

**Assessing Hospital Disparities Using Indirect Estimation of Race
and Ethnicity: Thirty-Day All-Cause Readmissions
Methodology Report for 2022 Confidential Reporting**

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1. Executive Summary

1.1 Background and Overview

The Centers for Medicare & Medicaid Services (CMS) uses quality outcome measures in accountability programs to improve patient health care and well-being. These measurement initiatives evaluate quality of care provided to *all* eligible Medicare patients cared for by a given provider. Despite evidence showing disparities in care and experience for patients along racial and ethnic lines,¹⁻³ there are few initiatives that focus attention on the care of patients with social risk factors or patients from minoritized racial and ethnic groups and few measurement initiatives that directly measure healthcare disparities.

To fill this gap and better inform consumers about hospitals' quality of care, CMS has contracted with Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHSC/CORE) to develop methodologies for reporting outcome measures stratified by social risk factors and race and ethnicity. Examining quality differences between subgroups of patients has two main goals: ensuring transparency around disparities in health care and improving care for minoritized and vulnerable groups. To this end, prior work has resulted in The CMS Disparity Methods,⁴ which are methodologies used to stratify outcome measures.

The gold standard for data on people's race and ethnicity is individual self-report. However, studies have shown that existing Medicare administrative race and ethnicity data contain inaccuracies. In this report, we focus on reporting disparities in outcomes measures related to patient race and ethnicity, where the latter is estimated using the Medicare Bayesian Improved Surname Geocoding Method Version 2.1 (MBISG). The MBISG is an algorithm developed for CMS that combines the original (SSA) Medicare administrative self-reported race and ethnicity variable with patient information to better estimate beneficiary race and ethnicity.

The methods for estimating racial and ethnic disparity are presented using the Hospital-Wide All-Cause Unplanned Readmission Measure (HWR). Results are also shown for six condition-specific readmission measures ([Appendix B](#)).

The methods are adapted from The CMS Disparity Methods⁴ for use with patient race and ethnicity. Two stratification approaches comprise the CMS Disparity Methods:

1. *The Within-Hospital Disparity Method* highlights differences in outcomes for patient groups based on social risk factors or demographic variables within a hospital.
2. *The Across-Hospital Method* allows for comparison of performance in care for patients with social risk factors or demographic variables across hospitals.

Both disparity methods are designed to be reported in addition to overall hospital performance measures, since both disparity results and overall performance results provide important but distinct information. The purpose of this report is to provide an example of how these original two methods can be adapted to new patient social risk factors or demographic variables, including social risk factors which are available as probabilities.

1.2 Results

Results from the Within-Hospital Disparity Method indicated that following eligible hospitalizations, patients identified by the MBISG as likely to self-identify as Black, Hispanic, or Asian or Pacific Islander (API) were, on average, more likely to be readmitted when compared to patients identified as likely to self-identify as White by the MBISG. The mean rate difference (RD) between Black, Hispanic, or API groups and the White comparison group were 1.35%, 0.40%, and 0.36% respectively. There was variation in the RD between hospitals, indicating overall variation in hospitals' disparity. While the percent of hospitals with adequate numbers of patients was low, the percent of patients in the racial and ethnic groups who were seen at them was high. For the Within-Hospital Disparity Method, between 35.2% and 57.25% of hospitals met the sample size threshold for reporting; within these reporting hospitals between 94.6% and 99.0% of readmissions for Black, Hispanic, and API patients were included.

Results from the Across-Hospital Disparity Method were completed for the Black, Hispanic, and API patient groups. The mean risk-standardized readmission rates (RSRRs) for these patient groups were 18.9%, 16.5%, and 15.4% respectively. Variation across hospitals in RSRR indicate different levels of quality for these populations at different hospitals. Similar to the Within-Hospital Disparity Method, the Across-Hospital Disparity Method showed low hospital reporting percentages, and high patient reporting percentages. For the Across-Hospital Disparity Method, between 33.3% and 58.5% of hospitals met the threshold to receive results; between 88.7% and 98.0% of readmissions for the Black, Hispanic, and API patient groups were included in reporting hospitals.

1.3 Implications

Taken together, our results show that the application of the Within-Hospital Disparity Method and the Across-Hospital Disparity Method to imputed race and ethnicity is technically feasible. The methods reveal variation across hospitals for both within- and across-hospital disparities. This suggests an opportunity for improvement of hospital performance for patients of different racial and ethnic groups could be incentivized by reporting hospitals' calculated disparities and race/ethnicity-specific readmission rates. As patient-reported race and ethnicity data become more available, these methods offer a meaningful way to stratify results to support historically marginalized populations.

