hospital to compute the case-mix costliness index. A formal description of the case-mix index calculation can be given by first defining AC_{ij} to be the average charge in 1980 for patients in the i th DRG in the j th hospital where $i=1, \dots, 383$ and $j=1, \dots, 46$. Denoting the 9 DRG's in the market basket by values of i from 1 to 9, the market basket average charge for the j th hospital is then $MB_j = \sum_i AC_{ij}/9$ ($i = 1, \dots, 9$). The relative average charge for the i th DRG in the j th hospital is $RAC_{ij} = AC_{ij}/MB_j$, where $i=1, \dots, 383$. The costliness weight for the i th DRG is $RC_i = \sum_j RAC_{ij}/46$. Finally, where P_{ijt} is the fraction of the j th hospital's patients in year t in the i th DRG, we compute the case-mix costliness index for the j th hospital in year t as $CI_{jt} = \sum_i (RC_i \times P_{ijt})$.

Note that the use of an index based on relative weights has one important advantage over a simpler index based on absolute charges. In particular, this index is much less sensitive to variations among DRG's in the distribution of patients across hospitals. Thus, any particular DRG that might happen to be more common in less efficient hospitals will not have a high relative costliness weight simply because of this fact.

Trends in dependent variable values for hospitals grouped according to GIR status are reported in Table 1. Comparing the length of stay results in the last two rows of the table, we observe a more rapid rise in the 1977-79 period for non-GIR hospitals and a slower decline in 1979-81. The latter result is because of a sharp decline (12.03 percent) in the capped hospitals in 1979-81.

Case-mix index values moved downward for all groups of hospitals in 1977-79. During the period from 1979 to 1981, case mix rose slightly in the non-GIR hospitals but declined slowly for most of the hospitals on per case payment. If per case payment induces "DRG creep," it is not evident from these data.

Admissions increased throughout the study period

for most groups of hospitals. The growth for GIR hospitals tended to be below that of other hospitals from 1979 to 1981; however, this may have resulted from, in large part, environmental factors such as slower population growth in Baltimore City (where many of the GIR hospitals are located). Results from our multiple regression analyses, controlling for these environmental factors, provide some evidence of the expected positive GIR effect on admissions.

Explanatory variables

A listing of explanatory variables is shown in Table 2. The input price measure is the average nursing wage level in the area where the hospital is located (NWAGE). Measures of the hospital's capital stock are bed days available (BDDYS) (i.e., average bed complement \times 365 days) and the ratio of special care to total beds (SPECRTO). As a measure of teaching activity, also included are the number of approved residency positions per bed in the hospital (POSBED). (Data on numbers of residents actually filling these positions were not available for the full study period.)

Hospital characteristics such as bed size and teaching programs may also be influenced by payment systems. Thus, GIR effects with our short-run model may differ from longer-term effects if the GIR system impacts on these characteristics. There is also a potential econometric problem of simultaneity bias if these hospital characteristics are influenced by the disturbance term; however, the short time period covered by our study and the inclusion of hospital-specific dummy variables to control for omitted but stable hospital-specific effects should mitigate this problem considerably.

Other explanatory variables (Table 2) include county population characteristics presumed to influence product-demand conditions (MEDAGE, HSIZE, HINC, PUBASST, AND MCARE) and the estimated service area population (HPOP), which is

Table 1
Comparison of percent changes in average dependent variable values, by guaranteed inpatient revenue (GIR) status: 1977-79 and 1979-81

GIR status	Length of stay		Case mix		Admissions	
	1977-79	1979-81	1977-79	1979-81	1977-79	1979-81
	Percent change					
Total (N = 46)	+2.33	-1.92	-6.93	0	+3.70	+1.44
Capped hospitals (N = 3)	+5.14	-12.03	-5.50	-1.94	+3.62	+0.28
On GIR since 1977 (N = 3)	+0.37	-0.86	-9.80	-1.09	+5.68	+9.15
On GIR since 1978 (N = 5)	-2.36	+3.85	-6.19	0	+1.16	+2.94
On GIR post-1978 (N = 5)	+5.40	-0.12	-6.86	-2.11	+5.60	-3.57
On GIR then off (N = 6)	-0.14	+2.85	-6.25	0	+1.66	-3.36
Never on GIR (N = 24)	+4.08	-0.37	-5.00	+1.05	+2.97	+4.70

NOTE: N is the number of cases.

