

City University of New York (CUNY)

CUNY Academic Works

School of Arts & Sciences Theses

Hunter College

Spring 5-6-2021

The Effects of Hospital-Acquired Condition (HAC) Reduction Program on Hospital Services and Finances

Yuting Chen
CUNY Hunter College

[How does access to this work benefit you? Let us know!](#)

More information about this work at: https://academicworks.cuny.edu/hc_sas_etds/732

Discover additional works at: <https://academicworks.cuny.edu>

This work is made publicly available by the City University of New York (CUNY).
Contact: AcademicWorks@cuny.edu

The Effects of Hospital-Acquired Condition (HAC) Reduction Program
on Hospital Services and Finances

by

Yuting Chen

Submitted in partial fulfillment
of the requirements for the degree of
Master of Arts in Economics, Hunter College
The City University of New York

2021

05/04/2021

Date

Partha Deb

Thesis Sponsor

05/03/2021

Date

Kenneth McLaughlin

Second Reader

Abstract

Effective October 1, 2014, the Hospital-Acquired Condition (HAC) Reduction Program was implemented by Centers for Medicare & Medicaid Services (CMS) under the Affordable Care Act. The purpose of this program is to incentivize hospitals to improve quality performance by linking Medicare payments to healthcare quality in hospitals. Starting from October 1, 2014, one-quarter of hospitals with the worst performance on Total HAC score lost 1% of their Medicare reimbursement. This paper analyzes the impact of the HAC Reduction Program using 2015-2017 hospital-level data from the CMS. I use a regression discontinuity design implemented using ordinary least squares method to measure the effects of HAC Reduction Program on hospital days, discharges, revenues, costs, and service performance among acute care inpatient hospitals. I find that between 2015 and 2017, compared to the non-penalized hospitals, penalized hospitals barely improved their healthcare performance in the following fiscal year; meanwhile they increased their numbers of patients by 12.0% to cover the penalties received.

Keywords: HAC Reduction Program, Medicare pay-for-performance program, healthcare quality indicators

Contents

Abstract	2
Contents.....	3
1. Introduction	5
2. Literature Review	7
3. Data	8
4. Method.....	11
5. Results	13
6. Conclusion.....	16
7. References	18
8. Tables	20
Table 1. Hospital Characteristics by Penalization Status in the HAC Reduction Program	20
Table 2. Main Variable by Penalization Status	21
Table 3. Regression Estimates of Distance of HAC Score from Cut-point in Year t.....	22
Table 4. Regression Estimates of Log Total Hospital Discharges	23
Table 5. Regression Estimates of Log Total Hospital Revenues.....	24
Table 6. Regression Estimates of Log Total Hospital Costs	25
Table 7. Regression Estimates of Log Total Hospital Days.....	26
Table 8. Regression Estimates of Hospital occupancy rate.....	27
9. Figures	28
Figure 1. Distance of HAC Score from Cut-point in Current Year.....	28
Figure 2. Total Hospital Discharges	29
Figure 3. Hospital Discharges per Bed.....	30
Figure 4. Total Hospital Revenues	31
Figure 5. Hospital Revenue per Discharge.....	32

Figure 6. Total Hospital Cost	33
Figure 7. Hospital Cost per Discharge	34
Figure 8. Total Hospital Days	35
Figure 9. Hospital Days per Discharge.....	36
Figure 10. Hospital Occupancy rate	37

1. Introduction

The Affordable Care Act (ACA), known as Obamacare, enacted in March 2010 and included many Medicare payment reforms on top of the traditional fee-for-service program. Using financial incentives and penalties, ACA introduced several pay-for-performance programs to send a clear signal to healthcare providers that they need to improve healthcare quality and effective patient outcomes. Some examples include initiatives to reduce 30-day readmission rates and initiatives to reduce hemoglobin A1c levels in patients with diabetes.

A Hospital-Acquired Condition (HAC) is a medical condition that a patient develops during hospitalization, which was not present at the time of admission, such as foreign object retained after surgery, air embolism and pressure ulcers. In most cases, hospitals can prevent HACs when they provide appropriate care to their patients. These conditions cause preventable harm to patients and may lead to disability, and even deaths. HACs generate substantial, additional health care expenditure, so it is important for hospitals to reduce these HACs (Pittet & Donaldson, 2006).

Under the Affordable Care Act (ACA), Centers for Medicare & Medicaid Services (CMS) began to implement a number of ACA-mandated pay-for-performance programs, which includes the Hospital-Acquired Condition (HAC) Reduction Program. CMS determines a hospital's Total HAC Score based on hospital performance on specified and pre-determined HAC measures which will be described in the context of the literature review (Section 2). Effective October 1, 2014, hospitals that ranked in the worst-performing 25% of hospitals with respect to Total HAC Score were subject to 1% Medicare payment reduction applied to total operating and capital payments. Around 3,300 acute care inpatient hospitals are potentially affected by this program. Total HAC Reduction Program penalties levied on hospitals reported by CMS are \$373 million in FY2015 (Sankaran et al, 2020) and \$364 million in FY2016 (CMS HACRP FY 2016 factsheet, 2015).

There are a few published studies on the effects of this countrywide program. Sankaran et al (2019) found that no clear clinical improvement was observed in hospital-acquired conditions, 30 day readmission, or 30 day mortality after HAC Reduction Program was implemented. Cochran (2019) discovered most of hospitals improved their quality performance during 2015-2018. 51% of hospitals with 1 year, 54% of hospitals with 2 years, and 73% of hospitals with 3 years of penalty improved their Total HAC Score.

This paper analyzes the effects of the 2015-2017 Hospital-Acquired Condition (HAC) Reduction Program on hospital services and finances at the hospital level in the United States. Using 2015-2017 HAC Reduction Program and cost report data from Centers for Medicare & Medicaid Services (CMS), I estimate the effects of the HAC Reduction Program on hospital day, discharge, revenue, and cost among all eligible acute care inpatient hospitals.

Since HAC Reduction Program has clear cutoff points, which is the Total HAC score of the worst-performing of hospitals for each fiscal year, I exploit a Regression Discontinuity Design (RDD) model and recenter the cutoff point at zero for simplify and create a running variable called "Distance". Hospitals which just barely did get penalized (just above the cutoff point) are likely to be ex ante comparable in all other respects with hospitals which barely did not get penalized. By using RDD method, I can expect hospitals on either side of an arbitrary cutoff to be as good as randomly assigned from year to year and examine the effects of HAC Reduction Program penalty. However, I'm not able to measure local treatment effect by comparing hospitals around the zero threshold of "Distance" due to the small sample size. Therefore, I use the ordinary least squares method to estimate many RDD models assess how penalized hospitals reacted in the following fiscal year.

I find that between 2015 and 2017, compared to the non-penalized hospitals, penalized hospitals barely improved their HAC scores which represent their performance in the following fiscal year; meanwhile they increased their numbers of patients by 12.0% to increase their total revenue to cover the penalty received in the prior year.

2. Literature Review

The intention of the HAC Reduction Program is to reduce preventable harm to patients and create incentives for hospitals to reduce the incidence of HACs. Since 2010, Agency for Healthcare Research and Quality (AHRQ) has been tracking rates of hospital-acquired conditions (HACs), such as health care-associated infections and other never events. The results shows that the decline of HACs has been sustained since 2011 and were reduced by 17% in 2014. With this decline in HACs, the analysis estimates that 87,000 fewer hospital patients died and \$19.8 billion in health care costs were saved from 2011 to 2014. Although HACs still exists despite incentives and strategies to eradicate them, the reduction reveals that hospitals have made significant progress in improving patient safety. (AHRQ, 2015)

Hospital performance is measured with CMS Recalibrated Patient Safety Indicator (PSI) 90 (CMS PSI 90) and Centers for Disease Control and Prevention (CDC) National Healthcare Safety Network (NHSN) healthcare-associated infection (HAI) measures: Central Line-Associated Bloodstream Infection (CLABSI), Catheter-Associated Urinary Tract Infection (CAUTI), Surgical Site Infection (SSI) – colon and hysterectomy, Methicillin-resistant *Staphylococcus aureus* (MRSA) bacteremia, and *Clostridium difficile* Infection (CDI). (Centers for Medicare & Medicaid Services, 2015)

To calculate the Total HAC Scores, hospitals are classified based on their measure results. Specifically, each hospital is assigned a score between 1 and 10 for each measure, which reflects the hospitals relative rank in 10 groups (or deciles) for that measure. Hospitals with lower Total HAC Score might expect to perform better. Effective October 1, 2014, the HAC Reduction Program reduces Medicare payments to the poorest-performing hospitals by 1 percent. The poorest performing are those hospitals that have HAC scores in the top 25 percent nationally (Centers for Medicare & Medicaid Services, 2015).

Economists were often interested in the effect of the HAC Reduction Program and characteristics of hospitals associated with penalties. Gulseren et al. (2020) finds that the penalties levied under the HAC Reduction Program was the \$361 million in penalties levied on hospitals per year for HACs.

