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Effects of Medicare Reimbursement Policies on the Quality of Hospital Care

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EFFECTS OF MEDICARE REIMBURSEMENT POLICIES ON THE QUALITY OF HOSPITAL CARE

by

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ABSTRACT

This dissertation is composed of two papers related to the role of social risk factors in the Hospital Readmissions Reduction Program (HRRP). As value-based initiatives like the HRRP become more commonplace, there is growing need to understand the relationship between performance in these programs and social risk factors, such as race and poverty, which are not incorporated in the program's risk adjustment methodology. To address this gap in the literature, this dissertation specifically focuses on three areas: 1) how hospital and community factors are related to average HRRP penalties, taking the context of geography into account, 2) how hospital and community factors are related to HRRP penalties across the entire distribution, and 3) how levels and associations of these factors relate to the penalty differential between hospitals that serve low versus high proportions of dual-eligible patients.

The first paper explores whether there is regional heterogeneity in how hospital and community factors are associated to average readmission penalties. Specifically, the paper investigates the potential for differential associations between these characteristics and penalties from hospitals belonging to different contexts (i.e., counties). The second paper expands on the first by examining how hospital and community factors relate to the entire distribution of HRRP penalties, beyond the mean. In addition, it decomposes differences in readmission penalties between hospitals that serve low versus high proportions of dual-eligible patients into 1) how much can be explained by differences in

levels of social risk factors and 2) how much remains unexplained due to differences in the associations of those characteristics and readmission penalties.

Keywords: Hospital Readmissions Reduction Program, HRRP, readmissions, Medicare, pay-for-performance, social risk factors.

DEDICATION

I dedicate this dissertation to the loving memory of my father Sham Aswani and my dissertation chair Dr. Meredith Kilgore, both of whom sadly passed away during its completion. Without their encouragement, support, and inspiration, this work would not have been possible, nor as gratifying of an endeavor.

I also dedicate this to the taxpayers who helped fund this research and scholarship. Your contributions have been instrumental to my educational pursuits and professional growth; I am forever indebted and sincerely hope my future undertakings reflect the gravity of your investment.

Lastly, I dedicate this work to anyone who works tirelessly, especially in the pursuit of social justice, and who treats others, regardless of their social standing or position, with compassion and respect. Collectively, the world is a better, kinder place because it is driven by your moral compass.

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INTRODUCTION

The Patient Protection and Affordable Care Act, passed in 2010, catalyzed a paradigm shift in healthcare to prioritize value-based care over traditional, volume-based care. It launched a range of pay-for-performance (P4P) pilot programs and initiatives, such as the Hospital Readmissions Reduction Program (HRRP). The HRRP aligns Medicare reimbursement with unplanned, 30-day readmissions for select conditions. Since value is defined as quality divided by costs, the goal of the HRRP and P4P broadly is to improve care delivery through increased quality and reduced costs.[1] Despite this purported objective, there is widespread concern these policies have the potential to paradoxically worsen performance, particularly for hospitals that serve vulnerable, disadvantaged populations.[2-7] While it is conceptually desirable to link reimbursement with care delivery and quality improvement, the financial savings from such policies are only attractive if additional health care consumption is wasteful and potentially harmful.[8,9]

In the HRRP, this worry is magnified due to its limited risk adjustment methodology. Outcome measures, such as unplanned readmissions, represent the result of care and can be influenced by patient risk factors, chance events, and social determinants of health.[10] Since they are driven by factors beyond the quality of care, they must be appropriately risk adjusted. The Centers for Medicare and Medicaid Services (CMS) only adjusts readmissions for patient age, gender, and illness severity, as documented in claims the year prior to an index admission; however, it does not account for social risk factors, such as race and socioeconomic status, or clinical factors, such as disability, which may also be associated with the likelihood of readmission.[11-15]

Conflicting views exist on the most appropriate risk-adjustment methods and whether P4P metrics should account for social risk factors. Risk-adjustment could hold hospitals to different standards and mask potential disparities in care, or it could inappropriately penalize hospitals for factors beyond their control that can influence patient outcomes.[16] Recent evidence suggests HRRP penalties may disproportionately affect hospitals that operate on slim margins and serve the most vulnerable and medically complex.[2,17-20] One study, conversely, found the inclusion of Medicaid status or neighborhood income did not significantly alter readmission rates.[21] Prior studies have also shown considerable variation in readmission rates can be attributed to community characteristics, which are also excluded from the HRRP risk adjustment.[7,20,22-27] For example, more than 50% of the variation in readmissions can be explained by community characteristics such as the number and quality of nursing homes.[22]

It remains unclear, therefore, if penalized hospitals represent the delivery of subpar quality of care, or if they serve select patient phenotypes characterized by features omitted in the risk adjustment. The 21st Century Cures Act, passed in December 2016, may partly address these concerns since it requires CMS to adjust for hospital proportion of dual Medicare and Medicaid eligible patients, who are low income and typically sicker in the seventh fiscal year, FY2019, of the HRRP.[28,29] As of this writing, the penalties for FY2019 were released within the past month.

A report to Congress titled "Social Risk Factors and Performance Under Medicare's Value-Based Purchasing Programs" states "in order to properly align payments and ensure value-based purchasing programs achieve their intended goals, the relationships between social risk and performance on these programs need to be better understood."[30] As such, the overarching objective of this dissertation is to explore the role of social determinants in the first six fiscal years of the HRRP.

Background: Readmissions and the HRRP

The HRRP targets unplanned 30-day readmissions, which affect nearly 20% of Medicare discharges and result in costs of more than $15 billion annually.[31] The aging population is at an increased risk for preventable harm due to multi-morbidity and polypharmacy, which often necessitate multiple providers and transitions between care settings.[32,33] Past research has shown that the risk of readmission is associated with the quality of inpatient care, and readmissions can often be prevented by focusing on handoffs in care and discharge planning.[9,34-38] As a result, the HRRP is intended to incentivize care coordination efforts, such as post-discharge medication reconciliation and primary care follow-up.

In Medicare, a readmission is defined as any unplanned admission, to any hospital and for any cause, within 30 days of discharge from the index hospitalization. For the HRRP, an index hospitalization is identified based on the primary discharge diagnosis for select conditions. At the program's inception in FY2013, these were heart failure (HF), acute myocardial infarction (AMI), and pneumonia (PN). The set expanded to include chronic obstructive pulmonary disease (COPD) and elective total hip/knee arthroplasty (THA/TKA) in FY2015 and coronary artery bypass graft (CABG) in FY2017. Likewise, the maximum percentage a hospital's base operating diagnosis-related group (DRG) payment could be penalized increased over time. It was 1% in FY2013, 2% in FY2014, and 3% in FY2015 onward.

Overview of the Dissertation

This dissertation is composed of two papers on HRRP, each of which addresses a gap in the literature. The first paper explores how hospital and community factors are associated to readmission penalties, while taking into account the context of geography. It employs a two-level hierarchical model with correlated random effects, also known as the Mundlak correction, to account for hospitals nested within counties. The study advances the P4P literature by accounting for regional heterogeneity through fixed effects, while still estimating group (county)-invariant coefficients through random effects to better understand the context of geography on HRRP penalties.

The second paper expands on the first by examining how hospital and community factors relate to the entire distribution of HRRP penalties, beyond the mean. Since the FY2019 risk adjustment incorporates dual-eligibility, hospitals are dichotomized into two groups, low and high, depending on the fraction of dual-eligible patients they serve. The penalty differential between the two groups is decomposed into what can be explained by differences in observed sociodemographic characteristics from the part attributable to differences in the associations of those characteristics and readmission penalties. The analysis utilizes the traditional Oaxaca-Blinder decomposition in combination with unconditional quantile regression (UQR) to decompose the LDE/HDE gap at different points of the marginal HRRP penalty distribution. It contributes to the literature by identifying the counterfactual distribution of HRRP penalties that would prevail in the absence of any advantage (disadvantage) for LDE (HDE) hospitals and what factors contribute to their penalty differential.

Taken together, these papers will provide new findings about the context of geography on HRRP penalties, how hospital and community factors are related to HRRP penalties, both at the mean and across the distribution, and how levels and associations of these factors relate to the penalty differential between hospitals that serve low versus high proportions of dual-eligible patients. In conjunction, these empirical analyses aim to provide policy-relevant evidence on the role of social risk and HRRP performance.

DIFFERENTIAL IMPACTS OF HOSPITAL AND COMMUNITY FACTORS ON MEDICARE READMISSION PENALTIES

by

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Format adapted for dissertation

ABSTRACT

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.

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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

Background/Objective:

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.[1]

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) calculate 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,[2-4] most notably its ability to account for patient sorting to hospitals on the basis of unobserved health status and sociodemographic/geographic factors.[5-7] Given this, emerging literature has focused on characterizing penalized hospitals[3,8-13] and the potential for P4P programs to exacerbate disparities in health care due to their risk-adjustment methodologies.[7,14-23] In particular, studies suggest hospitals that are large and/or academic,[8,10,24] that serve the most vulnerable and medically-complex,[9,14,19,20] and that are located in communities with lack of access to care may be disproportionately penalized.[3,20] 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 used for variable creation, while later files were required for hospital demo-graphics), 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)[25], 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 excel-lent internal consistency. The final composite represents the average percent-age 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.[26] In addition to general county characteristics, we tried to capture the variety of resident clinical factors and facility characteristics linked to readmissions.[27] 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 com-petition, ranges from 0 to 1, where 0 represents perfect competition and 1 rep-resents 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 (x 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.[28,29] 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.[30,31] 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).[32] The hierarchical nature of the data and proportional outcome are well suited to the fractional probit.[33] 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 geographical proximity to one another, this independence assumption would be violated.

