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The Association Between Residential Segregation and Hospital Readmissions Penalties

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Abstract

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By Antonio A. Henry

The Hospital Readmissions Reduction Program (HRRP) is a Medicare value-based program that encourages hospitals to improve care coordination and patient outcomes by applying financial penalties to hospitals identified as having excess 30-day unplanned readmission rates. Unfortunately, hospitals serving in the areas experiencing concentrated disadvantage are suffering the worst penalties. Historically, structural racism and socioeconomic inequities disproportionately expose Black Americans to these areas- a process that can be explored via racial residential segregation (RRS). The objective of this study was to investigate the association between RRS and hospital readmission penalties.

We used census tract and county level population counts by race from the 2020 Census to create the dissimilarity index measure for each county. Readmission penalty data was obtained from the CMS Hospital General information file via the Kaiser Family Foundation. County and hospital covariates were merged from the 2020-21 Area Health Resources Files and 2019 American Hospital Association Annual Survey. Bivariate analyses compared average readmission penalties across hospitals in low (HL), moderate (HM) and highly (HH) segregated counties. Generalized linear regression was used to estimate marginal effects, or the percentage point (ppt) difference in payment reductions between HL and HM/ HH. We considered a p-value of .05 as significant and analyses were performed using STATA.

The hospitals in the sample excluded those located in Maryland as well as cancer, rehabilitation, psychiatric, critical access, long-term care, and public-federal hospitals because they are exempt from the policy (n = 2,985). H_M (n = 2,077) experienced a .12-ppt greater reduction in Medicare payments due to excess 30-day readmissions compared to H_L (n = 423; p <.001). H_H (n = 485) experienced an even greater reduction (.17 ppt; p<.001). Controlling for county-level covariates attenuated this relationship.

Our findings are congruous with research stating areal factors are associated with inequities in hospital readmission penalties. Policies that acknowledge structural racism and other areal factors should be considered as a mechanism to eliminate inequities in financial penalties among hospitals Thus, adding RRS to risk-adjustment acknowledges the detrimental impact of structural racism on the healthcare system.

The Association between Residential Segregation and Hospital Readmissions Penalties

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2016

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CHAPTER I: INTRODUCTION

In 2003, the Center for Medicare and Medicaid services established Pay-for-performance (P4P) initiatives to improve quality of care and reduce healthcare costs nationally. One such program is the Hospital Readmissions Reduction Program (HRRP). The HRRP is a Medicare value-based program that encourages hospitals to improve care coordination and patient outcomes by applying financial penalties to hospitals with excess 30-day unplanned readmission rates. The policy, established under the Affordable Care Act in 2012, was motivated by a 2008 Medicare Payment Advisory Commission (MedPAC) report which estimated 12% of readmissions within 30-days are avoidable, and that preventing 10% of these could save Medicare $1 billion.[1] Ultimately, it was designed to provide a mechanism of public accountability – readmission rates are visible on the Hospital Compare site – and the first financial incentive to reduce readmissions.

Since the policy's announcement, national readmission rates have declined. From 2010 to the date of implementation (October 2012), hospitalizations with a principal diagnosis of heart failure declined by 1.09% per year.[2] Additionally, a 2018 MedPAC report found that between 2010 and 2016, readmission rates for the three initial target conditions fell between 2.3 and 3.6 percentage points, while rates for all other conditions fell by 1.7 percentage points.[3]

Despite these positive results, a granular perspective suggests the policy has been a detriment to some hospitals. Previous studies have shown safety-net hospitals (SNHs) had a 2.38x greater chance of being highly penalized – defined by Joynt (2013) as the top half of penalized hospitals - and also had on average two to three times higher penalties compare to than non-SNHs.[4, 5] Further healthcare disparities show why SNHs suffer worse penalties. SNHs deliver a disproportionately high amount of care to patients who are either uninsured or have Medicaid. A hospital is identified as an SNH if it falls within the top quartile of hospitals within its state who deliver care to such patients – in other words, they are the hospitals with the largest percentage of Medicaid and uninsured discharges.[6] Despite only representing 25% of all hospitals, they account for 33% of inpatient stays, and are more likely than non-SNHs to be located in large central metropolitan and micropolitan areas.[6] Additionally, 41% of inpatient stays at SNHs are in the lowest quartile for median income in their zip code of residence, compared to 24% for non SNHs and inpatient stays for Medicaid and uninsured patients are about two times as high for SNHs compared to non-SNHs. Because racial minorities are more likely to be in the lowest quartile of median income for their zip code and more likely to be uninsured or on Medicaid SNHs are more likely to serve them, meaning minorities are more likely to be served by hospitals that are more frequently penalized. As mentioned above, these hospitals are performing worse on HRRP quality standards.[7-9] Ultimately, this results in hospitals serving the most vulnerable experiencing worse penalization.

Research Justification, Objective, & Approach

Using a national sample, this study aims to elucidate structural racism's contribution to disparities in readmissions penalties. The conceptual model is synthesized from the Donabedian Model for quality of care and Anderson-Behavioral Model, showing how the structure of communities can affect processes of care and recovery, as well as behaviors of individuals. By implementing a Census-validated measure of residential segregation – the dissimilarity index – with population and outcome data from 2020 and 2021, respectively, we aim to show how structural racism sustains these disparities in hospital payment from CMS – the first of its kind.

CHAPTER II: LITERATURE REVIEW

HRRP Risk Adjustment

The discourse around readmission penalties suggests the root of the problem lies in the definition of readmissions and the risk-adjustment algorithm. Originally, the excess readmission ratio, which determines a hospital's penalty amount, adjusted for variations in hospitals' volume and case mix. This includes patient risk factors of age, gender, and diagnosis related group.[1] However, this does not account for factors associated with readmissions that are outside of hospitals' control. For example, Barnett et al. showed that patients admitted to hospitals with the highest readmission rates were more likely to have characteristics associated with higher probability of readmission, such as comorbidities and higher condition severity.[10]

Additionally, as highlighted by hospital leadership, the HRRP did not risk-adjust for patient-level socioeconomic differences between hospitals, such as poverty, income, and education.[11] Patient characteristics, such as socioeconomic status and pre-existing health conditions, are factors present prior to admission but associated with post-discharge recovery. Beginning in fiscal year 2019, CMS expanded risk-adjustment past sex, age, health condition, and discharge status, by assessing hospital performance relative to others with a similar proportion of patients dually eligible for Medicare and full Medicaid.[1, 12] This change seemed to strike a balance between those arguing for robust risk-adjustment and those against inclusion of socioeconomic status and social determinants of health measures in such risk-adjustment. Accounting for the Medicaid population in a hospital may be a rough proxy for elucidating the sociodemographic profile of an area. But arguments against further inclusion of areal factors in risk-adjustment cite concerns with holding hospitals to different standards and masking differences in quality among facilities necessary to identify to reduce disparities.[13]

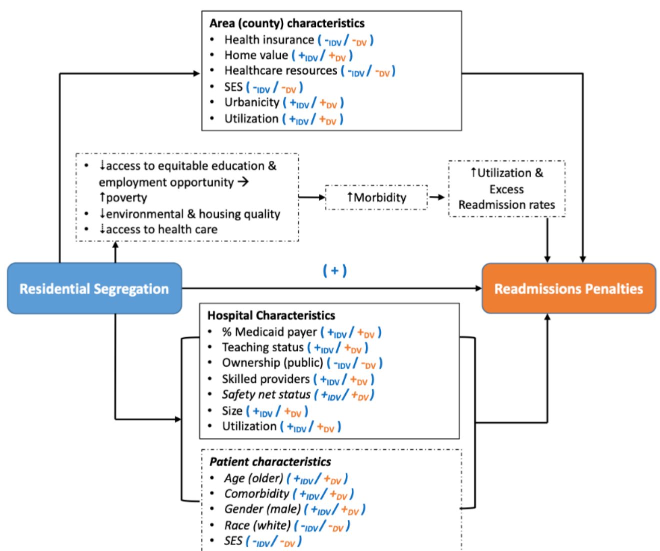
Nonetheless, the fiscal year 2019 change may still be inadequate in addressing disparities in readmissions between hospitals.

