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Is the Centers for Medicare and Medicaid Services Hierarchical Condition Category Risk Adjustment Model Satisfactory for Quantifying Risk After Spine Surgery?

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BACKGROUND: The Centers for Medicare and Medicaid Services (CMS) hierarchical condition category (HCC) coding is a risk adjustment model that allows for the estimation of risk—and cost—associated with health care provision. Current models may not include key factors that fully delineate the risk associated with spine surgery.

OBJECTIVE: To augment CMS HCC risk adjustment methodology with socioeconomic data to improve its predictive capabilities for spine surgery.

METHODS: The National Inpatient Sample was queried for spinal fusion, and the data was merged with county-level coverage and socioeconomic status variables obtained from the Brookings Institute. We predicted outcomes (death, nonroutine discharge, length of stay [LOS], total charges, and perioperative complication) with pairs of hierarchical, mixed effects logistic regression models—one using CMS HCC score alone and another augmenting CMS HCC scores with demographic and socioeconomic status variables. Models were compared using receiver operating characteristic curves. Variable importance was assessed in conjunction with Wald testing for model optimization.

RESULTS: We analyzed 653 815 patients. Expanded models outperformed models using CMS HCC score alone for mortality, nonroutine discharge, LOS, total charges, and complications. For expanded models, variable importance analyses demonstrated that CMS HCC score was of chief importance for models of mortality, LOS, total charges, and complications. For the model of nonroutine discharge, age was the most important variable. For the model of total charges, unemployment rate was nearly as important as CMS HCC score.

CONCLUSION: The addition of key demographic and socioeconomic characteristics substantially improves the CMS HCC risk-adjustment models when modeling spinal fusion outcomes. This finding may have important implications for payers, hospitals, and policymakers.

KEY WORDS: Centers for Medicare and Medicaid, Hierarchical condition category, Risk stratification, Spine surgery

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Spinal fusion surgery is a significant contributor to health care cost, accounting for approximately $12 billion in annual costs to the United States health care system.[1,2] In response, there have been recent efforts to maximize value and minimize cost through optimizing patient selection and identifying patients who may require increased perioperative resource utilization.[1,3] Several indices, including the Charlson Comorbidity Index (CCI), Elixhauser Comorbidity Index, frailty, and the American Society of Anesthesiologists score, have gained popularity within spine surgery with hopes of improving perioperative risk stratification.[4-10]

One noteworthy effort at risk stratification undertaken by the Centers for Medicare and Medicaid Services (CMS) is the CMS hierarchical condition category (HCC) risk adjustment model.

ABBREVIATIONS: CCI, Charlson Comorbidity Index; **CMS,** Centers for Medicare and Medicaid Services; **FIPS,** Federal Information Processing Standards; **HCC,** hierarchical condition category; **LOS,** length of stay; **MA,** Medicare advantage; **NIS,** National Inpatient Sample; **VIFs,** variance inflation factors.

TABLE 1. Comparison of Hierarchical, Mixed Effect Logistic Regression Models	
Model 1. CMS HCC score alone	**Model 2. CMS HCC score with additional covariates**
CMS HCC scores alone were used to predict outcomes.	Covariate selection involved univariable testing to identify a set of significant variables that may be of interest in our models. Next, we used multivariable regression to evaluate whether specific variables served as accurate predictors when considered with all other variables. This step allowed us to select the most predictive variables for our final models, with variables demonstrating significance in at least 3 of 5 of our total models included in our final multivariable model In addition to CMS HCC score, these included age, sex, CCI, race, insurance status, income quartile by ZIP code, unemployment rate by FIPS, poverty rate by FIPS, and life expectancy by FIPS

CCI, Charlson Comorbidity Index; CMS, Centers for Medicare and Medicaid Services; FIPS, Federal Information Processing Standards; HCC, hierarchical condition category.