Table 2
Definitions of explanatory variables

Variable	Definition
BDDYS	Acute care bed days available in the hospital.
SPECRTO	Ratio of special care beds to total acute care beds in the hospital.
POSBED	Positions in approved residency programs per available acute care bed day in the hospital.
DRGMIX	Case-mix costliness index value for the hospital.
MEDAGE	Median age of county population.
HSIZE	Mean number of persons per household in county.
HINC	Median county household income, deflated.
PUBASST	Ratio of county AFDC, general assistance, and SSI recipients to county population.
MCARE	Ratio of county Medicare aged and disabled enrollees in Part A or Part B to county population.
HPOP	Estimated population in hospital market area.
ACRATIO	Ratio of acute care bed days to total bed days available in the county.
DRGMIX	Case-mix costliness index.
MDPOP	Ratio of patient-care physicians in office-based practice to population in the county.
NWAGE	General duty nurse wage in the area, deflated.
GIRSTAT	Equals 1 if a hospital is on the GIR for at least 6 months of the fiscal year; equals 0 otherwise
GIRTEACH	Equals 1 if GIRSTAT equals 1 and the hospital has any approved residency programs; equals 0 otherwise
TIME	Time in months from date the hospital went on the GIR to the midpoint of the fiscal year (if GIRSTAT equals 1); equals 0 otherwise
TIMTEACH	Equals GIRTEACH multiplied by TIME
CAP	Equals 1 if GIRSTAT equals 1 and the hospital's per case rate is based on an external CAP; equals 0 otherwise
CAPTIVE	Time in months from the date the hospital went on the CAP to the midpoint of the fiscal year (if CAP equals 1); equals 0 otherwise
ONOFF	Equals 1 if the hospital was not on the GIR for 6 months of the fiscal year but has been previously; equals 0 otherwise
CAPOFF	Equals 1 if CAP equals 0 for the current fiscal year and CAP equals 1 for any previous fiscal year; equals 0 otherwise

NOTES: AFDC is Aid to Families with Dependent Children. SSI is Supplemental Security Income. GIR is guaranteed inpatient revenue.

the county population multiplied by the ratio of acute care beds in the hospital to acute care beds in the county.¹ To control for possible substitution or complementarity effects of other available health care resources, ACRATIO and MDPOP are included. Lower values of ACRATIO and higher values of MDPOP are indicative of greater availability of other health care resources. With HPOP and BDDYS

¹Note that this measure increases as the hospital increases its bed stock (unless there are no other hospitals in the county) and decreases as other hospitals in the county expand their bed stock.

already included in our regressions, we assume in effect that physicians are distributed among hospital service areas within the county in proportion to HPOP and nonacute beds (e.g., extended care facilities, chronic care hospitals) are distributed in proportion to BDDYS.

The independent variables expressed in dollars (HINC and NWAGE) were deflated by a cost-of-living index. Index values were computed for the Baltimore area, the Washington suburban area in Maryland, and for all other parts of the State. Although this deflation procedure controls for general economy-wide inflation, dummy variables for individual years are also included. Effects of technological change or other year-specific changes affecting all hospitals should be picked up by these dummy variables.

Three pairs of GIR variables were included. For all hospitals on the GIR for at least 6 months in a fiscal year, a GIR dummy (GIRSTAT) was set equal to one. The coefficient of this variable measures the one-time impact of going on the GIR. To allow for the possibility that the initial GIR impact changed over time, the number of months during which the hospital was on the GIR (TIME) was included.

Differences between teaching and nonteaching hospitals in GIR impacts are captured by the coefficients of GIRTEACH and TIMTEACH. Such differences might be expected because clinical decisions in teaching hospitals are more likely to rest with physicians who are salaried hospital employees and, therefore, arguably more sensitive to the hospital's financial incentives.

The third pair of variables, also analogous to GIRSTAT and TIME, is CAP and CAPTIME. These only take on nonzero values for the three capped hospitals; for these hospitals, the per case payment limit imposed a more stringent financial constraint.

In addition, to capture the impact of going off the GIR system, the dummy variable ONOFF was set equal to one for each year in which a previously GIR hospital was off the system. Similarly, CAPOFF equals one for 1981 for the two capped hospitals that went off the CAP; otherwise it equals zero.

