Published in final edited form as:

Med Care. 2020 November ; 58(11): 1022–1029. doi:10.1097/MLR.0000000000001396.

Patient Coded Severity and Payment Penalties under the Hospital Readmissions Reduction Program: A Machine Learning Approach

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Abstract

Objective.—To examine variation in hospital responses to the Centers for Medicare & Medicaid’s expansion of allowable secondary diagnoses in January 2011 and its association with financial penalties under the Hospital Readmission Reduction Program (HRRP).

Data sources/study setting.—Medicare administrative claims for discharges between July 2008 and June 2011 (N=3,102 hospitals).

Research design.—We examined hospital variation in response to the expansion of secondary diagnoses by describing changes in comorbidity coding before and after the policy change. We used random forest machine learning regression to examine hospital characteristics associated with coded severity. We then used a two-part model to assess whether variation in coded severity was associated with readmission penalties.

Results.—Changes in severity coding varied considerably across hospitals. Random forest models indicated that greater baseline levels of condition categories, case mix index, and hospital size were associated with larger changes in condition categories. Hospital coding of an additional condition category was associated with a non-significant 3.8 percentage point increase in the probability for penalties under the HRRP (SE=2.2) and a non-significant 0.016 percentage point increase in penalty amount (SE=0.016).

Conclusions.—Changes in patient coded severity did not affect readmission penalties.

Keywords

Pay-for-performance; value-based purchasing programs; patient severity; risk adjustment; coding

Introduction

Enacted in 2010, the Hospital Readmissions Reduction Program (HRRP) reduces Medicare payments to acute care hospitals with above-average, risk-standardized readmissions rates for targeted conditions among acute care hospitals¹. HRRP penalties totaled more than 280 million dollars in the first year of the program and have almost doubled in magnitude since then^{2,3}. Numerous studies examining early effects of the program document significant declines in readmissions rates for conditions targeted by the HRRP, including acute myocardial infarction (AMI), congestive heart failure, and pneumonia, between 2010 and 2012^{4–6}. However, more recent research posits that increases in patients' coded severity of illness explains much of the decline in risk-adjusted readmissions^{7,8}. Increases in coded severity were due in large part to a policy change on January 1, 2011 by the Centers for Medicare & Medicaid Services (CMS) which expanded the number of allowable secondary diagnosis codes for each discharge, from 9 to 24 codes^{8–11}. Greater opportunity for hospitals to code more secondary diagnoses on each discharge claim increased patients' measured severity of illness.

While CMS' expansion of secondary diagnoses may have led to overestimates of the HRRP's effects on readmissions, it is unknown whether the policy has affected penalties received by hospitals. On one hand, homogeneous increases in severity across hospitals would not change the distribution of penalties in the HRRP. On the other hand, heterogeneous responses could alter hospitals' relative rankings of risk-standardized readmission performance, which would subsequently affect the magnitude of imposed penalties. Therefore, it is unclear whether the effects of the coding expansion is an issue relevant only for evaluation of the program¹⁰ or also for the distribution of penalties. Furthermore, existing data suggest that provider proclivity to document patient diagnoses differs by region and by hospital characteristics – suggesting that changes in coding are unlikely to be uniform across hospitals^{12–14}. Increased coded severity of illness could be the result of more comprehensive capture of patient case-mix. Alternatively, if increased coded severity of illness is a strategy employed by some hospitals to lower penalties rather than improving underlying performance, then the behavior would be contrary to the objectives of CMS, particularly if this behavior is rewarded at the expense of other hospitals.

In this context, we used national data to examine variation in the effects of CMS' expansion of secondary diagnoses across hospitals. We then used machine learning techniques to identify hospital characteristics associated with larger increases in coded severity after the policy. Finally, we assessed whether variation in increases in coded severity was associated with the magnitude of penalties under the HRRP.

Methods

Data source and study population

We used 100 percent MedPAR inpatient claims data for all discharges among Medicare fee-for-service beneficiaries between July 1, 2008 and June 30, 2011 (n=20 462 254 beneficiaries). We included patients enrolled in Medicare Part A and Part B for at least 30 days after discharge, aged 65 and over, and discharged alive. We excluded patients that did

not have Medicare as the primary payer, transferred to another acute care facility, discharged from Maryland and Puerto Rico hospitals, discharged against medical advice, hospitalized for cancer treatment, primary psychiatric diagnoses, or rehabilitation.

