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RESEARCH ARTICLE

Differential Impact of Hospital and Community Factors on Medicare Readmission Penalties

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Objective. To identify hospital/county characteristics and sources of regional heterogeneity associated with readmission penalties.

Data Sources/Study Setting. Acute care hospitals under the Hospital Readmissions Reduction Program from fiscal years 2013 to 2018 were linked to data from the Annual Hospital Association, Centers for Medicare and Medicaid Services, Medicare claims, Hospital Compare, Nursing Home Compare, Area Resource File, Health Inequity Project, and Long-term Care Focus. The final sample contained 3,156 hospitals in 1,504 counties.

Data Collection/Extraction Methods. Data sources were combined using Medicare hospital identifiers or Federal Information Processing Standard codes.

Study Design. A two-level hierarchical model with correlated random effects, also known as the Mundlak correction, was employed with hospitals nested within counties.

Principal Findings. Over a third of the variation in readmission penalties was attributed to the county level. Patient sociodemographics and the surrounding access to and quality of care were significantly associated with penalties. Hospital measures of Medicare volume, percentage dual-eligible and Black patients, and patient experience were correlated with unobserved area-level factors that also impact penalties.

Conclusions. As the readmission risk adjustment does not include any community-level characteristics or geographic controls, the resulting endogeneity bias has the potential to disparately penalize certain hospitals.

Key Words. Hospital Readmissions Reduction Program, Medicare

An emerging emphasis has been placed on shifting healthcare reimbursements from volume to value to reconcile quality and cost. Pay-for-performance (P4P) programs are one mechanism to incentivize value through the linkage of payments to quality improvement metrics. The Patient Protection

and Affordable Care Act (ACA) established the Hospital Readmissions Reduction Program (HRRP), a P4P program to address the rising burden of unplanned 30-day readmissions, which affect nearly 20 percent of Medicare discharges and result in more than \$15 billion in costs annually (Jencks, Williams, and Coleman 2009).

Under the HRRP, hospitals face progressive reimbursement reductions based on risk-adjusted readmission rates for heart failure, acute myocardial infarction, and pneumonia, and more recently, chronic obstructive pulmonary disease and elective total hip/knee arthroplasty. The maximum fine was 1 percent in fiscal year (FY) 2013, 2 percent in FY 2014, and 3 percent in FY 2015 and beyond. In addition to the HRRP, the ACA also included two additional P4P programs: hospital value-based purchasing and hospital-acquired conditions. These programs also aim to improve the value of health-care spending by linking reimbursement to various hospital performance and quality metrics. Collectively, the share of Medicare diagnosis-related group payments at risk under these P4P programs increased from 2 percent in FY 2013 to 6 percent in FY 2018.

The HRRP risk adjusts for patient age, gender, and illness severity. Based on this adjustment, the Centers for Medicaid and Medicare Services (CMS) calculates a disease-specific excess readmission ratio for each hospital as compared to the national average for other hospitals with a similar patient mix. National benchmarking means roughly half of the hospitals will face a penalty each year. The incentives created by benchmarking hospitals against their peers reward relative, rather than absolute, improvement, so hospitals with substantially improved rates over time may still be penalized.

Despite the conceptual appeal of aligning reimbursement to quality, there are widespread concerns regarding the adequacy of the risk adjustment methodology (Gerhardt et al. 2013; Lichtman et al. 2013; Herrin et al. 2015), most notably its ability to account for patient sorting to hospitals on the basis of unobserved health status and sociodemographic/geographic factors

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(Lilford and Pronovost 2010; Lindenauer et al. 2013; Gohil et al. 2015). Given this, emerging literature has focused on characterizing penalized hospitals (Jha, Orav, and Epstein 2011; Joynt, Orav, and Jha 2011; Shoemaker and American 2012; Joynt and Jha 2013; Herrin et al. 2015; Rajaram et al. 2015; Horwitz et al. 2017) and the potential for P4P programs to exacerbate disparities in health care due to their risk adjustment methodologies (Bhalla and Kalkut 2010; Berenson and Shih 2012; Joynt and Rosenthal 2012; Calvillo-King et al. 2013; Lindenauer et al. 2013; Ryan 2013; Fiscella, Burstin, and Nerenz 2014; Gilman et al. 2014; Gu et al. 2014; Hu, Gonsahn, and Nerenz 2014; Fuller, Atkinson, and Hughes 2015). In particular, studies suggest hospitals that are large and/or academic (Joynt and Jha 2013; Kahn et al. 2015; Horwitz et al. 2017), that serve the most vulnerable and medically complex (Jha, Orav, and Epstein 2011; Berenson and Shih 2012; Gilman et al. 2014; Gu et al. 2014), and that are located in communities with lack of access to care may be disproportionately penalized (Gu et al. 2014; Herrin et al. 2015). While these studies have established that variation in hospital readmission rates and penalties exists, their underlying sources remain unclear.

