Impact of Inpatient Harms on Hospital Finances and Patient Clinical Outcomes

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Objective: The aim of this study was to determine the impact of all-cause inpatient harms on hospital finances and patient clinical outcomes.

Research Design: A retrospective analysis of inpatient harm from 24 hospitals in a large multistate health system was conducted during 2009 to 2012 using the Institute of Healthcare Improvement Global Trigger Tool for Measuring Adverse Events. Inpatient harms were detected and categorized into harm (F–I), temporary harm (E), and no harm.

Results: Of the 21,007 inpatients in this study, 15,610 (74.3%) experienced no harm, 2818 (13.4%) experienced temporary harm, and 2579 (12.3%) experienced harm. A patient with harm was estimated to have higher total cost ($4617 [95% confidence interval (CI), $4364 to 4871]), longer length of stay (2.6 d [95% CI, 2.5 to 2.8]), higher mortality probability (59%; odds ratio, 1.4 [95% CI, 1.0 to 2.0]), and higher 30-day readmission probability (74.4%; odds ratio, 2.9 [95% CI, 2.6 to 3.2]). A patient with temporary harm was estimated to have higher total cost ($2187 [95% CI, $2008 to 2366]), higher variable cost ($800 [95% CI, $709 to 892]), lower contribution margin ($669 [95% CI, $520 to $847]), longer length of stay (1.3 d [95% CI, 1.2 to 1.4]), mortality probability not statistically different, and higher 30-day readmission probability (54.6%; odds ratio, 1.2 [95% CI, 1.1 to 1.4]). Total health system reduction of harm was associated with a decrease of $108 million in total cost, $48 million in variable cost, an increase of contribution margin by $18 million, and savings of 60,000 inpatient care days.

Conclusions: This all-cause harm safety study indicates that inpatient harm has negative financial outcomes for hospitals and negative clinical outcomes for patients.

Key Words: patient safety, cost, harm reduction, DRG, contribution margin, readmissions, mortality, length of stay, Global Trigger Tool

(J Patient Saf 2015;00: 00–00)

Fifteen years after the report To Err Is Human: Building a Better Health System by the Institute of Medicine (IOM) and more than 3 years after the implementation of the Affordable Care Act, patient safety remains a major challenge for the U.S. health care system today. A recent IOM report suggests that, in the United States, one-third of all hospital patients experience harm during their stay...
Harm Identification

This study used a standardized centralized systematic review process to detect inpatient harm. This GTT methodology, which is refined from the Harvard Medical Practice Study’s methodology, is a 2-stage review process. It had a centralized team of registered nurse reviewers (primary reviewers) and physician authenticators (secondary reviewers) for all records sampled from the 24 hospitals for 4 years and has achieved a high degree of interrater reliability (Supplemental Digital Content, http://links.lww.com/JPS/A14, Appendix Exhibit A1 and A2). This method was described in a prior report. In this study, we used the following definition for harm: “unintended physical injury resulting from or contributed to by medical care that requires additional monitoring, treatment, or hospitalization, or that results in death.” All events found were classified using an adaptation of the National Coordinating Council for Medication Error Reporting and Prevention’s Index for Categorizing Errors: E, temporary harm requiring intervention; F, temporary harm requiring initial or prolonged hospitalization; G, permanent harm; H, intervention required to sustain life; and I, death. The inpatients in this study were classified as no harm, temporary harm (patients with $\geq 1$ E events), or harm (patients with $\geq 1$ F–I events).

Costs and Contribution Margin

This health system used a commercially available financial software to categorize actual general ledger expenses as either variable or fixed costs. Total cost included fixed and variable costs and is defined as all variable and fixed hospital expenditures required to provide direct patient care and to manage and operate the facility. Fixed costs are all expenditures that do not change with business volumes. Examples include management salaries and benefits as well as depreciation of equipment and buildings. Variable costs were defined as all expenditures that vary on the basis of changes in business volumes. Examples include nursing and other direct patient care salaries, benefits, supplies, and drugs. Each patient discharge was allocated a pro rata portion of the variable costs according to specific charges incurred. Contribution margin, an indicator of a hospital’s profitability, was defined as total actual payments minus variable costs.