The CMS HCC risk adjustment model is used by Medicare advantage (MA) plans to calculate reimbursement given a population's baseline characteristics. It allows for the quantification of risk scores by ranking diagnoses into categories with similar cost patterns. In this manner, it allows for CMS to reimburse MA plans more for taking on patients with higher baseline risk.[11] This helps to reduce the influence of risk selection and enhance market stability.[3,12] As such, higher CMS HCC scores indicate higher predicted health care costs.

Although HCC was developed as a cost prediction model, it was recently demonstrated as an automated and objective universal predictor of postoperative resource utilization in spine surgery.[3] However, further refinement of the model may improve its predictive capabilities and utility. Specifically, the present component parameters in the HCC models fail to include important metrics of socioeconomic status, including race, income, regional poverty rates, regional unemployment rates, regional housing vacancy rates, and regional life expectancy, among others. Patient socioeconomic status has been demonstrated to be a useful predictor of resource allocation in patients receiving spine surgery and has been correlated with the frequency of imaging, preventative care screenings, and physician and non-physician resources.[13-15]

We hypothesized that expanded models that augment CMS HCC risk adjustment methodology with socioeconomic data may potentially improve CMS HCC risk adjustment model performance by capturing a more comprehensive representation of the individuals receiving spinal fusion surgery. Such an improvement may enhance the ability to predict relevant perioperative outcomes—reflective of resource utilization—after spinal surgery.

METHODS

Patient Sample

Using ICD-9-CM (International Classification of Disease-9-Current Modification) coding, we identified discharges from nonfederal hospitals in the United States from 2005 to 2011 who underwent spinal fusion surgery using the Healthcare Cost and Utilization Project National Inpatient Sample (NIS). The NIS is a large public all-payer inpatient database in the United States and contains data on more than 7 million hospital discharges each year. Institutional Review Board approval and patient consent were waived because we used a deidentified public database.

Socioeconomic Variables

The Brookings Institution is a research organization that investigates the social sciences with specific foci in economics, government, and foreign policy.[16] Databases created by the Brookings Institution compile population-level demographic and socioeconomic characteristics—sorted by geographic location—in the United States. The database queried from the NIS was merged with Brookings Institution data regarding county-wide socioeconomic status variables, including poverty rates, unemployment rates, life expectancy, and housing vacancy, using Federal Information Processing Standards (FIPS) coding to give us the socioeconomic status of the counties in which the patients lived.

CMS HCC Risk Adjustment Model

CMS HCC score calculations were performed in SAS University Edition (SAS/STAT, SAS Institute Inc) using software provided by the CMS.[17] Traditionally, data analyzed by CMS software have corresponding provider-diagnosed disability information, which is used by the model for risk stratification. Because the NIS does not provide disability status, the Johns Hopkins Adjusted Clinical Groups frailty-defining diagnosis indicator was used as a proxy for disability status because frailty has been shown to accurately predict patient disability status.[18-20] The Johns Hopkins Adjusted Clinical Groups uses a set of 10 clinical clusters (malnutrition, dementia, visual impairments, decubitus ulcer, urine control, fecal control, weight loss, social support, difficulty walking, and history of falls) and has been shown to accurately predict patient frailty status.[6,7,21] In addition, the HCC model also uses end-stage renal disease as a variable within the model, and ICD-9 codes for renal disease, as defined by the CCI, were used to query end-stage renal disease.[4,22]

Outcomes

We considered the following outcomes: death (binary, dead vs alive); discharge not to home (binary, not at home vs at home); length of stay (top quartile); total charges (top 10%); and any perioperative complication (binary, complications vs no complications).

Statistics

All statistics were conducted in RStudio (RStudio: Integrated Development for R) (version 1.2.5042) and were 2-sided, and all *P*-values less than .05 were defined as significant. The DeLong test for two

TABLE 2. Characteristics of the 653 815 Discharges Undergoing a Primary Procedure of Spinal Fusion From 2005 to 2011