Cochran (2019) finds that most of hospitals in her study improved their quality performance between 2015 and 2018. "51% of hospitals with 1 year of penalty improved their Total HAC Score; 54% of hospitals with 2 years of penalty improved their Total HAC Score; 73% of hospitals with 3 years of penalty improved their Total HAC Score" (Cochran, 2019, page#7). Sankaran et al. (2019) find that hospitals receiving penalty weren't observed for significant clinical improvements in improved "acquired conditions, 30 day readmission, or 30 day mortality". Penalties from the HAC Reduction Program did not lead to improved conditions.

Kahn, Ault, Potetz, Walke, Chambers, and Burch (2015) evaluated the odds of receiving a penalty in the HAC Reduction Program using logistic regression analysis and found teaching status and bed size are influential factors in hospitals receiving penalties. Major teaching hospitals were more frequently penalized for the HAC Reduction Program for fiscal year 2015. Compared with hospitals in rural areas, those in urban areas are also more likely to receive the HAC penalty (Kahn et al, 2015, page#1285). Soltoff et al. (2018) has also indicated that penalized hospitals are more likely to be urban or voluntary non-profit owned.

Among hospitals participating in the HAC Reduction Program, hospitals that were penalized more frequently had more quality accreditations, offered advanced services, were major teaching institutions, and had better performance on other process and outcome measures.

(Rajaram et.al, 2015; Mohajer, 2018)

3. Data

Data for this research is compiled from 2 datasets compiled by the Centers for Medicare & Medicaid Services (CMS) – (1) the Hospital-Acquired Condition (HAC) Reduction Program,

and (2) Healthcare Cost Report Information System (HCRIS). They are merged by hospital IDs and fiscal year.

1) The Hospital-Acquired Condition (HAC) Reduction Program is conducted yearly by CMS in order to encourage hospitals to improve healthcare quality by linking Medicare payments to healthcare quality in the inpatient hospital setting. Around 3,300 eligible acute care inpatient hospitals provided their data to CMS by fiscal year. CMS measured the Total HAC score for each hospital on six measures: one claims-based composite measure of patient safety: CMS PSI 90 and five chart-abstracted measures of healthcare-associated infections (HAIs) submitted to the Centers for Disease Control and Prevention's (CDC) National Healthcare Safety Network (NHSN): Central Line-Associated Bloodstream Infection (CLABSI), Catheter-Associated Urinary Tract Infection (CAUTI), Surgical Site Infection (SSI) for abdominal hysterectomy and colon procedures, Methicillin-resistant Staphylococcus aureus (MRSA) bacteremia, Clostridium difficile Infection (CDI). The Total HAC score for each hospital in each fiscal year is the key variable used in this paper.

2) The second dataset used for this paper is CMS Cost Report which contains provider information such as facility characteristics, utilization data, cost and charges by cost center, Medicare settlement data, and financial statement data. CMS maintains the cost report data in the Healthcare Provider Cost Reporting Information System (HCRIS) which provides total hospital discharges, total hospital days, total revenue, and total cost for each hospital in each fiscal year. It also provides numbers of hospital beds, profit type, teaching status, and urban / rural indicator for each hospital.

The CMS Cost Report data utilized in this paper comes from National Bureau of Economic Research (NBER), which reorganized alpha, numeric and rollup data files from HCRIS, and produces "HCRIS Select Variables", "Costs-to-Charges", "Indirect Medical Education/Graduate Medical Education" datasets which are easier to access. (Sources: <https://data.nber.org/data/hcris.html>)

The (HAC) Reduction Program data is available from the FY 2015 to FY 2021 program years. The time range of my sample ends in 2017 because in FY2018, CMS used different scales for Total HAC score methodology. Under the Winsorized z-score method adopted in FY2018, a hospital's Total HAC score ranged between -3 and 3. However, in FY 2015, 2016, and 2017, CMS used decile-based scoring methodology to calculate Total HAC score, assigning a score from 1 to 10. Although the change of methodology does not affect how CMS determines the worst-performing quartile, Total HAC Scores between FY 2018 and previous program years cannot be compared. Therefore, the data in 2018 and 2019 are excluded in this research.

Moreover, my paper focus on the effect of HAC Reduction Program. In FY2015 which is the first year of HAC Reduction Program, hospitals didn't know whether they would be in the worst-performing quartile and won't take action in the first year of the program. Observations in 2015 are also excluded. Therefore, the period of my sample consists of 2016 and 2017.

Last but not least, fiscal year for HAC Reduction Program is between October to September in the following year (i.e., HAC Reduction Program payment adjustment applies to all Medicare discharges between October 1, 2014 and September 30, 2015 for FY 2015). The payment reduction happens when CMS pays hospital claims. To accurately estimate the effect of HAC Reduction Program, this paper only keeps the observations that reported data in the same time range in CMS Healthcare Cost Report Information System (HCRIS). After dropping the hospitals that provided data in different range in HCRIS (i.e. January to December and July to next June), the numbers of hospitals are 530+ per year. The sample size applied in this paper is 1,063 observations.

Table 1 shows numbers and percentage of hospitals with penalty. Among all hospitals in this sample, 234 of 1063 hospitals (22%) were penalized. Nonprofit hospitals (24.8%) were more likely to be penalized than proprietary (18.1%) and governmental (17.5%) hospitals. Hospitals in rural area (14.6%) were more likely to be penalized than hospitals in urban area (26.8%). Non-teaching hospitals (36.2%) were more likely to be penalized than teaching hospitals (15.5%).

Non-transplant center hospitals (66.7%) were more likely to be penalized than transplant center hospitals (19.6%). Large size hospitals with more than 400 beds (40.9%) were more likely to be penalized than medium size hospitals with 100-399 beds (25.1%) and small size hospitals with less than 100 beds (12.6%). Tables 2 exhibits the means and standard errors of the main variables in this paper, including total hospital discharges, total hospital days, total hospital revenues, total hospital costs, numbers of beds, occupancy rate, hospital profit type, hospital urban/rural indicator, teaching hospital status, and transplant center, which will be used in result (section 5).

4. Method

By specifying a cutoff or threshold above or below a specified intervention, the regression discontinuous design (RDD) triggers the causal effects of the interventions. By comparing observations close to either side of the cutoff, RDD developed to estimate average treatment effects in non-experimental settings and provides causal estimates of treatment effects. The first application is the evaluation of the scholarship program by Donald Thistlethwaite and Donald Campbell (1960). They studied the impact of scholarship on future academic outcomes. Scholarship allocated based on test scores, so test scores is the cutoff point in this case. Thistlethwaite and Campbell realized they could compare individuals just above and below the cutoff point. David Lee, Enrico Moretti and Matthew J. Butler (2004) estimated the role of elections in policy formation focusing on elections decided by a narrow margin of voter shares. In order to isolate external differences, they used a quasi-experiment embedded in the congressional election system, which essentially produced an essentially "random distribution", that is, which party has electoral seats and therefore which party holds an electoral advantage. With the random assignment, it would be possible to distinguish between any of the effects and differences under the quasi experiment. By using RDD method, I can expect hospitals on either side of an arbitrary cutoff to be as good as randomly assigned from year to year and examine the effects of HAC Reduction Program penalty. The RDD parameters are estimated in the ordinary least squares

method. Since the cutoff points are different every year, I reset the cutoff points at zero every year to analyze more easily. I also created a variable called “Distance”, which is Total HAC Scores for a hospital in a given year minus the cutoff in that year, so zero is a threshold. Hospitals with a Distance above zero were penalized, and hospitals with a Distance below zero were penalized.

Take the outcome “Distance” for example, to estimate whether hospitals with penalties in year t-1 reduced their HAC Scores by improving their healthcare quality, I run linear regression of distance of HAC score from cut-point in year t on whether hospitals were penalized in year t-1. The linear regression is as follows:

$$\begin{aligned}
 Distance_{it} = & \beta_0 + \beta_1 P_{i,t-1} + \beta_2 Distance_{i,t-1} + \beta_3 Distance_{i,t-1}^2 + \beta_4 P_{i,t-1} \cdot Distance_{i,t-1} \\
 & + \beta_5 Profit_i + \beta_6 urban_i + \beta_7 teaching_i + \beta_8 transplant_center_i \\
 & + \beta_9 Beds_{i,t-1} + u_{it}
 \end{aligned}$$

P_{t-1} : whether a hospital was penalized in previous year

Using the ordinary least squares method, I analyze how distance of HAC score from cut-point, total hospital days, total discharges, total revenue, total cost change, and hospital occupancy rate in the hospitals being penalized as a result of the HAC reduction program. I look at how these outcomes are affected in the following fiscal year, using hospitals not penalized as a control group.

The following outcomes are evaluated in this paper – (1) distance of HAC score from cut-point, (2) total discharges, (3) total revenues, (4) total costs, (5) total hospital days, and (6) hospital occupancy rate. To implement the penalty, CMS announced the cutoff for the 75th percentile of Total HAC Scores after they finalized current year HAC Reduction Program. Hospitals with a Total HAC Scores above the cutoff were subject to a 1% payment reduction; Hospitals with a Total HAC Scores below the cutoff were not subject to the payment reduction.