Analysis

Aggregate

We analyzed the study population (21,007) with the use of descriptive statistics using a traditional hospital financial analysis approach to show means or percentages for age, sex, race, insurance payor, total cost, variable cost, contribution margin, DRG weight, mortality rate, and readmission rate by harm category. We also provided the total population (566,325) for comparison (Table 1). We calculated the difference of the means for harm versus no harm and

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FIGURE 1. Flow Diagram for Study Population Selection
temporary harm versus no harm in total cost, variable cost, contribution margin, and LOS. On the basis of the total number of harms reduced, we estimated the cost savings to the study population. We then used a multiplier, a ratio of the total population over the study population, to extrapolate the cost savings to the total population.

**Statistical Modeling**

We applied a traditional health services research approach to the same data set using multivariate regression models and validated them against other models. We analyzed relationships between patient harms and financial and clinical outcomes using multivariate linear regression to estimate continuous outcome measures including costs, contribution margin, and LOS. Multivariate logistic models were used to estimate binary outcome measures including mortality and readmission. Both harm and temporary harm patients were modeled separately against no harm patients. To adjust for potential confounding factors, we included the following covariates in the models: DRG relative weight, age, sex, insurance payor, admission source, hospital, admission year, and MS-DRG. Discrete variables including race, insurance payor, admission source, hospital, admission year, and MS-DRG were coded as categorical variables; sex was coded as a binary variable. For each coded variable, we used the value with the largest percentage as default so it would not be included in the

**TABLE 1. Summary Statistics of Patient Count, Demographics, and Financial and Clinical Outcomes by Inpatient Harm Category 2009 to 2012**

| Harm Characteristic | No Harm | Temporary Harm | Harm | Total Population |
|---------------------|---------|----------------|------|-----------------|
| **Annual study population** |         |                |      |                 |
| Year (population), n % |         |                |      |                 |
| 2009 (n = 5199) | 3646 (70.1) | 718 (13.8) | 835 (16.1) |                 |
| 2010 (n = 5212) | 3731 (71.6) | 706 (13.5) | 775 (14.9) |                 |
| 2011 (n = 5283) | 3894 (73.7) | 782 (14.8) | 607 (11.5) |                 |
| 2012 (n = 5313) | 4339 (81.7) | 612 (11.5) | 362 (6.8) |                 |
| 2009-2012 (n = 21,007) | 15,610 (74.3) | 2818 (13.4) | 2579 (12.3) | 3.7% (21,007/566,325) |
| **Patient demographics** |         |                |      |                 |
| Age, mean (SD), y | 61 (21) | 63 (22) | 68 (18) | 60 (21) |
| Sex, % (N/D) |         |                |      |                 |
| Male | 38.0 (5932/15,610) | 34.0 (958/2818) | 42.0 (1083/2579) | 39.0 (220,867/566,325) |
| Female | 62.0 (9678/15,610) | 66.0 (1860/2818) | 58.0 (1496/2579) | 61.0 (345,458/566,325) |
| Race, % (N/D) |         |                |      |                 |
| White | 80.9 (12,628/15,610) | 80.4 (2266/2818) | 83.2 (2146/2579) | 82.0 (464,387/566,325) |
| Black | 9.1 (1421/15,610) | 9.5 (268/2818) | 8.5 (219/2579) | 9.1 (51,536/566,325) |
| Asian | 1.1 (172/15,610) | 1.4 (39/2818) | 1.2 (31/2579) | 1.1 (6230/566,325) |
| Hispanic | 1.3 (203/15,610) | 0.9 (25/2818) | 1.2 (31/2579) | 1.0 (5663/566,325) |
| **Insurance,** % (N/D) |         |                |      |                 |
| Managed care | 24.0 (3746/15,610) | 21.0 (592/2818) | 20.0 (516/2579) | 26.0 (147,245/566,325) |
| Medicaid | 14.0 (2185/15,610) | 14.0 (395/2818) | 8.0 (206/2579) | 14.0 (79,286/566,325) |
| Medicare | 52.0 (8117/15,610) | 58.0 (1634/2818) | 66.0 (1702/2579) | 54.0 (305,816/566,325) |
| Self-pay | 11.0 (1717/15,610) | 6.0 (169/2818) | 5.0 (129/2579) | 7.0 (39,643/566,325) |
| **Financial outcomes, mean (SD), $** |         |                |      |                 |
| Total cost/case | 6498 (5679) | 10,224 (8838) | 16,021 (15,599) | 8045 (9406) |
| Total variable cost/case | 2863 (3372) | 4538 (4576) | 7371 (7923) | 3820 (5307) |
| Contribution margin/case | 2368 (6236) | 2470 (8174) | 3960 (13,414) | 2596 (8296) |
| LOS, mean (SD), d | 3.6 (2.7) | 5.5 (4.2) | 8.0 (6.8) | 4.0 (4.5) |
| DRG weight, mean (SD) | 1.13 (0.77) | 1.44 (1.13) | 2.13 (1.87) | 1.31 (1.10) |
| **Clinical outcomes, % (N/D)** |         |                |      |                 |
| Mortality rate | 0.9 (140/15,610) | 1.8 (51/2818) | 3.2 (83/2579) | 1.9 (10,760/566,325) |
| Readmission rate |         |                |      |                 |
| 30-d | 10.2 (1592/15,610) | 13.3 (375/2818) | 26.4 (681/2579) |                 |
| 60-d | 15.9 (2482/15,610) | 20.0 (564/2818) | 32.2 (830/2579) |                 |
| 90-d | 20.1 (3138/15,610) | 24.7 (696/2818) | 35.4 (913/2579) |                 |
| 180-d | 28.1 (4386/15,610) | 32.4 (913/2818) | 42.4 (1093/2579) |                 |
| 1-y | 37.1 (5791/15,610) | 38.8 (1093/2818) | 51.6 (1331/2579) |                 |