To test this, the intra-class 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).[34] 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 $\mathrm{cov}(X_{ij}, \mu_j) \neq 0$, 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 byMundlak.[32] The unobserved heterogeneity in the level-2 error term is modeled by the equation: $\mu_j = \gamma_{02} X_j + \nu_j$ to deconstruct what can be explained by πX_j so that the error term ν_j is now conditionally orthogonal to X_{ij} by construction.

Final equation: $y_{ij} = \gamma_{00} + \beta X_{ij} + \gamma_{01} Z_j + \gamma_{02} X_j + \varepsilon_{ij} + \nu_j$ 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.[35]

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.[35,36] 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 (be-tween 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 multi-collinearity, 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).

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.[37,38] 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 maxi-mum 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 per-cent) observations had predicted outcomes outside of the plausible bounds 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 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 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.[35]

Before the county variables were included, the random effects assumption was rejected for percentage Medicare inpatient days, percent-age 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 under-lying 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,[20] 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."[39] 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."[40] 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;[21,41,42] however, appropriate risk adjustment is also necessary for accurate reimbursement.[43] 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.

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.

Table 1: Summary Table

Hospital Characteristics (n=3,156)	Mean	SD	Min	Max
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 (n=1,504)				
Nursing Home Compare 5-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

Table 2: 2-level Random Effects Models, without Mundlak Correction

	Hospital variables		Hospital + County variables	
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 5-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.

Table 3: Mundlak Correction

	Hospital variables		Hospital + County variables	
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 5-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	3156		3156	

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.

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UNCONDITIONAL QUANTILE REGRESSION-BASED DECOMPOSITION OF READMISSION PENALTIES

by

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ABSTRACT

Purpose: As value-based care becomes more widespread, it is imperative that reimbursement and quality are appropriately aligned. To ensure this, the role of social risk factors and performance in initiatives like the Hospital Readmissions Reduction Program need to be better understood. The objective of this study, consequently, is to investigate differences in readmission penalties, both at the mean and across the distribution, between hospitals that serve low versus high proportions of dual-eligible (LDE/HDE) patients.

Methods: Unconditional quantile regression-based counterfactual decomposition is employed to "decompose" the penalty differential into 1) how much can be explained by differences in levels of social risk factors and 2) how much remains unexplained due to differences in the associations of those characteristics and readmission penalties. Since the tails provide valuable information about low and high-performing hospitals that analysis at the mean may overlook, this method allows the explained/covariate and unexplained/coefficient effects to vary across the HRRP penalty distribution.

Results: The results reveal HDE hospitals are increasingly penalized more than their LDE counterparts across the entire penalty distribution. The variables in the model explain 51.1%, 69.9%, 74.4%, and 78.9% of the penalty differential between LDE/HDE hospitals at the 25th percentile, mean, median, and 75th percentile, respectively. Percent inactive, patient experience, and percent DNR nursing home patients had the largest explanatory contributions at the mean.

Conclusion: In the hypothetical absence of any advantage for LDE hospitals and disadvantage for LDE hospitals, the HRRP penalty gap would decrease from -5.4 to -1.6 at the mean. The ability of a hospital to influence the explanatory contributors likely varies considerably, with limited leverage for percent inactive to more leverage for patient experience.

Introduction:

Pay-for-performance (P4P) has become an integral part of reform efforts designed to promote quality and efficiency in the healthcare system. A major target has been unplanned hospital readmissions, which affect 20% of Medicare discharges and cost $15 billion annually.[1] To address this, Medicare's Hospital Readmission Reduction program (HRRP), established under the Patient Protection and Affordable Care Act, is a P4P program that penalizes hospitals for excessive readmissions within 30 days of discharge for certain conditions. The HRRP provides hospitals with incentives to improve discharge planning and to coordinate care transitions to better prepare patients for release.

Previous Medicare reform efforts and legislation, such as the Prospective Payment System and the Balanced Budget Act, have led to more patients being discharged in unstable conditions and operational cutbacks on staff and quality initiatives.[2-7] The financial cut to hospitals also has the potential to exacerbate these patient outcomes, depending on how it is operationalized. Although the HRRP is designed to address the quicker-and-sicker incentives, the potential for such unintended consequences may be heightened under the HRRP due to its penalty methodology.

Previous research has shown that readmissions are related to patient and community sociodemographic factors, such as race, socioeconomic status, and access to care, but the HRRP only risk-adjusts for patient age, gender, and illness severity.[8-10] Prior studies also suggest the HRRP may disproportionately penalize certain hospitals,[11,12] particularly those characterized as safety net and serving a high proportion of dual Medicare/Medicaid-eligible patients.[5,13-17] These hospitals typically serve the most vulnerable, such as minority and low-income patients.[11,16-22] Therefore, it remains unclear if these are truly under-performing hospitals, or if the HRRP risk-adjustment is inadequate.

The future inclusion of dual-eligibility in the HRRP risk adjustment under the 21st Century Cures Act may address this concern. The act, which passed in December 2016, requires the Centers for Medicare and Medicaid Services (CMS) to adjust for hospital proportion of dual-eligible patients starting in FY 2019 of the HRRP. To offer a more nuanced understanding of the future dual-eligibility adjustment, this study explores how observed hospital and community characteristics contribute to differential readmission penalties between hospitals that serve low versus high dual-eligible (LDE/HDE) patient populations.

<u>Data Sources:</u> Data from different sources capture a range of hospital and community characteristics during the HRRP measurement period. Penalties in each FY are based on a three-year average of readmission rates. For FY 2013, the measurement period is 2008-2011, and it rolls forward by one year meaning for FY 2018, the measurement period is 2013-2016.

<u>Sample:</u> 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). Additionally, hospitals with less than 25 cases across

all HRRP conditions, which is the minimum number CMS requires to calculate an expected readmissions ratio, were omitted.

Penalty Outcome: The HRRP outcome variable was derived from the 2013-2018 CMS final rule tables. We construct an aggregate outcome, the “HRRP penalty share,” to address missing data and the increasing upper bounds of the readmissions penalty over time. The theoretical maximum penalty for HRRP was 15% during this timeframe (1% in FY2013, 2% in FY2014, and then 3% from FY2015 onward). Collapsing the readmission penalty into a sum or an average over this timeframe could mask hospital performance since missing data would essentially be treated as a zero. To address this issue, the HRRP penalty was summed across all six years and divided by the theoretical hospital-specific maximum potential HRRP penalty to yield a percent. The motivation for this, rather a sum or an average, is illustrated in the Appendix (Figure A.1).

Hospital Characteristics: From the 2012 AHA survey, 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), hospital size (<200 = small, 200-399 = medium, or >400 = large), and ownership type (public, private not-for-profit, or private for-profit) were obtained. The survey also provides information related skilled nursing availability 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. A missing indicator was also created since almost a quarter of the skilled nursing data was missing.

From the 2008-2012 CMS impact files, a five-year average of percent Medicare inpatient days was derived. The uncompensated care per claim amount came from the FY 2015 file, which is based on a three-year average from FY 2010-2013. From the 2008-201 5% sample of Medicare inpatient claims, hospital averages of percent black and dual-eligible patients were constructed. The percent dual-eligible was used to split the groups into LDE and HDE hospitals using the sample median of dual-eligible patients, 31.4%, as the cutoff.

Lastly, from the 2009-2012 Hospital Compare data, a four-year average composite of Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey patient experience measures was derived. The percent who replied to the most favorable option on each question was used. For example, the percent who replied always to "… did nurses listen carefully to you?" or the percent who replied yes to "Would you recommend this hospital to your friends and family?" The Cronbach's 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 top-box percent value across all HCAHPS questions by hospital (Appendix, Table A.1).

<u>Community Characteristics:</u> Federal Information Processing Standard (FIPS) codes were used to merge geographical-level data.

From the 2009-2012 Nursing Home Compare data, 5-star nursing home ratings were derived by county (higher scores are better). From the 2010-2012 Long-term Care Focus, variables related to nursing home quality (registered nurses to total nurses ratio, direct care hours per resident day), market characteristics (Herfindahl-Hirschman index, home health agencies/1,000 elderly), and resident characteristics (acuity index and percent do-not-resuscitate) came pre-aggregated at the county level.

From the 2010 Health Inequity Data, variables related to socioeconomic status (mean household income/$10,000) and geographical variations in health care (percent of Medicare enrollees with at least one primary care visit) were obtained.

Population health variables came from the 2012 County Health Rankings, produced by the University of Wisconsin Population Health Institute and the Robert Wood Johnson Foundation.[23] These include the percent of smokers, obese, inactive, diabetics with an annual hemoglobin screening, and high school graduates, as well as an income ratio, which represents the fraction of household income at the 80th percentile to that at the 20th percentile (higher ratio indicates greater inequality).

From the 2012 ARF, per-capita population, general practitioners, and specialists were obtained. The latter two were used to construct a GP:specialist ratio, where specialist is the sum of medical, surgical, and other specialties. For counties with no GPs or specialists, 1 was added before calculating the ratio to prevent missing values.

Methods:

There are many statistical approaches to health disparities, but the most common is to test if an indicator for the characteristic, such as HDE hospital status, is significant in a regression. Rather than the typical "indicator" approach, the analytic strategy employed here is a counterfactual decomposition approach. Decomposition methods are widespread in the labor economics literature, where they are often applied to study disparities in wages between an "advantaged" group (i.e., males) and a "disadvantaged" group (i.e., females), parallel to LDE and HDE hospitals here. These methods have started to gain traction in the health disparities literature more recently.