Area-level characteristics, as opposed to simply patient-level characteristics, have proven important in explaining the disparities experienced by hospitals that serve the most vulnerable. Previous research has found that adding the Area Deprivation Index (ADI) - a measure of neighborhood disadvantage comprised of factors such as education, employment, income, and housing instability - into risk adjustment calculations reduced differences in readmission rates between SNHs and non-SNHs by 50%.[14] Moreover, approximately 6% of SNHs went from having a penalty to no penalty after adjusting for the ADI. Other studies have shown that much of the variation in readmission rates or HRRP penalties are explained by county characteristics such as education, proportion of Medicare beneficiaries by county, and/or supply of general practitioners per capita by county.[15, 16] Furthermore, worse hospital quality scores have been associated with location in a community with a higher proportion of Black residents; yet these differences were significantly reduced when controlling for urban-rural county designation and county median household income.[17] Overall, there is a growing body of literature to suggest that simply adjusting for dual-eligibility and other patient-level characteristics will be insufficient to eliminate the disparities in penalization observed by hospitals that serve the most vulnerable and in the areas experiencing concentrated disadvantage.

Racial Residential Segregation

Historically, structural racism and socioeconomic inequities disproportionately expose Black Americans to areas experiencing the most concentrated disadvantage.[18, 19] This exposure has manifested largely through racial residential segregation (RRS) and thus provides a mechanism that can elucidate differences in hospital quality via excess readmissions. RRS is a placed-based process, not simply a characteristic - such as socioeconomic status or racial composition, that produces poor outcomes at the individual, organizational, and community level.[19-21] Prior literature has explored the relationship and mechanisms through which residential segregation begets poor health outcomes.[20-23] For example, Gee et al. (2008) found that institutional housing discrimination, as measured by the dissimilarity index and redlining, are predictive of poorer self-reported physical and mental health status.[22] Mendez et al. (2011) also found that more Black exposure (e.g., lower segregation) to whites was significantly associated with higher birth weight.[23] These findings support research that posits RRS as a fundamental cause of healthcare disparities. RRS creates conditions in the social and physical environment that affect access to employment and education opportunities.[19, 20] Measuring RRS is also distinct from the capturing the proportion of minorities or a certain race residing in an area. Whereas RRS elucidates the spatial dynamics of an area – for example there could be freeways, traffic corridors, or landfills that physically prevent residents from accessing areas or locate them near sites deleterious to health – simple proportions obscure this. In other words, areas with similar proportions of Black residents could differ widely in their intensities of segregation. Thus, RRS would be important to control for in CMS risk-adjustment algorithms, separately from other measures of areal-deprivation and racial composition.[24]

Little is known about the relationship between racial residential segregation and disparities in hospital readmissions penalties. Much of the literature around readmissions focuses on disparities between patients of different racial categories *within* hospitals or on associations between contextual factors such as income and education.[25-28] Additionally, research investigating the impact of RRS focuses on patient risk and outcomes, as opposed to quality or the financial impact on hospitals.[20-23] This highlights a relevant gap in the literature: studies on the HRRP have not examined contextual-level factors, such as RRS, that are relevant to structural racism's impact on hospitals. This study adds to the literature by using 2020 Census data to highlight residential segregation's continued association with disparities in readmissions penalties *between* hospitals.



Theoretical Framework

This study draws on the Donabedian model for evaluating the quality of medical care. The Donabedian model suggests that an organization's structure influences the processes by which it delivers care, thereby influencing the health outcomes of those it serves.[29] Structure entails the administrative and operational features that enable a healthcare provider to engage in the processes of healthcare. These features include facilities, equipment, staff and organizational accreditation and qualifications, financial viability, and even other P4P penalties that hinder financial viability, potentially curbing necessary investment in quality improvement efforts.[29] The assumption, here, is that these features are positively correlated with quality. Donabedian states processes of healthcare delivery can be seen as the means to attaining desirable and appropriate health outcomes. Obtaining a clinical history, conducting physical examinations and diagnostic tests, preventative management in health and illness, and technical competence in performance of surgical procedures – reducing chances of post-procedural complications and readmission - are all examples of activities that produce health outcomes. In this study, the outcome is hospital quality as measured by hospital readmissions penalties. I draw on Donabedian's model to inform my study examining how a community process - residential segregation – is associated with differences in readmissions penalties. This model posits that these community characteristics influence organizational structure and thus health outcomes.

Mechanisms connecting Racial Residential Segregation to Hospital Readmissions Penalties

Current literature describes the mechanisms by which residential segregation influences racial disparities in health and hospital quality via readmissions. Williams posits that residential segregation creates conditions in the social and physical environment, including access to education and employment opportunities.[19] Residential segregation can be thought of as a process of spatial assimilation and place stratification.[24, 30] It involves not only putting people into areas with people who are racially concordant, but also hierarchically categorizing these areas based on assumptions about race.

Sundown towns and lynching, for example, have historically maintained this geographical separation. Sundown towns, locales shaped using formal, informal, and violent tactics to maintain all-white spaces, contributed strongly to the demographic and social landscape of the non-South.[31, 32] While largely a thing of the past, some exist today, but the history of sundown towns has implications on contemporary Black-white spatial inequality. Lynching, a violent tactic popularized in the slavery and post-slavery South, has also worked to keep minorities, particularly Blacks, concentrated amongst each other and separate from whiter, more affluent areas.[33] Social research has claimed that "history constrains the options available when making future decisions, and subsequently, history becomes embedded in a place and part of its character" thus its lingering social and structural impact connects to the inequality observed today.[31, 34] This inequality manifests in a separation of resources and opportunity. For example, evidence shows corporations explicitly use racial composition of areas to determine facility placement.[35] What results is a spatially and temporally disproportionate accumulation of health status and wealth gaps for Black residents. Lowered health status, such as increased prevalence of comorbidities amongst an area's residents, increases risk for more frequent undesired health system utilization and thus higher unplanned 30-day readmission rates. For example, black morbidity and mortality rates are higher in highly segregated urban areas.[36]

Another mechanism by which segregation influences hospital readmissions is through constraining a community's access to healthcare. This can mean low insurance coverage rates, low staff-to-patient ratios, and primary care provider shortages. For minority communities, the literature reports limited access to pharmaceuticals. For example, in a study done in New York city, a predominantly urban area, only 25% of pharmacies in nonwhite neighborhoods had sufficient opioid supplies to treat severe pain compared to 72% of pharmacies in predominantly white neighborhoods.[37] Additionally, a national study found zip codes with a high proportion of Black or Hispanic residents to be at higher risk for nursing home closure compared to zip codes with a lower proportion of these racial and ethnic minorities.[38] While it seems like Black proportion is being conflated with residential segregation, it is important to remember that while conceptually distinct, these concepts are related and moderately correlated (see Appendix B). Not only is the proportion of Black residents a component of the dissimilarity index, but Black residents are more likely to be in areas experiencing the most concentrated disadvantage, such as decreased access to healthcare. A loss of these resources ultimately puts people in these areas at higher risk for readmission, exposing the hospitals in these areas to higher readmission rates.

A last mechanism linking RRS to lower hospital readmissions is community exposure to environments inimical to health. Minority communities segregated in materially deprived and poverty-stricken areas also suffer exposure to physical environments that have adverse effects on health and well-being, leading to highly concentrated proportions of these communities having comorbidities and reduced ability to recover from poor-health.[39] A history of industrial concentration at urban centers coupled with selective economic investment and development in suburban areas exacerbated this segregation. Desirable land uses began to accumulate at the periphery of urban centers, where more affluent communities, typically White, could avoid the noise, air, and soil pollution resulting from being located near manufacturing, transportation, and waste corridors. For communities of color, especially Blacks, this meant disproportionate exposure to environmental contaminants such hazardous air pollutants, like ozone and sulfur dioxide, and soil and housing contaminants, like lead paint and soil slag.[39] These contaminants, if accumulated at high doses in the body, overwhelm the body's detoxification and immune defenses and can disable and damage organ systems. This environmental-physiological process has been attributed to increased risk of cancer, asthma, diabetes, and developmental delays and reflects a comorbidity that disproportionately affects Black communities.[39-41] This concentration of comorbidity and a lack of access to care (e.g., poverty-associated uninsurance, hospitals in Black communities being more likely to shut down[42]) limits individual ability to recover from preventable health conditions, putting them at risk for unnecessary hospitalization.