*Percentages do not sum to 100% because categories such as American Indian or Alaskan native, multiracial, native Hawaiian or Pacific Islander, other, and unknown are not listed.

†Percentages may not sum to 100% because of rounding.

N/D, numerator/denominator.
variable selection (defaults: female, white, Medicare, non-health care facility admission source, hospitals 23 and 24, admission year 2009, and MS-DRGs with fewer than 25 patients grouped as one). Model evaluation and refinements were also conducted (Supplemental Digital Content, http://links.lww.com/JPS/A14, Statistical Models Evaluation and Refinements Details Text). We used backward elimination methods to select significant independent variables in the model, with a \( P \) value of 0.05 or less as criterion.

To test the robustness of the model results and address potential hospital cluster effects, we used a hierarchical linear model for total cost, variable cost, contribution margin, and LOS as well as a hierarchical generalized linear model were very similar to linear regression and logistic model results, and significant hospital cluster effects were not found. We also tested a variety of severity adjustment approaches and found no significant change in the model outcomes with different severity adjusters. All statistical analyses were performed using SAS 9.3 software (SAS Institute Inc., Cary, NC). We used the parametric means of total cost, variable cost, contribution margin, and LOS for harm and temporary harm modeled against no harm and the case reduction to project cost savings to the study population. We projected the cost savings to the total population using the same multiplier described in the aggregate method above.

### MS-DRG Model

Because the traditional hospital financial analytic approach and the health services research analytic approach had different results, we performed a hybrid analysis using aspects of both approaches to look at the same data set with a new model approach. This new approach used an MS-DRG model that is broadly

### TABLE 2. Summary of Adjusted Model Parameter Estimate Results With 95% CI 2009 to 2012

| Outcome Measure | Harm Versus No Harm | Temporary Harm Versus No Harm |
|-----------------|---------------------|-----------------------------|
|                  | Mean Estimate | \( P \) | Mean Estimate | \( P \) |
| Total cost, $ (95% CI) | 4617 (4364 to 4871) | <0.001 | 2187 (2008 to 2366) | <0.001 |
| Variable cost, $ (95% CI) | 1774 (1648 to 1900) | <0.001 | 800 (709 to 892) | <0.001 |
| Contribution margin, $ (95% CI) | –1112 (–1378 to –847) | <0.001 | –669 (–891 to –446) | <0.001 |
| LOS, days (95% CI) | 2.6 (2.49 to 2.76) | <0.001 | 1.3 (1.17 to 1.38) | <0.001 |
| In-hospital mortality, odds ratio (95% CI) | 1.42 (1.02 to 1.97) | 0.0376 | Not significant |
| 30-d readmission, odds ratio (95% CI) | 2.88 (2.56 to 3.24) | <0.0001 | 1.2 (1.05 to 1.37) | 0.0062 |