The independent variable in this research P_{t-1} is a dummy variable whether a hospital was penalized in prior year. CMS took time to collect and analyze data from hospitals and announced the cutoff for that fiscal year, and hospitals with a Total HAC Scores above the cutoff would get penalized in the next fiscal year and react accordingly. The regressions include distance in year t-1 as continuous running variable, a quadratic polynomial in distance running variable and the interaction of penalized dummy and distance running variable. To estimate the average treatment effect in HAC Reduction Program which randomization is unfeasible, distance within an optimally chosen bandwidth around the cutoff is selected to compare hospitals lying on either side of the cutoff.

Then this paper also controls two fixed hospital characteristics - urban/rural indicator and profit type, since hospitals with different types have different chance to receive the HAC penalty per discovers showed in the literature review (Section 2).

Since hospitals are very different size and status, I also control for numbers of beds in year t-1, teaching status and whether a certain hospital is transplant center. The results of the hospitals characteristics are presented in table 1.

To estimate the effect of HAC Reduction Program on the rest five outcomes - total hospital days, total hospital discharges, total hospital revenues, total hospital costs and hospital occupancy rate, this paper uses similar steps and linear regressions as the outcome “Distance”.

5. Results

Throughout the paper the unit of observation is a hospital in each fiscal year. By recentering the cutoff in each year at zero, all the figures below present non-penalized hospitals on the left side of vertical line (Distance = 0) and penalized hospitals on the right side of vertical line, which means the hospitals with negative distance performed better and the hospitals with positive distance performed worse.

Outcome 1: Distance of HAC Score from Cut-point in Year t

For the first outcome – distance of the HAC Score from the cut-off point, figures 1 has previous year distance of HAC Score from the cutoff point on x axis and current year distance of HAC Score from the cutoff point on y axis. It clearly shows there is nearly no change between the left and the right side of the cutoff (distance = 0), which means the penalized hospitals at the right of the vertical line have barely improvement on the healthcare performance after one year of penalties.

By controlling for distance in year t-1, profit type, urban/rural indicator, hospital size teaching status, and transplant center, I run a OLS regression of previous year distance on current year distance. Results presents in table 3. The coefficient of dummy variable whether the hospital got penalized represents that penalize hospital improved 0.3 score in the following year (p-value 0.195). Compared to the range of Total HAC Score is between 1 and 10 in 2015-2017, the improvement of healthcare quality was marginally significantly small after penalized hospital got one year of penalties.

Outcome 2: Hospital Discharges

Figures 2 and 3 depict the total hospital discharge and discharge per bed in penalized hospitals compared to non-penalized hospitals. Penalized hospitals marginally significantly increased total discharge by 5,000 patients and discharge per bed by 10 patients by bed after they received one year of penalties.

Taking distance in year t-1, profit type, urban/rural indicator, hospital size, teaching status, and transplant center into account, table 4 displays the results of ordinary least squares of log of total hospital discharge. Compared to non-penalized hospitals, there is statistically significant evidence that penalized hospitals increased their total hospital discharge by 12.0% (p-value 0.025, exponentiating the coefficient of log of total discharge – 0.12 and minus 1). Taking the mean total discharge in penalized hospitals, which is 13,931 and multiplying by 12.0%, I get the estimates of the effect of total hospital discharge on the dummy variable. Penalized hospitals significantly increased their discharges by 1,776 after they received one year of penalties.

Outcome 3 & 4: Hospital Revenues & Hospital Costs

From figure 4-7, we can see total hospital revenues and total hospital costs increased in penalized hospitals because of additional discharges. However, revenue per discharge and cost per discharge decreased, which reveals that penalized hospitals spent less and earned less on each patient.

Controlling distance in year t-1, hospital profit type, urban/rural indicator, numbers of beds, teaching status, and transplant center, I exponentiate the coefficient of log of total hospital revenues – 0.063 (p-value 0.34) and log of total hospital costs – 0.024 (p-value 0.69) in table 5 and 6 and minus 1. Penalized hospitals increased their revenue per bed by 6.3% and increased costs per bed by 2.4%. These results provide no strong scientific evidence that by taking the mean of total revenues in penalized hospitals – 424 million dollars, multiplying that by 6.3% and dividing estimated change of discharge 1,776, penalized hospitals increased revenue per bed by \$15,518. By taking the mean of total costs in penalized hospitals – 325 million dollars, multiplying that by 2.4% and dividing estimated change of discharge 1,776, penalized hospitals increased costs per discharge by \$4,439.

Outcome 5: Hospital days

For the important outcome - hospital days, we can see total hospital days increased in penalized hospitals by 15,000 days due to additional discharges from figure 8, and hospital days per discharge remained almost the same in penalized hospitals from figure 9. Fortunately, to compensate the penalty charged in the HAC Reduction Program, penalized hospitals increased the number of patients to increase total hospital revenues, but they didn't reduce hospital day for each patient.

The results from the linear regressions on total hospital days is presented in tables 7. By controlling distance in year t-1, profit type, urban/rural indicator, numbers of beds, teaching status, and transplant center, I exponentiate the coefficient of log of total hospital days – 0.118

and minus 1. Penalized hospitals significantly increased days per bed per discharge by 11.8%. By taking the mean of total days in penalized hospitals, which is 68,877.71, multiplying that by 11.8%, and dividing estimated change of discharge 1,776, penalized hospitals increased 4.9 day per discharge.

Outcome 6: Hospital occupancy rate

Hospital occupancy rate is defined as the percentage of hospital beds that are in use at a given time and can be computed by dividing hospital days by hospital bed days available (Andrews, 2019). Increasing of occupancy rate in penalized hospital implies they utilized empty hospital bed to treat more patients, instead of treating patients for shorter days. Figure 10 depicts the hospital occupancy rate and shows that penalized hospital at the right of the vertical line (Distance = 0) increased their hospital occupancy rate by 10%.

Taking distance in year t-1, hospital profit type, urban/rural indicator, teaching status, and transplant center into account, table 8 displays the results of ordinary least squares of hospital occupancy rate. Since numbers of beds is calculated in bed day available, and bed day available is part of the formula of hospital occupancy rate, so hospital size is not controlled in the regression of hospital occupancy rate. Compared to non-penalized hospitals, penalized hospitals strongly significantly increased their total hospital occupancy rate by 7.9% (p-value 0.00) which reveals that penalized hospitals used existing empty beds to receive more patients, instead of building more space for additional patients.

6. Conclusion

During 2015-2017, most penalized hospitals significantly increased their total revenues by rising numbers of patients by 12.0 percent, to compensate the 1% reduction in Medicare reimbursement by the HAC Reduction Program. As a result, they barely focus on spending more time and money on each patient and improving their healthcare quality but increasing hospital

occupancy rates which have been considered a matter of reduced patient comfort and privacy instead.

I would like to specify few caveats. First, during this research, I tried local linear regression (regression discontinuity) directly, but sample size around the cutoff is not big enough to estimate the effect of dummy variable very closed to the cutoff. Therefore, I exploit the RDD running variable and optimal bandwidth in the ordinary least squares method and apply to all the outcomes in this paper. Second, CMS used different scales for Total HAC Score methodology in FY2018. This paper does not apply the data starting from FY2018 to avoid that the change in 2018 complicates the problem but the basic principles remain the same.

The 2015-2017 CMS data reveals how hospital reacted after they received one year of penalty by the HAC Reduction Program. Using a "pay for performance" payment strategy will put financial pressure on medical service providers and will not reflect the benefits or value of patients. The result demonstrates HAC Reduction Program alter provider behavior dramatically but fail to shift incentives in the health care system from "volume" to "value". CMS will need to re-evaluate the feasible measures of hospital performance that improve healthcare quality for each patient and meet patient needs.