We obtained corresponding HRRP payment adjustment factors from the fiscal year 2013 Inpatient Prospective Payment System Final Rule, covering discharges between July 1, 2008 and June 30, 2011 (N =3102 hospitals). We used the fiscal year 2012 Impact File to gather information on hospital characteristics in 2010, including: number of beds, percent of inpatient days that are for Medicare stays, transfer adjusted hospital case-mix index (the average diagnosis-related group relative weight for each hospital accounting for transfers), and disproportionate share index. We obtained hospital ownership information from the 2010 Provider of Service file. We used the American Hospital Association Annual Survey Database to identify hospitals integration with physicians defined as through employment or contractual agreement¹⁵, use of Electronic Health Records, urban/rural location, and teaching status.

Measures

To estimate changes in coded severity associated with CMS' expansion of secondary diagnoses on January 1, 2011, we calculated the hospital-level, average number of Condition Categories (CCs) for AMI, congestive heart failure, or pneumonia in two different periods: October 1, 2010–December 31, 2010; and January 1, 2011–March 31, 2011. Prior research showed the changes in coded severity increased discontinuously when CMS expanded secondary diagnoses in January 2011¹¹ (see also Figure 1). Evaluating changes in the average CCs immediately before and after this policy change allows us to identify hospital-level responses without confounding from longer-term increases in severity coding.

We measured patient severity using CCs because they are a part of CMS' risk-adjustment approach in the HRRP. Because CMS' documentation policy was not effective until January 2011, we truncated the number of secondary diagnoses to a maximum of 9 secondary diagnosis codes for discharges occurring before 2011. Less than 2 percent of discharge claims shortly before the documentation change contained more than 9 secondary diagnosis codes due to delayed claims processing¹¹. Next, we calculated the change in CCs as the difference between the average number of CCs per discharge in quarter 4 of 2010 and quarter 1 of 2011. In sensitivity tests, we also conduct checks without truncation as well as extend the window to 6 months before and after the policy change to calculate the change in CCs.

To examine the relationship between change in CCs and HRRP penalties, our outcome was the HRRP payment adjustment factors for fiscal year 2013 of the HRRP. Payment adjustment factors ranged from 0 to 1. A factor of 1 meant that the hospital faced the full one percent payment reduction and 0 meant that the hospital faced no payment reduction. Of the 3102 hospitals, 915 (29%) of hospitals faced no penalties in fiscal year 2013.

Statistical analysis

To examine how measured comorbidities differed across hospitals following the secondary diagnosis coding expansion, we categorized hospitals into tertiles based on the magnitude of

each hospital's change in CCs. We then described how measured severity varied daily from 2010 through 2011.

To determine whether certain hospital characteristics were associated with the magnitude of change in CCs after 2011, we examined permutation feature importance identified through random forest regression. This is our preferred approach as we had no strong priors about how various hospital characteristics were most likely to be associated with change in CCs. We first predicted the change in CCs using random forest regression¹⁶, where the hyperparameters were tuned by Bayesian Optimization using a 20 percent training data set with a resulting mean 10-fold cross-validation score of 0.14 (R-squared value). The parameters from our random forest regression included 13 features, a minimum of 155 samples to split an internal node, 500 trees in the forest, and no maximum depth on trees. Next, we randomly permuted each characteristic individually to identify its effect on the model R-squared value. Baseline 2010 characteristics that have little effect or no more effect than a randomly generated variable indicate little importance in our predictions. We then captured the marginal effects of each characteristic on the predicted change in CCs, averaged over the other variables in the model. These marginal effects are rendered in partial dependence plots¹⁷. We imputed characteristics for 830 hospitals with missing data (26%) by chained equations. Missing data were primarily due to missing information on hospital-physician integration and electronic health record adoption. We also examined hospitals with non-missing data as a sensitivity test.

As a robustness check, we also used a standard multivariate model to identify variable importance, where important variables were those with p -values less than 5 percent. Variables that were identified as most important via the machine learning approach were also identified as the most important contributors in the multivariable model.