Finally, note that other recent studies based on the same conceptual framework have assumed that case mix is exogenous (Becker and Sloan, 1983; Sloan and Becker, 1981; Sloan, Feldman, and Steinwald, 1983). This assumption may be justified on the grounds that case mix essentially reflects the facilities and services available at the hospital, and that these are fixed in the short run. Alternatively, one might argue that case mix measures exogenous demand characteristics that are analogous to demographic and socioeconomic characteristics of the population. Although we obviously do not generally maintain the exogenous case-mix assumption in our study, some length of stay models are estimated with our case-mix variable (DRGMIX) included as a regressor.

Functional form and estimation method

All regressions are estimated with the dependent and continuous independent variables entered in logarithmic form. Exceptions are POSBED, SPECRTO, TIME, TIMTEACH, and CAPTIME, which are entered in linear form because of zero values for many data points.

To control for possible correlation of regression disturbances for the same hospital over time, we have employed the fixed-effects method of least-squares regression with pooled data. This method involves the inclusion of dummy variables for each hospital in the sample (save one if a constant term is also included). Coefficient estimates obtained with this method will not be biased by omitted hospital-specific characteristics that are stable over the study period. This is important in that these hospital characteristics may have been correlated with the GIR variable (because hospitals were not randomly selected for the GIR program). Bear in mind, however, that this method does not take into account autocorrelation because of autoregressive disturbances, and that it is somewhat inefficient because any information from cross-sectional variation is not used in estimating the regression coefficients. Thus, it is a rather conservative method of measuring GIR effects in the sense that it will tend to yield less significant coefficient estimates than other methods that are more susceptible to omitted variable bias (Pindyck and Rubinfeld, 1981; Mundlak, 1978). Under the circumstances, we believe it is preferable to use the more conservative approach to minimize the risk of bias because of nonrandom assignment of hospitals to different payment systems.

Regression results

Length of stay regression results

Estimated length of stay regressions with GIRSTAT, TIME, and ONOFF included to capture overall average GIR effects are shown in Table 3. Regression (1) includes DRGMIX as an explanatory variable, but regression (2) does not. In both instances, the three GIR variables do not approach statistical significance individually; joint F-tests of these variables are also insignificant. Among the other explanatory variables, BDDYS, HPOP, and DRGMIX have the most significant coefficients; these results seem plausible because they indicate that increases in bed complement (holding population constant), decreases in market area population (holding bed complement constant), and increases in case-mix costliness raise length of stay. The Medicare variable (MCARE) coefficient also becomes significantly negative when DRGMIX is dropped, presumably reflecting a negative partial correlation between DRGMIX and MCARE. (The zero-order correlation between these two variables is, however, +0.223.)

Table 3

Independent variables, coefficients, and P values for length of stay regressions

Independent variable ¹	Regression 1		Regression 2	
	Coefficient	P ²	Coefficient	P ²
GIRSTAT	0.02511	0.2019	0.02333	0.2445
TIME	-0.00063	0.3266	-0.00080	0.2237
ONOFF	0.03612	0.2383	0.02963	0.3411
BDDYS	0.36721	0.0000	0.40695	0.0000
SPECTRO	0.17464	0.6548	0.33520	0.3952
POSBED	-54.23213	0.6283	-90.06446	0.4278
NWAGE	-0.07097	0.8271	0.03182	0.9230
MDPOP	-0.00752	0.9284	-0.01096	0.8978
ACRATIO	-0.04633	0.8192	0.02153	0.9164
HPOP	-0.19466	0.0553	-0.23492	0.0223
MCARE	-0.33555	0.1487	-0.46442	0.0460
PUBASST	0.10997	0.1929	0.03775	0.6441
HINC	0.11585	0.6627	0.18857	0.4844
HSIZE	-0.26006	0.3915	-0.31710	0.3048
MEDAGE	0.23904	0.6843	0.42038	0.4807
DRGMIX	0.36682	0.0063	—	—

¹All regressions include separate intercepts for each hospital and year. All continuous dependent and independent variables are expressed as logarithms except for SPECRTO, POSBED, and GIR-related time variables.
²P values are two-tailed.