It remains uncertain whether hospitals penalized under the HRRP are truly underperforming or whether this P4P policy is improperly calibrated. The objective of this study is to examine the potential for biased risk adjustment under the HRRP from FY 2013 to 2018. The primary goals of this study are twofold: (1) determine what hospital/county characteristics are associated with readmission penalties and (2) analyze the sources of heterogeneity in readmission penalties.

STUDY DATA AND METHODS

Sample

The unit of analysis was the hospital. The analysis concentrated on acute care hospitals reimbursed under Medicare's inpatient prospective payment system. Certain hospitals are exempt from P4P programs. These include hospitals located in Maryland, which have a unique all-payer rate-setting system, and those dedicated to specific services (cancer, rehabilitation, psychiatry, critical access, or long-term care) or populations (children or veterans). All hospitals with less than 25 cases across all HRRP conditions, which is the minimum number required, were also omitted.

Penalty Outcome

The theoretical maximum penalty for the HRRP was 15 percent during this time frame (1 percent in FY 2013, 2 percent in FY 2014, and then 3 percent from FY 2015 onward, respectively). The increasing upper bounds mean an average penalty may mask hospital performance. To address this issue, the HRRP penalty was summed across all 6 years and divided by the theoretical maximum potential HRRP penalty to yield a percentage. To prevent confusion, as the HRRP penalty already represents a percentage, the outcome will be referred to as the HRRP penalty share.

If Hospital A was penalized 0, 0, 2, 3, 3, and 3 percent, and Hospital B was penalized 1, 2, 3, 3, 3, and 3 percent, their average penalties would be 1.83 and 2.50 percent, respectively, using number of years in the program, 6 for both, as the denominator. If the denominator was the number of times penalized, 4 for Hospital A and 6 for Hospital B, their average penalties would be 2.75 and 2.50 percent, respectively. This issue is further compounded by the fact that not all hospitals meet the HRRP eligibility requirements all 6 years, such as the minimum case threshold. For example, if Hospital C is a newer hospital that does not show up in the FY 2013 data but is then penalized 2, 3, 3, 3, and 3 percent, its average penalty would be 2.80 percent, despite the fact that similar to Hospital B, it was penalized the maximum possible amount each FY it was in the program. Using the theoretical maximum penalty, 15 percent for Hospitals A and B and 14 percent for Hospital C, to address the changing bounds is more informative as Hospital A would have 73 percent and Hospitals B and C would have 100 percent (Figure 1).

Data Sources

Data were synthesized from different sources during the HRRP measurement period to capture a range of hospital and community characteristics. Penalties in each FY are based on a 3-year average of readmission rates. For FY 2013, the measurement period is 2008–2011, and it rolls forward by one year, meaning that for FY 2018, the measurement period is 2013–2016.

Hospital Characteristics

The HRRP outcome variable was derived from the 2013–2018 CMS final rule tables. The hospital variables were assembled from the 2012 Annual Hospital Association (AHA) survey, 2008–2018 CMS impact files (earlier files were

Figure 1: Example of Different Outcome Specifications

Hospital	FY2013 (1%)	FY2014 (2%)	FY2015 (3%)	FY2016 (3%)	FY2017 (3%)	FY2018 (3%)	Sum: FY2013 to FY2018
A	0%	0%	2%	3%	3%	3%	11%
B	1%	2%	3%	3%	3%	3%	15%
C	N/A	2%	3%	3%	3%	3%	14%

Hospital	Sum: FY2013 to FY2018	Avg = Sum/ # Yrs in Program	Avg = Sum/ # Yrs Penalized	Share = Sum/ Theoretical Max Penalty
A	11%	(11%/6) = 1.83%	(11%/4) = 2.75%	(11%/15%) = 73%
B	15%	(15%/6) = 2.50%	(15%/6) = 2.50%	(15%/15%) = 100%
C	14%	(14%/5) = 2.80%	(14%/5) = 2.80%	(14%/14%) = 100%

Note: Theoretical maximum readmission penalty underneath each FY in parentheses. A hospital, such as C in the example above, may be eligible for the program in certain years but not others for various reasons such as not meeting the minimum case requirement. The relative ranking of hospital penalties changes depending on the metric used, but only the penalty share is able to capture the variable bounds and that both hospitals B and C were penalized the maximum possible amount for all years they were eligible to be in the program.

used for variable creation, while later files were required for hospital demographics), 2008–2012 5 percent sample of Medicare inpatient claims, and 2009–2012 Hospital Compare (HC) archives.

From the 2012 AHA survey, hospital teaching status (determined by an AMA-approved residency program, membership of the Council of Teaching Hospitals, or a ratio of full-time equivalent interns/residents to beds ≥ 0.25) ((HCUP) HCUP 2008), hospital size (<200 = small, 200–399 = medium, or 400 or more = large), and ownership type (public, private not-for-profit, or private for-profit) were identified. AHA also provides binary skilled nursing availability indicators by type: hospital, health system, network, or joint venture. If a hospital had any skilled nursing (one or more of the four types), it was coded as available, otherwise not available. Additionally, the skilled nursing information had a large fraction of missing data, so an indicator was created to acknowledge this.