Cohort characteristics	All spinal fusion procedures (n = 653 815)
Age, y ± SD	53.0 ± 17.1
Sex	
Female, n (%)	356 074 (54.5%)
Male, n (%)	297 741 (45.5%)
CCI	4.2 ± 1.8
CMS HCC risk score	0.048 ± 0.12
Unemployment rate, mean percentage (percentiles)	6.5% ± 1.6% (0% = 1.1%; 25% = 5.2%; 50% = 6.3%; 75% = 7.4%; 100% = 20.4%)
Poverty rate, mean percentage (percentiles)	14.1% ± 4.3% (0% = 3.6%; 25% = 11.4%; 50% = 14.6%; 75% = 16.7%; 100% = 40.4%)
Life expectancy, (y ± SD) (percentiles)	79.6 ± 1.9 (0% = 70.2; 25% = 78.5; 50% = 79.8; 75% = 81.0; 100% = 86.5)
Insurance	
Medicare, n (%)	199 964 (30.6%)
Medicaid, n (%)	48 794 (7.5%)
Private, n (%)	323 128 (49.4%)
Self-pay, n (%)	12 546 (1.9%)
No charge, n (%)	1137 (0.2%)
Others, n (%)	68 246 (10.4%)
Median income by zip code	
Quartile 1, n (%)	130 495 (20.0%)
Quartile 2, n (%)	148 323 (22.7%)
Quartile 3, n (%)	148 829 (22.8%)
Quartile 4, n (%)	135 332 (20.7%)
Others, n (%)	90 836 (13.9%)
Hospital type	
Rural, n (%)	34 350 (5.3%)
Urban nonteaching, n (%)	287 329 (43.9%)
Urban teaching, n (%)	326 984 (50.0%)
Race	
White, n (%)	424 741 (65.0%)
Black, n (%)	43 891 (6.7%)
Hispanic, n (%)	33 170 (5.1%)
Asian/Pacific Islander, n (%)	6655 (1.0%)
Native American, n (%)	2373 (0.4%)
Others, n (%)	142 985 (21.9%)
Hospital bed size	
Small, n (%)	86 612 (13.2%)
Medium, n (%)	145 025 (22.2%)
Large, n (%)	417 026 (63.8%)
Others, n (%)	5152 (0.79%)
Region of hospital	
Northeast, n (%)	95 704 (14.6%)
Midwest, n (%)	146 495 (22.4%)
South, n (%)	271 481 (41.5%)
West, n (%)	140 135 (21.4%)
Admission type	
Elective, n (%)	531 148 (81.2%)
Nonelective, n (%)	122 667 (18.8%)

CCI, Charlson Comorbidity Index; CMS, Centers for Medicare and Medicaid Services; HCC, hierarchical condition category.

TABLE 3. Mortality, Perioperative Complication, LOS, and Mean Hospital Charges

Outcome	All spinal fusion procedures (n = 653 815)
Mortality, n (%)	2603 (0.4%)
Nonroutine discharge, n (%)	166 300 (25.4%)
Mean LOS, d	4.1 d (SD 5.1 d), top 25% = 4 d
Mean hospital charge, US dollars	$78 849.40 (SD $79 605.10), top 10% = $155 653.40
In-hospital, perioperative complication sustained, n (%)	89 879 (13.7%)

LOS, length of stay.

correlated receiver operating characteristic (ROC) curves was used to compare ROC area under the curves (AUCs). Odds ratios with post hoc χ^2 testing were implemented using the "Epitools" package in R (R: A Language and Environment for Statistical Computing) to independently evaluate the correlation between predictors and outcomes.

Two sets of hierarchical, mixed effects logistic regression models were developed (Table 1). As discharges were clustered at the hospital and county level, hospital identifiers and FIPS coding were both coded as nesting variables. The 2 models were compared using ROC curves using the "pROC" R package, with the AUC serving as a proxy for model predictive value. In general, an AUC of 0.50 demonstrates a random guess and AUC values greater than 0.70 are defined as acceptable.[23]

Variable importance was analyzed within each model using Wald testing for model optimization. These variable importance metrics allowed for estimation of the degree to which changes in the outcome are influenced by changes in the predictor variables.[24] This process allowed for the identification of socioeconomic data elements that would most improve the models for prediction of outcomes. Potential collinear data elements were investigated using variance inflation factors (VIFs), with VIFs exceeding 4.0 warranting further investigation and those greater than 10.0 indicating collinear model elements. It was ensured that all VIFs for all variables in all models were less than 3.0.