The standard Oaxaca-Blinder decomposition (OBD), which uses ordinary least squares (OLS) regression, is appropriate for decomposing mean penalty differences.[24] The widening gap in HRRP share between LDE and HDE hospitals across the distribution (Figure 1), underscores the importance of examining differences beyond the mean. Percentiles of the distribution are calculated separately for the two groups of hospitals, and at each percentile, the HRRP share of HDE hospitals is subtracted from the corresponding percentile value of LDE hospitals. For instance, the average HRRP share for LDE and HDE hospitals is 15.2% and 20.6%, respectively. The red line in Figure 1 denotes the mean gap of -5.4% in HRRP share between the two groups, which occurs at the 42nd percentile. The highest gap of 11.7% occurs at the 97th percentile, where the 97th percentile of the HRRP share for LDE and HDE hospitals is 53.8% and 65.5%, correspondingly. To address this, we employed the unconditional quantile regression (UQR) decomposition variant developed by Firpo et al.[25] Of note, the word unconditional here is not synonymous with unadjusted. It refers to the outcome and signifies that the coefficients are estimated at certain quantiles of the marginal HRRP penalty share distribution.

Oaxaca-Blinder Decomposition: The readmission penalty gap between high and low serving dual-eligible patient hospitals can be written as follows:

$$Y_{LDE} = \beta X_{LDE} + \varepsilon_{LDE}$$

$$Y_{HDE} = \beta X_{HDE} + \varepsilon_{HDE}$$

$$(\overline{Y_{LDE}} - \overline{Y_{HDE}}) = \Delta\overline{Y} = \overline{X}_{LDE}\hat{\beta}_{LDE} - \overline{X}_{HDE}\hat{\beta}_{HDE}$$

where $\hat{\beta}_{LDE}$ and $\hat{\beta}_{HDE}$ are the estimated OLS coefficients from the LDE and HDE hospitals, respectively. With some algebraic manipulation using OLS coefficients from the pooled sample that includes the binary LDE/HDE indicator and all the other hospital and community variables of interest, the difference can be decomposed as follows:

$$\Delta\overline{Y} = \sum\hat{\beta}_P[\overline{X}_{LDE} - \overline{X}_{HDE}] + \sum\overline{X}_{LDE}(\hat{\beta}_{LDE} - \beta_P) + \sum\overline{X}_{HDE}(\hat{\beta}_P - \hat{\beta}_{HDE})$$

The equation above parses out what part of the gap is due to average characteristics ($\overline{X}$) and the associations of those characteristics ($\hat{\beta}$) with readmission penalties. Since dual-eligible patient population was dichotomized by the authors to create groups (below median vs. above median), a group-neutral, pooled reference approach was chosen.[26,27] The reference group should represent a non-discriminatory state, and a-priori, both cases could be made: LDE hospitals receive preferential treatment or HDE hospitals receive discriminatory treatment due to the HRRP risk-adjustment methodology.

The first term of the equation, $\sum\hat{\beta}_P[\overline{X}_{LDE} - \overline{X}_{HDE}]$, also known as the endowment effect (i.e. explained), represents the fraction of the penalty share gap due to differences in hospital and community characteristics between groups. The second and third terms of the equation, $\sum\overline{X}_{LDE}(\hat{\beta}_{LDE} - \hat{\beta}_{P})$ and $\sum\overline{X}_{HDE}(\hat{\beta}_{P} - \hat{\beta}_{HDE})$, also known together as the structural effect (i.e. unexplained), capture the portion of the penalty gap due to deviations in LDE and HDE hospitals from the pooled benchmark. For a more nuanced breakdown, the decomposition can be further separated into variable-specific contributions to the overall penalty share gap.

Unconditional Quantile Decomposition: The OBD can be expanded, as outlined by Firpo et al, using unconditional quantile regression.[25] For each estimated quantile, an OBD can be run using the quantile-specific estimates obtained from the recentered influence function (RIF). In OLS, the conditional and unconditional/marginal expectation of $\hat{\beta}$ both equal β due to the law of iterated expectations ($E[Y_i|X_i] = E[Y_i]$). An obstacle to quantile regression is that this sample property does not hold $Q\tau[Y_i|X_i] \neq Q\tau[Y_i]$ for any quantile τ. Firpo et. al outline a workaround to estimation via the RIF.

The convenient result of this method is $E[RIF(Y, Q\tau|X)] = X\beta$, where β represents the marginal effect of x on the τth quantile, meaning the coefficients represent ceteris paribus associations at τth quantile of the unconditional HRRP share distribution. Consequently, the OBD can similarly be applied at any given quantile by replacing Y with the estimated quantile-specific RIF estimates (Appendix, Section A.1). In short, the unconditional quantile decomposition is carried out via the standard OBD, which allows for a comparable interpretation to the OLS case at the mean.

The UQR decomposition provides a way to estimate associations of hospital/community factors to assess if and how their influence changes across the HRRP share distribution. As in the case of the OBD, the interpretation of the explained and unexplained components remains unchanged. Both of these methods decompose the differences in readmission penalties between LDE and HDE hospitals into an "explained" and an "unexplained" component, either at the mean or across the entire penalty share distribution, respectively.

Conditional Quantile Regression (CQR) vs. Unconditional Quantile Regression (UQR):

To answer the hypothetical question what would happen to the HRRP penalty share if LDE (HDE) hospitals had the same distribution of hospital/community characteristics as HDE (LDE) dual serving hospitals, the characteristics one group is "swapped" to have the characteristics of the other group. In conditional quantile regression (CQR), however, a hospital may not remain in the same quantile during this process.

CQR can also only capture within-group dispersion at certain parts of the distribution, while UQR can capture both within- and between-group dispersion.[28] CQR captures dispersion within similar hospitals (i.e.; same covariates), who only differ on the covariate of interest. Unlike UQR, however, CQR cannot capture how changes in a covariate of interest relate to changes in the overall dispersion (i.e.; increase or decrease in the HRRP share differential between LDE and HDE hospitals).

UQR can address both of these issues, quantile order preservation and between-group dispersion since it provides estimates on the unconditional (marginal) distribution; therefore, UQR and thus its resulting decomposition has a more generalizable interpretation since its policy implications relate to the overall distribution.[29]

The models were estimated using the *oaxaca* and *rifreg* commands with county-clustered standard errors in STATA, version 14.1 (College Station, TX).[25,26]

Results:

Sample Characteristics: The final analytic sample after merging all the various datasets contained 3,043 hospitals nested in 1,398 counties. Descriptive statistics are provided in Table 1. Under the HRRP, the mean summed readmissions penalty from FY 2013-2018 was 2.6% overall, 2.2% for LDE hospitals, and 3.1% for HDE hospitals. In comparison, the average HRRP share was 17.9%, 15.2%, and 20.6%, respectively.

Compared to their LDE counterparts, HDE hospitals were less likely to be academic, larger in size, and private not-for-profit status, but more likely to receive higher uncompensated care payments and have a larger Black patient share. In addition, HDE hospitals were more likely to be located in counties with lower nursing home RN:nurses ratios, more monopolistic nursing home competition, and fewer DNR nursing home residents.

Regression Results: Table 2 displays the coefficients from a baseline ordinary least squares model (Column 1) and the RIFs for quantiles $\tau = 0.25$, 0.5, and 0.75 (Columns 2-4), stratified by LDE and HDE status. A graphical representation of the RIF coefficients is presented in Figures 3a and 3b to illustrate the heterogeneity in hospital and community characteristics across the HRRP penalty share distribution between LDE and HDE hospitals.

Gradient trends emerge across the HRRP share distribution for many characteristics. Percent Medicare days, HCAHPS, and percent inactive are significant for both groups, but the HDE coefficients are almost twice the magnitude of the LDE coefficients across the distribution. The other results seem to significantly differ by group. Small size and uncompensated care payments are associated with readmission penalties for LDE hospitals, while medium and large size, HHAs/1,000 elderly, and income ratio are associated with readmission penalties for HDE hospitals

Decomposition Results: The results of the OBD and RIF decompositions are presented in Table 3. HDE hospitals consistently had a higher penalty share so the difference, calculated as LDE hospitals minus HDE hospitals, was significant, negative, and increasing across the distribution.

The mean HRRP share gap was -5.4%. The explained contribution of the gap was 69.9% (-3.76/-5.38), which suggests almost two-thirds of that differential between HDE/LDE hospitals can be accounted for by mean differences in the observed factors. Similarly, 51.1% (-2.10/-4.11), 74.4% (-4.18/-5.62), and 78.9% (-5.53/-7.01) of the gap in the 25th, 50th, and 75th RIF decompositions, respectively, can be explained by collective differences in the covariates. A graph of the unexplained and explained contributions, relative to the total gap, across the entire distribution can be found in the Appendix (Figure A.2). The unexplained fraction reflects differences in in how these covariates are associated with the HRRP share. It represents how much of the penalty differential would theoretically remain even if LDE/HDE hospitals had the same variable means included in the model.

Furthermore, covariate contributions can also be summed into various permutations to better understand the decomposition breakdown. For example, of the total explained, the hospital characteristics represent 25.0% (-0.94/-3.76), and the community characteristics represent 75.0% (-2.82/-3.76) for the OBD decomposition.

Similar trends held for all of the RIF decompositions, with community characteristics having a larger explanatory role in aggregate, compared to hospital characteristics.