In summary, HRRP risk-adjustment continues to be inadequate in equitable incentivizing hospitals to reduce excess unplanned 30-day readmission. While the policy has transitioned from including only sex... to the proportion of dual-eligible patients a facility serves in fiscal year 2019, other social determinants of health measures are still absent. To reduce or eliminate disparities internalization between hospitals, these measures must not only be included, but acknowledge structural racism's impact on the healthcare system. Therefore, the objective of this study is to assess the association between a measure of structural racism, racial residential segregation, and hospital readmissions penalties.

CHAPTER III: METHODS

Data

Readmissions penalty data was retrieved from the CMS Hospital General Information Provider Data Catalog via Kaiser Health.[43, 44] This data is publicly available for download and contains Medicare identification numbers, addresses, and readmission penalty amounts from 2015-2021. This data was uploaded to Geocodio®, which geocoded hospitals to their respective census tracts, complete with latitudes and longitudes.[45]

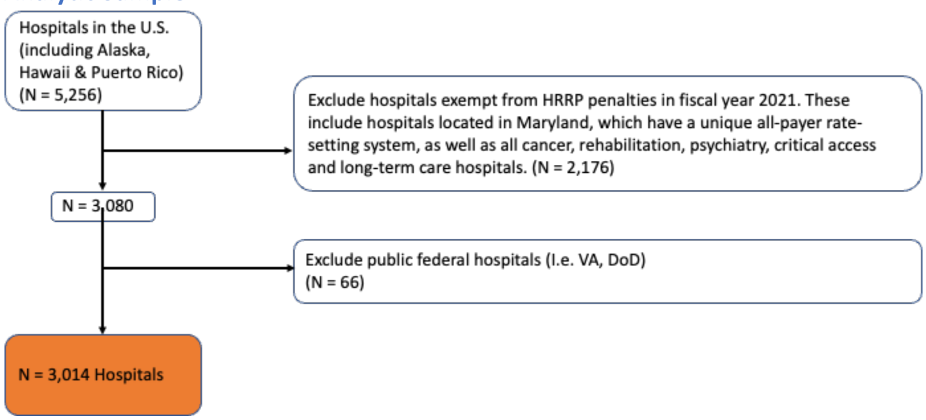
Population count data from the 2020 Census was used to construct the Black-white dissimilarity index. This data repository, publicly available from the National Historical Geographic Information System (NHGIS), contains a wide variety of sociodemographic information, including population counts by race, ethnicity, and different ethnoracial combinations at multiple geographic levels.[46] The dataset used in this study used Black non-

Hispanic and White non-Hispanic population counts at the census tract and county levels. These levels could only be downloaded as separate files, so to construct the dissimilarity index: 1) the different components of the index had to be created separately, such as p_i, the ratio of Black non-Hispanics to White non-Hispanics in each census tract, and 2) a unique state-county identifier had to be created - this identifier was the merge variable. Once the files were merged, the dissimilarity index was operationalized in STATA version 17 using the Census definition, derived from Massey & Denton (see Appendix A for STATA code).[24, 47] The continuous dissimilarity index measure is scored from 0 to 1: higher values meant more segregation of Black-non-Hispanics compared to White non-Hispanics within counties, assuming only these two groups resided in each county. We, then categorized the dissimilarity index into low, moderate, and high based on previous literature.[24] Finally, Using the unique census tract and state-county federal information processing standards (FIPS) codes, the dissimilarity index file was linked to the hospital readmissions penalty data.

Next, Area Health Resource File (AHRF) 2020-2021 files containing county-level covariates were merged onto the main file using the unique FIPS state-county codes. Hospital-level covariates from the 2019 American Hospital Association (AHA) Annual Survey of Hospitals were then merged onto this file using the Medicare provider number.

These data were chosen for their recency – no dataset is older than 2019 – and their relevancy in validly answer the research question in accordance with the conceptual model above. County-level covariates are included to account for unobserved characteristics at the county level associated with racial residential segregation. Hospital-level covariates are included to account for unobserved characteristics at the hospital level. Most relevantly, the Black-white dissimilarity index was chosen to isolate the manifestation of structural racism in relation to these two groups. This measure of the dissimilarity index, while reductive, is also commonly used in previous literature.

Analytic Sample



Hospitals subject to readmission penalties under the HRRP in fiscal year 2021 were the units of analyses. Hospitals (n = 5,256) that were neither cancer, rehabilitation, psychiatric, critical access, nor located in Maryland - which have a unique all payer rate-setting system - were included in the analysis. Finally, public federal hospitals (n = 66), such as Veterans Administration and Department of Defense were excluded from analyses because these facilities serve a significantly different payer mix than other hospitals, yielding an analytic sample of 3,014 hospitals.

Measurement & Constructs

Focal Relationship

The focal relationship of interest seeks to elucidate the association between RRS and hospital readmissions penalties. The primary predictor of interest is RRS, measured by the dissimilarity index, which current literature describes as place-based separation of individuals and groups of people due to their race, and further influenced by socioeconomic status.[24] The dissimilarity index, while composed of census tract and county Black resident proportions, actually measures the percentage of Black residents that would have to move to a different location for each census tract to have the same percentage of Black residents as the entire county (see Appendix A). Hospital readmission penalties are defined as the percent by which a hospitals Medicare payments are reduced by CMS.[12] The payment reductions result from a payment adjustment factor calculated for each hospital over the course of a fiscal year performance period (October 1 – September 30). CMS publishes the penalty data annually on the *Hospital Compare* and Inpatient Prospective Payment System websites after a 30-day review period.

Confounders

The following are factors at the areal, hospital, and individual level associated with the independent and dependent variables in the focal relationship.

Areal Confounders

Areal racial composition is often seen as a determinant of health inequities. The legacy of structural and systemic racism in the United States is such that areas with higher proportions of Black residents will experience worse health outcomes, and the facilities in these areas will be financially worse off.

At the area level, prior studies have measured socioeconomic status in a variety of ways. The higher an areas socioeconomic status, typically the more academic institutions of higher learning, higher median salary and education, and more resources available to its residents to have a higher quality of live and better health.[48] As residential segregation occurs with material degradation of a community, we expect it to be negatively associated with areal socioeconomic status. Further, areal socioeconomic status manifestation of a lack of healthcare and preventative health resources presumes its negative association with hospital readmissions penalties.[10, 14]

Home value and home ownership can elucidate the complex nature of residential segregation. While at an aggregate level (e.g. county) home values may obscure health and wealth realities and potential of residents when juxtaposed with the proportion of a county's residences that are owner-occupied paints a different picture. Areas with more owner-occupied homes contain residents with higher wealth potential. Furthermore, high owner-occupancy areas are typically healthier than low owner-occupancy areas.[49] While higher county-level home values may be positively associated with residential segregation and hospital readmission penalties, high owner-occupied counties may be negatively associated with residential segregation and hospital readmissions penalties.

Healthcare resources (e.g. access to care) in a community influence the ability of individuals to attain primary, secondary, and tertiary care. Black residents experience the worst segregation and hospitals in Black communities historically experience a higher risk of closure, constraining the ability of Black people to achieve adequate care.[24] Healthcare resources, therefore, are negatively associated with residential segregation and hospital readmission penalties.

Urbanicity is an areal factor often used as synonym for areas experiencing concentrated disadvantage. Dense accumulation of people and undesirable land use areas historically used for industrial purposes reflect patterns of exclusion of poor and minority people from peripheral, suburban areas. As such, urbanicity is positively associated with both RRS and hospital readmissions.

Hospital-level Confounders

The proportion of Medicaid days as a total of inpatient days can illuminate hospital's dependence on public reimbursement and its likelihood of serving lower socioeconomic status patients. There may still be variation within an area and across hospitals for the types of patients they serve. For example, proprietary hospitals in urban centers may not accept Medicaid, thus although they are in proximity to the demographic do not actually provide healthcare to them. The proportion of Medicaid days over total inpatient days is hypothesized to be positively associated with RRS and hospitals readmissions penalties.