A 5-year average of percentage Medicare inpatient days was derived from the CMS impact files. The uncompensated care per claim amount came from the FY 2015 file, which is based on a 3-year average from FY 2010 to 2013. Briefly, since the ACA’s passage, Medicare has begun shifting away from disproportionate share payments, which have typically been used to categorize safety-net hospitals, to uncompensated care payments. A binary indicator was also created to differentiate hospitals paid with special arrangements under the inpatient provider payment system, such as sole community and Medicare-dependent hospitals, versus those that are not.

Five-year (2008–2012) averages of percentage black and dual-eligible patients were constructed for each hospital using the 5 percent sample of Medicare inpatient claims. Lastly, a 4-year (2009–2012) average composite of Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey patient experience measures was derived from HC. The percentage who replied to the most favorable option on each question was used, for example, the percentage who replied always to “. . . did nurses listen carefully to you?” or the percentage who replied yes to “Would you recommend this hospital to your friends and family?” The alpha was 0.94 among the top-box percentage across all 10 HCAHPS measures, which represents excellent internal consistency. The final composite represents the average percentage value by hospital (Appendix SA2).

Community Characteristics

The community variables were constructed from the 2009–2012 Nursing Home Compare (NHC) data, 2010–2012 Long-term Care (LTC) Focus data developed at the Brown University Center for Gerontology and Healthcare Research, 2012 Area Resource File (ARF), and 2010 Health Inequality Data (HID). Federal Information Processing Standard (FIPS) codes were used to merge geographic-level data due to its commonality across datasets.

Individuals discharged to skilled nursing facilities have higher readmission rates than those discharged to the community (Bogaisky and Dezieck 2015). In addition to general county characteristics, we tried to capture the variety of resident clinical factors and facility characteristics linked to readmissions (Yoo et al. 2015). The median nursing home quality from the five-star rating system (range 10 to 50, higher is better) was derived by county from NHC. Variables related to nursing home quality (ratio of registered nurses to total nurses), market concentration (Herfindahl–Hirschman index [HHI]), access to care (home health agencies/1,000 elderly), and resident characteristics (acuity and percentage do-not-resuscitate) were preaggregated at the county level from LTC Focus. The HHI, a measure of nursing home bed competition, ranges from 0 to 1, where 0 represents perfect competition and 1 represents a monopoly in the county. HHI was multiplied by 100 to facilitate the reporting of results and coefficient comparisons. Documentation on the derivation of the HHI variables can be found at <http://ltcfocus.org/>.

From the ARF, percentage 65+ in deep poverty, percentage 25+ without a high school diploma, and per-capita ($\times 100,000$) measures for general practitioners (GPs) and total specialists (sum of medical, surgical, and other

specialties) were derived. The latter two were used to construct a GP/specialist ratio. For counties with no GPs or specialists, 1 was added before calculating the ratio to prevent missing values.

Variables related to social inequity (Putnam's social capital index) and variations in health care (percentage of Medicare enrollees with at least one primary care visit and Medicare reimbursement/enrollee) were derived from the HID. Putnam's social capital index by Rupasingha et al. is a hybrid measure of organizational density (civic organizations, bowling alleys, golf courses, fitness centers, sports organizations, religious organizations, political organizations, labor organizations, business organizations, and professional organizations), 2008 voter turnout, 2010 Census response rate, and number of nonprofits by county (Rupasingha, Goetz, and Freshwater 2006; Putnam 2001). Social capital has been linked to health outcomes through a variety of mechanisms, including exchange of information, improved societal norms, greater accessibility to health services, and increased psychosocial support, particularly in older adults (Laporte, Nauenberg, and Shen 2008; Scheffler and Brown 2008). Documentation on the derivation of the HID variables can be found at <https://healthinequality.org/data/>.

Statistical Analysis

A two-level hierarchical model with correlated random effects, also known as the Mundlak correction, was employed with hospitals (level-1) nested within counties (level-2) (Mundlak 1978). The hierarchical nature of the data and proportional outcome are well suited to the fractional probit (Papke and Wooldridge 2008). For simplicity, the ordinary least-squares (OLS) models and results are presented because they yielded qualitatively similar results.

Conventionally, the empirical approaches to account for hierarchical data are fixed effects (dummy variable for each higher level unit) or random effects (random intercept multilevel model). The analytical requirements of this investigation required the ability of both fixed effects to control for cluster-invariant geographic characteristics of hospitals and random effects to provide estimates of them. More importantly, the objective of this paper relies on a hybrid variant of both model types to test whether endogeneity due to regional confounding exists.

Hospital-level (level-1) equation: $y_{ij} = \beta_{00} + \varepsilon_{ij}$, where hospitals (level-1 units: $i = 1, 2, \dots, n_j$) are nested within counties (level-2 units: $j = 1, 2, \dots, m$), y_{ij} is the HRRP penalty share, β_{00} is the grand mean, and ε_{ij} is the level-1

random error term assumed to be independent and normally distributed, with a mean of 0 and a constant variance of σ^2 : $\varepsilon_{ij} \sim N(0, \sigma^2)$. In the presence of clustering, where groups of high- or low-performing hospitals may be in close geographic proximity to one another, this independence assumption would be violated.

