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Development of a Scalar Hospital-Specific Severity of Illness Measure

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Cost-function analysis of hospitals has been criticized for not including severity adjustments. We tested a scalar hospital-specific severity index, derived from Admission MedisGroup Scores. Alternative versions (i.e., linear/nonlinear) of the index were evaluated by estimating cost functions on a sample of 201 Pennsylvania hospitals. The scalar index was a strong predictor of costs. The results also suggest that the omission of a severity variable in a hospital cost function may cause a specification error.

INTRODUCTION

Economists and health policy analysts have advanced arguments for the inclusion of severity of illness adjustments in the analysis of hospital costs and revenues. Policy analysts have expressed concern that the omission of case-mix measures may cause a specification error in cost equations that may bias the estimated coefficients of other variables of interest. For example, the high cost of teaching hospitals relative to non-teaching hospitals has influenced the debate on funding graduate medical education.[1] Univariate analysis has shown that the cost per adjusted admission in teaching hospitals was 33.3% greater than that of nonteaching hospitals. The use of regression analysis that included variables to control case-mix complexity, payer-mix and market area differences reduced the cost differential between teaching and non-teaching hospitals to 16 percent.[2] Sloan and Valvona[1] found similar differences in their more recent univariate and multivariate analyses. Rosko and Broyles[3] speculated that these differences may have been narrowed even more if severity measures were included in the regression analyses.

The absence of severity adjustments has been noted in discussions of payment policy.[4] Critics of the Medicare Prospective Payment System (PPS) have argued that the well documented heterogeneity with respect to resource consumption within Diagnosis Related Groups represents ''unfair'' bias in Medicare's payment methodology.[5,6] The

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Medicare PPS does not adjust payments for differences in severity of illness; however, expenses per case within a diagnostic group may be positively related to severity of illness. As a result, hospitals with patients who are more severely ill may suffer financial losses, whereas hospitals with patients who are less severely ill may receive windfall profits. Thus, the impact of severity of illness on hospital profitability and its components—expenses and revenues—is of interest as long as prospective, case-based payment methods, including Medicare's, fail to adjust for differences in severity.

In classical economic theory, a cost function describes the relationship between costs, quantities, mix of outputs a firm produces, and the input prices a firm faces. Health economists have been challenged by the need to fully capture the multiple dimensions of outputs produced by hospitals. These output dimensions include case-mix complexity (i.e., types of patients treated) and severity of illness (i.e., seriousness of illness holding case-mix complexity constant). To capture output mix differences, health economists have estimated multi-output cost function equations. These analyses have relied on flexible functional forms that were first evaluated using data sets compiled from firms operating in the electric power generation industry and the railroad industry.[7,8] Conrad and Straus estimated a translog cost function for 114 hospitals in North Carolina.[9] Their specification required the estimation of 36 parameters. Other hospital multi-output cost function studies have estimated even more parameters. Cowing and Holtman[10] estimated 106 coefficients, while Grannemann, Brown and Pauly[11] used 63 variables. Even with large numbers of coefficients these studies have not included measures of severity. Obviously, the inclusion of a severity measure in each patient grouping would impose a substantial restriction on the degrees of freedom that could not be overcome in most data sets. This prompted us to develop a scalar severity of illness measure that would incorporate another dimension of output in hospital cost function analysis without consuming a large number of degrees of freedom in regression analysis.

In this paper we address the following research questions:

1. does the scalar severity of illness measure predict adjusted hospital costs per admission?;
2. should a continuous or discrete measure of severity be used?;
3. what is the incremental predictive power of the severity measure(s) beyond the control variables typically used in behavioral cost functions?; and,
4. what are the implications of omitting a severity measure from the estimated cost function equation?

METHODS

This study is based on cross-sectional data for the fiscal year ending June 30, 1989. The individual hospital constitutes the unit of analysis for this study. The study group ($n = 201$) consists of all general acute care hospitals in the Commonwealth of Pennsylvania. Hospitals in Pennsylvania are required to report financial and patient care data to the Health Care Cost Containment Council (HCCCC) on an annual basis. Thus, all hospitals are included in the database. The use of this data base allows us to avoid the selection bias that may have occurred in hospital cost function studies that relied on voluntarily reported data.