Finally, to test the association between the magnitude of change in CCs and HRRP penalties, we used a two-part model analyzed at the hospital level. In the first part, we used a logistic regression model to estimate the probability for hospitals to receive any HRRP penalty. In the second part, we used a generalized linear model with log link and Poisson family to estimate penalty size among hospitals that received a penalty. We chose the log link function and Poisson distribution family based on a Box Cox and modified Park test¹⁸. We controlled for covariates based on components in CMS' penalty algorithm, which is based entirely on risk-adjusted readmissions. In our models, we controlled for hospitals' baseline severity using the average number CCs per hospital determined from the first 9 secondary diagnosis codes among discharges during the performance period. This variable was chosen to reflect each hospital's patient case-mix or risk for readmissions. We also controlled for condition-specific, 30-day, hospital-level unplanned readmissions rates for conditions targeted by the HRRP. This included AMI, congestive heart failure, and pneumonia, adjusted for age and sex. In sensitivity analyses, we also include additional covariates such as minority patient share, disproportionate share hospital percentage, and other hospital characteristics¹⁹. We used heteroskedasticity-robust standard errors in all regressions. We report average marginal effects for each part separately and combined²⁰ to facilitate interpretation. We performed our analyses using Stata 15 SE, and Python 3.6 (using eli5 and skopt libraries).

Because the HRRP's risk adjustment approach is based on each patient's severity at the time of discharge in addition to severity from the previous year, we performed an additional sensitivity analysis by examining fiscal year 2016, reflecting discharges between July 1, 2011 and June 30, 2014 (N=3092 hospitals), discharges occurring entirely after the policy change. This analysis used MedPAR claims data for the same period and payment adjustment factors from the fiscal year 2016 Inpatient Prospective Payment System Final Rule.

Results

Table 1 presents descriptive statistics of the hospitals in the study sample. The readmissions rates for AMI, congestive heart failure, and pneumonia were 18.9% for AMI, 23.0% for congestive heart failure, and 17.0% for pneumonia. On average, 15.1% of all discharges were AMI, congestive heart failure, and pneumonia. The average increase in the number of CCs before and after January 2011 was 0.43 (SE=0.01). CCs changed by an average of -0.03 (SE=0.01) among hospitals in the lowest tercile of CC change (tercile 1) and by +0.87 (SE=0.01) among hospitals in the highest tercile. Compared with hospitals in tercile 1, hospitals in tercile 3 had lower proportions of discharges for AMI, congestive heart failure, and pneumonia (14.3% vs. 16.3%), lower disproportionate share payment percentage (29.4% vs. 30.4%), and lower share of inpatient days that were for Medicare patients (43.4% vs. 46.8%). However, tercile 3 hospitals tended to have higher overall case-mix index (1.50 vs. 1.31); more beds (233.8 vs. 138.5); higher proportion of hospitals with not-for-profit ownership (67.5% vs. 55.1%), teaching affiliation (36.3% vs. 23.4%), full EHR implementation (32.7% vs. 22.6%), and physician integration with hospitals (61.3% vs. 57.0%).

Figure 1 shows the average daily number of CCs from 2010 through 2011 for AMI, congestive heart failure, and pneumonia across the hospital tertiles. Consistent with Table 1, Figure 1 indicates an immediate and larger discontinuous jump in number of CCs after January 2011 for tercile 3 than tercile 1. It also shows different levels of CCs over time, where hospitals in tercile 3 appear to have higher baseline CCs levels than hospitals in tercile 1. The discontinuous jump in CCs suggest an increase in coded severity induced by the coding policy, while the varying levels of CCs across hospitals reflect severity and/or coding variation across hospitals. Hospitals with the smallest change in CCs (i.e., tercile 1) had fewer number of CCs throughout 2010 compared to hospitals in higher tertiles of CCs change.

Results from the random forest regression models found baseline hospital characteristics appear to be influential in predicting the magnitude of change in CCs (Figure 2). Influence is assessed by the R-squared value, which is shown on the x-axis. The most influential baseline hospital characteristics include the average number of secondary diagnoses; hospital case-mix index; number of beds; average patient age; percent of female patients; percent of Medicare inpatient days; proportion of discharges for AMI, congestive heart failure, and pneumonia; and disproportionate share payment percentage. Other characteristics, such as for-profit status and teaching affiliation, were less important than a randomly generated variable. The permutation importance results using the imputed characteristics are similar to

results obtained on the sample of hospitals with non-missing characteristics (Appendix Figure 2).