NOTE: Explanations of variables are given in Table 2.

Although the overall GIR results were not significant, regressions including other GIR variables indicated the possibility of more substantial length of stay effects for some groups of hospitals. When each of the eight GIR variables was entered as the sole GIR variable in our regression, with DRGMIX included, a significantly negative coefficient (-0.00253 with a one-tailed $P = 0.0137$) was obtained for CAPTIME. When DRGMIX was excluded, a significantly negative coefficient was obtained for CAPTIME and the negative TIMTEACH coefficient approached significance. (Coefficient values were -0.00296 and -0.00083, respectively, and corresponding one-tailed P -values were 0.0053 and 0.0868.)

Results obtained when GIR variables are entered stepwise are shown in Table 4. In column 1 of the table, with DRGMIX included, CAP enters with a significantly positive coefficient; also the negative CAPTIME coefficient increases in magnitude (from -0.00253 to -0.00404) when CAP is entered. Because CAP only changed from zero to one for one hospital over the study period, and it changed from one to zero for two hospitals in 1981, its positive coefficient may be picking up the persistence of length of stay reductions as hospitals went off the CAP. This accords with the result in column 2 that when CAPOFF is included, the positive CAP coefficient diminishes in size and becomes insignificant. A similar change is observed when DRGMIX is not included in the regression (compare columns 3 and 4).

Case-mix regression results

As in the length of stay analysis, overall GIR

Table 4
Length of stay stepwise regression results for guaranteed inpatient revenue (GIR) variables

GIR variable	Regression 1 ¹	Regression 2 ¹	Regression 2 ²	Regression 2 ²
CAPTIVE	-0.00404 (0.0021)	-0.00401 (0.0057)	-0.00466 (0.0004)	-0.00473 (0.0012)
CAP	0.11108 (0.0210)	0.07090 (0.2791)	0.12963 (0.0070)	0.10664 (0.1005)
CAPOFF	—	-0.05002 (0.4618)	—	-0.03334 (0.6251)
GIRSTAT	—	0.00122 (0.9690)	—	0.00088 (0.9779)
GIRTEACH	—	0.01264 (0.7546)	—	0.00488 (0.9043)
TIME	—	0.00078 (0.5439)	—	0.00036 (0.7826)
TIMTEACH	—	-0.00093 (0.5237)	—	-0.00043 (0.7702)
ONOFF	—	0.03171 (0.2824)	—	0.02398 (0.4196)

¹All non-GIR explanatory variables shown in Table 3, Regression 1 are included.

²All non-GIR explanatory variables shown in Table 3, Regression 2 are included.

NOTE: Explanations of variables are given in Table 2. Two-tailed *P* values are in parentheses.

Table 5
Independent variables, coefficients, and *P* values for case-mix and admission regressions

Independent variable	Case mix		Admissions	
	Coefficient	<i>P</i> ²	Coefficient	<i>P</i> ²
GIRSTAT	-0.00485	0.6742	-0.05137	0.0153
TIME	-0.00045	0.2338	0.00172	0.0133
ONOFF	-0.01770	0.3237	-0.07320	0.0259
BDDYS	0.10634	0.0349	0.48333	0.0000
SPECRTO	0.43772	0.0550	-0.64140	0.1220
POSBED	-97.68440	0.1363	331.296	0.0060
NWAGE	0.28022	0.1409	0.23930	0.4889
MDPOP	-0.00937	0.8489	-0.01773	0.8431
ACRATIO	0.18501	0.1189	-0.25825	0.2314
HPOP	-0.10975	0.0630	0.37223	0.0006
MCARE	-0.35132	0.0091	-0.35942	0.1401
PUBASST	-0.19689	0.0000	-0.02370	0.7822
HINC	0.19823	0.2027	0.21715	0.4429
HSIZE	-0.15547	0.3822	-0.08927	0.7828
MEDAGE	0.49436	0.1510	-0.29600	0.6360

¹All regressions include separate intercepts for each hospital and year. All continuous dependent and independent variables are expressed as logarithms except for SPECRTO, POSBED, and GIR-related time variables.

²*P* values are two-tailed.