Our choice of the hospital as the level of empirical analysis deserves further elaboration since most studies that have examined the impact of severity of illness on "costs" or charges have been conducted at the patient level. In the context of our study, hospital level analysis is more appropriate than patient level analysis for a number of reasons.

First, the use of patient level data has required researchers to estimate costs by using the ratio of cost to charges (RCC) method. When this technique is used, a patient's cost is first calculated at the revenue center level by multiplying the patient's charges from each revenue center times the center's RCC. Next the patient's total cost is computed as the sum of the revenue center-specific costs.[12] This approach is valid to the extent that costs are related to charges. However, given the commonly acknowledged existence of "cost shifting", whereby hospitals establish charge structures to maximize revenues and not to reflect costs, the use of the RCC method to establish patient level costs can lead to incorrect conclusions. This problem is particularly acute in DRG-level analyses that have been performed by several researchers because hospitals, practicing cost-shifting, have an incentive to "underprice" or "overprice" procedures specific to certain DRGs according to the composition of the payer-mix in their facility.[5,13,14] The systematic nature of cost-shifting causes the data to be biased. However, when these data are pooled together across the entire hospital, as we did in this study, the arbitrary variations in charges that occur from department to department or from DRG or DRG offset each other to eliminate this problem.

Second, similar to the problems with the RCC method, revenue center cost allocations for indirect expenses such as administrative overhead and other expenses are often based on arbitrary formulas. These inaccuracies affect individual patient cost estimates but obviously do not affect total hospital costs.

Third, an important focus of this study is the impact on the institution as a whole of not adjusting expenses for severity of illness. Indeed, if variations in severity cause a hospital to be more expensive in the provision of service to some patients but provide other services less expensively, then the "severity problem" is self-correcting and may not need to be addressed by making a severity adjustment.

Fourth, a logical extension of the severity measure to be constructed in our study is the use of a severity adjustment in multi-product cost function analysis or in data envelopment analysis.[15] These analytical techniques require a large number of independent variables, creating a potential degrees of freedom problem. Accordingly, a single hospital-level severity of illness index (or a small set of categorical variables) would be the best way to adjust for severity of illness in these types of studies. This study enables an evaluation of the utility of a scalar, hospital-level severity index.

Model Specification

A behavioral cost function was used in this study. Granneman, Brown and Pauly[11] developed a continuum to classify a wide variety of models that have been used to estimate hospital cost functions. At one end of the continuum are what Evans[16] termed behavioral cost functions that are based on a standard short-run model of hospital decision making.[17] In these models, the hospital decision-makers are presumed to select output prices and input quantities to maximize an objective function that has quantity, quality and profit as its arguments and is constrained by prevailing input and product market conditions and technology. Accordingly, behavioral models typically include explanatory variables to reflect market demand conditions (e.g., ability to pay and need for hospital services), factor prices (e.g., wages) and the hospital's fixed capital stock (e.g., beds). In addition, independent variables are often entered to control for differences in case-mix (e.g., DRG Index or Resource Need Index), objectives (e.g., teaching orientation or ownership), and regulatory environment (e.g., hospital rate-setting or capital controls).

At the other extreme of the cost function continuum are structural cost models that exploit the duality between production and cost functions. In these models, which are called technological or neoclassical cost functions, total cost is used as the dependent variable and prices of inputs and quantities of outputs constitute the only independent variables.[8,9] Recognizing the unique features of hospitals, a number of researchers have estimated quasi-technological cost functions by adding hospital characteristics variables (e.g., teaching status or ownership) to the technological cost function.[10,11,18–20]

Our decision to use a behavioral model of hospital costs was influenced by the constraints of budget and data availability. Behavioral models are subject to criticism when used to estimate the structural aspects of production such as economies of scale or scope; however, this is not the intent of this study.[3] Thus, we feel it is appropriate to use this type of model in our preliminary analysis of severity measures. Further, many health policy analysts continue to use behavioral cost functions, and it is instructive to see if the inclusion of a scalar severity variable changes the estimated coefficients of variables typically used in these types of models.