Appendix Figure 1 shows the marginal effects of the characteristics most important in predicting the change in CCs, holding all other variables at their average. Having more secondary diagnoses per diagnosis in 2010 is associated with an increase in CCs. For example, the average marginal effect of having 7 secondary diagnoses is approximately 0.1 CCs more following the documentation policy change (Figure 3). Having hospital-level case-mix index up to 1.4 is positively associated with the magnitude of CCs change. The marginal effect is nonlinear and flattens once the case-mix index is above 1.38. The marginal effect of the number of beds is positive up to 287 beds and then flattens. The remaining characteristics have smaller marginal effects and are also relatively uninfluential.

An increase by one CC after the expansion of secondary diagnoses was associated with a small and non-significant 3.8 percentage point increase in the probability for a hospital to receive a penalty (average marginal effect of 0.038, SE=0.022) in fiscal year 2013 of the HRRP, holding all other variables constant (Panel A, Table 2). We also did not find a statistically significant or meaningful effect on the size of penalties received among hospitals that received any penalties (average marginal effect of 0.016 percentage point, SE=0.016). The combined average marginal effect from the two-part model indicates that a one-unit increase in CCs is associated with a non-significant 0.022 (SE=0.013) percentage point increase in the overall penalty size. We find similar non-significant results, although the direction of the combined effects is negative, when examining fiscal year 2016 of the HRRP, which included discharges from July 1, 2011 and June 30, 2014 (Panel B, Table 2). Furthermore, our results are robust to using an ordinary least squares regression model (Appendix Table 1), controlling for additional hospital characteristics, not truncating secondary diagnoses captured among discharges in the quarter before the documentation policy change, and allowing for a longer window of time to determine the magnitude of CCs change (Appendix Table 2).

Figure 3 shows a Sankey diagram depicting changes in the distribution of hospital penalties under the HRRP between fiscal year 2013 and 2016. We found that hospitals that received penalties in fiscal year 2013 were likely to continue to be penalized in fiscal year 2016. The inertia found across penalty categories suggest that the coding change had little influence on the distribution of penalties among hospitals, consistent with the regression results across the fiscal years. Furthermore, the majority of hospitals continue to remain in the same categories of penalties. For example, 50.4% of hospitals that received a high penalty in fiscal year 2013 also received a high penalty in fiscal year 2016.

Discussion

In this national study of hospital responses to CMS' expansion of secondary diagnoses, we report 3 main findings. First, changes in severity coding varied considerably across hospitals. Hospitals in the bottom tertile of severity changes barely changed, while those in the top tertile increased coded severity by more than 35%. Second, hospitals with larger increases in their coded severity tended to be facilities with higher case-mix indices and

more secondary diagnoses before the coding change. Third, increases in coded severity was not associated with the probability for hospitals to be penalized under the HRRP nor was it associated with the size of penalties. Collectively, these findings suggest that while the coding expansion introduced more variation in the measured severity across hospitals, it did not appear to have substantively affected which hospitals were penalized under the HRRP.

Our findings show that measures of patient baseline severity were the most influential predictors in explaining the magnitude of CCs change, as opposed to other factors, such as the structural characteristics of hospitals. One possible explanation for these findings could be that the expanded documentation more accurately reflects the patient populations of hospitals, such that hospitals that treat sicker patients are able to code these patients as such. Another explanation, however, could be that some hospitals are more strategic than others, rather than some hospitals having sicker patients than others. If true, those hospitals that were better at capturing patient risk at baseline were also more effective in increasing coded severity after the expansion of secondary diagnoses. We observe a positive relationship between the share of HRRP discharges and the magnitude of change in CCs but only for hospitals at the tails of the distribution (Appendix Figure 1), which suggests that a subset of hospitals may have engaged in strategic behavior. Distinguishing these two explanations will remain important moving forward.

Our finding that the structural characteristics of hospitals did not play a large role in explaining the magnitude of CCs change is in contrast to other literature that suggest a correlation between certain hospital characteristics and the adoption of revenue-increasing coding practices¹². Examining a coding change that could affect 2% of hospital revenue, Sacarny found that hospitals that integrated with physicians and were equipped with health information systems changed coding practices more. The coding expansion examined in our paper, however, is different in nature. It affected all major electronic transactions such as claims requests and payments, not just 2% of revenue. Therefore, coordination between hospitals and professionals to adopt new coding practices may have been easier. Further, the coding expansion was seen by the industry as an improvement in functionality from the prior version⁹. Thus, all hospitals may have faced a similar urgency to transition to the new coding system.

