Predicting Your Hospital's Readmission Penalty And Gauging Your ROI: A New Approach

ReInforcedCare™

Abstract (August 2013 Revision)

Many hospital leaders would like to pinpoint both future readmission-related penalties and the return on investment (ROI) associated with readmission reduction. However, the particularities of Medicare's penalty calculations do not allow for precise determination of either of these quantities. Using publicly available national data, we devised an original method that uses regression to predict penalties and then builds that information into a Monte Carlo simulation of the revenue implications of each readmission added or prevented. For each of three diagnostic-related groups (DRGs) on which penalties depend, the prevention of a single readmission was found to save the average hospital $8,700, or between $8,200 and $10,500 depending on DRG, for FY 2013 and FY 2014, and quite possibly more looking ahead to FY 2015 and beyond.

The Problem

Many hospital officials in the U.S. have asked how they can predict the amount of revenue that will be lost or saved as a result of changing readmission rates. And many would like to go a step further and be able to pinpoint the return on investment (ROI) gained from each readmission they could prevent. But anecdotally we find that few understand exactly how changes in their readmission performance will affect their penalty, as assessed by the Centers for Medicare and Medicaid Services (CMS).

We have delved into the systems and calculations devised on behalf of CMS by their vendors, QualityNet and the Yale-New Haven Hospital Center for Outcomes Research and Evaluation. These analysts' calculations are not for the faint of heart. A paper describing their statistical methods features no fewer than eighteen authors. Each of their three diagnosis-specific readmission equations incorporates nearly 50 variables. The authors make use of relationships computed based on multi-level, hierarchical logistic regression models, and they derive separate

Sample Showing Complexity of CMS Penalty Equations

Step	Risk Factors Based on: Administrative Data
1	Compute Bivariate and Univariate summaries Z & Y
2	Generalized Linear Model $h(Y_{ij}) = \alpha^A + \beta^A Z_{ij}$ Obtain R^2, residuals, etc.
3	Hierarchical Generalized Linear Model $h(Y_{ij}) = \alpha_i^A + \beta^A Z_{ij}$ $\alpha_i^{(A)} \sim N(\mu_A, \tau_A^2)$
4	Hospital-Specific Predicted Outcomes $\hat{y}_i^A(\mathbf{Z}) = \frac{1}{n_i}\sum_{j=1}^{n_i} h^{-1}(\hat{\alpha}_i^A + \hat{\beta}^A \mathbf{Z}_{ij})$ Hospital-Specific Expected Outcomes $\hat{e}_i^A(\mathbf{Z}) = \frac{1}{n_i}\sum_{j=1}^{n_i} h^{-1}(\hat{\mu}_A + \hat{\beta}^A \mathbf{Z}_{ij})$ Hospital-Specific Standardized Outcomes $\hat{s}_i^A(\mathbf{Z}) = \frac{\hat{y}_i^A(\mathbf{Z})}{\hat{e}_i^A(\mathbf{Z})} \times \bar{y}$

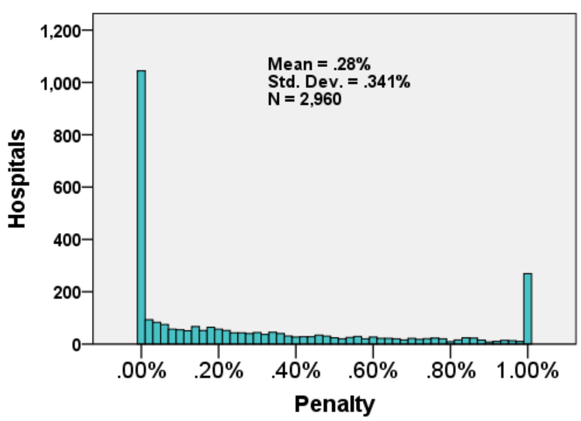
coefficients to characterize each of several thousand hospitals.
What's more, in our detailed communications with them, these organizations have made it clear that **penalties for future years are not directly calculable**. This is not only because future years' penalties will incorporate readmission rates for additional conditions, but also because the CMS system in a sense "grades on the curve" and because future penalties will depend in part on how the entire nation fares in its readmission reduction efforts.

In light of all this, **is there a workable way to identify penalty changes that would result from specified changes in readmission rates?** We believe we have found one. We can claim a fair degree of precision for our solution, and we believe our statistical model can be useful in helping hospitals form realistic expectations about revenue lost or saved due to changes in readmission rates.