### TABLE 3. Harm Reduction and Financial Impact 2009 to 2012

| Study and Total Population | Harm | Temporary Harm | Total |
|----------------------------|------|----------------|-------|
| Study population           |      |                |       |
| No. cases without reduction (HT* using 2009 level) | 3340† | 2872‡ |
| No. cases with reduction (actual cases in study data) | 2579 | 2818 |
| Case difference between HT and actual | 761 | 54 |
| Total population actual‡ | 350 | 168 | 518 |
| Opportunity total cost, $M | 153 | 74 | 227 |
| Opportunity variable cost, $M | 58 | 34 | 92 |
| Opportunity contribution margin, $M | 195 | 103 | 298 |
| Opportunity LOS (1000 d) | 105§ | 3.4§ | 108 |
| Total cost savings, $M | 46 | 1.5 | 48 |
| Variable cost savings, $M | 17 | 0.7 | 18 |
| Contribution margin savings, $M | 58 | 2.1 | 60 |

*Hypothetical total, using 2009 harm, temporary harm level to estimate for 4 years.
†Calculation: 761/3340 = 23% of HT, and $350 million was estimated using actual 2579 harms, which is 77% of HT. Thus, 350/77% = 455, which is the total excess cost for harm using HT, then 455 × 23% = 105, which is the savings due to 23% case reduction. Values 46, 17, and 58 were calculated using the same approach.
‡Total population estimation using the MS-DRG model method. These estimates were excess use due to the existence of harm and temporary harm.
§Calculation: 54/2872 = 2% of HT, and $168 million was estimated using actual 2818 harms, which is 98% of HT. Thus, 168/98% = 171, which is the total excess cost for temporary harm using HT, then 171 × 2% = 3.4, which is the savings due to 2% case reduction. Values 1.5, 0.7, and 2.1 were calculated using the same approach.

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applicable to hospital departments such as finance and revenue management to improve financial estimations. Because each patient falls into an MS-DRG and “DRGs are a meaningful way to group patients and procedures that fall together naturally,” our sensitivity-adjusted MS-DRG model calculates means at the DRG level.28 Of the 641 MS-DRGs in the study population, 383 had at least 1 harm. For MS-DRGs with large numbers of harm, we used the difference of means between harm and no harm, multiplied the difference by the number of harm cases in that MS-DRG, and extrapolated to the total population using its specific MS-DRG multiplier. The MS-DRG multiplier is the ratio of patients of an MS-DRG in the total population to the patients of the same MS-DRG in the study population. To account for MS-DRGs with small numbers of harm, we grouped them into 1 category. To obtain the optimal threshold, the minimum number of harms in each MS-DRG, we performed a sensitivity analysis by testing harms ranging from 1 to 50 (Supplemental Digital Content, http://links.lww.com/JPS/A14, Appendix Exhibit A3. MS-DRG Level Sensitivity Analysis Graphs). The final total population projection included all 383 MS-DRGs with harms (Supplemental Digital Content, http://links.lww.com/JPS/A14, Detailed MS-DRG Level Analysis Description Text).

RESULTS

Aggregate Financial Model Results

The descriptive statistics in Table 1 show that, of the 21,007 inpatients, 15,610 (74.3%) had no harm detected, 2818 (13.4%) experienced temporary harm, and 2579 (12.3%) had harm. We found that the mean total cost of hospitalization was $6498 for patients with no harm, $10,224 for patients with temporary harm, and $16,021 for patients with harm. The annual percentage of patients with harm declined during the study period. When projected to the total population, the total cost savings was $201 million, the variable cost savings was $95 million, and the contribution margin loss was $3 million. In addition, we found that LOS savings was 93,000 inpatient days.

Health Services Research Statistical Model Approach

The statistical models’ parametric mean estimation is shown in Table 2. In the regression analysis, both harm and temporary harm were positively correlated with total cost, variable cost, and LOS. The odds ratios of harm and temporary harm were all significant at less than 0.0001. After controlling the covariates, on average, the patients with harm had $4617 more in total cost and $1774 more in variable cost than no harm, the patients with temporary harm had $2187 more in total cost and $800 more in variable cost than no harm, and the patients with harm stayed in the hospital 2.6 days longer and the patients with temporary harm stayed in the hospital 1.3 days longer than no harm. Harm and temporary harm reduced the contribution margin by $1112 and $669 per patient, respectively, compared with no harm. Multivariate logistic models showed that harm was associated with increased risk for mortality (odds ratio, 1.42; \( P = 0.0376 \)) and risk for 30-day readmission (odds ratio, 2.88; \( P < 0.0001 \)). Temporary harm was associated with increased risk for 30-day readmission (odds ratio, 1.20; \( P = 0.0062 \)) but was not significantly correlated with mortality (Supplemental Digital Content, http://links.lww.com/JPS/A14, Detailed Model Results Text and Appendix Exhibit A4 and A5). When projected to the total population, savings for total cost was $98 million, variable cost was $37 million, contribution margin was $24 million, and LOS was 56,000 inpatient days.