7. References

- Andrews, K., 2019. "Analyzing Hospital Medicare Cost Report Data Using SAS® - Updated with Output." *The SouthEast SAS® Users Group (SESUG) 239*.
- Cassidy, A., 2015. "Medicare's Hospital-Acquired Condition Reduction Program." *Health Affairs Health Policy Brief*.
- Cochran, E., 2019. "Hospital Characteristics Associated with Hospital Acquired Condition (HAC) Reduction Program Payment Penalties across Program Years." *Unpublished manuscript*.
- Kahn, C., Ault, T., Potetz, L., Walke, T., Chambers, J., and Burch, S., 2015. "Assessing Medicare's Hospital Pay-For-Performance Programs and Whether They Are Achieving Their Goals." *Health Affairs*. 34(8).
- Lee, D., Moretti, E., and Butler, M., 2014. "Do Voters Affect or Elect Policies? Evidence from the U. S. House." *The Quarterly Journal of Economics*. 119(3), 807–859.
- Mohajer, M., Joiner, K., and Nix, D., 2018. "Are Teaching Hospitals Treated Fairly in the Hospital-Acquired Condition Reduction Program?" *Academic Medicine*. 93(12).
- Pittet, D., and Donaldson, L., 2006. "Challenging the world: patient safety and health care-associated infection." *International Journal for Quality in Health Care*. 18(1), 4–8.
- Rajaram, R., Chung, J., Kinnier, C., Barnard, C., Mohanty, S., Pavey, E., McHugh, M., and Bilimoria, K., 2015. "Hospital Characteristics Associated With Penalties in the Centers for Medicare & Medicaid Services Hospital-Acquired Condition Reduction Program." *JAMA*. 314(4):375-383
- Rockville, MD., 2018. "Saving Lives and Saving Money: Hospital-Acquired Conditions Update - Interim Data From National Efforts To Make Care Safer, 2010-2014." *Agency for Healthcare Research and Quality*

- Sankaran, R., Gulseren, B., Nuliyalu, U., Dimick, J., Sheetz, K., Arntson, E., Chhabra, K., and Ryan, A., 2020. "A comparison of estimated cost savings from potential reductions in hospital-acquired conditions to levied penalties under the CMS hospital-acquired condition reduction program." *The Joint Commission Journal on Quality and Patient Safety*. 46(8),438–447.
- Sankaran, R., Sukul, D., Nuliyalu, U., Gulseren, B., Engler, T., Arntson, E., Zlotnick, H., Dimick, J., Zuidema, G., and Ryan, A., 2019. "Changes in hospital safety following penalties in the US Hospital Acquired Condition Reduction Program: retrospective cohort study" *BMJ*. 366.
- Soltoff, S., Koenig, L., Demehin, A. A., Foster, N. E., and Vaz, C. 2018. "Identifying Poor-Performing Hospitals in the Medicare Hospital-Acquired Condition Reduction Program: An Assessment of Reliability." *Journal for Healthcare Quality: Official Publication of the National Association for Healthcare Quality*. 40(6), 377-383.
- Thistlethwaite, D., and Campbell, D. 1960. "Regression-discontinuity analysis: An alternative to the ex post facto experiment." *Journal of Educational Psychology*. 51(6), 309–317.

8. Tables

Table 1. Hospital Characteristics by Penalization Status in the HAC Reduction Program

(N = 1063)

	No. (%)	
	Penalized	Not Penalized
No. of hospitals	234 (22.0%)	829 (78.0%)
Profit type		
Nonprofit	159 (24.8%)	481 (75.2%)
Proprietary	30 (18.1%)	136 (81.9%)
Governmental	45 (17.5%)	212 (82.5%)
Urban/rural indicator		
Urban	61 (14.6%)	357 (85.4%)
Rural	173 (26.8%)	472 (73.2%)
Teaching status		
Teaching hospital	113 (15.5%)	616 (84.5%)
Non-teaching hospital	121 (36.2%)	213 (63.8%)
Transplant center		
Transplant center	198 (19.6%)	811 (80.4%)
Non-transplant center	36 (66.7%)	18 (33.3%)
Numbers of beds in year t-1		
<100	53 (12.6%)	369 (87.4%)
100–399	129 (25.1%)	385 (74.9%)
400 or more	52 (40.9%)	75 (59.1%)

Table 2. Main Variable by Penalization Status

Variable	Total		Penalized		Non-Penalized	
Total discharges (Thousand)	9.10	(9.81)	13.93	(11.54)	7.74	(8.80)
Total days (Thousand)	42.76	(52.13)	68.88	(64.47)	35.38	(45.49)
Total revenue (Million)	263.09	(368.91)	423.85	(445.69)	217.71	(330.60)
Total cost (Million)	202.41	(251.76)	324.61	(305.71)	167.92	(222.68)
Numbers of beds	225.02	(1,142.75)	436.14	(2,409.08)	165.43	(160.04)
Occupancy rate	50%	(21%)	58%	(20%)	47%	(20%)
Profit type	64%	(85%)	51%	(80%)	68%	(86%)
Urban indicator	61%	(49%)	74%	(44%)	57%	(50%)
Teaching hospital	31%	(46%)	52%	(50%)	26%	(44%)
Transplant center	5%	(22%)	15%	(36%)	2%	(15%)

Note: Standard errors in parentheses. 1,063 total hospitals, 234 penalized hospitals, and 829 non-penalized hospitals in the sample size

Table 3. Regression Estimates of Distance of HAC Score from Cut-point in Year t

	(1) Classic RDD specification	(2) Control for hospital size	(3) Add other controls	(4) Restrict bandwidth +/- 3
Penalized in year t-1	0.028 (0.213)	-0.187 (0.203)	-0.196 (0.201)	-0.272 (0.210)
Distance of HAC score in year t-1	0.670*** (0.119)	0.687*** (0.116)	0.680*** (0.118)	0.241 (0.241)
Distance of HAC score in year t-1 ²	0.023 (0.024)	0.033 (0.023)	0.031 (0.023)	-0.132 (0.086)
Penalized in year t-1 * Distance in year t-1	-0.127 (0.234)	-0.117 (0.229)	-0.128 (0.228)	0.777 (0.476)
ln(beds in year t-1)		0.337*** (0.059)	0.263*** (0.069)	0.282*** (0.079)
Proprietary			-0.039 (0.135)	0.012 (0.150)
Governmental			-0.120 (0.131)	-0.030 (0.157)
Urban/rural indicator			-0.004 (0.116)	0.035 (0.140)
Teaching hospital			0.212** (0.104)	0.300** (0.121)
Transplant center			0.158 (0.132)	0.076 (0.135)
Constant	-0.480*** (0.127)	-2.108*** (0.332)	-1.780*** (0.362)	-2.114*** (0.412)
N	1,063	1,063	1,063	779
R ²	0.353	0.376	0.379	0.285

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

Table 4. Regression Estimates of Log Total Hospital Discharges

	(1) Classic RDD specification	(2) Control for hospital size	(3) Add other controls	(4) Restrict bandwidth +/- 3
Penalized in year t-1	0.909*** (0.161)	0.112** (0.051)	0.104** (0.052)	0.120** (0.053)
Distance of HAC score in year t-1	-0.129 (0.092)	-0.066** (0.031)	-0.065** (0.030)	0.022 (0.075)
Distance of HAC score in year t-1 ²	-0.041*** (0.016)	-0.007 (0.006)	-0.007 (0.006)	0.029 (0.026)
Penalized in year t-1 *	0.026	0.064	0.051	-0.132
Distance in year t-1	-0.041***	-0.007	-0.007	0.029
ln(beds in year t-1)		1.251*** (0.043)	1.153*** (0.059)	1.165*** (0.073)
Proprietary			-0.095*** (0.036)	-0.056 (0.041)
Governmental			-0.218*** (0.032)	-0.247*** (0.040)
Urban/rural indicator			0.177*** (0.040)	0.152*** (0.046)
Teaching hospital			0.162*** (0.033)	0.144*** (0.044)
Transplant center			-0.084 (0.082)	-0.074 (0.093)
Constant	8.347*** (0.116)	2.316*** (0.216)	2.706*** (0.263)	2.699*** (0.336)
N	1,063	1,063	1,063	1,063
R ²	0.059	0.306	0.311	0.883

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

Table 5. Regression Estimates of Log Total Hospital Revenues

	(1) Classic RDD specification	(2) Control for hospital size	(3) Add other controls	(4) Restrict bandwidth +/- 3
Penalized in year t-1	0.629*** (0.160)	0.057 (0.070)	0.047 (0.063)	0.063 (0.065)
Distance of HAC score in year t-1	0.007 (0.089)	0.012 (0.042)	-0.015 (0.037)	0.080 (0.089)
Distance of HAC score in year t-1 ²	-0.025 (0.015)	-0.000 (0.008)	-0.005 (0.007)	0.030 (0.031)
Penalized in year t-1 * Distance in year t-1	0.010 (0.162)	0.039 (0.076)	0.024 (0.067)	-0.173 (0.172)
ln(beds in year t-1)		1.126*** (0.045)	0.964*** (0.057)	0.966*** (0.070)
Proprietary			-0.428*** (0.042)	-0.383*** (0.051)
Governmental			-0.357*** (0.041)	-0.335*** (0.051)
Urban/rural indicator			0.177*** (0.044)	0.176*** (0.052)
Teaching hospital			0.303*** (0.040)	0.318*** (0.049)
Transplant center			0.314*** (0.088)	0.303*** (0.098)
Constant	4.976*** (0.111)	-0.571** (0.235)	0.138 (0.262)	0.148 (0.329)
N	1,025	1,025	1,025	748
R ²	0.107	0.770	0.819	0.826