Moreover, our analysis has allowed us to estimate something more specific, and potentially even more useful. This is the amount of **revenue that would be saved per patient prevented from readmitting**. This ROI figure will, we hope, help inform your decisions about readmission-reduction interventions you put into place.

Our Approach to Predicting Penalties

Our predictive model[1] depends first on a statistical technique called *censored regression*. This approach differs from ordinary linear regression in that it takes into account the unusual shape of the distribution of FY 2013 CMS penalties nationwide (shown below).



This shape is so far from the ideal shape for ordinary linear regression—a bell curve—that linear methods won't do the best job of prediction. Although the mean penalty assessed by CMS for FY 2013 was about 0.3% of a hospital's Traditional-Medicare-based revenue, most U.S. hospitals were assessed with penalties nowhere near that mean. There was a very large group, more than a third, with zero penalty, while another fairly large group was assigned the maximum of 1.00%. Censored regression can draw the most information from data that features these sorts of spikes at the upper and lower limits.

Using this regression approach, we arrived at a model that could describe the penalty as a function of four variables. These were the readmission rates for patients admitted for acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN) – the three "core measures" considered by CMS for FY 2013 – plus an indicator of hospital size. (Hospitals with more patients tend to have slightly higher penalty rates.)

[1] Statistical analysis was conducted using IBM's SPSS package (formerly the Statistical Package for the Social Sciences) and the open-source software *R*, in addition to Microsoft Excel.

We obtained an equation following this structure:

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Predicted Penalty (%) =  a + b1*rar.AMI + b2*rar.HF + b3*rar.PN + b4*Size,

where rar = readmission rate,
a = the regression constant, and
b1 through b4 are regression coefficients.
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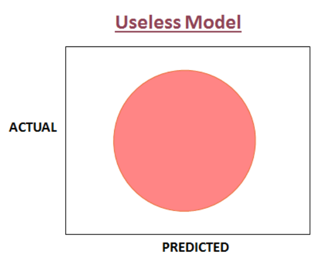
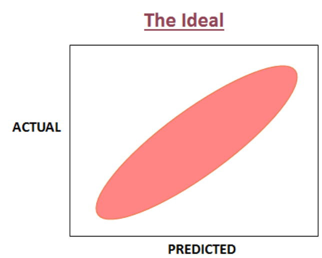
We then made an adjustment so as to bring all predicted penalties into the range of 0% to 1%, inclusive. (We recoded any values below 0% into 0%, and any above 1% into 1%.)

When this equation was tested with brand-new data to see how well it performed, it indeed predicted the penalty better than the linear regression method could. The *R*-squared, or percent of the variance the model could explain, was 64% in the original dataset (as compared to linear regression's 60%). Encouragingly, predictive power shrank only a bit, to 58%, when the censored regression equation was tested on a new set of hospitals. (For linear regression, the *R*-squared shrank to 54% when so tested.)

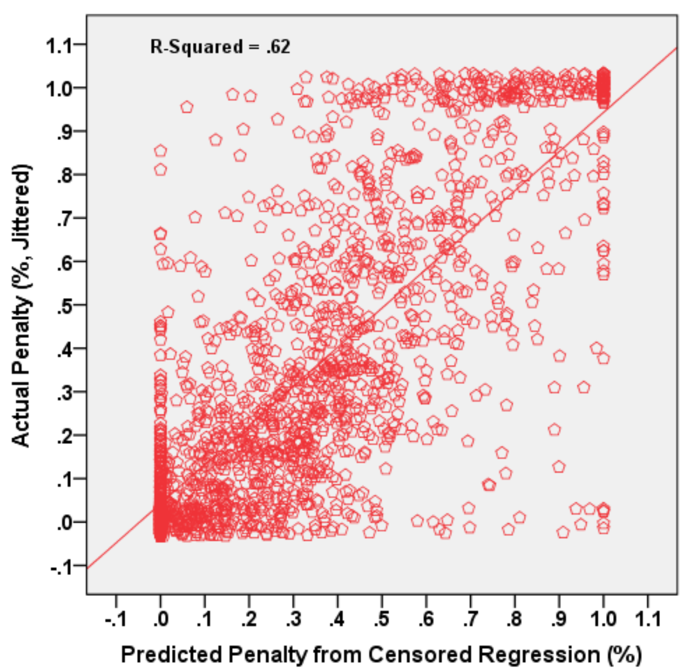
If we were to graph the predicted vs. actual penalties in a scatterplot, how would we want such a graph to look? If predictive power were very great, a low predicted penalty would usually mean a low actual one; high predicted, high actual. We'd see a narrow band of points, one for each hospital, running from lower left to upper right. The points would form a cloud looking something like the one at far right.