Our study also contributes to a better understanding of the interaction between the expansion of secondary diagnoses and the HRRP. While other investigators have examined the interaction between the expansion of secondary diagnoses and evaluations of the HRRP^{8,10}, our study is the first to examine the consequences of hospital variation in coding on the policy implications of the program. The direct effects on the HRRP is important to ensure that the interplays across the two policies are not countervailing. Our findings suggest that the changes in coding did not affect the distribution of HRRP penalties in a meaningful way.

It is important to note that our study measures patient severity derived from secondary diagnoses from the inpatient discharge claim. CMS determines penalties based on readmission rates that are risk adjusted using both inpatient and outpatient claims from up to the year prior to hospitalization. Thus, an alternative approach is to calculate CCs from one years' prior claims, using both inpatient and outpatient claims. However, because our goal

was to examine each hospitals' influence on coded severity and in turn its impact on penalties under the HRRP, examining CCs from the discharge claim more accurately captures each hospital's direct influence.

The rise in the number of value-based payment programs has increased the public's scrutiny on whether the penalty and reward systems are structured correctly. Our findings suggest that while the expansion of allowable secondary diagnosis codes may have inadvertently complicated evaluations of the HRRP, the coding policy did not appear to have altered which hospitals were penalized.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements:

We thank Blanche Blumenthal, BS, of the Center for Evaluating Health Reform, for providing invaluable administrative support.

Disclosures

This project was supported by grant 5R01AG047932-05 from the National Institute on Aging (Dr. Ryan). The funding organization had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication. No conflicts of interest disclosures are applicable.

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Figure 1. Average number of condition categories (CCs) among acute myocardial infarction, congestive heart failure, and pneumonia discharges over time.

Note: Tertiles are based on the change in the average number of CCs among AMI, congestive heart failure, and pneumonia discharges between October 2010 and April 2011.

Source: Authors' calculations using MedPAR data.

Figure 2. Permutation importance plot of hospital characteristics and change in number of condition categories (CCs)

Note: N = 3102. Cross-validation score = 0.13. This permutation importance plot shows the effect of breaking the relationship between a characteristic and the change in CCs in our random forest regression model. The effect is quantified in terms of R-squared value. A random variable was included to identify characteristics that are less important than random. Missing characteristics data for 831 hospitals were imputed.

Source: Authors' calculations using MedPAR, American Hospital Association Annual Survey, Impact File, and Provider of Service data.

Figure 3. Distribution of hospitals across varying levels of Hospital Readmissions Reduction penalties, between fiscal year 2013 and 2016.

Note: N=3092. Low, medium, and penalty categories refer to tertile of all hospitals receiving any penalties of fiscal year 2013 and fiscal year 2016.

Source: Authors' calculations using Impact File data.

Table 1.

Characteristics of hospitals and those with highest and lowest change in condition categories (CCs).