RESULTS

Characteristics

A total of 653 815 patients (mean [SD] age, 53.0 [17.1] years; 356 074 [54.5%] female) who underwent spinal fusion were included in the study (Table 2). The mean CMS HCC score was 0.048 ± 0.12. Average rates of unemployment (mean [SD], 6.5% [1.6%]), poverty (mean [SD], 14.1% [4.3%]), and life expectancy (mean [SD] age, 79.6 [1.9] years) in the counties where patients lived were calculated after merging the NIS and Brookings data sets by FIPS coding.

Outcomes

Rates of mortality were low within this surgical cohort (n = 2603; 0.4%) (Table 3). Nonroutine discharges were found in more than a quarter of all patients (n = 166 300; 25.4%). The top quartile of

TABLE 4. AUC Values for ROC Curves for Nonroutine Discharge, Mortality, Length of Stay, Hospital Cost, and Perioperative Complication

AUC values for ROC curves	Only CMS HCC score	CMS HCC score with demographics and SES
Mortality	0.802	0.843
Nonroutine discharge	0.676	0.776
Length of stay (top quartile)	0.681	0.709
Cost (top decile)	0.817	0.836
Any complication	0.693	0.725

AUC, area under the curve; CCI, Charlson Comorbidity Index; CMS, Centers for Medicare and Medicaid Services; HCC, hierarchical condition category; ROC, receiver operating characteristic; SES, socioeconomic status.
A comparison of AUC values for models using solely the CMS HCC score (left column) and CMS HCC score augmented with demographic and SES characteristics (specifically, age, sex, CCI, race, insurance type, income quartile, unemployment rate, and poverty rate).

LOS was found to be 4 days, and the top decile of hospital costs was \$155 653.40. Inpatient perioperative complications were present in 89 879 patients (13.7%).

Model Development

The expanded models outperformed the models using CMS HCC score alone for mortality (AUC: 0.843 vs 0.802), nonroutine discharge (AUC: 0.776 vs 0.676), LOS (AUC: 0.709 vs 0.681), total charges (AUC: 0.836 vs 0.817), and complication occurrence (AUC: 0.725 vs 0.693) (Table 4). The expanded models outperformed the CMS HCC models in all cases (P < .0001 for all comparisons on DeLong testing) (Figure). For the expanded models, mixed effect and variable importance analyses demonstrated that the CMS HCC score was of chief importance for models of mortality, LOS, total charges, and complication occurrence. For the model of nonroutine discharge, age was the most important variable. For the model of total charges, unemployment rate was nearly as important as CMS HCC score (Table 5). No collinear data elements were found after analysis with VIFs.

DISCUSSION

Through a robust 7-year analysis of 653 815 patients, we demonstrated that the addition of key demographic and socioeconomic characteristics to the CMS HCC risk adjustment models may substantially improve models for outcomes after spinal fusion. Although variable importance analysis found that CMS HCC scores were highly predictive of outcomes in all models, some demographic and socioeconomic variables, including age and regional unemployment rate, outweighed or were nearly as important as CMS HCC scores for prediction of discharge status and total charges, respectively. This improvement in predictive power may have important implications for multiple stakeholders including payers, hospitals, and policymakers.

Value-based health care delivery[25] is founded on the premise of maximizing predetermined outcomes while limiting cost and is being implemented in the United States.[26-28] Any system that reimburses based on outcomes must take into account baseline patient risk, lest it penalize providers who take on sicker patients while incentivizing others to cherry-pick healthy enrollees.[29] Risk adjustment models also allow for more efficient value-based health care delivery by streamlining perioperative allocation of resources required by patients.[29,30] Using such models, it may be possible for hospitals and providers to identify patients who may need varying degrees of care or resources, including discharge to skilled nursing facilities and longer inpatient hospitalizations.