Percent inactive was the largest contributor to the total explained portion, regardless of specification. It accounted for almost half of the HRRP share gap between HDE and LDE hospitals (OBD: -2.43/-5.38 = 45.2%). The HCAHPS composite (OBD: -1.07/-5.38 = 19.97%) and percent DNR nursing home residents (OBD: -1.07/-5.38 = 19.88%) were the second and third largest contributors, respectively, regardless of model specification, although their explanatory powers are virtually tied at the mean and 75th percentile. Since the contributions of all of these variables are negative, as is the HRRP share gap, they disfavor HDE hospitals and help explain the penalty differential. Thus, increases in these variables would further increase the gap in HRRP share between LDE/HDE hospitals. In contrast, positive contributions from characteristics such as uncompensated care payments and GP:specialist ratio favor HDE hospitals; hence, increases in these variables would decrease the gap. The same interpretation is true for the unexplained part, except now the results pertain to differences in associations rather than differences in characteristics.

Discussion:

In this study, we explore whether hospital and community differences in demographics, social risk factors, and health care system characteristics were associated with observed differences in readmission penalties between hospitals that serve LDE vs. HDE patient populations. We decompose differences in readmission penalties, both at the mean and across the distribution, to isolate the part of the penalty differential which can be explained by differences observed in levels of these characteristics from the part attributable to differences in the associations of these characteristics with readmission penalties.

The results reveal HDE hospitals are penalized at higher proportions than their LDE counterparts. It's particularly noteworthy that variables with similar means across the two groups, such as 5-star nursing home rating and income ratio, had markedly different associations across the outcome distribution. This suggests that comparable attributes result in different associations with the HRRP penalty share for LDE hospitals versus HDE hospitals.

The explained portion of the decomposition represents what part of the gap is attributable to differences in the observed levels of hospital and county characteristics between LDE/HDE hospitals. The variables in the model explain 51.1%, 69.9%, 74.4%, and 78.9% of the penalty differential between LDE/HDE hospitals at the 25th percentile, mean, median, and 75th percentile, respectively. While the percentages explained do not radically change beyond the mean, since both the total explained and the penalty share difference increase somewhat proportionately subsequently, there is still evidence of gradient effects. In contrast, the remaining unexplained portion represents the fraction of the HRRP penalty share differential (OBD = -1.62/-5.38 = 30.1%) that would remain, even in the absence of any advantage for LDE hospitals and disadvantage for LDE hospitals, relative to the pooled structure.

Characteristics such as patient experience, percent DNR nursing home patients, and percent inactive exhibit increasing contributions across the distribution, while other characteristics such as income ratio, percent diabetics screened, and GP:specialist ratio are only significant at one tail of the distribution. The latter results highlight the policy relevance of looking beyond the mean and employing UQR. An intervention to ensure all diabetic Medicare enrollees receive an annual hemoglobin HbA1c test, for example, is best targeted at hospitals with an HRRP share at the median or above. Using CQR, the median may change depending upon observed characteristics of the hospitals and where they are located.

In aggregate, county characteristics explained a larger fraction of the HRRP share gap across the entire distribution versus hospital characteristics. Percent inactive, the HCAHPS composite, and percent DNR nursing home residents had the greatest explanatory contributions. Overall, they explained 85.1% of the total gap (-4.57/-5.38) at the mean. Public hospital designation, uncompensated care payments, percent diabetics screened, and GP:specialist ratio were also significant in various specifications but had positive signs, which suggests these characteristics curbed the penalty differential from being even larger than it would have been otherwise.

To expound, the explained contribution of a variable is the product of the β from the pooled equation and the difference between average values of a variable for LDE and HDE hospitals: $\hat{\beta}_{\mathrm{P}}[\overline{\mathrm{X}}_{\mathrm{LDE}} - \overline{\mathrm{X}}_{\mathrm{HDE}}]$. As such, a positive (negative) contribution can only occur when both the sign of the β and Δx are the same (opposite). The same logic extends to the unexplained portion, except now the contribution relates to differences in associations between characteristics, rather than differences in levels of characteristics. The two terms of the unexplained component, $\sum\overline{\mathrm{X}}_{\mathrm{LDE}}(\hat{\beta}_{\mathrm{LDE}} - \beta_{\mathrm{P}}) + \sum\overline{\mathrm{X}}_{\mathrm{HDE}}(\hat{\beta}_{\mathrm{P}} - \hat{\beta}_{\mathrm{HDE}})$, highlight whether each group has an advantage or disadvantage compared to the pooled benchmark.

Percent inactive has negative explained and unexplained contributions, which both favor LDE hospitals, because they tend to be located in counties with fewer inactive residents, and they have a relatively smaller positive association ($\overline{X}_{LDE}$ = 22.5, $\overline{X}_{HDE}$ = 25.7, $\hat{\beta}_{P}$ = 0.75). Collectively, this reveals LDE hospitals not only have less of an unfavorable characteristic, but the association with HRRP penalties is also attenuated. Conversely, for HCAHPS and percent DNR nursing home residents (HCAHPS: $\overline{X}_{LDE}$ = 70.2, $\overline{X}_{HDE}$ = 67.8, $\hat{\beta}_{P}$ =-0.46; DNR: $\overline{X}_{LDE}$ = 57.1, $\overline{X}_{HDE}$ = 51.2, $\hat{\beta}_{P}$ =-0.18), LDE hospitals have a negative explained and a positive unexplained contribution. These characteristics are concentrated in LDE hospitals; however, they have larger, negative associations for HDE hospitals, which suggest an unexplained advantage for HDE hospitals that is not being leveraged.

Furthermore, almost half of the penalty differential is attributed to percent inactive, which unsurprisingly is highly correlated with percent obese (Pearson correlation = 0.76); however, they both had variance inflation factors less than 5, which does not signal a serious multi-collinearity problem as values 10 or higher would. In the fully adjusted model with the dual-eligibility group indicator (Table 1), percent inactive (β=0.75, $p<0.001$) is positive and significantly associated with HRRP share, while percent obese (β=-0.19, $p<0.22$) is not significant. In univariate regressions with either percent inactive (not shown: β=0.76, $p<0.001$, R^2=0.06) or percent obese (not shown: β=0.42, $p<0.001$, R^2=0.01) alone, both coefficients are positive and significant; however, when the two are combined in the same model, the percent obese coefficient sign flips from positive to negative. An interaction between the two variables was not significant (p=0.69). Collectively, these results seem to align with the ‘obesity paradox’ that being overweight may be “neutral or beneficial” in the geriatric population, which is why “physical fitness may be a more useful measure … of health risk in obese older adults.”[30]

Unlike a typical OBD in labor economics, where the explained portion can highlight targets to equalize between groups, and the unexplained portion can highlight possible discrimination, the explained portion here also captures potential sources of disparate readmission penalties between LDE/HDE hospitals. None of the variables in our model, which explain about three-quarters of the LDE/HDE penalty share differential, are included in the HRRP risk adjustment methodology; however, this doesn’t necessarily imply any of them should be incorporated either. It is plausible that the penalty gap signifies that the underlying quality of care in HDE hospitals is lower than that of their counterparts and accounting for such factors may inappropriately enable HDE hospitals to provide inferior care. On the other hand, a hospital’s ability to influence the physical activity and income of its patient population is likely limited in scope, particularly since these social determinants are challenging targets even for policy interventions. Conversely, factors such as patient experience and, to a lesser extent, GP:specialist ratio and percent nursing home DNR residents may be within a hospital’s control. Moreover, they provide insights on how to strategically invest resources and coordinate care.

The unexplained portion should be interpreted with caution, despite the illustrations given above. It captures a combination of omitted variables, systematic measurement error, and lastly, the potential for variations – which may be disparities – that contribute to the penalty gap. Despite these caveats, it is worthwhile to speculate on the latent issues that may contribute to the unexplained portion of the gap. For example, evidence suggests dual-eligible patients have higher survival rates than their Medicare-only counterparts, receive lower quality and under-provision of preventative and post-acute care, and experience functional limitations to due to unmet disability support needs.[31-37] These differences in care may contribute to increased obstacles for HDE hospitals, since the readmission potential for this vulnerable population is further compounded by increased interactions with the health care system, which are potentially substandard in quality and fragmented.

Likewise, it is difficult to parse out if the greatest explanatory factors (i.e. percent inactive, patient experience, and percent DNR) are proxies of underlying health status above and beyond what the HRRP takes into account or if they represent true modifiable risk factors on a causal pathway of readmissions. Regardless of which option is more probable, they do suggest systematic differences related to disease burden, how care delivery resonates with patients, and the propensity to preemptively pursue advanced planning versus potentially aggressive end-of-life care exist; moreover, these differences manifest in disparate readmission penalties between LDE/HDE hospitals. One underlying goal of the HRRP is to incentivize care coordination from primary to post-acute. It remains unclear if and how factors beyond any provider's control on the care continuum, such as how a patient's religion or social support may factor into their decision-making about resuscitation status, can and should be addressed?