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

Table 6. Regression Estimates of Log Total Hospital Costs

	(1) Classic RDD specification	(2) Control for hospital size	(3) Add other controls	(4) Restrict bandwidth +/- 3
Penalized in year t-1	0.706*** (0.149)	0.029 (0.063)	0.012 (0.056)	0.024 (0.059)
Distance of HAC score in year t-1	-0.054 (0.084)	0.000 (0.038)	-0.029 (0.033)	0.011 (0.079)
Distance of HAC score in year t-1 ²	-0.035** (0.014)	-0.005 (0.007)	-0.010* (0.006)	0.004 (0.028)
Penalized in year t-1 * Distance in year t-1	0.060 (0.151)	0.092 (0.068)	0.096 (0.060)	0.012 (0.154)
ln(beds in year t-1)		1.062*** (0.039)	0.904*** (0.050)	0.898*** (0.061)
Proprietary			-0.447*** (0.037)	-0.396*** (0.044)
Governmental			-0.265*** (0.036)	-0.241*** (0.045)
Urban/rural indicator			0.225*** (0.040)	0.225*** (0.047)
Teaching hospital			0.255*** (0.035)	0.266*** (0.043)
Transplant center			0.299*** (0.081)	0.310*** (0.088)
Constant	4.670*** (0.103)	-0.453** (0.198)	0.211 (0.227)	0.233 (0.284)
N	1,063	1,063	1,063	779
R ²	0.110	0.788	0.836	0.842

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

Table 7. Regression Estimates of Log Total Hospital Days

	(1) Classic RDD specification	(2) Control for hospital size	(3) Add other controls	(4) Restrict bandwidth +/- 3
Penalized in year t-1	0.941*** (0.170)	0.098** (0.049)	0.091* (0.049)	0.118** (0.049)
Distance of HAC score in year t-1	-0.115 (0.095)	-0.047 (0.030)	-0.055* (0.029)	0.036 (0.072)
Distance of HAC score in year t-1 ²	-0.045*** (0.016)	-0.009 (0.006)	-0.010* (0.006)	0.030 (0.026)
Penalized in year t-1 * Distance in year t-1	-0.009 (0.179)	0.031 (0.057)	0.024 (0.054)	-0.176 (0.142)
ln(beds in year t-1)		1.324*** (0.046)	1.215*** (0.062)	1.215*** (0.077)
Proprietary			-0.103*** (0.037)	-0.072* (0.040)
Governmental			-0.173*** (0.032)	-0.210*** (0.041)
Urban/rural indicator			0.201*** (0.041)	0.195*** (0.047)
Teaching hospital			0.168*** (0.034)	0.158*** (0.045)
Transplant center			0.049 (0.084)	0.060 (0.096)
Constant	9.844*** (0.119)	3.459*** (0.229)	3.866*** (0.276)	3.902*** (0.350)
N	1,063	1,063	1,063	779
R ²	0.088	0.882	0.894	0.901

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

Table 8. Regression Estimates of Hospital occupancy rate

	(1) Classic RDD specification	(2) Add other controls	(3) Restrict bandwidth +/- 3
Penalized in year t-1	0.124*** (0.027)	0.071*** (0.023)	0.079*** (0.024)
Distance of HAC score in year t-1	-0.027* (0.015)	-0.033*** (0.012)	0.002 (0.027)
Distance of HAC score in year t-1 ²	-0.008*** (0.003)	-0.007*** (0.002)	0.009 (0.009)
Penalized in year t-1 * Distance in year t-1	0.026 (0.028)	0.026 (0.023)	-0.050 (0.053)
Proprietary		-0.037** (0.015)	-0.030* (0.017)
Governmental		-0.069*** (0.013)	-0.075*** (0.016)
Urban/rural indicator		0.130*** (0.012)	0.132*** (0.014)
Teaching hospital		0.137*** (0.012)	0.140*** (0.014)
Transplant center		0.126*** (0.016)	0.129*** (0.017)
Constant	0.473*** (0.017)	0.364*** (0.017)	0.370*** (0.020)
N	1,063	1,063	779
R ²	0.066	0.392	0.407

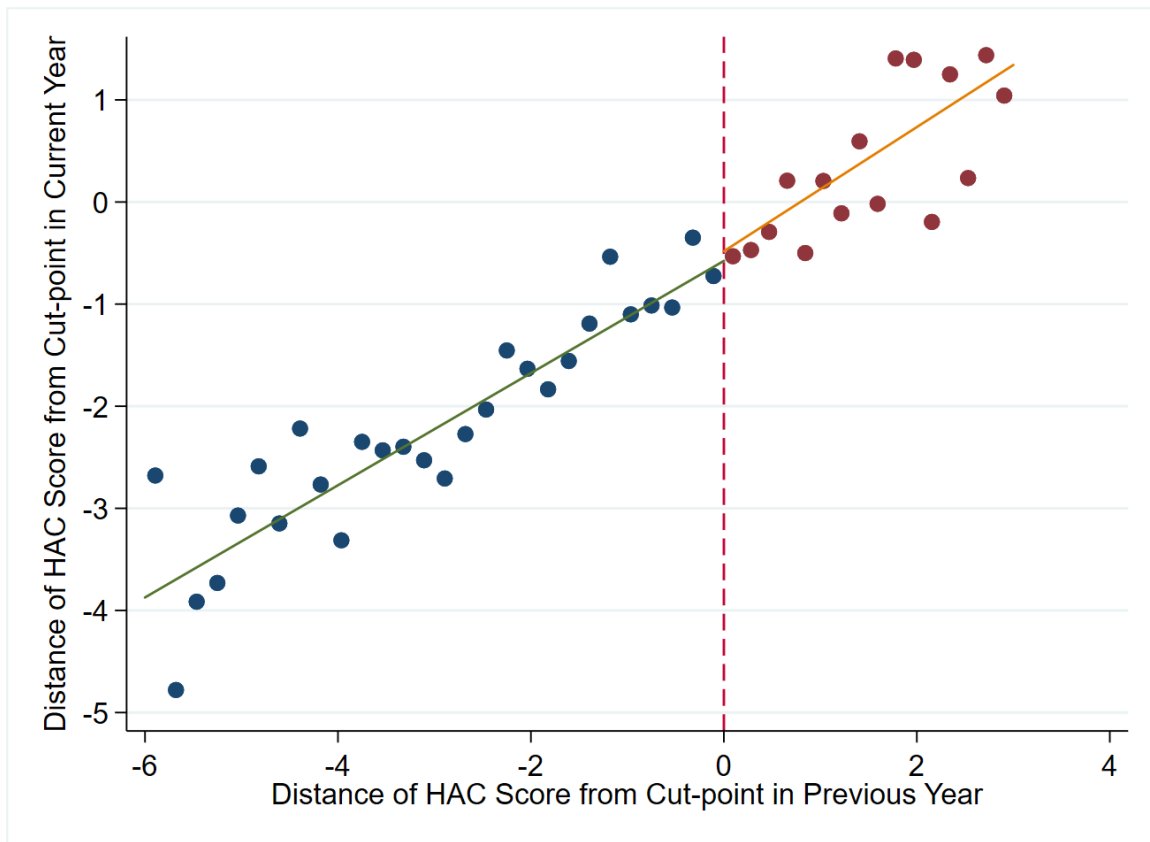
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Base hospital type = Nonprofit, Regression uses ordinary least squares method

9. Figures

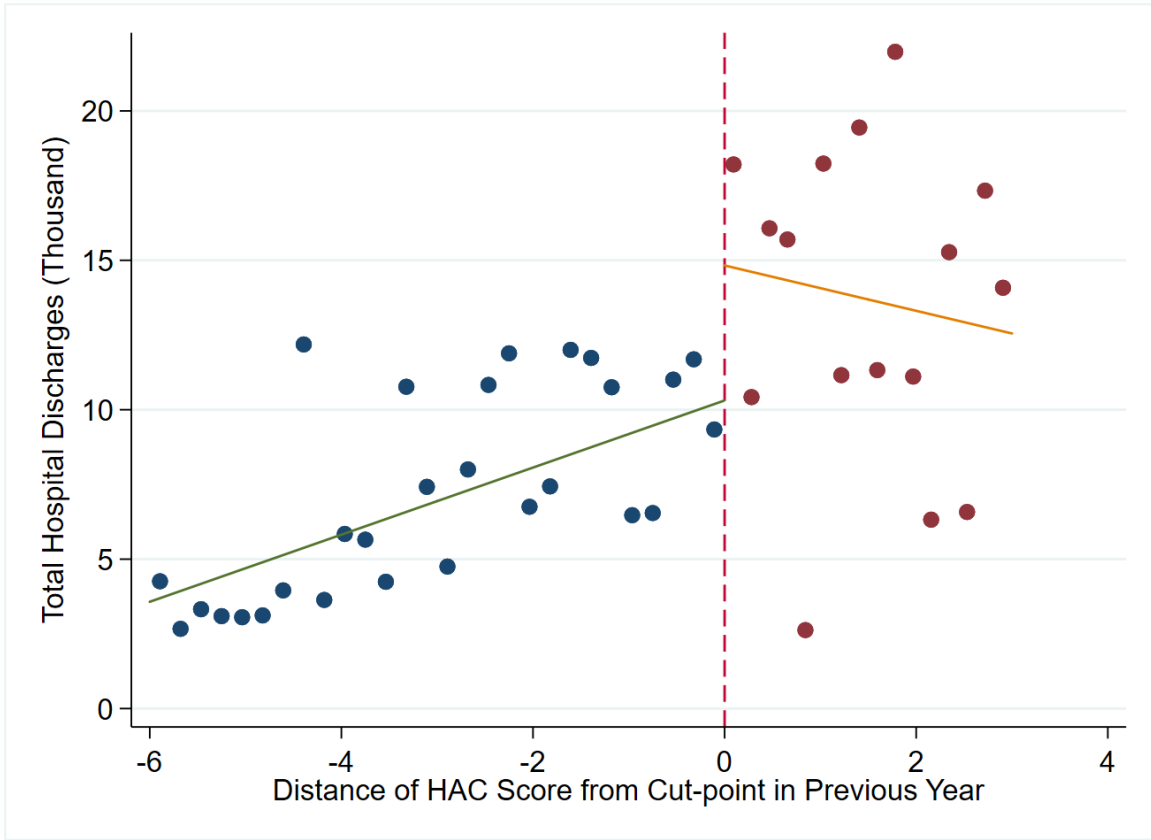
Figure 1. Distance of HAC Score from Cut-point in Current Year