Teaching status is determined by whether a hospital has an American Medical Association-approved residency program, membership in the Council of Teaching Hospitals, or above a 25% ratio of full-time interns and residents to beds.[16] Hospitals who have accredited training programs have been shown to have lower rates of readmission and post-surgical complication, perhaps due to the culture of constant instruction and reliance on checks and balances between residents, fellows, and attending physicians.[1, 50] As such teaching hospital status is expected to be associated with lower hospital readmissions penalties. Since teaching hospitals are more likely to be in urban areas and thus serve more minority and lower socioeconomic status patients, teaching status is expected to be positively associated with RRS.

Ownership status can illuminate the financial foundation and incentives of a hospital, and thus the behavior and patient population. Public hospitals are usually required to treat lower socioeconomic status patients, such as the Medicaid and uninsured population.[51] Private non-profit hospitals, while proprietary, predominantly receive federal funding in exchange for tax exemption, but are also required to treat the indigent population. Contrastingly, private for-profit hospitals typically have higher charges, profit margins, and are under no obligation to provide service to the indigent population (e.g. accept Medicaid).[52] Therefore, it is hypothesized that public ownership, and more generally public financial relationships, with be positively associated with both RRS and hospital readmissions penalties.

Skilled nursing facilities (SNFs) have significantly better staff ratings and facility inspection ratings compared to non-skilled nursing facilities.[53] Across SNFs, the higher these ratings, the lower the readmissions rates.[54] Therefore, SNF status is expected to be negatively correlated with hospital readmissions penalties. In 2014, national study of SNFs showed that about 70% are for-profit.[39] Since most for-profit hospitals are expected to be correlated with low segregation, SNF availability is hypothesized to be negatively associated with RRS.

SNHs are in the top quartile of inpatient days serving Medicaid or uninsured patients.[6] Since they are more likely to be in proximity to the areas and patients experiencing concentrated disadvantage, SNH status is expected to be positively associated with RRS. Similarly, and as the body of literature shows, it is expected to be positively associated with hospital readmissions penalties.

Hospital size (determined by bed count) tends to reflect the potential population need for care of the area it is in. For example, larger hospitals are more likely to be in or around more densely populated areas. Research also shows that large hospitals are more likely to be SNHs and teaching hospitals. Therefore, in concordance with the above hypothesized relationships, hospital size is expected to be positively correlated with both RRS and hospital readmissions penalties.

Patient-level confounders

The body's aging process results in increasing susceptibility to illness, chronic and acute. This exposes disproportionately exposes older residents to comorbidity and thus increase risk for unplanned readmissions. Therefore, age is expected to be positively associated with hospital readmissions penalties. On the other hand, life-expectancies in areas experiencing concentrated disadvantage are shorter, therefore age is expected to be negatively associated with RRS.

Like the above, comorbidity – the state of having multiple diseases or ill-health conditions – is expected to be positively associated with both RRS and hospital readmissions penalties.[55, 56]

Research has shown female gender is associated with lower readmission rates compared to males, therefore male gender is hypothesized to be positively associated with readmissions penalties.[9] Gender's relationship to RRS, however, may be indeterminate.

Given the literatures depiction of the manifestations of structural racism and socioeconomic stratification, it is no surprise to expect white race and socioeconomic status to be negatively associated with both RRS and hospital readmissions penalties.

Measurement

Construct	***Measure***	***Hypothesized Relationship to the DV***
Hospital Quality (DV)	**Hospital Readmissions Penalties** • Continuous variable: the percentage by which a hospital's Medicare payments are reduced by CMS. • The higher the penalty(%), the lower the quality	Hospital Readmissions Penalties will be the dependent variable
Racial Residential Segregation (IV)	**The Black-white Dissimilarity index** • Continuous variable: % Black residents that would have to change their area of residence to achieve an even distribution of the population, *assuming the only members of the population are Black-only and white-only*	The Black-white dissimilarity index will be positively associated with readmissions penalties.

Socioeconomic status (area)	**% County residents aged 65+ in deep poverty[1] (2015-19)** • Continuous variable **% County residents aged 18-64 without health insurance (2015-19)** • Continuous variable **"Low-education" county** • Yes • No **"Low-employment" county** • Yes • No	Medicare-eligible patients in deep poverty will be positively associated with readmissions penalties. The proportion of residents 18-64 without health insurance will be positively associated with readmissions penalties. Low-education County status will be positively associated with readmissions penalties. Low-employment County status will be positively associated with readmissions penalties.
Home value (area)	**% owner-occupied homes (2010)** • Continuous variable **Median home value (2015-19)** • Continuous variable	% Owner-occupied homes will be negatively associated with readmissions penalties. Home value will be positively associated with readmissions penalties.
Healthcare resources (area)	**# County nursing home beds per 10,000 people (2015-19)** • Continuous variable **County general practitioner to specialist ratio** • Continuous variable	Nursing bed count will be negatively associated with readmissions penalties. General practitioner to specialist ratio will be negatively associated with readmissions penalties.
Urbanicity (area)	**Urban-metropolitan County (vs. Urban-non metro + rural counties)** • Urban-metro • Non urban-metro	Urbanicity will be positively associated with readmissions penalties.

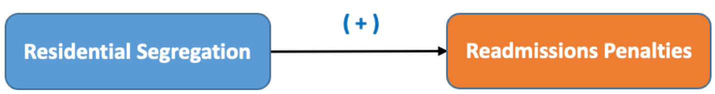
[1] As defined by the American Community Survey, deep poverty is living with income below half of one's poverty threshold.

Payer mix (hospital)	**% Medicaid inpatient days to total inpatient days** • Continuous variable	% Medicaid inpatient days will be positively associated with readmissions penalties.
Teaching status (hospital)	**membership of AAMC Council of Teaching Hospitals or ratio of full-time equivalent interns/residents to beds >= .25, or residency training approval by the Accreditation Council for Graduate Medical Education** • Yes • No	Teaching hospital status will be negatively associated with readmissions penalties.
Ownership status (hospital)	**Public or private ownership** • Public, non-federal • Private, non-profit • Private, for-profit	Public ownership, compared to private non-profit and private for-profit, will be negatively associated with readmissions penalties.
Skilled providers (hospital)	**Unmeasured**	Skilled providers will be negatively associated with readmissions penalties.
Safety-net status (hospital)	**Unmeasured**	Safety-net status will be positively associated with readmissions penalties.
Hospital size (hospital)	**# Inpatient beds available in facility** • Small • Medium • Large	Higher bed count will be positively associated with readmissions penalties.
Age (patient)	**Unmeasured**	Greater age will be positively associated with readmissions penalties.
Comorbidity (patient)	**Unmeasured**	Comorbidity will be positively associated with readmissions penalties.

Gender (patient)	**Unmeasured**	Male gender will be positively associated with readmissions penalties.
Race (patient)	**Unmeasured**	White race will be negatively associated with readmissions penalties
Socioeconomic status (patient)	**Unmeasured**	Socioeconomic status will be negatively associated with readmissions penalties.

Hypothesis

H_1: After controlling for confounders, racial residential segregation will be positively associated with hospital readmissions penalties.