To test this, the intraclass correlation (ICC), which represents the fraction of the total variance that can be attributed to each level, was calculated from a null two-level model (not shown) (Raudenbush SW 2002). The variances of the hospital- and county- specific random effects from the unconditional model were 208.10 and 111.04, respectively. The ICC signified 34.79 percent ($111.04/319.14$) of the variance in the HRRP penalty share is at the county level. Similarly, the ICC signified 37.4 percent ($2.62/7.01$) of the variance in the untransformed summed penalty is at the county level. As significant county differences in HRRP penalties exist, the dependence among hospitals within the same county needs to be explicitly modeled by replacing β_{00} with β_{0j} so the level-1 intercept is allowed to vary across counties.

Modified hospital-level equation: $y_{ij} = \beta_{0j} + \beta X_{ij} + \varepsilon_{ij}$, where β_{0j} is a random intercept for each county, explicated below, and X_{ij} is a vector of hospital-level covariates.

County-level (level-2) equation: $\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + \mu_j$, where γ_{00} is the population grand mean, Z_j is a vector of county-level covariates, and μ_j is the level-2 random error term assumed to be independent and normally distributed with a mean of 0 and a constant variance of τ^2 : $\varepsilon_{ij} \sim N(0, \tau^2)$.

Combined equation: $y_{ij} = \gamma_{00} + \beta X_{ij} + \gamma_{01}Z_j + \varepsilon_{ij} + \mu_j$.

The main concern with hierarchical data is level-2 endogeneity, where there is a correlation between hospital characteristics and unobserved characteristics at the regional level. If there is cross-level violation of the independence assumption $\text{cov}(X_{ij}, \mu_j) \neq 0$, which can be assessed by the Hausman test for endogeneity, the random effects specification above would result in biased coefficients, so a fixed-effects specification may be more appropriate. A plausible violation here, for example, could result from unobserved regional characteristics (i.e., degree of healthcare market competition) that are correlated with observed hospital characteristics (i.e., patient experience) related to readmissions. County means of the hospital covariates are included to capture the correlation between hospital characteristics and unobserved regional effects to relax this assumption, as proposed by Mundlak (1978). The unobserved heterogeneity in the level-2 error term is modeled by the equation:

$\mu_j = \gamma_{02}X_j + v_j$ to deconstruct what can be explained by $\gamma_{02}X_j$ so that the error term v_j is now conditionally orthogonal to X_{ij} by construction.

Final equation: $y_{ij} = \gamma_{00} + \beta X_{ij} + \gamma_{01}Z_j + \gamma_{02}X_j + \varepsilon_{ij} + v_j$, where X_j is a vector of cluster means.

This specification, often considered to be a hybrid RE-FE model, has an intuitive appeal for multiple reasons. First, the county mean coefficients γ_{02} represent contextual effects (difference in the between and within effects: $\beta_c = \beta_b - \beta_w$). Second, the hospital-level coefficients β are equivalent to those from a traditional fixed-effects model and represent relative within-cluster effects (β_w). Third, the contextual and within coefficients for any given variable can be summed to get the between-cluster effect (β_b). Lastly, and most importantly, this specification permits a Hausman-type test to assess whether the within-group vs. between-group effects significantly differ for each covariate. If their equivalence is rejected, it suggests that the variable is correlated with the regional intercept. Consequently, the assumption of no correlation between the random effects and explanatory variables may not be appropriate (Schunck and Perales 2017).

Of note, including hospital deviations through group demeaned data, $(X_{ij} - X_j)$, instead of the raw X_{ij} , would produce an equivalent model, known as the within/between method. The only difference is the between effect would be directly modeled, and subtracting the within effect from it would yield the contextual effect (Allison 2009; Schunck and Perales 2017). Mundlak's specification with raw data can be interpreted as the average difference in readmission penalties for two identical hospitals that differ by one unit on their county mean of a given variable (contextual effect). In contrast, the within/between specification would be interpreted as the overall difference in readmission penalties between two counties that differ by one unit (between effect). As the question of interest here is the expected difference in penalties for hospitals, rather than counties, the Mundlak approach was employed.

Finally, there is an inherent third level of state clustering, but the Mundlak approach cannot easily be scaled up to accommodate it. As a parallel, county and state fixed effects cannot coexist in a typical regression due to perfect collinearity between their geographic dummy variables. Moreover, state fixed effects would address unobservable, time-invariant factors at the state level, and characteristics stable at that level would remain similarly stable at the county level. Conversely, there may be a wide range of systematic county-level differences across a state. Accounting for state clustering has the potential to introduce bias as it collapses all of the county variation.