The following general model was used in the analysis:

Adjusted expense per admission = f(patient mix, payer mix, organizational characteristics, market characteristics)

Table 1 presents operational definitions for the dependent and independent variables. Most of these variables, including the dependent variables, severity and payer mix are measured using HCCCC data. The data from the HCCCC are for the fiscal year reporting period that ended June 30, 1989. In contrast, data from other sources are for the calendar year ending December 31, 1988. We do not expect the use of overlapping data to create a problem. The binary variables (e.g., teaching status and size) are not expected to vary over the study period. Market characteristics will vary somewhat over time, but probably not much in a 6-month time period.

INDEPENDENT VARIABLES

Patient Mix

Two patient mix variables were used—severity of illness and complexity. Complexity and severity often are used interchangeably; however this is not correct. Complexity refers to the diagnostic mix of patients that tend to predispose the hospital to require more or less expense per discharge. For example, ceterus paribus, a community hospital with a large proportion of admissions for routine procedures should be less expensive than a tertiary hospital with a large proportion of complex surgical procedures. Case-mix complexity has been measured frequently in empirical studies of hospital costs by using scalar

Table 1. Variable Definitions and Descriptive Statistics

Variable name	Description	Mean (Standard Deviation)
	Dependent variable	
Adjusted expense per admission	Adjusted expenses/total admissions[a]	$4,293.30 (1,847.81)
	Independent variables	
Severity index (SEVILL)	(Discussed in text)	1.127 (0.226)
Medicare case mix index (MCMI)	(Discussed in text)	1.250 (0.170)
Medicare share (MCARE%)	(Medicare revenue/total patient revenue) × 100	0.501 (0.094)
Medicaid share (MCAID%)	(Medicaid revenue/total patient revenue) × 100	0.108 (0.095)
Member Council of Teaching Hospitals (COTH)	Binary variable (0, 1) for COTH Members	0.144 (0.352)
Other teaching hospitals (MINTEACH)	Binary variable (0, 1) for non-COTH teaching hospitals	0.398 (0.491)
SIZE2	Binary variable (0, 1) for hospitals with more than 150 beds but less than 300 beds	0.418 (0.494)
SIZE3	Binary variable (0, 1) for hospitals with 300 or more beds	0.284 (0.452)
Industry concentration (HERF)	Herfindahl index based on admissions to hospitals in the county	0.316 (0.279)
Wage index (WAGEINDX)	HCFA area wage index	0.983 (0.090)
Percent unemployment (UNEMPLOY%)	Civilian unemployment rate	5.406 (1.574)
Population density (POPDENSE)	Total population/square miles	2,876.018 (4,391.247)
Percent physician specialists (MDSPEC%)	Percentage of office-based physicians who are specialists	84.319 (12.506)

[a] Adjusted expenses = total expenses * (gross inpatient revenue/total gross revenue).

measures such as the Resource Need Index (RNI) and the Medicare Case-Mix Index (MCMI).[3] We used the MCMI in our analysis. It is calculated as follows:

$$\mathrm{MCMI}_j = \left[\sum_{i=1}^{n} w_i p_{ij}\right] \div [1/N\Sigma\Sigma w_i p_{ij}],$$

where MCMI represents the case-mix index of the jth hospital; w_i represents the weighting factor (average cost) for the ith DRG; p_{ij} represents the proportion of cases in the ith category in hospital j; and N represents the number of hospitals. Since the MCMI reflects intensity of resource consumption and payment adjustments for more expensive DRGs, this variable should be positively correlated with adjusted expense per admission.