These results should be interpreted in the context of several limitations. First, the LDE/HDE group dichotomy using the sample median of percent dual-eligible of patients is an arbitrary cutoff. Moreover, it's possible the 5% sample of inpatient Medicare claims, which is a simple random sample, may not adequately reflect the percent dual-eligible population a hospital serves, although we tried to mitigate this by using a five-year average; therefore, the directionality of many associations is unclear, since patient experience could be both predictive of or due to readmissions as an example. Second, the unexplained portion of the decomposition captures not only potential inequality between LDE/HDE hospitals, but also unobserved differences that the model could not take into account. Next, the summation of readmission penalties across six FYs has the potential to mask temporal trends or variations. We chose not to address the skewed nature of the penalty outcome since estimates on a transformed scale, such as log, are less policy relevant.[38] In addition, parameter estimates are still consistent if the normality assumption of the residuals is violated in larger samples. Next, decompositions are sensitive to the choice of reference group; however our results were not sensitive to changing the reference group to HDE hospitals or LDE hospitals instead of the pooled reference. Finally, the HRRP penalty depends on the base diagnosis-related group payment a hospital receives. Two hospitals can receive same percent penalty, yet the one with a higher payment will have more money at risk. We are unable to account for this beyond the crude approach of controlling for share of Medicare inpatient days as a proxy for Medicare volume.

Despite these limitations, this study augments the readmissions literature by elucidating hospital and community factors that account for almost 75% of the differential HRRP penalties between LDE/HDE hospitals (-3.8/-5.4). Further investigation is warranted to determine the causal relationship between social determinants and readmissions, particularly since community characteristics accounted for three-quarters of the explained contribution (-2.8/-3.8). To our knowledge, it is the first study to employ a decomposition method, in addition to its quantile regression variant, in the context of readmission penalties. The results reveal that the gap between HDE hospitals and their LDE counterparts widens across the penalty distribution, which suggest the recent inclusion of dual-eligibility in the HRRP risk adjustment is merited. In addition, the social risk factors have heterogeneous effects across the penalty distribution, which provide policy-relevant insights about low and high-performing hospitals that analysis at the mean would fail to capture.

Figure 1: HRRP penalty share distribution: raw gap (blue line) vs. the mean gap (red line) between low vs. high dual-eligible serving hospitals.

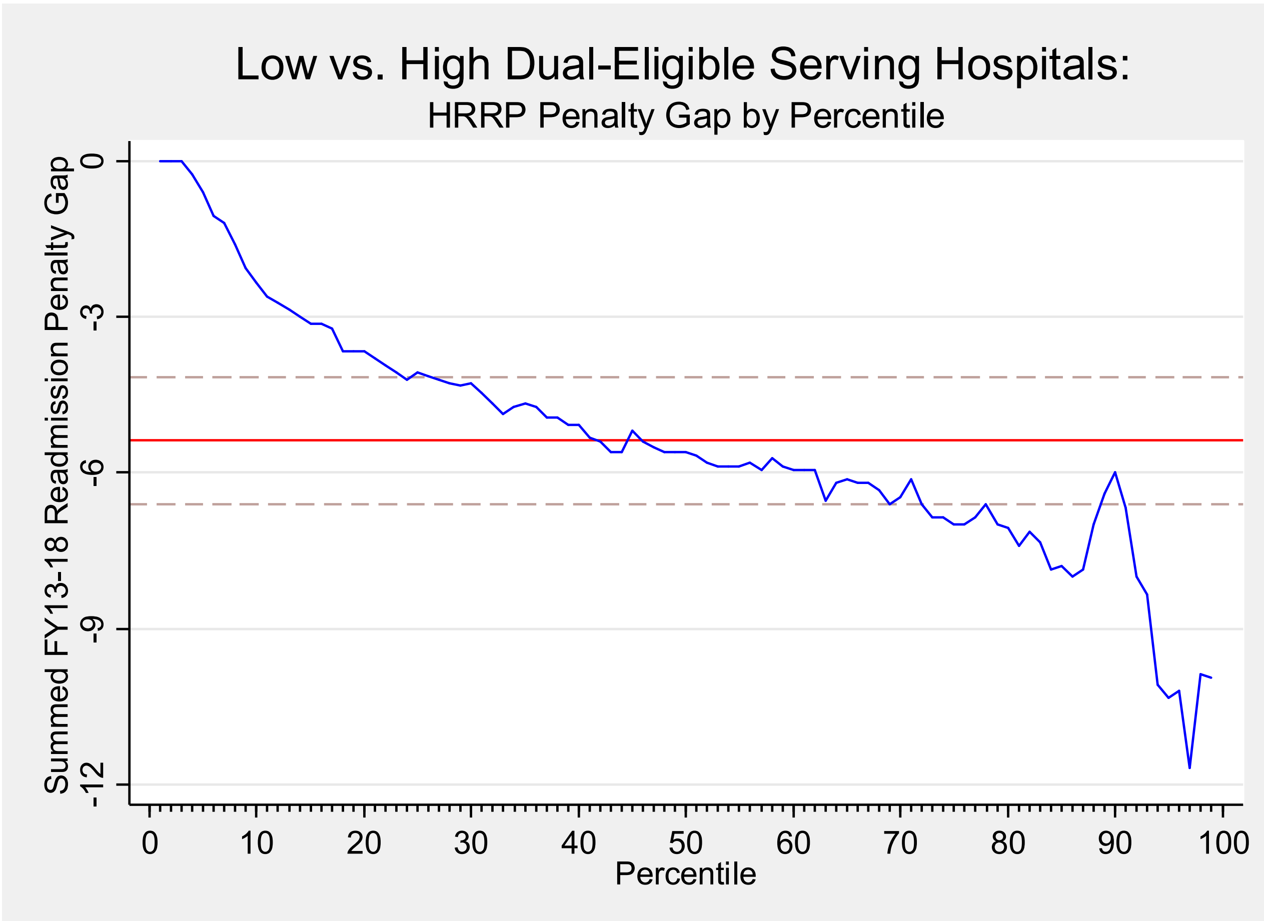

Table 1: Descriptive statistics for the full sample and stratified by low dual-eligible (LDE) hospitals and high dual-eligible (HDE) hospitals. Group classification was determined by whether a hospital's % dual-eligible patient share was below or above the sample median of % dual-eligible patients.

	Full Sample (n = 3043)				LDE Hospitals (n = 1522)	HDE Hospitals (n=1521)
	Mean	SD	Min	Max	Mean	Mean
FY13-18 summed HRRP % penalty	2.64	2.56	0.00	15.00	2.24	3.05
HRRP share	17.87	17.37	0.00	100.00	15.19	20.56
% Dual-eligible patients (used to create groups)	33.22	16.11	0.00	96.08	21.01	45.44
Teaching (vs. not)	0.34	0.47	0.00	1.00	0.38	0.31
Medium (200-400 beds, vs. small < 200 beds)	0.25	0.43	0.00	1.00	0.27	0.22
Large (>400 beds, vs. small < 200 beds)	0.11	0.31	0.00	1.00	0.12	0.10
Private, not-for-profit (vs. public hospital)	0.63	0.48	0.00	1.00	0.69	0.57
Private, for-profit (vs. public hospital)	0.24	0.43	0.00	1.00	0.23	0.25
Uncompensated care payments/$1,000	0.93	7.62	0.00	399.38	0.51	1.35
% Medicare inpatient days	46.58	14.68	0.06	88.38	45.77	47.40
% Black patient share	11.87	16.22	0.00	98.57	6.78	16.97
HCAHPS composite	68.98	5.79	41.92	94.13	70.15	67.81
Hospital skilled nursing availability – yes (vs. no)	0.31	0.46	0.00	1.00	0.33	0.29
Hospital skilled nursing availability – missing (vs. no)	0.16	0.37	0.00	1.00	0.14	0.19
Nursing Home Compare 5-star rating	29.33	5.65	10.00	50.00	29.73	28.93
Registered nurses : nurses ratio	31.96	13.70	0.00	91.03	34.48	29.44
Direct care hours per resident day	3.69	0.54	2.17	11.55	3.72	3.65
Herfindahl Index - nursing home competition	18.16	21.09	0.17	100.00	15.59	20.74
Nursing home acuity index	11.69	0.81	6.21	16.66	11.60	11.77
% DNR residents	54.14	16.39	12.51	94.27	57.05	51.22
Home health agencies (HHAs)/1,000 elderly	0.29	0.32	0.00	3.42	0.27	0.31
Mean household income per $10,000	3.78	8.88	1.56	7.79	4.05	3.52
% Medicare enrollees with >= 1 primary care visit	78.94	5.40	50.82	95.67	79.11	78.76
% smokers	18.88	5.28	3.10	49.20	17.85	19.90
% obese	28.51	4.88	13.20	44.10	27.51	29.51
% inactive	24.08	5.54	9.70	42.70	22.47	25.70
% diabetes screening	84.33	4.34	26.68	94.51	84.94	83.73
% high school graduates	81.14	8.36	28.94	100.00	81.64	80.63
Income ratio (80:20 inequality percentile ratio)	4.72	0.70	2.95	8.63	4.55	4.90
GP:specialists ratio	0.03	0.10	0.00	3.00	0.02	0.05
Population/100,000	8.82	17.63	0.09	98.89	6.75	10.89

Table 2: Ordinary least squares (OLS) and recentered influence function (RIF) regressions, stratified by low dual-eligible (LDE) hospitals and high dual-eligible (HDE) hospitals. Group classification was determined by whether a hospital's % dual-eligible patient share was below or above the sample median of % dual-eligible patients.