The adjusted R^2 , Akaike's information criterion, and Bayesian information criterion from county and state fixed effects regressions (38.5 percent; 23,456.2; 23,535.6 vs. 30.0 percent; 26,059.6; 26,211.0) with geographic dummy variables empirically support this notion. As the county fixed-effects model excludes all of the county-level variables, due to perfect multicollinearity, yet has a higher adjusted R^2 and lower AIC/BIC, it suggests that county is the more appropriate level of clustering.

The multilevel models were estimated using the *xthybrid* command with clustered standard errors in *STATA* version 14.1 (College Station, TX, USA).

STUDY RESULTS

Sample Characteristics

The final analytic sample contained 3,156 hospitals nested in 1,504 counties. Descriptive statistics are provided in Table 1. Of importance, 895 hospitals are singletons (only hospital in the county), which means that there is no within-county variation for these hospitals. These observations still contribute to the identification of the county effects, and therefore, they are included in the analysis. While a larger unit of area like hospital referral region or state could avoid this problem, research indicates that Medicare patients tend to stay within their county for healthcare services, particularly nursing facilities (Gertler 1989; Banaszak-Holl, Zinn, and Mor 1996). Furthermore, as many of the variables came preaggregated at the county level, the risk of averaging preaveraged data could not be dismissed.

Under the HRRP, the summed FY 2013 to FY 2018 penalty ranged from 0 to 15 percent, and the mean was 2.74 percent. With respect to the outcome, HRRP share, hospitals were penalized 18.0 percent of their theoretical maximum penalty on average. In general, two-thirds of the hospitals were non-teaching status, small size, or private not-for-profit, and they served 34 percent dual-eligible and 12 percent Black patients on average.

Table 2 presents the classical two-level random effects models without the Mundlak correction, and Table 3 presents the same series of models with the Mundlak correction (inclusion of county-level means). For the sake of brevity and clarity, only significant contextual effects are shown in Table 3. Each table presents a model with only hospital-level covariates and a model with both hospital-level and county-level covariates. Only $n = 11$ (0.35 percent) observations had predicted outcomes outside of the plausible bounds

Table 1: Summary Table

	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
Hospital characteristics (<i>n</i> = 3,156)				
Outcome: HRRP share	18.00	17.53	0.00	100.00
Summed HRRP penalty FY13–17	2.74	2.59	0.00	15.00
Teaching status (vs. not teaching status)	0.33	0.47	0.00	1.00
Medium size: 200–400 beds (vs. small: <200 beds)	0.24	0.43	0.00	1.00
Large size: >400 beds (vs. small: <200 beds)	0.11	0.31	0.00	1.00
Private, not-for-profit (vs. public hospital)	0.62	0.49	0.00	1.00
Private, for-profit (vs. public hospital)	0.23	0.42	0.00	1.00
IPPS special arrangement	0.24	0.43	0.00	1.00
Uncompensated care/claim amount (per \$1,000)	0.91	7.48	0.00	399.38
% Medicare inpatient days	47.09	14.78	0.06	88.38
% Dual-eligible patient share	33.55	16.20	0.00	96.08
% Black patient share	11.83	16.22	0.00	98.57
Hospital Compare HCAHPS composite	69.12	5.81	41.92	94.13
Hospital skilled nursing availability—yes (vs. no)	0.30	0.46	0.00	1.00
Hospital skilled nursing availability—missing (vs. no)	0.16	0.37	0.00	1.00
County characteristics (<i>n</i> = 1,504)				
Nursing Home Compare five-star rating	29.23	5.81	10.00	50.00
Registered nurses : nurses ratio	31.44	13.75	0.00	91.03
Herfindahl index—nursing home competition	19.85	23.10	0.17	100.00
General practitioners-to-specialists ratio	0.04	0.12	0.00	3.00
% 65+ in deep poverty	2.61	0.96	0.00	10.20
% 25+ less than high school diploma	13.98	5.87	2.30	53.70
Home health agencies/1,000 elderly	0.30	0.33	0.00	3.42
Nursing home acuity index	11.67	0.81	6.21	16.66
% DNR residents	54.27	16.40	12.51	94.27
% Medicare enrollees with ≥ 1 primary care visit	79.07	5.42	50.82	95.67
Avg Medicare reimbursement per enrollee/\$1,000	9.68	1.40	5.83	15.68
Putnam’s social capital index	−0.63	0.82	−3.38	3.67
Population/100,000	8.49	17.39	0.03	98.89

between 0 and 100 with OLS. The fractional probit results, as well as the full Mundlak results, are available upon request.