The primary hypothesis is grounded in Donabedian's model for evaluating quality of care. It reflects the expression of poor quality metrics and concentrated disadvantaged experienced by hospitals in racially segregated communities. Current literature also demonstrates negative effect of areal community context on hospital performance.[57-59]

Analytic Plan

This investigation will use two types of analyses to assess the association between RRS and hospital readmissions penalties – we hypothesize that there will be a positive association between the two. Bivariate analyses will compare average readmission penalties, county-level covariates and hospital-level covariates across hospitals in low (H_L), moderate (H_M) and highly (H_H) segregated counties. Specifically, ANOVA and chi-square tests were performed to determine whether the means and frequencies for respective variables differed across

Dissimilarity groups. Cutoffs for low (H_L:0 to 30%), moderate (H_M:31 to 60%) and high (H_H: >60%) segregation were established in accordance with previous literature.[60, 61]

Stepwise generalized linear regression models will estimate marginal effects, or the percentage point (ppt) difference in payment reductions between H_L and H_M/ H_H. Model 1 will be an unadjusted regression of hospital readmissions penalties on the categorical Black-white categorical dissimilarity index measure (H_L, H_M, and H_H):

$$\text{Model 1: } Penalty_i = \beta_0 + \beta_1 Dissimilarity_i + \varepsilon_i$$

Model 2 will include Model 1 and county-level covariates:

$$\text{Model 2: } Penalty_i = \beta_0 + \beta_1 Dissimiliarity_i + \beta_2 Countyi + \varepsilon_i$$

Model 3 will include Model 1 and hospital-level covariates:

$$\text{Model 3: } Penalty_i = \beta_0 + \beta_1 Dissimiliarity_i + \beta_2 Hospital_i + \varepsilon_i$$

Model 4, the fully adjusted model, will include Model 1, county-level, and hospital-level covariates:

$$\text{Model 4: } Penalty_i = \beta_0 + \beta_1 Dissimiliarity_i + \beta_2 County_i + \beta_3 Hospital_i + \varepsilon_i$$

A generalized linear model with a logarithmic link was used because the distribution of the dependent variable is heavily right skewed. The Modified Park Test verified that a gamma distribution was adequate for the estimation of marginal effects. A correlation coefficient threshold of .5 was used to minimize collinearity between all independent variables in the model. Variables with disproportionately large values relative to other measures in the sample (e.g., median home-values, per capita Medicare costs, and total expenses per inpatient day) were standardized prior to inclusion in all regression models. An alpha level of .05 was determined as the threshold for significance in all analyses. Lastly, 29 hospitals were in counties where the number of specialists equaled zero. All zero values for this variable were replaced with "1" before creation of the general practitioner-to-specialist ratio.

CHAPTER IV: RESULTS

Descriptive Statistics

Table 1 displays summary statistics for hospitals in the analytic sample. The average readmission penalty, ranging from 0 to 3%, in 2021 was .57%. The average tract-county dissimilarity index score, ranging from 0 to .81, was .45. This means that, on average, a hospital was in a county where 45% of the Black residents had to move to a different census tract to obtain an even population distribution with white residents. Majority of hospitals in the sample were in urban-metropolitan areas (63.22%), were private non-profit (64.13%), and small bed-size (59.59%).

Table 1: Summary Statistics of nonfederal hospitals subject to Hospital Readmissions Reduction Program penalties (n = 3,014)

	Mean/%	SD	Min	Max
Outcome Variable				
% by which payments are reduced because of excess hospitalizations (2021) [0-3%], %	.57	.67	0	3
Main predictor				
Dissimilarity Index	.45	.14	0	.81
County-level characteristics				
%Black NH residents assuming only Black NH and White NH people reside in county	16.57	15.90	.13	88.80
% Black NH residents as a proportion of the total population	11.92	12.82	.05	84.54
%White NH residents as a proportion of the total population	61.65	20.97	1.78	96.95
% Residents ages 65+ in deep poverty (2015-2019)[1]	2.98	1.04	0	10.80
% Residents ages 18-64 without health insurance (2019)[2]	13.28	6.09	2.80	43.40
% Residents ages 25+ without a HS Diploma	12.34	5.35	1.90	46.70

Unemployment rate	7.90	2.20	2.70	22.50
% Owner-occupied homes in 2010[3]	65.86	9.71	19.30	89.70
Median home value (2015-2019)	235,785	166,675	35,000	1,097,800
Standardized, risk-adjusted per capita Medicare costs	10,958.41	993.81	7,685.35	14,664.26
# Nursing home beds per 10,000 people	1.68	7.69	0	117.83
General practitioner to specialist ratio	1.27	1.34	0	20.00
General practitioners per 10,000 people	7.51	3.24	0	59.00
Urban/Rural, %		-	-	-
Urban-metro	76.01	-	-	-
Urban non-metro	23.06	-	-	-
Rural	.93	-	-	-
Hospital Characteristics				
Total expenses per inpatient day	7,450.08	6,734.78	280.57	111,043.20
%Medicare days per total inpatient days	52.06	13.15	0	97.47
%Medicaid days per total inpatient days	20.19	12.56	0	97.47
Ownership, %				
Public, non-Federal	13.64	-	-	-
Private, non-profit	64.13	-	-	-
Private, for-profit	22.23	-	-	-
Bed size, %				
Small (<200 beds)	59.59	-	-	-
Medium (200-399 beds)	25.71	-	-	-
Large (400+ beds)	14.70	-	-	-
Teaching Hospital[4], %	50.93	-	-	-
Skilled nursing available in hospital, %	13.53	-	-	-
Skilled nursing (missing), %	29.24	-	-	-

[1] As defined by the American Community Survey, deep poverty is living with income below half of one's poverty threshold.
[2] Insured was defined from the American Community Survey as being covered SOME TIME during the respective calendar year
[3] A housing unit is owner-occupied if the owner or co-owner lives in the unit even if it is mortgaged or not fully paid for. The owner or co-owner must live in the unit and usually is Person 1 on the questionnaire. Owner-occupied environments have been associated with better resident health profiles and outcomes.[49]
[4] Teaching status is defined as being a Member of the Council of Teaching Hospitals of the Association of American Medical Colleges, having at least one program accredited by the Accreditation Council for Graduate Medical Education, or having a full-time resident-to-hospital-bed ratio greater than 25%[16]

Bivariate Analysis

Table 2 presents hospital characteristics stratified by low, moderate and high segregation categories. On average, hospitals in moderately (H_M) and highly (H_H) segregated counties had significantly higher readmission penalties, with the average percent payment reduction due to excess readmissions being .59% and .63%, respectively, compared to hospitals in lowly (H_L)segregated areas (.48%).

Compared with H_L, H_M and H_H were in counties with higher proportions of Black non-Hispanic residents, residents 65 years of age older in deep poverty, higher median home values more urban-metropolitan areas, more private non-profit and teaching hospitals, and more medium and large-sized hospitals. In addition, compared to H_L, H_M and H_H were more likely to locate in areas with lower proportions of owner-occupied homes, fewer nursing home beds per 10,000 people, lower general practitioner to specialist ratios, less public non-federal and small hospitals. Furthermore, only H_H were more likely than H_L to be in counties with a lower proportion of residents ages 18-64 without health insurance and had lower total expenses per inpatient day, and lower proportion of private for-profit hospitals. There were no differences in per-capita Medicare costs and proportion of Medicare days per inpatient days across hospitals based on the degree of segregation.

Table 2: Comparison of % payment reduction, county & hospital characteristics by residential segregation category

	All hospitals Mean (SD) / %	Low Segregation (D < .3) (ref)	Moderate Segregation (.3<= D < .6)	High Segregation (D>= .6)
No. Of hospitals	3,014	438	2,091	485
Outcome Variable				
% by which payments are reduced because of excess hospitalizations (2021) [0-3%]	.57 (.67)	.48 (.66)	.59** (.67)	.63*** (.65)
County-level characteristics				
% Black NH residents as a proportion of the total population	11.92 (12.82)	9.28 (15.13)	11.09* (11.98)	17.92*** (12.28)
% Residents ages 65+ in deep poverty (2015-2019)[1]	2.98 (1.04)	2.71 (1.13)	2.91*** (.97)	3.56*** (1.02)
% Residents ages 18-64 without health insurance (2019)[2]	13.28 (6.09)	13.97 (5.60)	13.70 (6.41)	10.86*** (4.29)
% Owner-occupied homes in 2010[3]	65.86 (9.71)	69.95 (7.77)	66.68*** (8.01)	58.62*** (13.59)
Median home value (2015-2019)	235,785 (166,675)	200,572 (111,868)	224,865*** (160,518)	314,666*** (206,168)
Standardized, risk-adjusted per capita Medicare costs	10,958 (994)	10,890 (1,147)	10,994 (1,015)	10,866 (702)
# Nursing home beds per 10,000 people	1.68 (7.69)	3.55 (14.84)	1.32** (5.91)	1.53** (3.85)
General practitioner to specialist ratio	1.27 (1.34)	1.86 (1.57)	1.26*** (1.34)	.79*** (.77)
Urban/Rural (%)				
Urban-metro	76.01	52.28	77.28***	91.96***
Hospital Characteristics				
Total expenses per inpatient day	7,450 (6,735)	8,119 (6,711)	7,562 (7,044)	6,361*** (5,077)
%Medicare days per total inpatient days	52.06 (13.15)	52.34 (14.84)	52.28 (12.75)	50.85 (13.18)
Ownership (%)				
Public, non-Federal	13.64	20.55	13.20***	9.28***
Private, non-profit	64.13	56.16	63.18**	75.46***
Private, for-profit	22.23	23.29	23.63	15.26**
Bed size (%)				
Small (<200 beds)	59.59	82.19	59.59***	39.18***
Medium (200-399 beds)	25.71	15.07	25.97***	34.23***
Large (400+ beds)	14.70	2.74	14.44***	26.60***
Teaching hospital[4], %	50.93 (50.00)	31.51	49.78***	73.40***

Note: SD = standard deviation. D = Dissimilarity index

[1] As defined by the American Community Survey, deep poverty is living with income below half of one's poverty threshold.