LDE Hospitals (n=1522) HDE Hospitals (n=1521)	OLS Pooled	OLS - LDE	OLS – HDE	RIF 25th - LDE	RIF 25th - HDE	RIF 50th - LDE	RIF 50th - HDE	RIF 75th - LDE	RIF 75th - HDE
HDE hospital (vs. LDE hospital)	1.62*								
Teaching (vs. not)	-1.64*	-1.88*	-0.83	0.45	0.41	-1.85	-0.32	-2.51	-1.03
Medium (200-400 beds, vs. small < 200 beds)	0.79	-0.58	3.34*	-0.7	2.13*	-1.09	4.47***	-0.67	3.38
Large (>400 beds, vs. small < 200 beds)	0.69	-0.73	3.31*	-0.14	3.49*	-1.48	3.62	-1.17	3.45
Private, not-for-profit (vs. public hospital)	2.24*	-0.16	3.59**	-1.15	1.3	-0.11	2.48	0.71	5.51**
Private, for-profit (vs. public hospital)	4.31***	3.3	3.48**	-1.77	2.01	3.13	3.40*	6.99*	7.16**
Uncompensated care payments/$1,000	-0.04	-0.15**	-0.02	-0.12*	-0.06**	-0.14**	-0.02	-0.16*	0
% Medicare inpatient days	0.18***	0.15***	0.26***	0.09***	0.20***	0.21***	0.27***	0.24***	0.37***
% Black patient share	-0.03	-0.06	-0.04	-0.10**	-0.02	-0.04	-0.02	-0.08	0.01
HCAHPS composite	-0.46***	-0.38***	-0.68***	-0.44***	-0.47***	-0.61***	-0.72***	-0.55***	-0.88***
Hospital skilled nursing availability – yes (vs. no)	-0.05	1.23	-0.98	-0.31	-0.07	-0.17	-1.74	3.14	-1.94
Hospital skilled nursing availability – missing (vs. no)	1.09	1.09	0.75	0.68	0.55	-0.55	-0.25	3.45	2.93
Nursing Home Compare 5-star rating	-0.07	0	-0.14	0	0	0.09	-0.11	-0.01	-0.14
Registered nurses : nurses ratio	0.03	-0.07	0.13*	-0.06*	0.02	-0.06	0.05	-0.04	0.20**
Direct care hours per resident day	-0.91	-0.88	-0.6	-0.68	0.47	-1.14	0.15	-1.61	-2.65*
Herfindahl Index - nursing home competition	0.05*	0.04	0.05	0.03	0.01	0.05	0.01	0.09	0.03
Nursing home acuity index	0.52	0.99	0.58	0.19	0.32	1.27	0.27	2.06	1.28
% DNR residents	-0.18***	-0.17***	-0.19***	-0.09***	-0.08*	-0.15***	-0.16***	-0.26***	-0.22**
Home health agencies (HHAs)/1,000 elderly	-2.67*	-0.53	-4.41**	0.43	-1.65	-0.59	-7.10***	-2.31	-6.14**
Mean household income	0.90	1.01	0.44	0.91*	1.52**	1.33	0.02	1.85	0.31
% Medicare enrollees with >= 1 primary care visit	-0.28**	-0.29*	-0.29*	-0.01	-0.08	-0.17	-0.25	-0.68***	-0.41
% smokers	0.10	0.15	0.12	0.02	-0.07	0.19	0.04	0.14	0.16
% obese	-0.19	-0.17	-0.11	0.02	0	-0.1	-0.04	-0.12	-0.14
% inactive	0.75***	0.43*	0.94***	0.18	0.56***	0.47**	0.82***	0.76*	1.21***
% diabetes screening	0.21**	0.30*	0.12	0.02	0.02	0.09	0.22*	0.47*	0.38*
% high school graduates	0.10*	0.1	0.14*	0	0	0.14*	0.12	0.18	0.11
Income ratio (80:20 inequality percentile ratio)	1.52*	-0.05	2.78**	-0.26	1.52**	0.28	2.97***	-0.08	3.61*
GP:specialists ratio	-10.29**	-25.9	-8.83*	5.79	-1.79	-41.79*	-7.93*	-47.85	-9.19
Population/100,000	-0.05	-0.04	-0.04	0	-0.03	-0.03	-0.03	-0.11	-0.05
_cons	17.91	17.23	21.39	30.05**	4.21	18.33	14.18	23.75	15.65
R^2	0.17	0.13	0.21	0.14	0.13	0.142	0.16	0.10	0.13
adj. R^2	0.16	0.11	0.20	0.13	0.11	0.126	0.14	0.085	0.11