In the context of our study, severity refers to the relative costliness of patients within

DRGs. As indicated previously, DRGs may reflect case-mix complexity very well (i.e., it is clear that DRG 106, coronary bypass, is more expensive than DRG 54, mastoid procedures); however, DRGs are very heterogeneous with respect to resource consumption and need to be adjusted for severity.[21]

One of the distinguishing features of our study is the use of a hospital-level measure of severity of illness in the analysis of the determinants of hospital expenses. We used the Admission MedisGroup Score to form a severity of illness variable in our empirical analysis. MedisGroup Severity of Illness Scores depend on chart reviews and include data on a wide variety of physiological findings. The assignment of a severity score is based upon key clinical findings (KCFs). KCFs indicate clinical abnormalities detected by laboratory, radiology, pathology, or physical examinations. KCFs represent continuous variables (e.g., laboratory findings) or binary variables (e.g., presence or absence of an abnormality). KCFs are assigned to one of four levels, from 0 to 3. Level 3 KCFs indicate the most serious clinical abnormality. A computer algorithm assigns an admission severity of illness score. This score is independent of the patient's diagnosis.[14]

Our choice of a severity measure has been influenced by cost and availability considerations. However, support for our use of MedisGroup scores is provided by a study that suggests the MedisGroup method explains variations in hospital costs better than DRGs and is comparable to other severity of illness measures.[5]

We used the MedisGroup scores to construct a hospital-level index of severity of illness. We constructed a scalar variable that is represented by the following formula:

$$\mathrm{SEVILL}_j = \Sigma\ \mathrm{MGS}_{ij}P_{ij},$$

where SEVILL_j represents the severity of illness index for the jth hospital; MGS_{ij} represents the average MedisGroup severity score of the ith DRG in hospital $_j$; and P_{ij} represents the proportion of cases in the ith DRG in hospital $_j$. As discussed above, we expected severity of illness to be positively related to adjusted expense per admission.

OTHER CONTROL VARIABLES

Payment policies have an impact on hospital profits. We used two variables—Medicare share and Medicaid share—to reflect payer mix. Since prospective payment mechanisms induce hospitals to contain expenditures by placing them at financial risk with a predetermined payment rate, the Medicare and Medicaid share of revenue should have a negative impact on adjusted expense per admission.

In addition to patient mix and payer mix, organizational characteristics may influence hospital expenses. A substantial body of evidence suggests that hospital expenses increase with medical education activities.[3] To reflect differences in the extent of teaching activities, we used two binary (0,1) teaching variables—one for hospitals that are members of the Council of Teaching Hospitals (COTH), the other for smaller teaching institutions (MINTEACH). The reference group is non-teaching hospitals. To reflect possible economies of scale, two binary (0,1) size variables, SIZE2 and SIZE3, were included in the model. The smallest bed size category, SIZE1, served as the reference category. Most studies have shown a monotonically increasing relationship between the binary size variables and cost per admission.

The final set of variables reflect the environment in which the hospitals operate. We defined the market as the county in which the hospital is located, a definition used in many hospital studies. The degree of industry concentration was measured by a Herfindahl index based on hospital admissions. This index is constructed by combining the squared market shares of all facilities in the county. Market share is defined as each facility's percentage share of total admissions in the county. The index ranges from 0 to 1 with higher values signifying greater concentration. Thus, a Herfindahl of 1.0 would indicate a market with one sole provider. Hospitals typically engage in service-based competition. Increases in the degree of hospital competition (i.e., decreases in industry concentration) should be positively related to adjusted expense per admission.[3] The ability to pay for hospital care, a factor positively related to average hospital costs, is measured by the unemployment rate and population density. The unemployment rate is inversely related to income and the extent of employer-sponsored health insurance. It should have a negative coefficient. Population density, a surrogate for transportation costs, is expected to have a positive coefficient. The influence of the mix of specialist and generalist physicians on the demand for hospital services is measured by the percentage of physicians who are specialists. Since specialists tend to practice a more expensive style of medicine than generalists, we expect adjusted expense per admission will be positively associated with the percentage of physicians who are specialists.[3] We also included an area wage rate variable. Adjusted expense per admission should be directly related to wage rates.