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

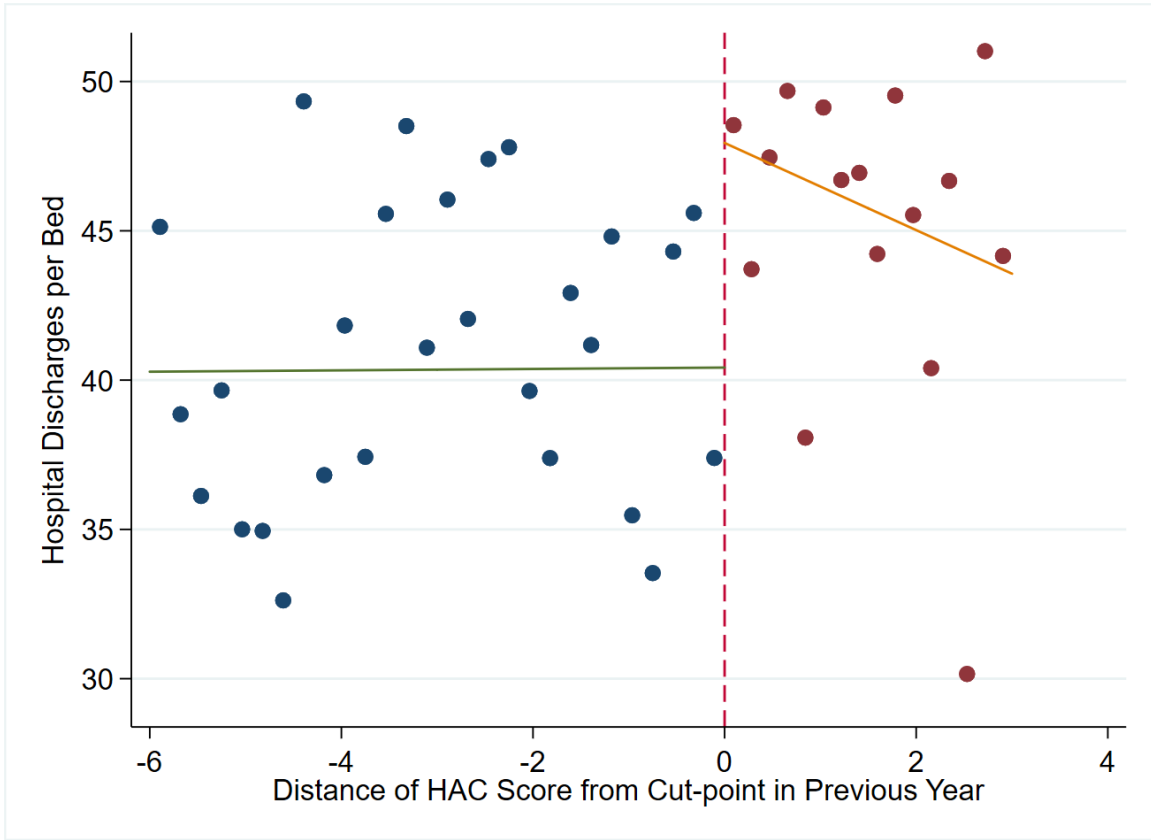
Figure 2. Total Hospital Discharges



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

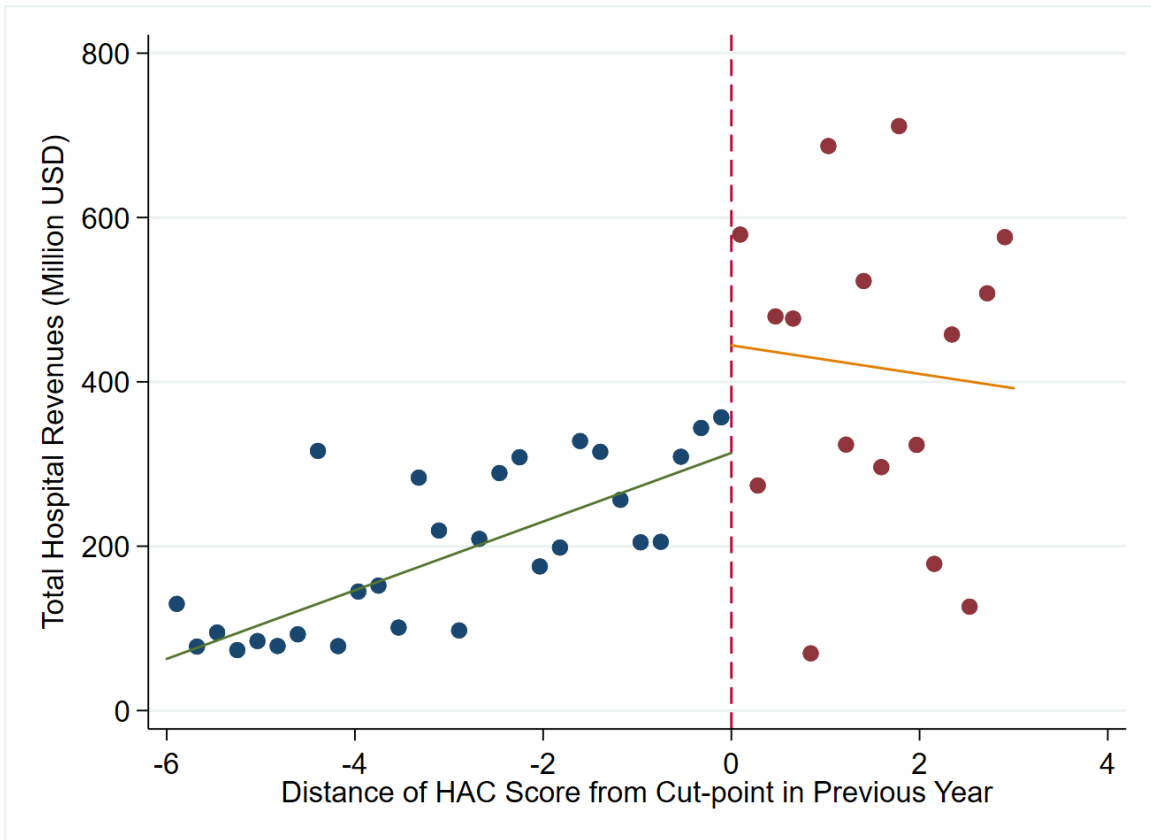
Figure 3. Hospital Discharges per Bed



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

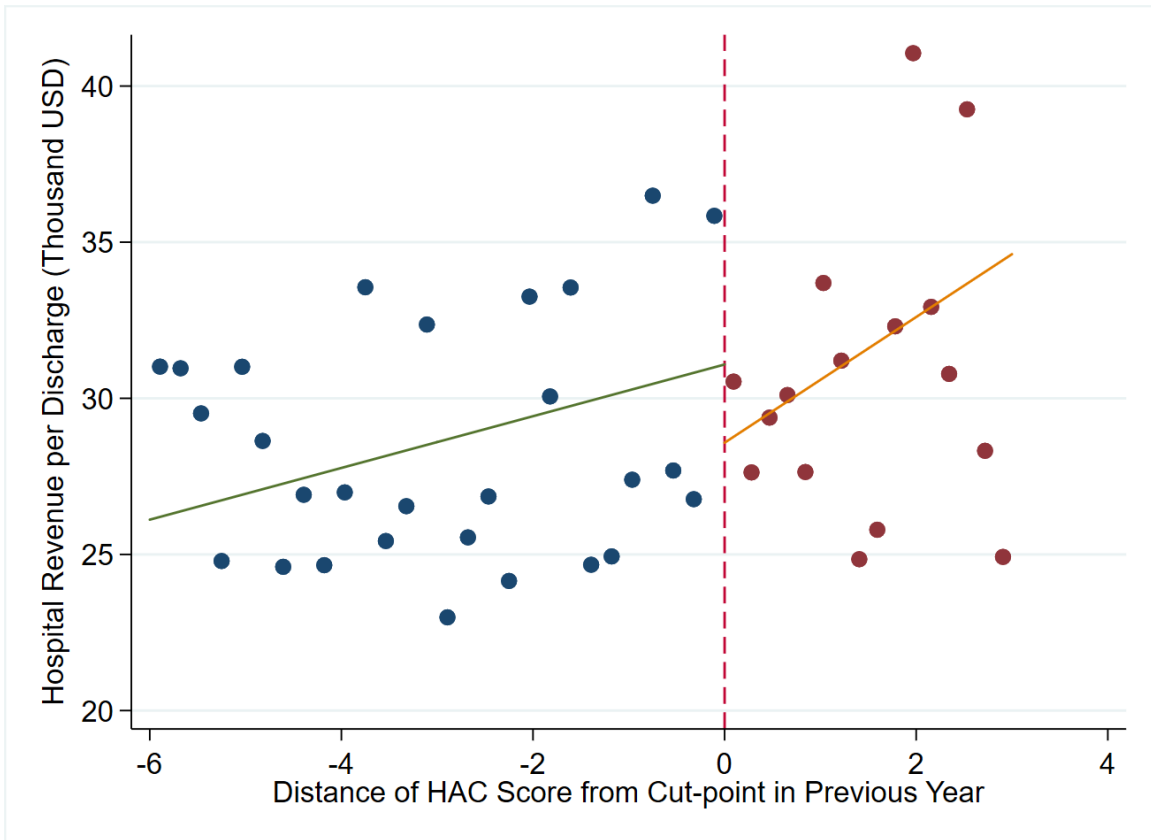
Figure 4. Total Hospital Revenues



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

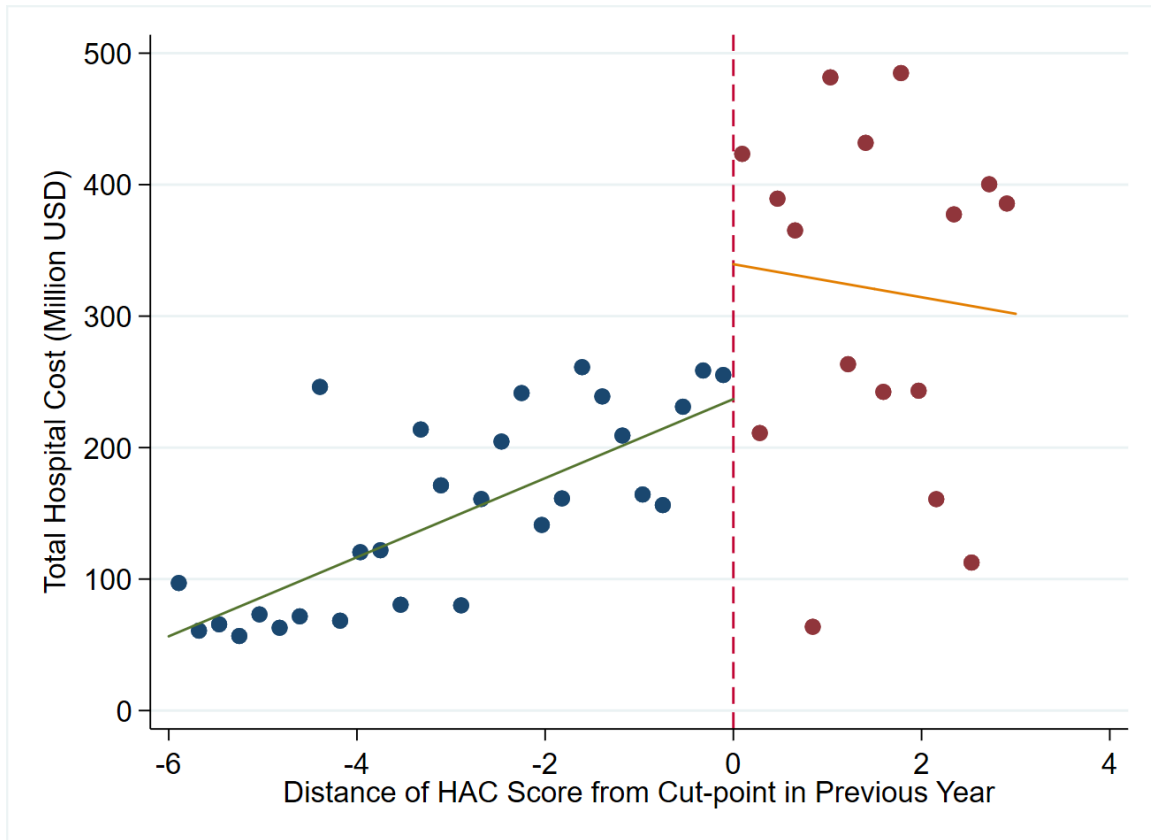
Figure 5. Hospital Revenue per Discharge