Two-Level Random Effects Models, without Mundlak Correction

In the fully adjusted model, teaching status, HCAHPS patient experience composite, and hospitals located in counties with increased nursing home quality, GP/specialist ratio, HHAs/1,000 elderly, percentage nursing home residents with DNR orders, and Medicare enrollees with at least 1 primary care visit were all associated with decreased HRRP penalties (Table 2). In contrast, percentage Medicare inpatient days, monopolistic nursing home

Table 2: Two-Level Random Effects Models, without Mundlak Correction

	<i>Hospital Variables</i>	<i>Hospital+ County Variables</i>
Teaching status (vs. not teaching status)	−2.475*** (−3.37)	−1.587* (−2.20)
Medium size: 200–400 beds (vs. small: <200 beds)	1.704* (2.26)	1.105 (1.48)
Large size: >400 beds (vs. small: <200 beds)	2.284* (2.10)	1.061 (0.98)
Private, not-for-profit (vs. public hospital)	1.492 (1.69)	1.931* (2.21)
Private, for-profit (vs. public hospital)	5.565*** (5.48)	4.314*** (4.32)
IPPS special arrangement	0.0637 (0.08)	1.320 (1.54)
Uncompensated care/claim amount (per \$1,000)	−0.0343 (−0.96)	−0.0281 (−0.79)
% Medicare inpatient days	0.213*** (8.80)	0.196*** (7.78)
% Dual-eligible patient share	0.0769** (3.24)	0.0287 (1.15)
% Black patient share	0.0303 (1.32)	−0.0145 (−0.59)
Hospital Compare HCAHPS composite	−0.379*** (−6.54)	−0.385*** (−6.58)
Hospital skilled nursing availability—yes (vs. no)	0.0219 (0.03)	0.403 (0.62)
Hospital skilled nursing availability—missing (vs. no)	0.130 (0.15)	0.168 (0.20)
Nursing Home Compare five-star rating		−0.151** (−2.62)
Registered nurses/nurses ratio		0.0283 (0.89)
Herfindahl index—nursing home competition		0.0646*** (3.62)
General practitioners-to-specialists ratio		−6.810* (−2.44)
%65 + in deep poverty		0.105 (0.27)
%25 + less than high school diploma		−0.0296 (−0.33)
Home health agencies/1,000 elderly		−5.460*** (−4.06)
Nursing home acuity index		0.942* (1.98)
% DNR residents		−0.119*** (−3.74)
% Medicare enrollees with ≥ 1 primary care visit		−0.227** (−2.75)
Avg Medicare reimbursement per enrollee/\$1,000		3.002*** (8.74)
Putnam's social capital index		−0.520 (−0.88)
Population/100,000		−0.107 (−1.71)
FIPS random effect (SE)	85.824 (9.606)	58.847 (8.053)
Residual random effect (SE)	202.124 (7.189)	200.872 (6.968)
N	3156	3156

Note. *t*-statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

competition, nursing home acuity, and Medicare reimbursement/enrollee were all associated with increased HRRP penalties. Once the county variables were included, medium size, large size, and percentage dual-eligible patient share were no longer significant, while private not-for-profit became significant. Similar trends in direction and significance remained for the other hospital variables.

With Mundlak Correction

Once the county-level means are included, the coefficients for hospital-level covariates now represent fixed effects (Table 3). As a result, they remain

Table 3: Mundlak Correction

	<i>Hospital Variables</i>	<i>Hospital+ County Variables</i>
W: Teaching status (vs. not teaching status)	−2.375** (−2.58)	−2.375** (−2.58)
W: Medium size: 200–400 beds (vs. small: <200 beds)	1.295 (1.14)	1.295 (1.14)
W: Large size: >400 beds (vs. small: <200 beds)	0.955 (0.82)	0.955 (0.82)
W: Private, not-for-profit (vs. public hospital)	0.468 (0.40)	0.468 (0.40)
W: Private, for-profit (vs. public hospital)	5.351*** (3.90)	5.351*** (3.90)
W: IPPS special arrangement	−1.330 (−0.85)	−1.330 (−0.85)
W: Uncompensated care/claim amount (per \$1,000)	−0.0293 (−1.28)	−0.0293 (−1.28)
W: % Medicare inpatient days	0.134*** (4.33)	0.134*** (4.33)
W: % Dual-eligible patient share	−0.0186 (−0.56)	−0.0186 (−0.56)
W: % Black patient share	−0.0244 (−0.63)	−0.0244 (−0.63)
W: Hospital Compare HCAHPS composite	−0.367*** (−3.89)	−0.367*** (−3.89)
W: Hospital skilled nursing availability—yes (vs. no)	0.137 (0.17)	0.137 (0.17)
W: Hospital skilled nursing availability—missing (vs. no)	−1.726 (−1.46)	−1.726 (−1.46)
C: % Medicare inpatient days	0.168*** (3.56)	0.150** (2.90)
C: % Dual-eligible patient share	0.220*** (4.16)	0.118* (2.24)
C: % Black patient share	0.119* (2.19)	0.0362 (0.61)
C: Hospital Compare HCAHPS composite	−0.270* (−1.96)	−0.158 (−1.13)
C: Hospital skilled nursing availability—missing (vs. no)	4.719* (2.52)	4.323* (2.35)
Nursing Home Compare five-star rating		−0.128* (−2.14)
Registered nurses/nurses ratio		0.0261 (0.83)
Herfindahl index—nursing home competition		0.0701** (3.17)
General practitioners-to-specialist ratio		−8.122** (−3.15)
% 65 + in deep poverty		−0.0666 (−0.15)
% 25 + less than high school diploma		−0.123 (−1.25)
Home health agencies/1,000 elderly		−4.113*** (−3.30)
Nursing home acuity index		0.780 (1.56)
% DNR residents		−0.107** (−2.81)
% Medicare enrollees with ≥ 1 primary care visit		−0.220* (−2.43)
Avg Medicare reimbursement per enrollee/\$1,000		2.920*** (7.41)
Putnam’s social capital index		−1.226 (−1.91)
Population/100,000		−0.119** (−2.62)
FIPS random effect (SE)	77.115 (12.672)	53.124 (10.645)
Residual random effect (SE)	200.308 (11.510)	200.602 (11.381)
N	3,156	3,156