RESULTS

The results of the regression analyses of adjusted expense per admission are shown in Table 2. In equation 1 only the severity index is regressed against expenses. This equation was significantly different from 0 ($p < 0.001$) and had an adjusted R-squared statistic equal to 0.268. This suggests that our scalar measure of severity is a relatively strong predictor of average expenses. However, severity measures are expensive to obtain and are not available for all hospitals. Further, since they have only been collected recently, severity measures cannot be used to support lengthy time-series analyses. These limitations stimulated the question—will the absence of severity measures result in a serious estimation bias? We addressed this question by estimating equations with and without the severity index. Since it is reasonable to believe that hospitals that attract a more complex case-mix also have a more severely ill patient population, we first compared equations that included only these variables. As equation 2 shows, MCMI with an adjusted R^2 of 0.409 is a stronger predictor of costs than is SEVILL. When SEVILL is added to the equation with MCMI the adjusted R^2 increases to 0.568, yielding an incremental adjusted R^2 of 0.159. This represents a 38.9 percent increase in the predictive power of the expense equation. This increase in predictive power combined with the relatively low correlation between SEVILL and MCMI ($r = 0.203$) suggests that SEVILL captures a dimension of case-mix other than complexity. Going from equation 2 to 3 the coefficient of MCMI decreases from 6967.64 to 6070.39, a change of 12.9 percent. This suggests that while MCMI itself is a strong predictor of costs, an equation that does not include a severity measure or variables correlated with severity may be underspecified, resulting in an upward bias in the estimated coefficient of the MCMI.

In equation 5 we estimated the full model and in equation 4 we estimated the full

Table 2. Regression Results: Adjusted Expense per Admission—Focus on Continuous Measures of Severity.[a]

Variable	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
SEVILL	4266.751		3338.034		1938.244
	(494.886)*		(388.300)*		(373.363)*
MCMI		6967.638	6070.396	3621.352	3337.467
		(589.119)*	(514.687)*	(683.626)*	(643.158)*
MCARE%				−32.150	−33.952
				(10.095)*	(9.469)*
MCAID%				−32.838	−31.629
				(10.733)*	(10.064)*
COTH				1160.325	1087.518
				(347.520)*	(326.066)*
MINTEACH				272.717	244.511
				(180.887)	(169.650)
SIZE2				4.900	−37.046
				(192.889)	(180.994)
SIZE3				175.691	211.728
				(261.056)	(244.811)
HERF				−442.176	−393.851
				(417.859)	(391.810)
WAGEINDX				4404.232	3655.998
				(1514.690)*	(1427.161)**
UNEMPLOY%				113.453	83.409
				(69.884)	(65.764)
POPDENSE				0.108	0.074
				(0.028)*	(0.027)*
MDSPEC%				8.310	7.409
				(7.667)	(7.189)
CONSTANT	−513.303	−4418.081	−7056.675	−4412.973	−5077.048
	(568.541)	(743.329)*	(706.119)*	(2116.821)**	(1988.418)**
ADJUSTED R^2	0.268	0.410	0.568	0.660	0.701

[a] Standard error in parentheses. $*p < .01$, $**p < .05$.

model except SEVILL was omitted. The adjusted R^2 of equation 4 is 0.659 and the adjusted R^2 of the full model is 0.701. Thus, the incremental adjusted R^2 resulting from the addition of SEVILL is 0.042, a 6.4 percent increase in explanatory power. Given the large number of variables and high adjusted R^2 of equation 4, the relatively small incremental explanatory power of SEVILL in equation 5 was expected.

Teaching hospitals have been criticized by policy analysts for excessive costs. However, about one-half of the differential in adjusted expense per admission can be explained by case-mix complexity and other variables. This differential might be narrowed further in a more completely specified model that included a severity variable.[3] As a test of the sensitivity of the omission of severity adjustments, we estimated equations that focused on the costs of major (COTH) and minor (MINTEACH) teaching hospitals with and without our severity measure. The results are shown in Table 3.