Figure 2: Recentered influence function (RIF) hospital coefficients

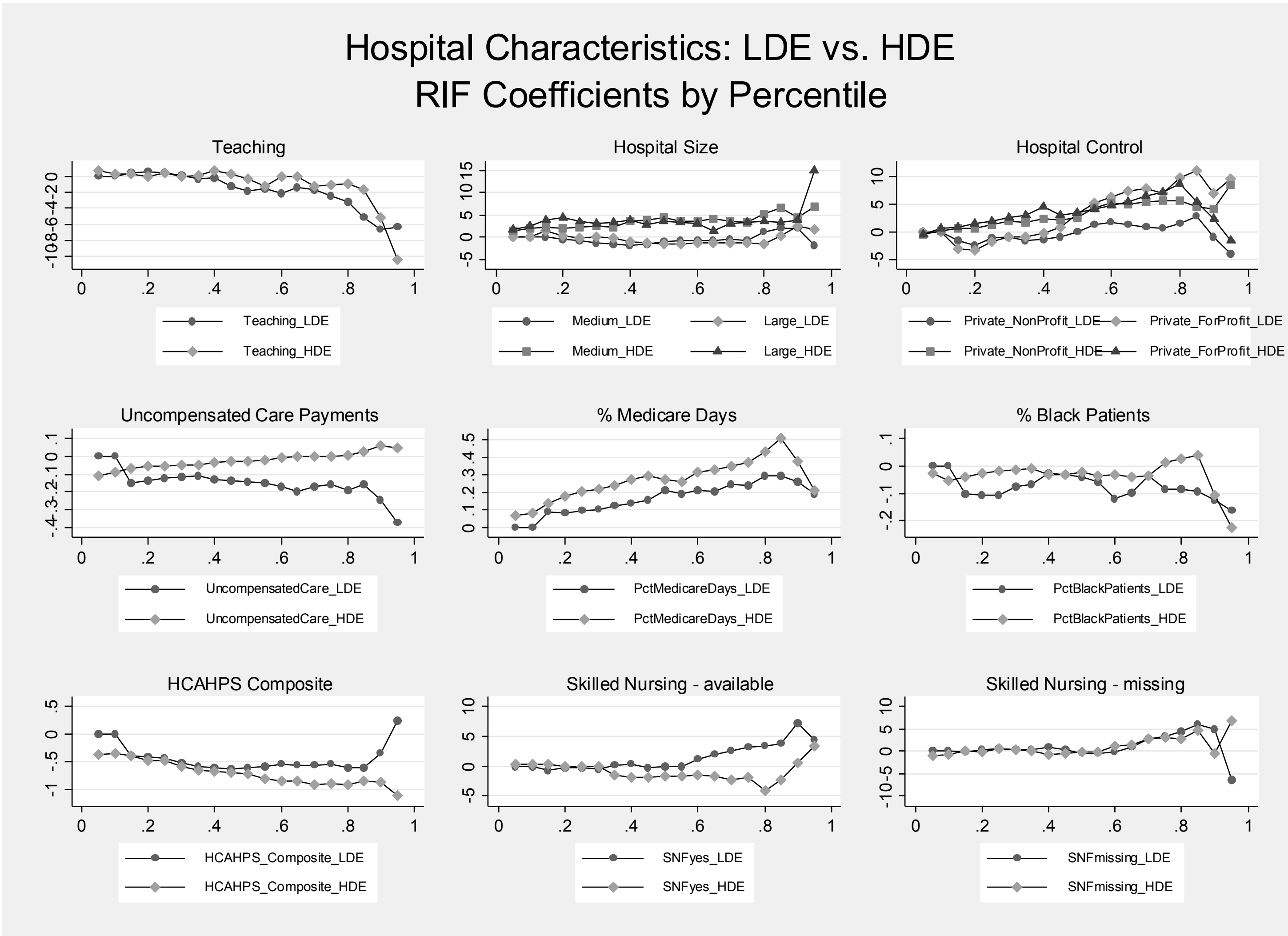

Figure 3a: Recentered influence function (RIF) county coefficients

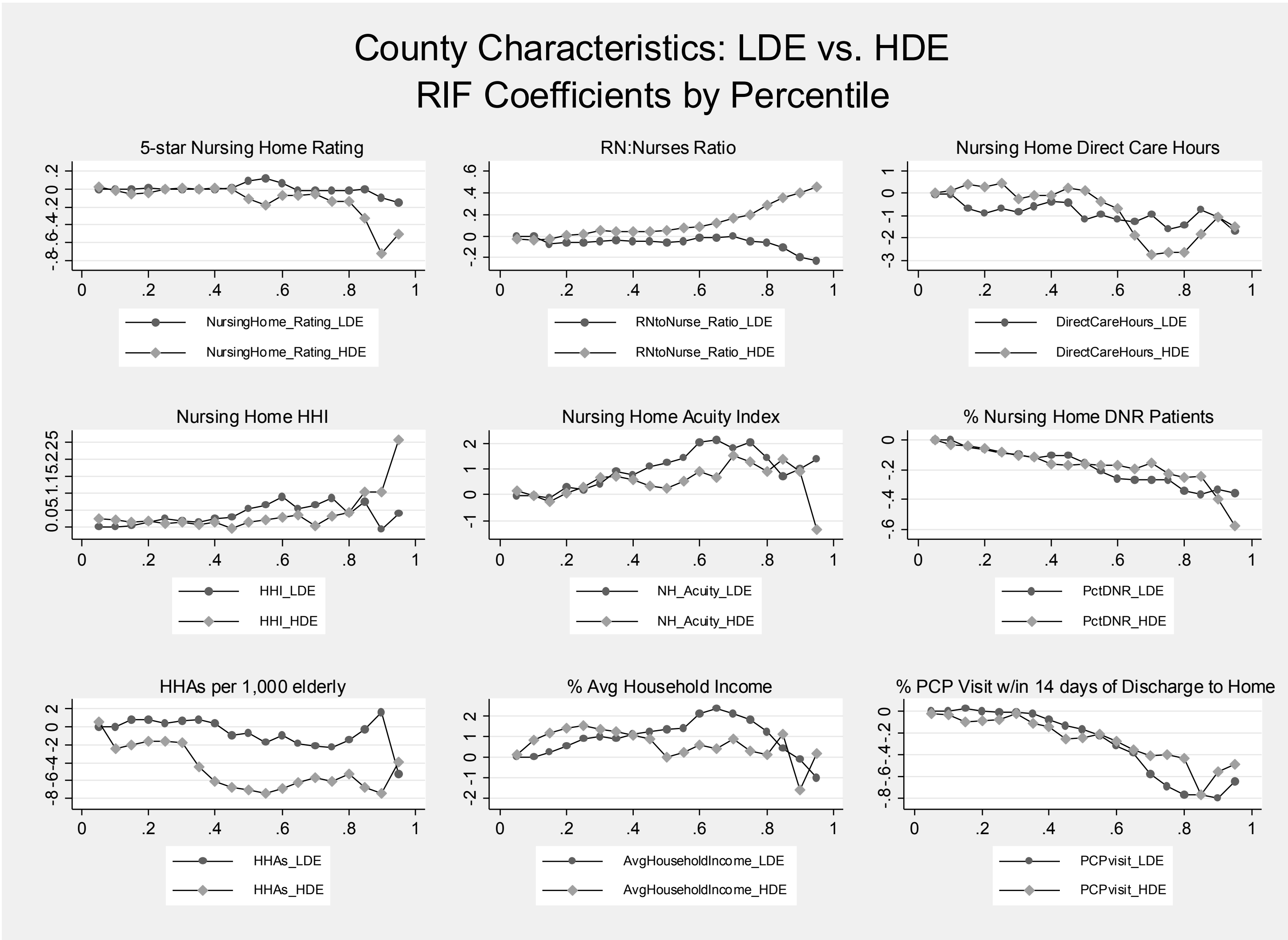

Figure 3b: Recentered influence function (RIF) county coefficients

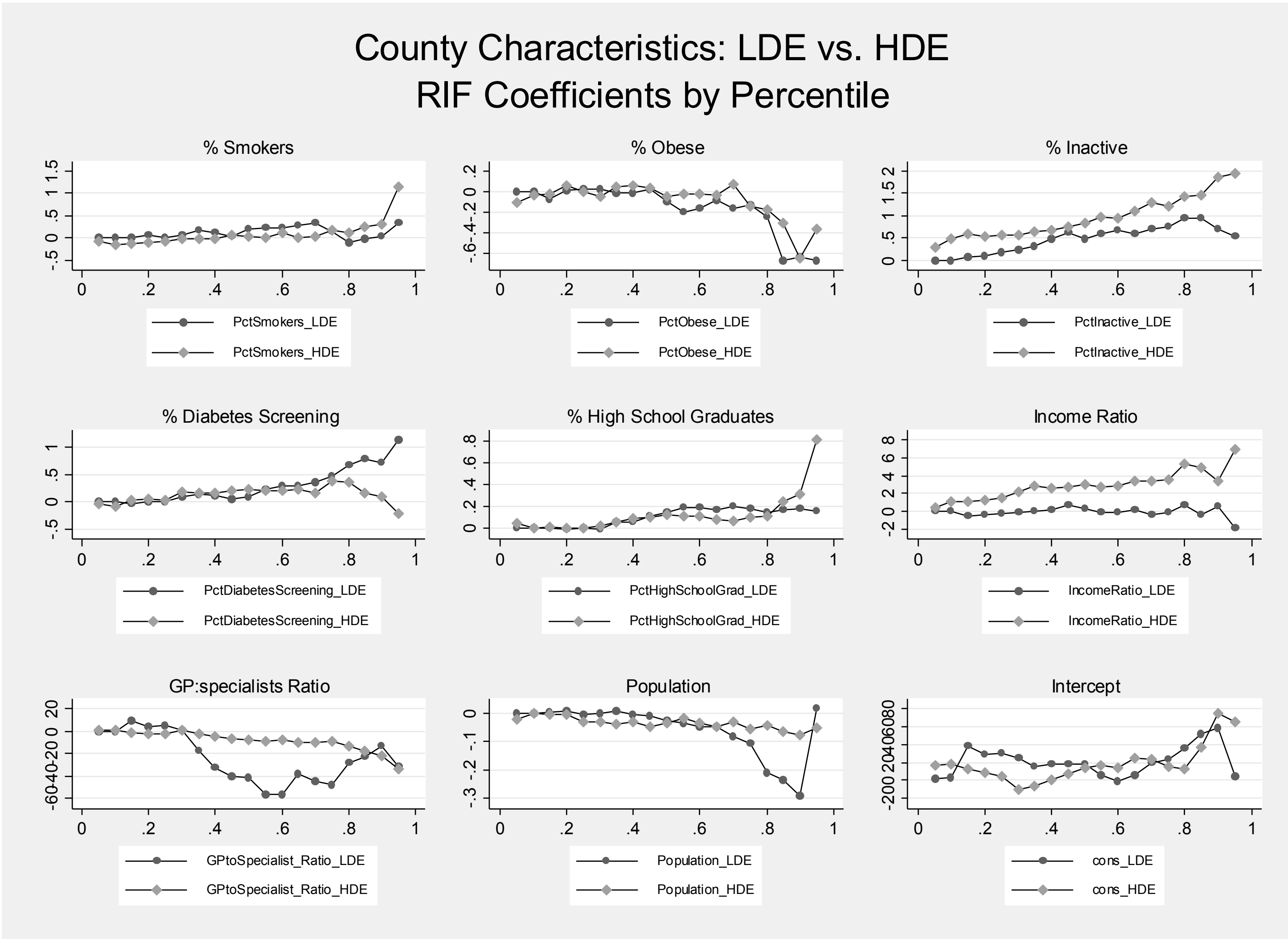

Table 3: Oaxaca-Blinder and unconditional quantile regression decompositions.

Decompositions	**OBD**	**RIF – 25^{th}**	**RIF – 50^{th}**	**RIF – 75^{th}**
HRRP share – LDE hospital prediction	15.19^{***}	2.61^{***}	10.29^{***}	22.52^{***}
HRRP share – HDE hospital prediction	20.56^{***}	6.72^{***}	15.91^{***}	29.54^{***}
Difference	-5.38^{***}	-4.11^{***}	-5.62^{***}	-7.01^{***}
Explained				
Non-teaching	-0.06	0.01	-0.05	-0.08
Teaching	-0.06	0.01	-0.05	-0.08
Small (< 200 beds)	0.03	0.03	0.04	0.02
Medium (200-400 beds)	0.01	-0.01	0.03	0.02
Large (>400 beds)	0.00	0.01	-0.00	-0.00
Public hospital	0.22^{***}	0.05	0.17^{*}	0.40^{**}
Private, not-for-profit (vs. public hospital)	0.01	0.01	-0.03	-0.02
Private, for-profit (vs. public hospital)	-0.04	-0.01	-0.04	-0.08
Uncompensated care payments/$1,000	0.03	0.05^{*}	0.03	0.02
% Medicare inpatient days	-0.29	-0.22	-0.36	-0.45
% Black patient share	0.34	0.26	0.13	-0.13
HCAHPS composite	-1.07^{***}	-1.01^{***}	-1.43^{***}	-1.47^{***}
Hospital skilled nursing availability – no	-0.00	-0.00	0.00	-0.01
Hospital skilled nursing availability – yes	-0.01	-0.01	-0.02	-0.03
Hospital skilled nursing availability – missing	-0.03	-0.02	-0.01	-0.10
Nursing Home Compare 5-star rating	-0.05	0.01	-0.02	-0.06
Registered nurses : nurses ratio	0.16	-0.03	0.02	0.45
Direct care hours per resident day	-0.06	-0.01	-0.04	-0.18
Herfindahl Index - nursing home competition	-0.25	-0.13	-0.16	-0.29
Nursing home acuity index	-0.09	-0.02	-0.09	-0.23
% DNR residents	-1.07^{***}	-0.43^{**}	-0.93^{**}	-1.44^{**}
Home health agencies (HHAs)/1,000 elderly	0.10	0.02	0.17	0.18
Mean household income	0.48	0.60^{**}	0.47	0.79
% Medicare enrollees with >= 1 primary care visit	-0.10	-0.02	-0.09	-0.19
% smokers	-0.21	0.10	-0.14	-0.25
% obese	0.38	-0.01	0.16	0.35
% inactive	-2.43^{***}	-1.32^{***}	-2.22^{***}	-3.39^{***}
% diabetes screening	0.26^{*}	0.05	0.25^{*}	0.53^{**}
% high school graduates	0.10	-0.01	0.12	0.14
Income ratio (80:20 inequality percentile ratio)	-0.54^{*}	-0.25	-0.60^{*}	-0.68
GP:specialists ratio	0.33^{**}	0.07	0.35^{**}	0.39^{*}
Population/100,000	0.19	0.10	0.15	0.33
Sub-total: Explained (raw)	-3.76^{***}	-2.10^{***}	-4.18^{***}	-5.53^{***}
Sub-total: Explained (%)	69.85%	51.16%	74.33%	78.78%
Unexplained				
Non-teaching	0.35	-0.01	0.51	0.50
Teaching	-0.17	0.01	-0.26	-0.24
Small (< 200 beds)	1.73^{**}	1.40^{**}	2.30^{**}	1.89
Medium (200-400 beds)	-0.30	-0.16	-0.49	-0.28
Large (>400 beds)	-0.15	-0.16	-0.17	-0.19
Public hospital	0.13	0.24^{*}	0.10	0.17
Private, not-for-profit (vs. public hospital)	-1.53^{**}	-0.24	-1.03	-1.98
Private, for-profit (vs. public hospital)	0.28	-0.40^{*}	0.17	0.36
Uncompensated care payments/$1,000	-0.09^{**}	-0.04	-0.07^{*}	-0.10^{*}
% Medicare inpatient days	-4.86^{*}	-5.01^{*}	-2.87	-5.94
% Black patient share	-0.03	-0.63	-0.03	-0.63
HCAHPS composite	20.37^{*}	1.90	7.53	22.94
Hospital skilled nursing availability – no	-0.45	0.02	-0.22	-0.99
Hospital skilled nursing availability – yes	0.42	-0.06	0.36	0.99
Hospital skilled nursing availability – missing	-0.08	0.02	-0.11	-0.21
Nursing Home Compare 5-star rating	4.04	-0.16	5.82	3.71
Registered nurses : nurses ratio	-6.35^{**}	-2.54	-3.64	-7.86^{*}
Direct care hours per resident day	-0.99	-4.21	-4.75	3.86
Herfindahl Index - nursing home competition	-0.17	0.27	0.70	0.94
Nursing home acuity index	4.78	-1.51	11.63	9.08