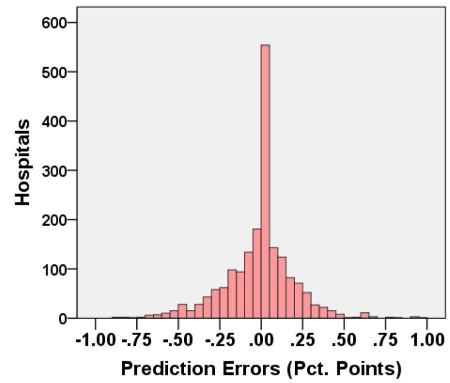
How Accurate Are Our Regression Predictions?

The plot at right shows the extent to which our predicted penalties lined up with the actual penalties, for all 1,913 hospitals with publicly available data complete enough to be included in our analysis. The diagonal line shows the line of best fit. This line is heavily influenced by the large number of cases with actual penalties of 0% or 1%. (In the chart the actual penalties are "jittered" or mixed with a small amount or random noise so that fewer points will fall on top of one another.)



Gratifyingly, there was indeed a strong lower-left-to-upper-right trend, as reflected in the overall *R*-squared of .62. As you might expect, prediction was more accurate for hospitals at the extremes than for those few in the middle. Almost all penalties predicted to be very low (at left) were indeed very low; almost all predicted to be very high (at right) were very high; but for those predicted to be around 0.5%, the degree of uncertainty was greater.

Altogether, 74% of the hospitals' actual penalties were within 0.20 percentage points of the prediction, and 81% were within 0.25. Such results constitute an improvement over others currently available. They enable better prediction than do the best guidelines we have encountered from CMS and its vendors in this regard. Since few hospitals possess the cutting-edge modeling capabilities that CMS can command, their guidelines boil down to the truism that penalties will tend to go up or down in tandem with readmission rates for AMI, HF, and PN.



Simulation Results: Predicted Penalties

Building on the regression equation described above, we constructed a model that simulated the potential revenue effects of various possible changes in hospitals' core-measure readmission rates. All data related to FY 2013 penalties, which depend on readmission rates for the 36-month period from July 2008 to June 2011. Although some of the specifics of this Monte Carlo simulation go beyond the scope of this paper, the method depended on a series of inputs:

- The average hospital's annual revenue from Traditional Medicare;
- The average hospital's annual number of discharges overall;
- The average hospital's annual number of discharges categorized under each of the core measures;
- The coefficients from our regression solution; and
- Parameters governing possible, randomly assigned changes in readmission rates.

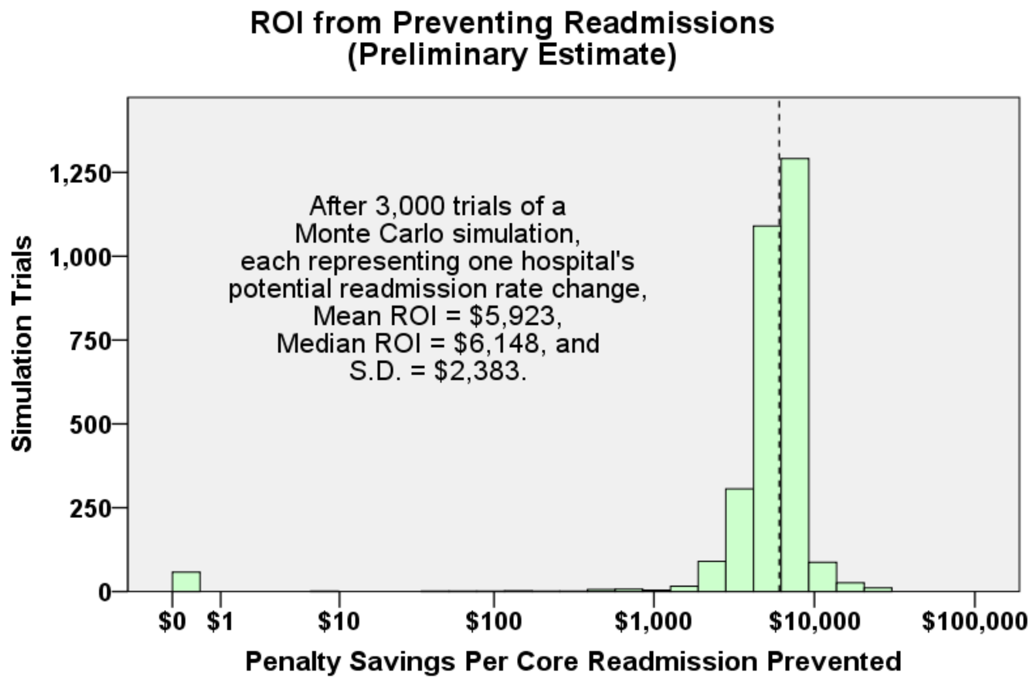
With each trial of the simulation, we fed through this system the information that might characterize a single hospital's year-to-year changes, and we recorded three key outputs:

1. The change in the number of core-measure readmits;
2. The dollar change in CMS penalty, based on our regression equation; and
3. The dollar change per core-measure readmit prevented (or added). This represented our preliminary ROI estimate.

For a robust simulation, we conducted 3,000 such trials.

- The ROI figure averaged about $6,000, as the chart below shows.
- At the high end, 3.3% of results exceeded $10,000, and one trial even produced a figure of $28,930.
- In 1.9% of trials ROI turned out to be zero, which makes sense when you consider that hospitals already at the maximum penalty will not have their penalty affected by additional readmissions, nor will those currently unpenalized stand to gain by reducing them. (At least as far as CMS

penalties are concerned. Readmissions' financial implications under capitated payments and accountable care organization plans are another matter.)



DRG-Specific Offsets

While the average core-measure readmission may cost the average hospital $6,000 in CMS penalties, that is not the end of the matter. Caring for patients with some conditions tends to add to a hospital's ledger; for others, to subtract. We were completely prepared to find that the DRGs central to the CMS penalties would typically involve profits that would offset the $6,000 figure. What we found was the opposite.

We used data files publicly available from CMS and from Health and Human Services' Agency for Healthcare Research and Quality (AHRQ) to determine the average net margin realized by US hospitals from caring for patients readmitted with the three core measures.[2] Provided with 2011 figures, we extrapolated to 2013 using AHRQ's figures about annual increases in health care costs controlling for inflation and using an inflation calculator to account for additional increases due to inflation. Even when we limited these offsets to the estimated 70% portion that would relate to a hospital's variable costs,

[2] Costs and net margins were often quite different for readmissions than for index admissions. Figures also varied considerably for different diagnoses within each DRG. We obtained weighted averages within each DRG to inform our net margin calculations.

the offsets turned out negative for all three conditions.[3] Net margin results were all losses: approximately -$4,500 per readmission for AMI, -$2,200 for HF, and -$2,500 for PN.

Adding these losses to the average $6,000 cost described above, we arrived, in round terms, at the following final estimates:

Average Cost to a Hospital Per Medicare Readmission by DRG

DRG	CMS Penalty	Cost of Care (Net Margin)	Total Cost
Acute myocardial infarction (AMI)	$6,000	$4,500	$10,500
Heart failure (HF)	$6,000	$2,200	$8,200
Pneumonia (PN)	$6,000	$2,500	$8,500
Average (unweighted)	$6,000	$3,100	$9,100
Total Average (weighted by numbers of discharges in each DRG)	$6,000	$2,700	**$8,700**

FY 2014 and Beyond

When CMS announced its readmission penalties for FY 2014, some hospitals saw their penalty change by a full percentage point; observers had expected this to happen to many more hospitals, given the planned upper limit increase from 1% to 2%. One unfortunate California hospital saw its rate increase from 0% to 1.33%. But on average, penalties stayed nearly flat. This leads us to believe that our analysis based on FY 2013 data will hold true and remain relevant at least until CMS announces its next round of changes, probably in August 2014, and quite likely beyond that date. To the extent that one expects penalties to increase in future years, the ROI implications of preventing readmissions can only increase as well.

[3] The figure for chronic obstructive pulmonary disease (COPD) was negative as well.

Conclusion

Our analysis uses publicly available data and draws on a specialized form of regression known as censored regression; Monte Carlo simulation; and other calculations. It indicates that $8,700, or somewhere in the range from $8,200 to $10,500 depending on DRG, is a reasonable estimate of the amount of money saved in CMS penalties and other costs when a hospital prevents a single core-measure Medicare patient from readmitting.

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About ReInforced Care

ReInforced Care, Inc., based in Ashland, Massachusetts, assists hospitals with proactive patient outreach post-discharge. We work to reduce readmissions and increase patient satisfaction and loyalty while increasing efficient use of nursing staff and supporting hospitals' understanding of patient outcomes. For more information, contact:

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