NOTE: Explanations of variables are given in Table 2.

effects as measured by the coefficients for GIRSTAT, TIME, and ONOFF in Table 5 are clearly not significant, though in this case all have negative signs. Among the other included variables, BDDYS and SPECRTO have highly significant positive coefficients; the former result suggests that increases in bed complement were accompanied by additions of equipment and more sophisticated facilities. The availability of alternative facilities (ACRATIO) also has a positive impact on the case-mix index. The population variable (HPOP) is strongly negative, suggesting that as the demand for beds increases, reductions in length of stay are accompanied by relatively greater increases in less costly admissions. The Medicare and public assistance variables are also significantly negative.

When GIR variables are included one at a time in the case-mix regression, only the CAPTIME

coefficient (-0.00132) is strongly negative (one-tailed *P* = 0.0244). This parallels the analogous length of stay result described above.

In the stepwise case-mix regressions shown in Table 6, CAPTIME continues to be significantly negative. Both CAP and CAPOFF are strongly positive. For the two hospitals going off the CAP in 1981, the values of CAPTIME in 1980 were 18 and 42. With the former value, the coefficients in column 1 of Table 6 imply virtually no change in DRGMIX from 1980 to 1981; with the latter value for CAPTIME, DRGMIX rose by about .05 when the hospital went off the CAP. Thus, the question of reversibility of the CAP effect is left in doubt by these findings.

Table 6
Case-mix and admission stepwise regression results for
guaranteed inpatient revenue (GIR) variables

GIR variable	Case-mix regressions			Admission regressions	
	(1)	(2)	(3)	(4)	(5)
CAPTIVE	-0.00191 (0.0137)	-0.00194 (0.0116)	-0.00210 (0.0113)	0.00215 (0.0829)	0.00273 (0.0737)
CAP	0.08397 (0.0157)	0.10103 (0.0055)	0.11075 (0.0038)	—	-0.07337 (0.2910)
CAPOFF	0.04799 (0.2030)	0.06542 (0.0952)	0.06539 (0.0978)	—	-0.03471 (0.6331)
GIRSTAT	—	—	0.00480 (0.7966)	-0.03738 (0.0491)	-0.04452 (0.1914)
GIRTEACH	—	-0.02093 (0.1169)	-0.03330 (0.1816)	—	0.00883 (0.8396)
TIME	—	—	-0.00099 (0.1948)	—	0.00108 (0.4378)
TIMTEACH	—	—	0.00121 (0.1664)	0.00136 (0.0474)	0.00022 (0.8875)
ONOFF	—	—	-0.01717 (0.3280)	-0.07422 (0.0180)	-0.06885 (0.0312)

NOTES: All regressions include all non-GIR explanatory variables shown in Table 5. Explanations of variables are given in Table 2. Two-tailed *P* values are in parentheses.

Results of the admissions regressions

The admission regression in Table 5 shows significant coefficients for all three included GIR variables; a joint F-test of these variables was also significant. Two of these coefficients (for TIME and ONOFF) are in the hypothesized direction, but the negative GIRSTAT coefficient is not. One possible explanation for this unexpected result is the nonrandom process by which hospitals were selected into the GIR. If a hospital had an unusually low volume of admissions in a particular year and this caused a large increase in unit costs and rates, this could have encouraged the Commission's staff to propose putting a hospital on the GIR.

Among the other explanatory variables, the bed complement (BDDYS), teaching activity (POSBED), and market area population (HPOP) variables all had highly significant positive coefficients.

Inclusion of GIR variables one at a time in the admissions regression yielded significant positive coefficients (as hypothesized) for TIME, TIMTEACH, and CAPTIME; coefficient values were 0.00121 (*P* = 0.0333), 0.00146 (*P* = 0.0249), and 0.00254 (*P* = 0.0419), respectively. A significant negative coefficient (-0.06035; *P* = 0.0374) was also obtained for ONOFF. When GIR variables were entered stepwise (Table 6, columns 4 and 5), the positive CAPTIME result and the negative ONOFF result seemed most robust.

Discussion

In comparing the results of the various regressions and alternative specifications of the GIR variables, several conclusions emerge. First, although many of the coefficients of the GIR variables are not

significant, it is also true that the time-related GIR variables (TIME, TIMTEACH, and CAPTIME) tend to be more significant and to display coefficients with the expected sign than is true for the other GIR variables (GIRSTAT, GIRTEACH, CAP). Because the latter variables are more likely to be picking up unobservable factors relating to selection into a particular payment status, and because it is plausible to assume that hospital responses to per case payment will be gradual (and thus, time-related), rather than instantaneous, we view our results as providing support for the general hypothesis that admissions, case mix, and length of stay will be influenced by per case payment incentives.