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

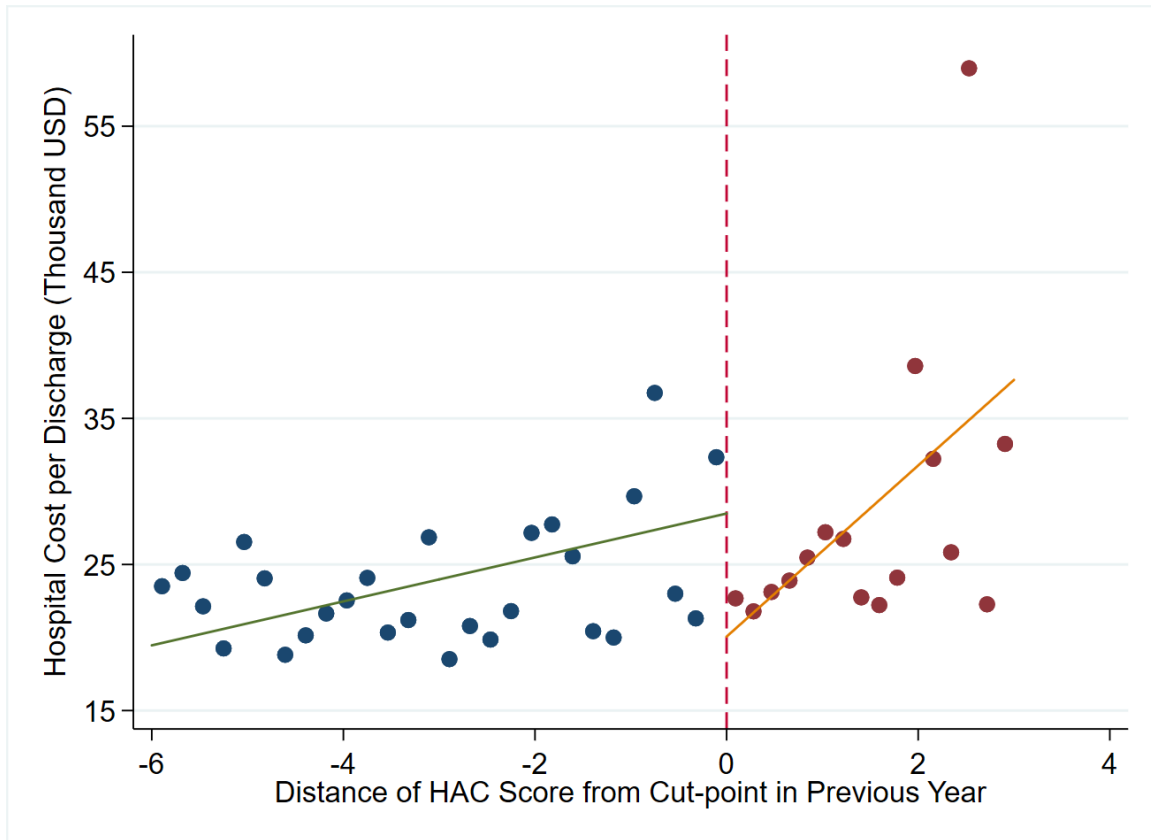
Figure 6. Total Hospital Cost



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

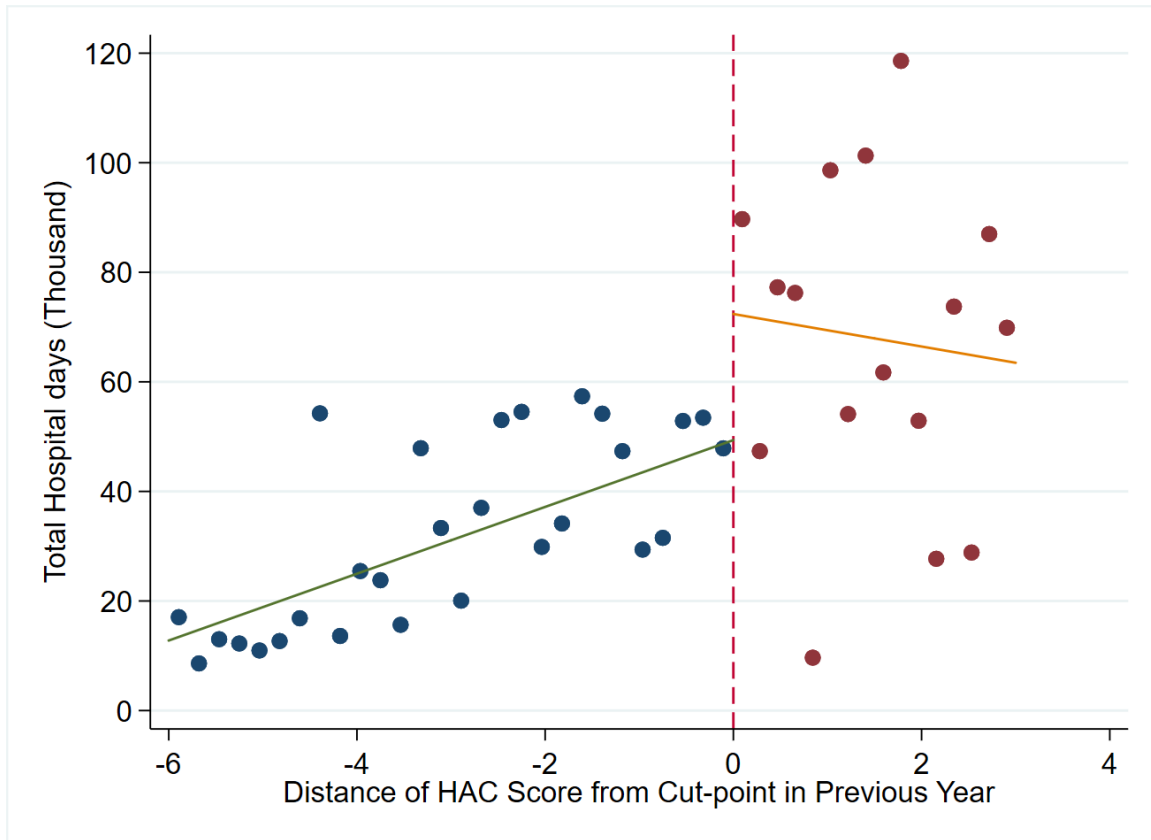
Figure 7. Hospital Cost per Discharge



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

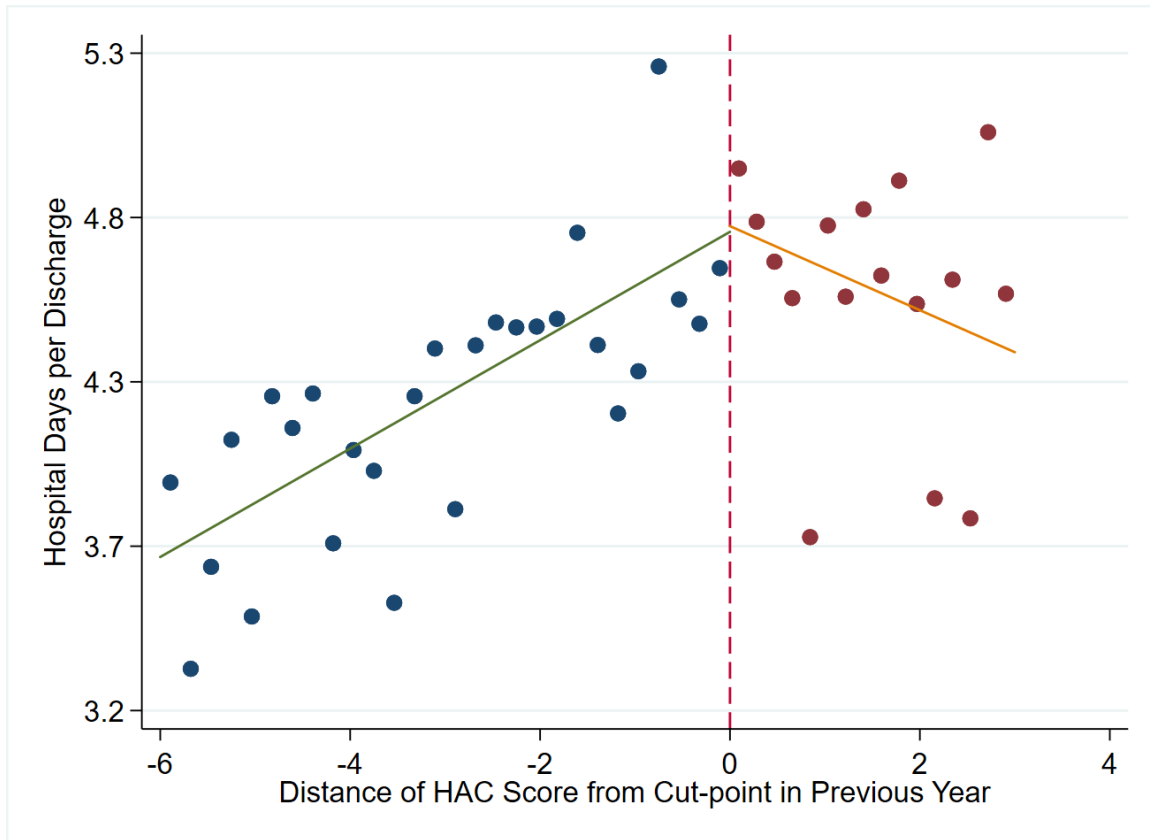
Figure 8. Total Hospital Days



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

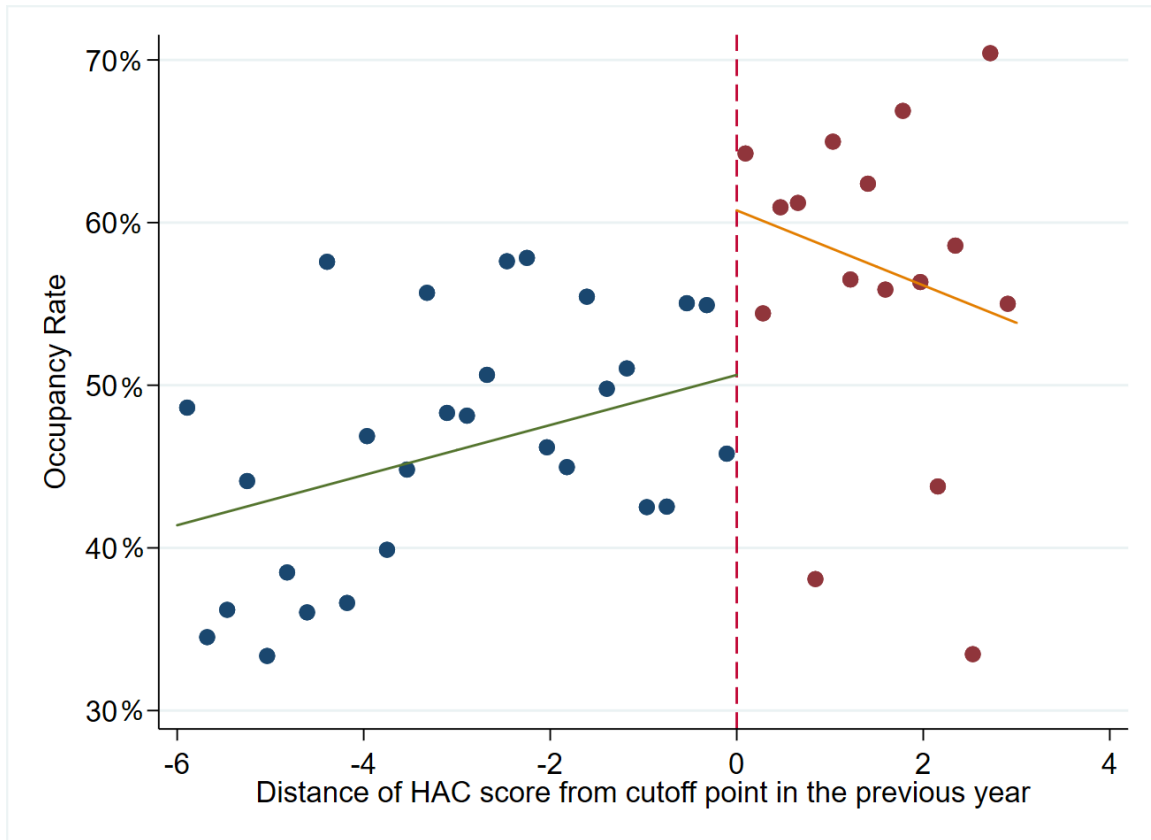
Figure 9. Hospital Days per Discharge



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

Figure 10. Hospital Occupancy rate



Note: Blue dots on the left side of the vertical line represent non-penalized hospitals with lower HAC scores performed better in the previous year. 30 hospitals in each blue dot.

Red dots on the right side of the vertical line represent penalized hospitals with higher HAC scores performed worse in the previous year. 15 hospitals in each red dot.

Hospital occupancy rate is defined as the percentage of hospital beds that are in use at a given time and can be computed by dividing hospital days by hospital bed days available. (Andrews, 2019)