MS-DRG Model Approach

The MS-DRG model results are shown in Table 3. We observed a decrease in harm and a slight decrease in temporary harm during the study period. If we assume no decrease in harm, the total number of harms would be 3340 (hypothetical total [HT]) based on the 2009 harm level. However, the actual number of harm cases was 2579 (77% of HT), and harm decreased by 761 (23% of HT) cases. On the basis of the MS-DRG model estimation described above, we used the actual 2579 harms to calculate the “actual” excess use due to harm and calculated the “savings” based on harm reduction. The impact of temporary harm reduction was derived in the same manner. When projected to the total population, this health system saved $108 million in total cost, $48 million in variable cost, $18 million in contribution margin, and 60,000 inpatient days. However, most of the harms (77% harm and 98% temporary harm) still had a large negative financial impact on hospitals.

Comparison of All 3 Models

The comparison of total population costs, contribution margin, and LOS savings is shown in Table 4. Estimations from statistical and MS-DRG models are in agreement and different from the results of the aggregate approach.

DISCUSSION

Among the 3 cost estimation models, the aggregate approach is typically used in cost analysis, which takes the grand mean of each harm category without weighing the cost differences among
different MS-DRGs. It is an intuitive approach and easy to use; however, its results in this study are misleading and provide a mean in a nonnormal distribution, potentially overestimating the costs. Statistical models use parametric mean estimation and a single multiplier to estimate total population impact in this study. They are popular among researchers to severity adjust populations and are the primary approaches in the literature. The novel sensitivity-adjusted MS-DRG model presented in this study takes differences among various MS-DRGs into consideration and calculates costs within each specific MS-DRG. It uses a specific MS-DRG multiplier for each MS-DRG to estimate total population impact. Although sensitivity adjustments are not typically used by hospital financial departments, we used this approach for MS-DRGs with low volumes of harm cases to reach optimal estimations. Whereas statistical models can provide predictive power in a population study, the MS-DRG method can be more applicable for hospital finance, revenue management, and quality department to analyze costs and achieve results comparable with those of the statistical models. Both methods generate similar total population estimation results, which we believe are more accurate than the aggregate estimates. The IOM Report Best Care at Lower Cost: The Path to Continuously Learning Health Care in America suggests that improving patient safety may be 1 of the best health care cost reduction opportunities for hospitals.29 One of the challenges with the current state of patient safety is the narrow focus of harm measurement, which may be misleading as to the magnitude of patient harm and financial burden. Recent reports have suggested that hospitals fiscally benefit with an improved financial contribution margin from the occurrence of serious selected inpatient complications.30-31 In contrast, our study reveals that the financial contribution margin is negative for hospitals when the analysis includes all-cause harm compared with no harm, suggesting that, collectively, hospitals have both quality and financial incentives to drive down the incidences of harm.

In our model, we found adverse clinical and financial outcomes for inpatients who experience harm. We also found that these adverse effects extended beyond the hospitalization to the 30-day postdischarge period with an almost 3-fold increased risk for readmission compared with no harm, suggesting that, collectively, hospitals have both quality and financial incentives to drive down the incidences of harm. This study demonstrates that inpatient harm reduction is associated with reduced inpatient LOS, mortality, and readmission rates, which will benefit patients. Harm reduction is also associated with lower costs and higher contribution margin for hospitals. Therefore, reducing harm not only is the right thing to do for patients but also is financially and clinically prudent. The DRG approach proposed in this study provides a novel and practical approach for hospitals or health systems to evaluate the financial impact of harm.
ACKNOWLEDGMENTS

The authors thank Paul R. Garrett, Jr, MD, for providing invaluable leadership of the GTT project and Donald Kennerly, MD, for conceptualizing cost analysis with all patient harm.

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