Toward this end, payers, such as MA plans, use the CMS HCC risk adjustment model to quantify risk and adjust reimbursement given a population's baseline characteristics.[31] Although initially only intended to guide cost prediction, the model has demonstrated utility in outcome prediction after spine surgery as well.[3] In a study by Turcotte et al,[3] CMS HCC scores were leveraged to predict resource utilization, outcomes, readmission, and reoperation, thereby demonstrating broader potentials for risk stratification after spine surgery. The CMS HCC models represent promising frameworks for risk stratification after spine surgery, given several advantages compared with previous metrics for evaluating patient risk. In contrast to previous comorbidity indices (including CCI/Elixhauser Comorbidity Index), frailty indices, and American Society of Anesthesiologists scores, which are limited by several factors including the absence of key variables, subjectivity, and lack of interrater reliability,[8,10,32-35] the CMS HCC risk stratification system is widely implemented, universally recognized, and captures more complications (70 categories) that may better reflect the patient's burden of disease and health state. In addition, the HCC methodology is readily implemented in existing electronic health record systems.[3] Recent revisions in ICD coding, expansions of variables included in CMS data sets, and computational improvements will only further enhance models created by the CMS by providing additional, readily accessible data elements for tool inclusion.[36] For example, Krumholz et al[36] demonstrated that the incorporation of present on admission coding and the use of ungrouped index and historical ICD-9-CM codes improved pre-existing CMS models significantly. They demonstrated that the addition of these variables allowed for the improvement of the patient-level C statistics from 0.720 to 0.826 for acute myocardial infarction, 0.685 to 0.776 for heart failure, and 0.715 to 0.804 for pneumonia.

Despite the strides that have been made in risk adjustment modeling, there remain important limitations. Notably, the lack of socioeconomic variables and race in such models may fail to capture important patient characteristics that may significantly alter risk. Multiple studies have observed an association between socioeconomic status and resource utilization in spine care.[13-15,37] Indeed, our results support the importance of socioeconomic factor inclusion in markedly improving models of mortality,