As equation 6 shows, without controlling other factors, the adjusted expense per admission relative to non-teaching hospitals is estimated to be \$3,561 and \$895 higher in major and minor teaching hospitals, respectively. When MCMI is added to the model (eq.

Table 3. Regression Results: Adjusted Expense per Admission—Focus on Case Mix and Teaching Variables.[a]

Variable	Equation 6	Equation 7	Equation 8
SEVILL			3050.475
			(371.581)*
MCMI		4193.805	3928.306
		(745.993)*	(645.965)*
COTH	3561.749	2111.441	1689.520
	(303.848)*	(382.776)*	(335.001)*
MINTEACH	895.952	530.601	419.869
	(218.113)*	(213.139)**	(184.821)**
CONSTANT	3422.821	−1465.879	−4465.429
	(148.752)*	(880.550)	(844.642)*
ADJUSTED R^2	0.404	0.484	0.614

[a] Standard error in parentheses. *$p < .01$, **$p < .05$.

7), the implied cost differences decrease to $2111 and $530. The addition of SEVILL (eq. 8) causes the coefficients of the teaching variables to fall further to $1689 and $419. The results imply that when severity of illness and other factors are not held constant, the cost differential between major teaching facilities and non-teaching hospitals is overstated by about 20 percent. However, when the coefficients of the teaching hospital variables are compared in the full model we see that the specification error is not as severe. In equation 4 the coefficient of COTH is 1160; when SEVILL is included in the full model (i.e., equation 5) the estimated coefficient of COTH is 1087. Thus, the estimated differential per admission changes by $73 from equation 4 to equation 5. Although the magnitude of the specification error is not as dramatic as in equations 7 and 8, the omission of SEVILL results in a 6.7 percent increase in the estimated coefficient of COTH.

To determine whether it is better to use a continuous or discrete measure of hospital severity of illness, we converted SEVILL into binary (0,1) variables for each tritile. We estimated regression equations using the lowest (LOWSEV) and highest (HISEV) tritiles in the analysis, reserving the middle tritile for the reference category. Then we repeated the type of comparison that we made when analyzing SEVILL. The results of this analysis are shown in Table 4. Table 5 presents a summary of adjusted R-squares that facilitates the comparison of the predictive power of the various regression models we estimated. Equation 9, which uses HISEV and LOWSEV, had an adjusted R^2 of 0.152. This is lower than the adjusted R^2 for equation 1 in Table 2 which used SEVILL and had an adjusted R^2 of 0.268. Next, we added MCMI to the model (eq. 10). As Table 4 shows, this caused the adjusted R^2 to increase to 0.515. Comparing these results to those for equation 2 in Table 2, we see that the incremental adjusted R^2 of the binary severity variables is 0.105. This is less than the increase in accuracy when SEVILL is added to the model with MCMI. Comparing the equations (i.e., eq. 3 and eq. 10) that contain only MCMI and severity, we see that SEVILL performs better than the binary measures. Finally we estimated the full model, substituting LOWSEV and HISEV for SEVILL. The adjusted R^2 for equation 11 is 0.689, a value only slightly less than the adjusted R^2 of 0.701 that was achieved for the full model when SEVILL was used. Part of the reason for the lower predictive power of the models in Table 3 is that in each equation the coefficient of LOWSEV is not significantly ($p < 0.10$) different from zero.