[2] Insured was defined from the American Community Survey as being covered SOME TIME during the respective calendar year
[3] A housing unit is owner-occupied if the owner or co-owner lives in the unit even if it is mortgaged or not fully paid for. The owner or co-owner must live in the unit and usually is Person 1 on the questionnaire. Owner-occupied environments have been associated with better resident health profiles and outcomes.[49]
[4] Teaching status is defined as being a Member of the Council of Teaching Hospitals of the Association of American Medical Colleges, having at least one program accredited by the Accreditation Council for Graduate Medical Education, or having a full-time resident-to-hospital-bed ratio greater than 25%[16]
*p<.05, **p<.01 ***p< .001; ANOVA was performed for continuous variables, chi-square was performed for categorical variables, reference category was hospitals in low dissimilarity counties (HL)

Regression Analyses

Table 3 presents the estimated Medicare payment reductions (in percentage points [ppt]), or penalties, due to excess readmissions with the main independent variable – i.e., the dissimilarity index - and model covariates. Unadjusted analysis (Model 1) showed that H_M experienced an average payment reduction of .12 ppt due to excess 30-day readmissions, compared to H_L ($p < .001$). H_H experienced a greater average reduction in Medicare payments compared to H_L (marginal effect [ME] =.17 ppt; $p<.001$). After county-level covariate (Model 2), the MEs for H_M (.08 ppt; $p<.05$) and H_H (.14 ppt; $p<.01$), as compared with H_L, were reduced in magnitude but remained statistically significant. In Model 3, the ME between H_H and H_L was approximately the same as model 1, but the ME between H_M and H_L was attenuated, albeit to a lesser degree than Model 1 (.10; $p<.01$). Lastly, in the fully adjusted model (Model 4), MEs for readmission penalties between H_L, H_M and H_H were about the same as Model 2.

In Model 2, penalties were lower for hospitals with higher county proportion of residents ages 18-64 without health insurance, higher median home values, and higher general practitioner-to-specialist ratios. Higher per capita Medicare costs and urbanicity, on the other hand, was associated with higher penalties. In Model 3, higher total hospital expenses per inpatient day was associated with lower penalization, whereas higher proportion of Medicare days per inpatient days, and private ownership (non-profit or for-profit) was associated with higher penalization compared to public-federal ownership. In the fully adjusted model, margins for the county-level covariates remained stable, whereas margins for the hospital-level covariates were attenuated, however all estimates remained significant.

Table 3: Unadjusted and Adjusted % payment reductions associated with residential segregation

	Model 1		Model 2		Model 3		Model 4	
	Adjusted		County covariates		Hospital covariates		County & Hospital covariates	
	ME (ppt)	95% CI	ME (ppt)	95% CI	ME (ppt)	95% CI	ME (ppt)	95% CI
Main Predictor								
Segregation (Dissimilarity Index)								
Low (ref)	-	-	-	-	-	-	-	-
Moderate	.12***	(.05, .18)	.08*	(.01, .14)	.10**	(.04, .17)	.08*	(.01, .14)
High	.17***	(.08, .25)	.14**	(.04, .24)	.17***	(.08, .27)	.14**	(.04, .25)
County-level characteristics								
% Black NH residents	-	-	-.01	(-.26, .23)	-	-	.06	(-.20, .32)
% Residents ages 65+ in deep poverty (2015-2019)[1]	-	-	.01	(-.02, .04)	-	-	.00	(-.02, .03)
% Residents ages 18-64 without health insurance (2019)[2]	-	-	-.01*	(-.01, -.00)	-	-	-.01**	(-.01, -.00)
% Owner-occupied homes in 2010[3]	-	-	.00	(-.00, .01)	-	-	.00	(-.00 - .00)
Median home value (2015-2019)	-	-	-.05**	(-.08, -.02)	-	-	-.05**	(-.08, -.01)
Standardized, risk-adjusted per capita Medicare costs	-	-	.09***	(.06, .12)	-	-	.09***	(.06, .12)
# Nursing home beds per 10,000 people	-	-	-.00	(-.00, .00)	-	-	.00	(-.00, .01)
General practitioner to specialist ratio	-	-	-.05***	(-.06, -.03)	-	-	-.04***	(-.06, -.02)
Urban/Rural (%)								
Urban metro	-	-	.09**	(.03, .15)	-	-	.08*	(.01, .15)
Hospital Characteristics								
Total expenses per inpatient day	-	-	-	-	-.07***	(-.09, -.05)	-.07***	(-.10, -.05)
%Medicare days per total inpatient days	-	-	-	-	.52***	(.30, .73)	.45***	(.22, .67)
Ownership (%)								
Public, non-Federal (ref)	-	-	-	-	-	-	-	-
Private, non-profit	-	-	-	-	.09**	(.03, .15)	.07*	(.00, .14)
Private, for-profit	-	-	-	-	.29***	(.20, .37)	.23***	(.14, .33)
Bed size (row %)								
Small (<200 beds) (ref)	-	-	-	-	-	-	-	-
Medium (200-399 beds)	-	-	-	-	.05	(-.02, .12)	.02	(-.05, .09)
Large (400+ beds)	-	-	-	-	-.03	(-.11, .05)	-.07	(-.15, .01)
Teaching Hospital[4]	-	-			-.04	(-1.0, .01)	-.06	(-.12, .00)

Note: N = 3,014. CI = confidence interval. ME = marginal effect

Marginal effects = percentage point difference in payment reduction compared to reference category calculated at the mean.

[1] As defined by the American Community Survey, deep poverty is living with income below half of one's poverty threshold.

[2] Insured was defined from the American Community Survey as being covered SOME TIME during the respective calendar year

[3] A housing unit is owner-occupied if the owner or co-owner lives in the unit even if it is mortgaged or not fully paid for. The owner or co-owner must live in the unit and usually is Person 1 on the questionnaire. Owner-occupied environments have been associated with better resident health profiles and outcomes.[49]

[4] Teaching status is defined as being a Member of the Council of Teaching Hospitals of the Association of American Medical Colleges, having at least one program accredited by the Accreditation Council for Graduate Medical Education, or having a full-time resident-to-hospital-bed ratio greater than 25%[16]

*p< .05, **p< .01, ***p< .001

CHAPTER V: DISCUSSION

Summary

The motivation for this study was to investigate the association between a manifestation of structural racism that creates these spatial inequities in hospital penalties. Racial residential segregation was found to be significantly associated with higher readmissions penalties. Adjustment for county and hospital covariates attenuated this relationship, but significance remained. Bivariate analyses (Table 2) showed hospitals in moderately segregated areas experience, on average, 23% higher payment reductions compered to hospitals in lowly segregated areas, and hospitals in highly segregated areas experienced 34% higher reductions on average.