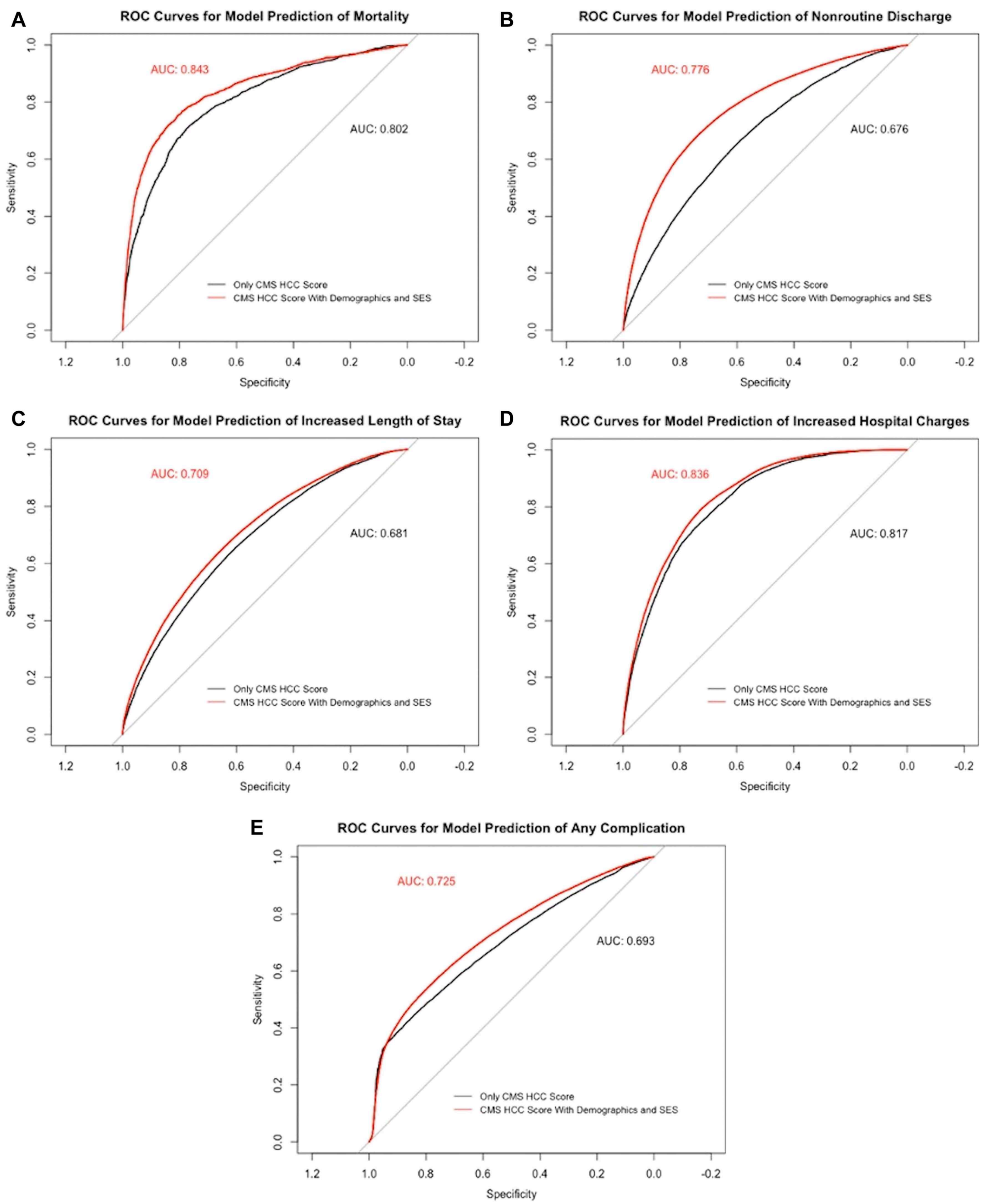

FIGURE. *A comparison of ROC curves—for* **A**, *the prediction of mortality,* **B**, *nonroutine discharge,* **C**, *top quartile of length of stay,* **D**, *top decile of hospital charges, and* **E**, *perioperative complications—for models using solely the CMS HCC score (black line) and CMS HCC score augmented with demographic and socioeconomic status characteristics (specifically, age, sex, Charlson Comorbidity Index, race, insurance type, income quartile, unemployment rate, and poverty rate) (red line). The expanded models (red) outperformed the CMS HCC score models in all cases on DeLong testing (P < .0001). AUC, area under the curve; CMS, Centers for Medicare and Medicaid Services; HCC, hierarchical condition category; ROC, receiver operating characteristic.*