Table 4. Regression Results: Adjusted Expense per Admission—Focus on Discrete Measures of Severity[a]

Variable	Equation 9	Equation 10	Equation 11
LOWSEV	−172.889	−20.946	−48.555
	(293.993)	(222.693)	(185.207)
HISEV	1472.648	1290.787	762.546
	(293.993)*	(222.843)*	(200.890)*
MCMI		6572.113	3435.226
		(538.112)*	(659.220)*
MCARE%			−38.733
			(9.777)*
MCAID%			−36.584
			(10.322)*
COTH			990.333
			(335.377)*
MINTEACH			205.631
			(174.012)
SIZE2			121.678
			(188.567)
SIZE3			409.955
			(255.261)
HERF			−474.461
			(399.461)
WAGEINDX			3912.512
			(1452.633)*
UNEMPLOY%			100.211
			(67.032)
POPDENSE			0.086
			(0.027)*
MDSPEC%			5.236
			(7.403)
CONSTANT	3860.050	−4346.852	−3222.421
	(207.884)*	(690.113)*	(2042.090)
ADJUSTED R^2	0.152	0.515	0.689

[a] Standard error in parentheses. $^{*}p < .01$, $^{**}p < .05$.

DISCUSSION

The study is restricted to one state and this may preclude valid generalizations to other areas. However, the hospital industry in Pennsylvania has some characteristics that are relevant to the industry as a whole. The state has a good mix of urban and rural hospitals and a number of large, teaching institutions. Like many other states, both Medicaid and Blue Cross utilize case-based payment for inpatient services. Thus, our results have implications for other states as well.

A second limitation is that our construction of SEVILL implicitly assumes that the MedisGroup data, which is based on an ordinal scale, approximates an interval scale. Nunnally[22], a leading expert in measurement theory, writes "The author strongly believes that it is permissible to treat most of the measurement methods in psychology and other behavioral sciences as leading to interval scales (and in some cases, ratio scales)."

Table 5. Summary of the Predictive Power of the Regression Models

Model (Eq. number)	Adjusted R^2
SEVILL only (Eq. 1)	0.268
LOWSEV and HISEV only (Eq. 9)	0.152
CMI only (Eq. 2)	0.410
SEVILL and CMI (Eq. 3)	0.568
LOWSEV, HISEV, and CMI (Eq. 10)	0.515
Full Model with SEVILL (Eq. 5)	0.701
Full Model with LOWSEV and HISEV (Eq. 11)	0.689

Kerlinger [23] also provides support for our approach. Although it is common practice to treat ordinal measures as if they were interval scales, we are concerned about the validity of this assumption. The data base for this study is aggregated at the hospital level and does not permit testing of this assumption. However, we are in the process of acquiring patient-level data that will enable us to test this assumption.

Conceptually, the relationship between severity of illness and expense per admission may be viewed as linear or non-linear. For example, as patients get sicker they may require more services per admission and expense per case should increase; however, if patients are extremely ill they may die shortly after admission and the cost per case for these patients may be less than that for patients who are less severely ill. In equations 9, 10, and 11 binary variables were entered for LOWSEV and HISEV to capture any non-linear relationship. The magnitude of the coefficients of the binary severity variables was monotonically increasing, a result consistent with the assumption that the relationship between severity and expense per case is linear. This result, however, may be an artifact of the hospital level of aggregation that was employed. It is quite likely that for some DRGs the most severely ill patients die and consequently have a shorter length of stay and consume fewer resources than less severe cases. However, mortality in most diagnostic categories is a rare event.[24] Accordingly, for most DRGs it is probably more appropriate to view the relationship between severity of illness and expense per admission as linear. For similar reasons, our results indicate that it is better to use a linear measure of severity at the hospital level of analysis.

Despite some potential problems and limitations, we think our analysis has made a contribution to the development of a scalar hospital severity of illness measure. The results suggest that the continuous measure of severity, SEVILL, is a strong predictor of adjusted expense per admission. Its sign is consistent with expectations and this provides some face validity for the scalar severity index. The heterogeneity of DRGs is well documented and our results indicate that the omission of a severity measure, even in regression equations that include a number of other variables including case-mix complexity, may lead to a specification error.[3] In our analysis, the absence of a severity measure appeared to create an upward bias for the major teaching hospital variable, another result that is intuitively appealing.

Although our results should be viewed with caution, they suggest that a scalar severity of illness measure has considerable utility in health services research and health policy analysis. We hope this paper will stimulate further development or refinements in hospital-level severity measures.

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