Note. t-statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
W—within effect, C—contextual effect (coefficient of county-level mean). Only significant contextual effects are shown in the table for the sake of brevity and clarity. Full results are available upon request.

unchanged, regardless of specification. In the fully adjusted specification, the major differences are the contextual effects for percentage black patients and patient experience are no longer significant, while the ones for Medicare

volume and percentage dual-eligible patients are attenuated but remain significant. The other hospital and county characteristics remain relatively unchanged with respect to both significance and direction/magnitude, compared to the prior models. The county-level coefficients are very similar but not identical to those without the Mundlak correction because the county means absorb some of the between-cluster variation (Schunck and Perales 2017).

Before the county variables were included, the random effects assumption was rejected for percentage Medicare inpatient days, percentage dual-eligible patients, percentage black patients, the HCAHPS composite, and the AHA missing indicator for skilled nursing availability. Substantively, this presents a level-2 endogeneity issue because the underlying regional characteristics of where a hospital is located, as captured by the county-level means, have a contextual effect on the hospital's HRRP penalty. Simply put, correlations between these five hospital characteristics and unobserved area-level effects exist and, if not properly accounted for, would result in biased estimation.

In this case, due to the Mundlak device, the bias is absorbed by the cluster means and does not manifest in the estimates of the hospital coefficients. Once the county variables are included, this assumption is no longer violated for percentage black patients and the HCAHPS composite but still exists for percentage Medicare days and dual-eligible patient share.

DISCUSSION

The risk adjustment debate in P4P programs continues to be a timely and salient concern. To address that, the overarching motivation of this study was to investigate the sources of heterogeneity in the hospital/community factors associated with hospital penalties during the first six fiscal years of the HRRP. Notably, over a third of the variation in HRRP penalties is attributed to the county level, which suggests an important role of area-level factors in readmissions.

The findings further highlight the joint influence of hospital/community characteristics related to social risk factors and the surrounding access to and quality of postacute care. Hospital for-profit control and Medicare inpatient days were associated with higher HRRP share, while teaching status and HCAHPS were associated with lower HRRP share. At the county level, primary care visits, Medicare reimbursement, and nursing home quality, competition, and percentage DNR patients were all associated with increased

penalty share. In addition, GP/specialist ratio and HHA/1,000 elderly suggest that access to care is associated with lower HRRP share.

This study also advances the P4P risk adjustment literature by accounting for geographic heterogeneity (fixed effects) while still estimating group-invariant effects (random effects). By parsing out the compositional effects of hospitals from contextual effects of location, it is evident that the omission of geographic means leads to inconsistent estimation of the hospital characteristics. Compared to the random effects specification, the Mundlak approach results in attenuated magnitudes of the significant hospital-level coefficients. This suggests that selection results in upward-biased coefficients because characteristics of the hospital and its patient population are correlated with unobserved area-level factors that also impact HRRP penalties. Failure to take this into account erroneously indicates attributes such as percentage black patients (random effects vs. Mundlak: $\beta = 0.119$, $t = 2.19$; $\beta = 0.0362$, $t = 0.61$) or percentage dual-eligible patients ($\beta = 0.220$, $t = 4.16$; $\beta = 0.118$, $t = 2.224$) have larger associations with HRRP share than they actually may.

The Mundlak models provide interesting insights, even if hospitals are not necessarily benchmarked against their geographic neighbors in the HRRP. Hospital characteristics such as teaching and for-profit status had significant within effects, but not contextual effects, pointing to the role of relative standing within a county. On the flip side, if the contextual effect was significant, it was larger in magnitude compared to its respective within effect because it absorbed the bias related to that variable being correlated with the county-level intercept. The coefficients of the contextual effects, which should equal zero in the absence of level-2 endogeneity, offer insight into the degree of unobserved regional heterogeneity. Controlling for area-level characteristics made the contextual effects for percentage black patients and patient experience insignificant. Although attenuated, an endogeneity problem for Medicare inpatient days and dual-eligible fraction remained, which indicates a significant contextual effect of geography on the relationship between these variables and HRRP share.