% DNR residents	0.76	-0.66	0.30	-2.29
Home health agencies (HHAs)/1,000 elderly	1.13	0.61	1.89*	1.10
Mean household income	2.10	-2.26	4.84	5.58
% Medicare enrollees with >= 1 primary care visit	0.02	5.38	6.26	-21.92
% smokers	0.50	1.73	2.74	-0.49
% obese	-1.86	0.68	-1.65	0.46
% inactive	-12.14*	-9.03*	-8.22	-10.56
% diabetes screening	15.82	-0.17	-10.88	8.18
% high school graduates	-3.35	-0.55	1.83	6.36
Income ratio (80:20 inequality percentile ratio)	-13.32*	-8.38*	-12.66*	-17.38
GP:specialists ratio	-0.34	0.11	-0.68	-0.77
Population/100,000	-0.09	0.22	0.03	-0.46
_cons	-7.80	21.59	-0.70	4.67
Sub-total: Unexplained (raw)	-1.62*	-2.01***	-1.44	-1.49
Sub-total: Unexplained (%)	30.15%	48.84%	25.67%	21.22%

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CONCLUSIONS

This dissertation contributes to the literature with salient findings about the hospital and community factors associated with HRRP penalties. The studies apply rigorous and under-utilized econometric methods, such as correlated random effects and unconditional quantile regression, to better understand the role of social risk factors omitted from the HRRP. Additionally, this dissertation contributes to the broader policy discussion of P4P risk adjustment and provides insights on potential levers to improve care coordination and transitions of care.

Findings from the first study revealed more than a third of the variation in readmission penalties are at the county level, which highlights the importance of geography in the HRRP. Hospital for-profit control and Medicare inpatient days were associated with higher HRRP penalties, while teaching status and HCAHPS were associated with lower HRRP penalties. At the county level, primary care visits, nursing home quality, competition, and percentage DNR patients were all associated with increased penalties, while access to care measures like GP/specialist ratio and HHA/1,000 elderly were associated with lower HRRP penalties.

To explore the contextual effect of geography further, a hybrid model with both fixed effects and random effects was employed. Hospital measures of Medicare volume, percentage dual-eligible and black patients, and patient experience were correlated with unobserved area-level factors that were also associated with HRRP penalties. After controlling for community characteristics, the results related to the contextual effects were attenuated or no longer significant.

Since the HRRP does not include any community-level characteristics or geographic controls, the resulting endogeneity bias has the potential to disparately penalize certain hospitals, such as those that serve a large percentage of minority or dual-eligible patients. These findings suggest the HRRP risk adjustment may result in biased penalties since it does not account for the contextual effect of geography.

Findings from the second study illustrate similar directions and magnitudes for the relationships between social risk factors and readmission penalties; however, additional evidence of gradient trends across the penalty distribution emerges since unconditional quantile regression allows for analysis beyond just the mean. Moreover, results suggest that HDE hospitals are increasingly penalized across the penalty distribution compared to their LDE counterparts. At the mean, percent inactive, patient experience, and percent DNR nursing home patients had the largest explanatory contributions to the LDE/HDE penalty differential of -5.4. The variables explain more than two-thirds of the gap, which signifies that in the hypothetical absence of any advantage for LDE hospitals and disadvantage for LDE hospitals, the HRRP penalty gap would decrease from -5.4 to -1.6

These analyses were primarily limited by the inability to leverage the longitudinal nature of the penalties. The hospital and community characteristics were often not available at a similar level of temporal granularity, and also had to be averaged to mitigate noise and measurement concerns. In addition, these variables are aggregated proxies for social risk factors that are similarly difficult to capture at a more nuanced level. As such, the need for more robust, quasi-experimental research that includes patient-specific risk factors and longitudinal data are needed to advance our understanding of these complex relationships.

The findings from this dissertation, although limited by the observational and aggregated nature of the data, provide new evidence about the context of geography on HRRP penalties, how hospital and community factors are related to the entire distribution of HRRP penalties, and how levels and associations of these factors contribute to the penalty gap between hospitals with dissimilar proportions of dual-eligible patients. Overall, these empirical analyses support the recent inclusion of dual eligibility in the HRRP risk adjustment; however, they also suggest a myriad of other factors, such as geography and access to care, are related to HRRP penalties. It remains to be seen how well dual eligibility is able to proxy for these other characteristics in the updated risk adjustment algorithm.

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APPENDIX A

IRB APPROVAL

THE UNIVERSITY OF ALABAMA AT BIRMINGHAM

Institutional Review Board for Human Use

Form 4: IRB Approval Form
Identification and Certification of Research
Projects Involving Human Subjects

UAB's Institutional Review Boards for Human Use (IRBs) have an approved Federalwide Assurance with the Office for Human Research Protections (OHRP). The Assurance number is FWA00005960 and it expires on January 24, 2017. The UAB IRBs are also in compliance with 21 CFR Parts 50 and 56.

Principal Investigator: ASWANI, MONICA

Co-Investigator(s):

Protocol Number: **X150420003**

Protocol Title: *Effects of Medicare Reimbursement Policies on the Quality of Hospital Care*

The IRB reviewed and approved the above named project on 7-10-15. The review was conducted in accordance with UAB's Assurance of Compliance approved by the Department of Health and Human Services. This Project will be subject to Annual continuing review as provided in that Assurance.

This project received EXPEDITED review.

IRB Approval Date: 7-10-15

Date IRB Approval Issued: 7-10-15

IRB Approval No Longer Valid On: 7-10-16

HIPAA Waiver Approved?: N/A

Marilyn Doss

Member - Institutional Review Board for Human Use (IRB)

Investigators please note:

The IRB approved consent form used in the study must contain the IRB approval date and expiration date.

IRB approval is given for one year unless otherwise noted. For projects subject to annual review research activities may not continue past the one year anniversary of the IRB approval date.

Any modifications in the study methodology, protocol and/or consent form must be submitted for review and approval to the IRB prior to implementation.

Adverse Events and/or unanticipated risks to subjects or others at UAB or other participating institutions must be reported promptly to the IRB.

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APPENDIX B

ADDITIONAL INFORMATION

APPENDIX

Table A.1: HCAHPS Index construction, Cronbach's alpha in parentheses

Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) Composite (0.94)	
% (Replied) nurses always communicated well	% Room always clean
% Doctors always communicated well	% Room always quiet
% Quick help always received	% Yes post-discharge information was given
% Pain always well-controlled	% Would rate the hospital a 9 or 10
% Medications always well-explained	% Would recommend hospital to family/friends

Figure A.1: Example of Different Outcome Specifications - 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.

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%

Section A.1 – Unconditional Quantile Regression:

The RIF can be defined as follows:

RIF $(Y, Q\tau) = Q\tau + \frac{\tau - \mathbb{1}\{Y \leq Q\tau\}}{f_Y(Q\tau)}$,

where $Q\tau$ is the τ-th quantile of the unconditional outcome distribution, $\mathbb{1}\{y \leq Q\tau\}$ is an indicator function equal to 1 if a given observation is $\leq Yq$ and zero otherwise, and $f_Y(Q\tau)$ is the density of Y at τ. The RIF is estimated by substituting the unknown $Q\tau$ and $f_Y(Q\tau)$ with their observable counterparts. The former is easily obtained from the sample τ-th quantiles of Y, while the latter is commonly obtained using kernel density methods.

The convenient product of this method is $E[RIF(Y, Q\tau)] = Q\tau$ since the expected value of the influence function is zero. Therefore, $E[RIF(Y, Q\tau|X)] = X\beta$, where β represents the marginal effect of x on the τth quantile and can be estimated by OLS.

Figure A.2: Total HRRP share gap, broken down into explained and unexplained contributions, across the HRRP share distribution.