	Overall	Tertile 1 (Lowest change in coding)	Tertile 3 (Highest change in coding)
Hospitals, N	3102	1034	1034
2010 quarter 4 Condition Categories, Mean (SE)	2.39 (0.01)	2.38 (0.01)	2.38 (0.01)
2011 quarter 1 Condition Categories, Mean (SE)	2.82 (0.01)	2.35 (0.02)	3.25 (0.02)
Percent of targeted discharges, Mean (SE)	15.1 (0.1)	16.3 (0.2)	14.3 (0.1)
Number of targeted discharges, Mean (SE)	298.9 (4.8)	202.1 (6.0)	333.6 (8.9)
Readmission rates, adjusted for age and sex, Mean (SE)			
Acute myocardial infarction	18.9 (0.2)	19.1 (0.4)	18.8 (0.3)
Congestive heart failure	23.0 (0.1)	22.9 (0.2)	23.1 (0.2)
Pneumonia	17.0 (0.1)	16.7 (0.1)	17.3 (0.1)
Number of secondary diagnoses in 2010, mean (SE)	7.47 (0.01)	7.25 (0.02)	7.63 (0.01)
Case-mix index, Mean (SE)	1.43 (0.01)	1.31 (0.01)	1.50 (0.01)
Percent of disproportionate Share Patient, Mean (SE)	29.1 (0.3)	30.4 (0.6)	29.4 (0.5)
Percent of Medicare days, Mean (SE)	45.3 (0.2)	46.8 (0.5)	43.4 (0.4)
Bed size, Mean (SE)	199.3 (3.3)	138.5 (4.3)	233.8 (6.2)
Patient demographics			
Percent Female, Mean (SE)	55.5 (0.1)	56.3 (0.2)	55.1 (0.2)
Age, Mean (SE)	80.2 (0.0)	80.4 (0.1)	79.9 (0.1)
Ownership			
Not-for-profit, N (%)	1,938 (62.5)	570 (55.1)	698 (67.5)
For-profit, N (%)	566 (18.3)	179 (17.3)	183 (17.7)
Government, N (%)	598 (19.3)	285 (27.6)	153 (14.8)
Teaching Status			
Major, N (%)	266 (8.6)	51 (4.9)	122 (11.8)
Minor, N (%)	722 (23.3)	191 (18.5)	253 (24.5)
None, N (%)	2,114 (68.2)	792 (76.6)	659 (63.7)
EHR implementation			
Full, N (%)	634 (27.7)	162 (22.6)	257 (32.7)
Partial, N (%)	1,427 (62.5)	461 (64.4)	467 (59.3)
None, N (%)	228 (10.0)	93 (13.0)	63 (8.0)
Integration with physicians			
Employed, N (%)	1,053 (40.3)	316 (37.6)	364 (41.1)
Contract, N (%)	522 (20.0)	163 (19.4)	179 (20.2)
None, N (%)	1,036 (39.7)	361 (43.0)	343 (38.7)
Rural Status			
Metropolitan, N (%)	1,583 (63.3)	431 (50.0)	584 (71.7)
Micropolitan, N (%)	604 (24.2)	250 (29.0)	168 (20.6)
Rural, N (%)	314 (12.6)	181 (21.0)	62 (7.6)

Notes: All differences in characteristics between Tertile 1 and 3 are statistically significant at the $p < 0.01$ level, except for 1) 2010 quarter 4 Condition Categories, 2) readmissions rates for acute myocardial infarction, 3) readmissions rates for congestive heart failure, 4) disproportionate

share patients, and 5) integration with physicians. Targeted discharges refer to acute myocardial infarction, congestive heart failure, and pneumonia. The mean change in CCs is 0.43 (0.01) overall, -0.03 (0.01) in Tertile 1, 0.87 (0.01) in Tertile 3.

Source: Authors' calculations using MedPAR, American Hospital Association Annual Survey, Impact File, and Provider of Service data.

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Table 2.

Relationship between change in condition categories (CCs) and the probability and size of penalties for hospitals under the Hospital Readmissions Reduction Program for fiscal year 2013 and 2016.

	Probability of any penalty			Size of penalty, conditional on being penalized			Overall magnitude of penalty		
	Estimate (SE)	p-value	95% CI	Estimate (SE)	p-value	95% CI	Estimate (SE)	p-value	95% CI
<i>Panel A. 2013</i>									
No covariates	0.031 (0.020)	0.121	(−0.008, 0.070)	−0.038 (0.016)	0.019	(−0.070, −0.006)	−0.014 (0.014)	0.333	(−0.042, 0.014)
Covariates	0.038 (0.022)	0.076	(−0.004, 0.081)	0.016 (0.016)	0.306	(−0.015, 0.048)	0.022 (0.013)	0.085	(−0.003, 0.047)
<i>Panel B. 2016</i>									
No covariates	0.020 (0.019)	0.287	(−0.017, 0.057)	−0.059 (0.026)	0.023	(−0.111, −0.008)	−0.037 (0.024)	0.127	(−0.085, 0.011)
Covariates	−0.030 0.017	0.084	(−0.064, 0.004)	0.010 (0.027)	0.714	(−0.043, 0.063)	−0.004 (0.024)	0.854	(−0.052, 0.043)

Notes: The two-part model consists of logit and GLM with log link function and Poisson distribution family. Standard errors are heteroskedasticity robust. Dependent variable is payment penalty size, ranging from 0 percent to 1 percent penalties for fiscal year 2013 and 0 to 3 percent for fiscal year 2016. Covariates include average condition categories as determined by the first 9 secondary diagnosis codes; condition-specific, 30-day, hospital-level unplanned readmissions rates adjusted for age and gender for the targeted conditions of the HRRP of each fiscal year. Fiscal year 2013: N=3102 in the logit and N=2187 in GLM. Fiscal year 2016: N=3092 in the logit and N=2566 in GLM.

Source: Authors' calculations using MedPAR and Impact File data.