TABLE 5. Variable Importance Analysis on Regression Analyses

Outcomes and predictor variables	Odds ratio	95% CI	Wald test *P*-value	Variable importance
Mortality				
CMS HCC score	20.1271	16.5368-24.4970	<.0001	49.09
Age	1.0204	1.0158-1.0250	<.0001	3.53
Sex	0.5464	0.4890-0.6106	<.0001	11.16
CCI	1.2443	1.2095-1.2800	<.0001	20.00
Race	1.1325	1.0786-1.1891	<.0001	6.01
Insurance type	0.8768	0.8327-0.9233	<.0001	2.83
Income quartile	0.9467	0.9071-0.9881	.01	1.71
Unemployment rate by FIPS	1.0591	0.001445-776.49	.99	5.88
Poverty rate by FIPS	1.3560	0.09433-19.4918	.82	2.33
Life expectancy by FIPS	0.9401	0.08885-0.9946	.03	4.92
Nonroutine discharge				
CMS HCC score	12.1613	11.2970-47.1455	<.0001	71.04
Age	1.0319	1.0311-1.3092	<.0001	71.30
Sex	1.2135	1.1920-1.2355	<.0001	17.96
CCI	1.2069	1.1987-1.2153	<.0001	60.25
Race	1.0465	1.0367-1.0564	<.0001	11.63
Insurance type	0.8730	0.8667-0.8793	<.0001	48.45
Income quartile	0.9769	0.9701-0.9839	<.0001	7.74
Unemployment rate by FIPS	242.9398	1.7386-33 667.48	.03	30.99
Poverty rate by FIPS	0.03495	0.0044388-0.2752	.0014	6.98
Life expectancy by FIPS	1.0178	0.9631-1.0687	.48	22.12
Top 25% LOS				
CMS HCC score	23.9219	22.1519-25.8334	<.0001	91.88
Age	0.9933	0.9927-0.9940	<.0001	20.59
Sex	1.1243	1.1067-1.1421	<.0001	13.16
CCI	1.2610	1.2529-1.2693	<.0001	73.87
Race	1.0416	1.0331-1.0501	<.0001	13.89
Insurance type	0.9424	0.9367-0.9480	<.0001	16.67
Income quartile	0.9578	0.9519-0.9638	<.0001	10.64
Unemployment rate by FIPS	0.8801	0.0073948-104.74	.96	13.32
Poverty rate by FIPS	2.3992	0.3231-17.8149	.39	39.21
Life expectancy by FIPS	1.0764	1.0262-1.1290	.003	57.09
Top 10% charges				
CMS HCC score	16.3911	15.0403-17.8633	<.0001	64.79
Age	0.9798	0.9788-0.9808	<.0001	37.00
Sex	0.8710	0.8488-0.8938	<.0001	12.86
CCI	1.3311	1.3191-1.3431	<.0001	60.13
Race	1.0516	1.0388-1.0644	<.0001	8.55
Insurance type	0.9567	0.9475-0.9661	<.0001	6.42
Income quartile	1.0672	1.0564-1.0781	<.0001	22.01
Unemployment rate by FIPS	2.4488e8	1.52e3-3.95e13	.002	55.24
Poverty rate by FIPS	0.4583	0.002808-74.7772	.76	10.63
Life expectancy by FIPS	1.0737	0.9528-1.2098	.24	43.58
Any complication				
CMS HCC score	85.7558	79.3647-92.6616	<.0001	113.93
Age	1.0111	1.0101-1.0120	<.0001	24.74
Sex	1.2034	1.1773-1.2300	<.0001	16.65
CCI	1.0889	1.0802-1.0977	<.0001	20.38
Race	0.9606	0.9490-0.9722	<.0001	8.46
Insurance type	1.0286	1.0202-1.0372	<.0001	9.39
Income quartile	1.0210	1.0122-1.0299	<.0001	3.53
Unemployment rate by FIPS	1.4127	0.05191-38.45	.84	4.33
Poverty rate by FIPS	1.7064	0.4369-6.6653	.44	1.56
Life expectancy by FIPS	1.0411	1.0088-1.0744	.01	9.18

CCI, Charlson Comorbidity Index; CMS, Centers for Medicare and Medicaid Services; HCC, hierarchical condition category; LOS, length of stay.

discharge disposition, LOS, total charges, and complications after spinal fusion. Our models may outperform prior models because the incorporation of socioeconomic variables may better characterize and capture various social determinants of health that negatively associate with patient outcomes.[38] Other studies support the notion that that the combination of both inpatient characteristics and socioeconomic variables may better characterize and capture various social determinants of health that negatively associate with patient outcomes, providing an opportunity to optimize patient care.[30,39,40]

Still, it is important to note that the use of socioeconomic variables remains controversial.[41] Proponents argue that in pay-for-performance programs without socioeconomic inclusion, providers may receive relatively fewer resources to serve disadvantaged populations[30,39,40] or may avoid serving disadvantaged populations altogether.[42,43] However, opponents to inclusion of socioeconomic variables in modeling are concerned that hospitals treating lower socioeconomic patients may be held to a lower standard—potentially exacerbating baseline health disparities.[42] Similarly, including race into clinical algorithms is controversial. Adding race may propagate race-based medicine, potentially depriving minority populations of useful interventions.[44] In our model, the differences because of race may reflect even more social determinants of health not accounted for by our socioeconomic variables alone. Further discussion on the inclusion of race in clinical algorithms is beyond the scope of our study but warrant thorough investigation.