Comparisons with previous literature

These findings are congruous with the extant literature stating area level factors continue to be determinants of disparities in hospital readmissions & readmissions penalties. Prior to the implementation of the HRRP, research showed that, from 2007 to 2010, county-level factors explained 58% of the variation in 30-day readmission rates. In this study, number of general-practitioners per capita and urbanicity were the second and third highest explainers of variation (11.9% and 13.3%, respectively).[15] Even after the policy implementation, Aswani et al. Found that, from 2013 to 2018, similar county-level factors, such as the general practitioner-to-specialist ratio and nursing home access and quality of care, explained 30% of the variation in readmissions penalties.[16] In that study, higher general practitioner-to-specialist ratio and nursing access and quality were associated with lower readmissions penalties.[14] The current study found similar results. For example, a one unit increase general practitioner-to-specialist ratio was associated with a .03 ppt decrease in penalization. On the other hand, hospital level variables explained more of the variation in readmission penalties in the model compared with county covariates. Overall, this study expands on previous ones by explicitly investigating how a spatial manifestation of structural racism is associated with such penalties.

Table 3 adjusted analyses, like previous research, show attenuated but sustained significant differences in payment reduction between hospitals. Compared to hospitals located in lowly segregated areas, hospitals in moderately and highly segregated areas saw the magnitude of their payment reduction reduced by approximately the same amount compared to the unadjusted model. Joynt Maddox found that differences in unplanned readmissions, despite experiencing attenuation after adjustment, remained significant for individuals in neighborhoods experiencing the most disadvantage.[14] Ultimately, hospitals in highly segregated areas saw a 34%, reduction in Medicare payments compared to hospitals in lowly segregated areas, while hospitals in moderately segregated areas only saw a 23% reduction.

Previous literature also shows that hospitals who treat more socioeconomically disadvantaged patients experience greater penalization. In 2011, Joynt found that minority-serving hospitals, defined as hospitals in the highest decile of minority patients in their payer mix, had higher readmission rates for both black and white patients compared to non-minority serving hospitals.[62] This lends support to the conclusion that where people receive care, not simply the racial category of those who receive it, determines outcomes. The results in this study also align with extant access to care theory and evidence showing minority-serving hospitals are more likely to be in areas with a higher proportion of minorities (and that people will be hospitalized closer to their home of residence). Bivariate results showed significantly positive associations with the level of segregation hospitals experienced and the proportion of Black residents at the county level. Notably, the proportion of Black residents at the tract or county level did not show any significance in the adjusted glm model. This finding strengthens the theory of structural racism that residential segregation, not simply the demographic makeup of a neighborhood or county, is a prime determinant of differences in readmissions penalties.

Bivariate analyses show highly and moderately segregated areas have a higher proportion of the Medicare-aged population in deep poverty, a lower proportion of owner-occupied homes, and lower general practitioner to specialist ratios compared to lowly segregated areas. Additionally, urban-metro areas were more likely to be highly segregated. Comparing this to Herrin et al.'s findings that non-urban-metro counties (e.g., rural areas) had lower readmission rates than urban-metro areas suggest some robustness to the theory and evidence that hospitals in urban-metro areas are more likely to be highly penalized.[15] Herrin et al. also found higher general practitioner-to-specialist ratios resulted in lower readmission rates, supporting our results that higher general practitioner-to-specialist ratios are associated with lower penalties.

There were some inconsistencies with previous literature. Whereas our results showed higher per capita Medicare costs by county were associated with higher penalties, lower proportions of Medicare beneficiaries in a county have been associated with higher readmission rates.[15] It would be logical to assume that more beneficiaries in area means more utilization, thus higher costs. But here that is not the case. Furthermore, Joynt and Desai found that large hospitals were more likely to be highly penalized compared to small hospitals, but our results showed no significant differences in the *lower* penalization experienced by large hospitals.[4, 55] Regardless, if large hospitals are more likely to exist in highly segregated areas compared to small hospitals, as our bivariate results show, and large hospitals are more highly penalized, as results of the extant literature show, then results support the theory and evidence that hospitals in highly segregated areas experience greater penalization.

Strengths & Limitations

This study exhibits strengths important in the progression of health services research around disparities between hospitals. First, this is the first study to assess the association between a measure of structural racism and hospital readmissions penalties. Second, the use of population data from the most recent Census and readmissions penalty data from 2021 serve as the foundation for the claim that structural racism continues to be associated with differential distribution of outcomes in the healthcare system nationwide. Lastly, the regression results show that: 1) alone, the dissimilarity index is a significant explainer of differences in hospital readmissions penalties, 2) these results are attenuated by further inclusion of county and hospital characteristics, and 3) simple measures of county or tract racial composition were insignificant in explaining differences in penalization. The last point distinguishes racial residential segregation from racial composition as a determinant of differences in penalization, justifying its consideration as a social determinant of health for in a robust HRRP risk-adjustment algorithm.

There are also some limitations to this study. The cross-sectional study design limits the ability to infer any causal relationships between racial residential segregation and hospital readmissions penalties. Specifically, no temporal relationship can be established to determine, for example, how penalization has changed since implementation of the HRRP. More broadly, the HRRP implementation is relatively young, occurring after the 2010 Census, so no appropriate causal relationship of residential segregation can be established either. Secondly, the study data are spread across six years, with some data points, such as the county-level covariates, encompassing five-year aggregates of certain sociodemographic characteristics. These aggregate measures collapse the variation within years, potentially attenuating the effect of these characteristics on the dependent variable. Omitted variable bias exists in a few instances. For one, patient-level characteristics are unobserved in the model. Hospital-level variables for the racial and ethnic identity of patients treated were absent from the AHA dataset, and therefore unobserved in the model. Finally, there is no endogenous measure of hospital quality in the model. Exclusion of such a measure of hospital quality, such as inpatient quality indicators or patient safety indicators from the Agency for Healthcare Research and Quality, that may certainly exist between hospitals experiencing different degrees of segregation results in the error term being correlated with the dissimilarity index during regression analyses.

Third, the Dissimilarity index assumes census tract and county populations include only Black non-Hispanic & white non-Hispanic. This eliminates additional variation in the segregation of areas because it excludes presence of other races and ethnicities, and subsequently their unique dissimilarity measure compared to whites. The measure in this study is effectively the Black-white dissimilarity index, for which a high score does not necessarily mean a high score for the Asian-white index. The nature of how Blacks and Asians are segregated compared to whites could vary based on the U.S. region and nationality of Asians. Overall, these limitations serve to underestimate the association between racial residential segregation and hospital readmissions penalties and, thus, do not detract from the contribution of this study towards the current body of literature.

Implications

It has been known for some time that there are spatial differences in hospitals that serve the most vulnerable and that they continue to suffer worse penalties. Despite this, the only changes to risk-adjustment made in 2018 was the addition of controlling for a patient-level factor: the burden of dual-eligible patients a hospital serves. Previous literature has shown how adding these spatial differences into readjustment can attenuate differences between hospitals. Joynt Maddox also found that differences in readmission ratios between SNHs and non-SNHs were cut in half (table 3 of Joynt Maddox, 2019) after controlling for social risk factors such as education, employment, income, and housing quality.[14]

These findings are consistent with evidence from previous studies stating current risk-adjustment in penalization is inadequate. Policies that acknowledge and address racial residential segregation as a measure of structural racism may be considered in the conversation of eliminating disparities between hospitals. In 2019, the average penalty dollar amount was approximately $375,000 – up from $217,000 in 2018 - and the maximum exceeded $2,000,000.[63, 64] This estimate may seem minor, but when considering hospitals serving the most vulnerable have smaller margins *and* higher penalties the impact of this financial loss becomes important. Furthermore, these facilities typically rely on forms of nonpatient revenue to make up for their higher penalties, but with significant government-backed financial support decreasing, such as the elimination of Disproportionate-Share Hospital payments, there is cause for concern.[65-67] If robust risk-adjustment accounting for the existence of structural racism is not implemented, the gap between providers will remain and may continue to widen.

Commented [GI1]: per hospital penalized?

Commented [GI2R1]: can you quantify the average $$ difference for a high segregation and low segregation hospital?

Recommendations for Future Research

Future research should explore longitudinal relationships between residential segregation and hospital readmissions penalties. Temporal analyses stratified by segregation category investigating changes in penalization since the HRRP's implementation would add a unique layer to the debate around drivers of disparities between hospitals. They would also elucidate to what extent the policy may be working or having unintended effects. Such analyses would address the cross-sectional data limitation in the current study, but if conducted would need careful consideration of the policy specifications. For example, despite the HRRP penalties taking effect beginning fiscal year 2013, the maximum penalty began at 1%, and was increased another 1% the following fiscal year until being capped at 3% beginning fiscal year 2015. In such a model, year fixed effects may be appropriate to be included in regression models.