The results related to dual-eligible patients, who are low-income and typically sicker (Gu et al. 2014), are particularly noteworthy as the 21st Century Cures Act requires CMS to adjust for this starting in FY 2019. While biased, the random effects model suggests hospitals that serve 10 percent more dual-eligible patients are associated with a 0.77 percentage point ($t = 3.24$) increase in HRRP share. Once county characteristics, such as access to care, are taken into account, this relationship is no longer significant ($t = 1.15$). It

seems plausible, therefore, that the future adjustment of dual eligibility will likely proxy for some of these community characteristics.

The Mundlak correction further suggests that for two otherwise identical hospitals, including their percentage dual-eligible population, the one located in a county with 10 percent more dual-eligible patients is associated with a 2.2 percentage points ($t = 4.16$) higher penalty share. With the adjustment for county-level covariates, this finding remains significant ($\beta = 0.12$, $t = 2.4$), but the coefficient magnitude is approximately halved. As the HRRP share sample mean is 18.0 percent, these contextual effects, while small, are not trivial. Admittedly, the contextual effects are confounded with the level-2 error, but comparing it to the within effect provides a gauge for the “strength of the selection effects” (Schunck 2014). The within effect suggests no significant difference in mean penalty share ($\beta = -0.19$, $t = -0.56$) for two hospitals that belong to the same county but serve different dual-eligible proportions, which remains unchanged by county-level adjustment due to the nature of fixed effects. Taken together, the dual-eligibility results connote meaningful differences in readmission penalties exist for similar hospitals located in different counties, but not different hospitals located in the same county. Interestingly, evidence from the fully adjusted Mundlak model supports the reverse phenomena (a within effect but not a contextual effect) for HCAHPS, both effects for Medicare inpatient days, and neither effect for percentage black patients.

Given that geography and patient population are correlated, it is unsurprising that after controlling for county characteristics, the contextual effects are no longer significant for black patient share and patient experience and are attenuated for Medicare volume and dual-eligible patient share. As the HRRP risk adjustment does not include area-level factors or geographic fixed effects, it remains unclear how such contextual effects should be addressed. Perhaps, the larger question is whether the risk adjustment methodology should account for such factors, and more nuanced, to what extent are they within a hospital’s control? Our results can hopefully inform the broader policy discussion of risk adjustment in P4P programs and provide insights on how to optimally coordinate efforts across the continuum of primary to postacute care.

Moreover, to benchmark hospitals, the HRRP employs a hierarchical generalized linear model of patients nested within hospitals. While the primary objective of this paper was different, the methodological concerns encountered would be similar. It would be insightful to know the Hausman test results for the patient-specific covariates that comprise case mix in the HRRP model. Of note, case mix index was not included here to avoid “double adjustment” as penalty amounts are in part determined by it. It is not

inconceivable, however, that certain patient conditions, such as stroke, are correlated with the hospital intercept. A report titled “Statistical Issues in Assessing Hospital Performance” highlights that “when sicker patients are admitted systematically to either better- or worse-performing facilities, then basic RE estimates are biased” and recommends “CMS augment its current model to include hospital-level attributes” (Ash et al. 2012). Although the HRRP model is a more complicated variant of random effects, with a Bayesian shrinkage estimator, its ability to produce unbiased coefficients that appropriately benchmark hospitals requires further investigation.

This analysis has certain limitations beyond those expected in observational studies. First, the hospital and community variables in these analyses are (aggregated) proxies for patient sociodemographic factors of interest that are difficult to capture elsewhere. Also, similar to Herrin et al., we consider county-level measures to capture community characteristics, but the two are not synonymous. We were also unable to capture certain constructs, such as social support and different sources of income, without considerable loss to sample size. Next, because of the limited time span, various hospital/community characteristics were averaged to mitigate noise and measurement issues. Over 25 percent of the sample were singletons, so they did not contribute to the within estimates of the analyses. As the focus of this study was on the higher-level variation, potential endogeneity issues related to the unobserved hospital level were not taken into account. Lastly, the penalty amount depends on the base diagnosis-related group payment a hospital receives. Two hospitals can receive same percentage penalty, but the one with a higher payment will obviously have more money at risk, which could not be accounted for beyond controlling for Medicare inpatient days.

Despite these limitations, this work augments the current knowledge base by elucidating hospital and community drivers of readmission penalties, while addressing methodological concerns related to the skewed outcome and hierarchical endogeneity issues. Conflicting views exist on whether and how P4P metrics should be adjusted for sociodemographic/geographic characteristics. It may hold hospitals to different standards and mask potential disparities in care (Hu, Gonsahn, and Nerenz 2014; Center for Medicare and Medicaid Services 2015; Bernheim et al. 2016); however, appropriate risk adjustment is also necessary for accurate reimbursement (James et al. 2013). Results from this study suggest that a third of the variation in readmission penalties is at the county level and significant within and contextual effects exist for various social risk factors.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix SA1: Author Matrix.

Appendix SA2: Hospital Consumer Assessment of Healthcare Providers and Systems Composite Construction.