Second, the estimated per case payment effects are strongest for the hospitals under the tightest fiscal constraint, that is, the CAP hospitals. In particular, CAPTIME coefficients are all highly significant, with expected signs, and large in magnitude. CAPTIME coefficients as large as .0025 (as shown in Tables 4 and 6) combined with a mean CAPTIME value for CAP hospitals of 26 months, imply an impact of about 7 percent on the dependent variables. The greater impact on the CAP hospitals probably reflects a differential response of nonprofit hospitals to financial incentives. Threats of substantial losses under a stringent payment mechanism (the CAP) appear to evoke a stronger response than do opportunities to earn positive net revenues (under the GIR in general).

Third, the positive coefficients of time-related GIR variables (and particularly CAPTIME) in admissions regressions support the general proposition that per case payment systems are not immune from the possibility of perverse utilization responses. Thus, simply switching from per diem (or per service) to per case payments may not yield dramatic reductions in total cost and "unnecessary" utilization. Provision

for utilization monitoring systems, such as the peer review organizations under the Medicare PPS, may also be a key element of a successful cost control strategy. Comparison of per case versus per diem (or per service) systems should also extend to quality concerns if the per case limits are stringent. This point is amply illustrated by recent discussions of the Medicare PPS.

Conclusion

Although our results may support more general conclusions about the relative merits of per case and per service payment systems, it is important to take note of a number of qualifications. First, the generalizability of our results to other States may be limited. When compared with experience in other States, the per service payment system in Maryland appears to be fairly stringent.² Thus, the difference in incentives between the GIR and non-GIR hospitals might be less pronounced in comparison with the overall pressures for unit cost control imposed by the Maryland system on both GIR and non-GIR hospitals. Recent evidence, however, suggests that our conclusions at least generalize to the experience in one other State, New Jersey. Rosko and Broyles (1986) report that the introduction of per case payment in that State produced decreases in length of stay and cost per case; however, most of the cost savings from these impacts were offset by a significant increase in numbers of admissions.

Second, absence of clear overall GIR effects may, in part, result from the fact that the length of time on the GIR for hospitals in the study was fairly short (averaging a little more than 2 years). Subsequent research is now under way with a longer timeframe of cost impacts.

Third, the inability to reject the null hypothesis for a number of the GIR-related coefficients may reflect the conservative statistical procedures we have employed. The fixed-effects model tends to produce lower significance levels because it excludes information from cross-sectional variation in estimating the parameters of interest. This also makes estimation of differences in impacts among groups of hospitals more difficult. Although it is necessary to use a number of GIR variables to test for these differences in impacts (CAP versus non-CAP, teaching versus nonteaching), many of these variables will be strongly correlated with one another. Our ongoing research with a longer time series of data for Maryland will yield more powerful tests and also allow us to compare per case and fixed budget payment approaches.

Finally, note that there are important differences between the Maryland GIR system and Medicare PPS. The Maryland system offers a weaker financial incentive for reducing per case costs because only a portion of the savings below the GIR target are

returned to the hospital; this was even more true for the capped hospitals because bonuses for beating the cap were not paid. The use of per case rates based on the hospital's own experience in the GIR system also results in weaker incentives than in PPS where the regional and national DRG rates can vary widely from the individual hospital's experience thereby providing large positive (or negative) profit margins on additional Medicare admissions. These differences in incentives provide a plausible explanation for the apparently stronger utilization responses to PPS relative to the GIR impacts reported here.

Acknowledgments

The authors would like to acknowledge the financial support from the U.S. National Center for Health Services Research under Grant HS 03831, and the thoughtful advice and comments of our project officer, Herbert Traxler, of Michael Rosko, and our colleagues, Richard Frank and Robert Seidman. Major contributions to the development of the data base and the approaches to the measurement of variables were made by Agnes Rupp. Programming support were provided by Alison Jones and Sharon Paul. Finally, we thank Valerie Waudby for her assistance in preparing this article for publication.

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