Future research should also compare robust areal sociodemographic and social determinants of health to each other to discover which may be more adequate to include in risk-adjustment. Comparative models displaying the separate and combined associations of racial residential segregation and other aggregate measures of socioeconomic inequity, such as Putnam's Social Capital Index and the Area Deprivation Index would prove useful in progressions of the risk-adjustment initiatives led by the National Quality Forum.[16, 68]

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Appendices

Appendix A: The Dissimilarity Index

$$\frac{\sum_{i=1}^{n}(t_i|p_i - P|)}{2TP(1-P)}$$

$\boldsymbol{n}$ = the number of census tracts in the county

$\boldsymbol{i}$ = the $\boldsymbol{i}$'th census tract

$\boldsymbol{t_i}$ = the total population of census tract $\boldsymbol{i}$ (assuming only Black non-Hispanic & White non-Hispanic reside in the census tract)

$\boldsymbol{p_i}$ = the proportion of census tract $\boldsymbol{i}$'s population that is Black

P = the proportion of the county's population that is Black

T = the total county population (assuming only Black non-Hispanic & White non-Hispanic reside in the county)

Appendix B: Covariates Correlation Matrix

	n_r~2021	dissim	pc_bwpop	pc_wbpop	pc_bnh~p	pc_wnh~p	c_totpop	pt_bnh~p	t_totpop	p_65pl~v	p_25pl~l	p_own_~g	c_unem~e	med_ho~e	gp_spec1	gp	gp_10k	c_stdz~t	c_nr~10k	lowedc~y
n_readm~2021	1.0000																			
dissim	0.0834	1.0000																		
pc_bwpop	0.0474	0.3983	1.0000																	
pc_wbpop	-0.0474	-0.3983	-1.0000	1.0000																
~~pc_bnhpop~~	0.0476	0.2762	0.9363	-0.9363	1.0000															
~~pc_wnhpop~~	0.0226	-0.3132	-0.6398	0.6398	-0.4370	1.0000														
c_totpop	-0.0210	0.4080	0.2251	-0.2251	0.0219	-0.4988	1.0000													
~~pt_bnhpop~~	0.0234	0.1969	0.6275	-0.6275	0.6930	-0.2496	-0.0165	1.0000												
t_totpop	0.0298	-0.0654	-0.0751	0.0751	-0.1132	-0.0505	0.0543	-0.1682	1.0000											
p_65pl_dee~v	-0.0065	0.2604	0.4252	-0.4252	0.3157	-0.4966	0.2853	0.1921	-0.0648	1.0000										
p_25pl_noh~l	-0.0172	0.0604	0.2741	-0.2741	0.1634	-0.4925	0.2527	0.1170	-0.0442	0.4315	1.0000									
p_own_occ_~g	0.0379	-0.3685	-0.4424	0.4424	-0.2741	0.6056	-0.4568	-0.1369	-0.0024	-0.3804	-0.2179	1.0000								
c_unemprate	0.0690	0.4485	0.3073	-0.3073	0.1764	-0.4821	0.4621	0.1189	-0.0442	0.3248	0.3633	-0.3708	1.0000							
med_home_v~e	-0.0385	0.1865	-0.0309	0.0309	-0.1662	-0.3662	0.4509	-0.1629	0.1721	0.0861	-0.0921	-0.4899	0.2397	1.0000						
gp_spec1	-0.0934	-0.2670	-0.1939	0.1939	-0.1240	0.2472	-0.2141	-0.0677	-0.0088	-0.1005	0.1200	0.2934	-0.2031	-0.2489	1.0000					
~~gp~~	-0.0268	0.4429	0.2223	-0.2223	0.0307	-0.4889	0.9827	-0.0048	0.0542	0.2751	0.1946	-0.4752	0.4464	0.5041	-0.2328	1.0000				
gp_10k	-0.0332	0.2261	0.0492	-0.0492	0.0384	-0.0632	0.0937	0.0092	-0.0073	-0.0171	-0.3891	-0.3086	-0.0386	0.3709	-0.2822	0.1935	1.0000			
c_stdz_rsk~t	0.1164	0.0113	0.1522	-0.1522	0.1735	0.0066	0.0535	0.1641	0.0047	0.0277	0.0694	0.2184	-0.1837	-0.2414	0.1037	0.0292	-0.1939	1.0000		
c_nrs_be~10k	-0.0324	-0.0903	0.0059	-0.0059	0.0414	0.0825	-0.0741	0.0366	-0.0349	-0.0101	0.0293	0.0508	-0.0583	-0.0756	0.0998	-0.0742	-0.0185	-0.0469	1.0000	
lowedcnty	-0.0238	0.0207	0.1618	-0.1618	0.0425	-0.3977	0.3733	0.0185	-0.0089	0.2648	0.7131	-0.1824	0.2866	0.0223	0.0470	0.3057	-0.2349	0.0109	0.0049	1.0000
lowempcnty	0.0104	-0.0999	0.1215	-0.1215	0.1905	0.0227	-0.1708	0.1457	-0.1093	0.1638	0.3999	0.1594	0.1241	-0.2839	0.2260	-0.1883	-0.2888	0.0338	0.1085	0.2305
urb_rur_di	-0.0878	-0.2990	-0.1740	0.1740	-0.0750	0.3028	-0.2767	-0.0319	-0.0951	-0.0137	0.2254	0.2778	-0.1793	-0.3493	0.4360	-0.2938	-0.3189	0.0351	0.2027	0.0910
totexp_per~d	-0.1248	-0.0729	-0.1278	0.1278	-0.1414	-0.0078	-0.0500	-0.1343	0.0268	-0.0059	-0.0268	0.0091	-0.0555	-0.0045	0.0866	-0.0544	0.0057	0.0088	-0.0762	-0.0090

```
       teach |  -0.0066   0.2800   0.1584  -0.1584   0.1060  -0.1906   0.1457   0.0860  -0.0410   0.0719  -0.1326  -0.2653   0.1573   0.1721
-0.2558   0.1786   0.3371  -0.1025  -0.0620  -0.0905

   p_mcr_ipd |   0.1131  -0.0451  -0.1043   0.1043  -0.0624   0.2099  -0.0922  -0.0701   0.0219  -0.1288  -0.0780   0.1885  -0.0696  -0.1147
0.0583  -0.0962  -0.0679   0.0718  -0.2639  -0.0683

   p_mcd_ipd |  -0.0303   0.1239   0.0902  -0.0902   0.0707  -0.0795   0.0746   0.1336  -0.0760   0.0866   0.1150  -0.1721   0.2076   0.1185
-0.0385   0.0778   0.0183  -0.2276   0.3368   0.0733

   ownership |  -0.0406  -0.0363  -0.0601   0.0601  -0.0649  -0.1028  -0.0166  -0.0538  -0.0170   0.0808   0.0394   0.0174   0.0239  -0.0635
0.0388  -0.0220  -0.0399   0.0502   0.0065   0.0022

     bedsize |   0.0067   0.3063   0.2403  -0.2403   0.1863  -0.2430   0.1879   0.1392  -0.1117   0.1293  -0.0676  -0.3055   0.1685   0.1876
-0.2741   0.2141   0.3277  -0.0570  -0.0095  -0.0437


             | lowemp~y urb_ru~i totexp~d    teach p_mcr_~d p_mcd_~d owners~p  bedsize

-------------+------------------------------------------------------------------------

  lowempcnty |   1.0000

  urb_rur_di |   0.3949   1.0000

totexp_per~d |  -0.0075   0.0711   1.0000

       teach |  -0.1520  -0.3197  -0.1221   1.0000

   p_mcr_ipd |  -0.0086   0.0101  -0.0992  -0.1022   1.0000

   p_mcd_ipd |   0.0558   0.0423  -0.2876   0.1180  -0.5526   1.0000

   ownership |   0.0921   0.0717   0.4660  -0.0406  -0.2922  -0.1758   1.0000

     bedsize |  -0.1673  -0.3441  -0.2120   0.4901  -0.1963   0.2257  -0.0810   1.0000
```