The question remains as to the extent—relative to the breadth of patient characteristics—to which socioeconomic metrics associate with risk adjustment model predictions. In response to this point, we observed that demographic and socioeconomic variables, including regional unemployment rate and age, were similar or even more important for model performance than CMS HCC score for prediction of several outcomes, including total charges and discharge disposition. Importantly, the National Quality Forum recommends assessment of each performance measure individually—within a given model—to determine appropriateness of sociodemographic status adjustment.[41] Therefore, our results support the appropriateness of socioeconomic inclusion in risk adjustment models after spinal fusion.

Over the past 5 years, multiple changes have been proposed to the CMS HCC model to improve its predictive performance. In fact, it has been explicitly discussed that socioeconomic variables may soon be included in CMS models to improve risk adjustment capabilities.[45,46] Our data support the inclusion of socioeconomic variables and future iterations of the CMS HCC model may be tested in predictive performance of perioperative outcomes after spinal fusion surgery.

Limitations

First, this investigation relies on data sourced from an administrative data set and thus holds the inherent limitations. NIS data only capture data for an index hospitalization (ie, until patient discharge). Thus, mortality and complication that occurs after index hospitalization would not be captured. Moreover, complications not captured accurately by billing codes may further lead to an underestimation of perioperative complications. Second, a primary concern lies in potential collinear data elements within the CMS HCC model.[3] However, an analysis of collinearity through VIF testing revealed no collinear data elements in any of our models for all patient outcomes. This finding further bolsters the strength of our study conclusions. Third, our analysis includes patient records between 2005 and 2011 and corresponding CMS models. The inclusion of data and/or CMS models from additional years may potentially alter the findings of our models. However, utilization of the NIS after 2011 was not feasible because variables required for county-level information—specifically FIPS coding necessary to merge the NIS with the Brookings data set—was no longer captured by the NIS after 2011. Fourth, county-wide socioeconomic variable estimates were applied to individual discharge records. Similarly, disability status was estimated from a separate clinical grouping approach. Thus, both socioeconomic variables and disability status are indirect estimates, and our results should be interpreted accordingly. Finally, the HCC system uses 70 unique condition categories to stratify risk, which is more comprehensive than comparable risk adjustment models such as the Ambulatory Care Groups or Adjusted Clinical Groups (32 categories) and Chronic Illness and Disability Payment Systems (20 categories).[47,48] The greater number of condition categories may increase the difficulty of implementation because it requires a greater number of patient data elements. Still, this increase in effort is offset by the improved risk-stratification abilities of the HCC model, and the addition of socioeconomic factors may further optimize this approach.

CONCLUSION

In the era of value-based health care delivery in spine surgery, optimized models for risk stratification are necessary for accurate assessments of resource utilization. With the addition of key demographic and socioeconomic characteristics, the CMS HCC risk adjustment models can be substantially improved when modeling mortality, discharge disposition, LOS, total charges, and complications after spinal fusion. This finding may have important implications for payers, hospitals, and policymakers.

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COMMENT

This is an elegant study that combines data elements from two separate data sets to offer an opportunity for improvement on the CMS Hierarchical Condition Category (HCC) risk adjustment model, an approach used by CMS for risk adjustment. The HCC model has wide applicability throughout Medicare and Medicare Advantage systems.

The authors use the Nationwide Inpatient Sample and combine it on a county-level to a separate tool and a data set maintained by the Brookings Institution to estimate socioeconomic status. They assess the predictive accuracy of CMS HCC and CMS HCC augmented with population based socioeconomic data.

While the differences between the approaches are not tremendous, the predictive accuracy of the augmented CMS HCC model was greater. Consideration of socioeconomic status appears to improve the ability of risk adjustment models to predict length of stay, total charges, mortality, non-routine discharge, and complications.

This study was completed with a relatively coarse data set and a data match based on county-level, population-based socioeconomic adjustment. I look forward to the authors taking a similar approach with more granular data, such as the Optum or Marketscan databases. Understanding the impact of socioeconomic status on predictive model behavior is vitally important for accurate risk adjustment.

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