2. Introduction

2.1 Background

The Centers for Medicare & Medicaid Services (CMS) use quality outcome measures in accountability programs, such as the Hospital Inpatient Quality Reporting Program, with the goal of improving patient health care and well-being. These measurement initiatives evaluate quality of care provided to all patients cared for by a given hospital. Despite evidence showing that patients with social risk or who belong to minoritized racial and ethnicity groups often experience lower quality of care, there are few initiatives that focus attention on the care of these patients or that directly measure healthcare disparities.¹⁻⁴

To fill this gap, CMS has contracted with Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHSC/CORE) to develop methodologies for presenting stratified results of outcome measures in order to report hospitals' quality of care for patients with minoritized racial and ethnicity groups. Examining quality differences between subgroups of patients (measure stratification) has two main goals: to ensure transparency around disparities in health care for patients with social risk factors or along demographic lines and to improve care for at-risk populations. In 2014, the Improving Medicare Post-Acute Care Transformation Act (IMPACT Act) (H.R. 4994) tasked the Assistant Secretary for Planning and Evaluation (ASPE) to examine the effect of social risk factors on Medicare quality and payment programs. In their report, ASPE recommended that CMS 1) develop statistical techniques to report performance measures for patients with social risk factors, and 2) introduce health equity measures to illuminate disparities in healthcare quality.⁵ In addition, CMS's Meaningful Measures Framework also highlighted the need to develop health equity measures.

With these guidelines in mind, CORE developed two methods to quantify disparity by stratifying quality measure results by patient variables:

1. The *Within-Hospital Disparity Method* measures the difference in health outcomes between patients with and without a given social risk factor or demographic variable.
2. The *Across-Hospital Disparity Method* assesses hospitals' performance for only patients with a given social risk factor or demographic variable.

These methods were first developed using patient eligibility for both Medicare and Medicaid ("dual eligibility (DE) status") as an indicator for patient financial risk, and stratified results using this social risk factor were confidentially reported for the Pneumonia Readmission Measure (NQF #0506) in 2018 in the Hospital Inpatient Quality Reporting Program, followed by expansion to six readmission measures in the Hospital Readmission Reduction Program (HRRP) beginning in 2020.* CMS initially focused on

* (1) Hospital 30- Day, All-Cause, Risk-Standardized Readmission Rate (RSRR) Following Acute Myocardial Infarction (AMI) Hospitalization (NQF #0505) (AMI Readmission measure); (2) Hospital 30- Day, All-Cause, Risk-Standardized Readmission Rate (RSRR) Following Coronary Artery Bypass Graft (CABG) Surgery (NQF #2515) (CABG Readmission measure); (3) Hospital 30- Day, All-Cause, Risk-Standardized Readmission Rate (RSRR) Following Chronic Obstructive Pulmonary Disease (COPD) Hospitalization (NQF #1891) (COPD Readmission measure); (4) Hospital 30-Day, All-Cause, Risk- Standardized Readmission Rate (RSRR) Following Heart Failure (HF) Hospitalization (NQF #0330) (HF Readmission measure); and (5) Hospital- Level 30-Day, All-Cause,

stratification by DE as consistent with recommendations from ASPE's report identifying dual eligibility as the most available and robust indicator of social risk for health outcome reporting.⁵

On January 20, 2021, Executive Order 13985 identified the advancement of racial equity as a federal priority. In response to this order, and in consideration of frequent literature published identifying lower quality of care, poorer experience in care, and more frequent hospital readmission and procedural complication for patients identifying as racial and ethnic minorities, CMS sought to adapt the existing disparity methods for use with patient race and ethnicity.

Early examination of existing data on patient race and ethnicity identified a key limitation. Self-reported race and ethnicity data are the gold standard for classifying an individual according to their race or ethnicity. However, CMS does not currently collect self-reported race and ethnicity for Medicare beneficiaries in a consistent way. Instead, CMS gets these data from the Social Security Administration, which in turn collects this information upon enrollment in Social Security; thus, for Medicare beneficiaries over 65 years of age, any race and ethnicity data were likely collected several decades ago. Though self-identified race and ethnicity is likely stable over time, when these data were collected several decades ago, methods were inconsistent and there were limited possible responses.⁶ Numerous initiatives have been undertaken in prior decades to improve the collection of patient race and ethnicity for Medicare beneficiaries; however, until more accurate and more complete data sources are available, alternatives will need to be considered to allow for stratification by these demographic variables.

Therefore, CMS investigated a statistical approach, similar to one that is used by the US Census as well as in other CMS programs for accounting for missing/incorrect information on individual-level race and ethnicity. We believe methods such as these can help overcome the current limitations of demographic information and allow for timelier reporting of equity results until validated data sources are available. After reviewing available methods, CMS identified the Medicare Bayesian Improved Surname Geocoding (MBISG) method⁷ as providing the most accurate (sensitive and specific) indirect estimation technique for use with disparity reporting. This method, and its advantages, will be discussed in further detail in [Section 4.2](#).

In this technical report, we provide detailed information on the adaptation of The Within-Hospital Disparity Method and the Across-Hospital Disparity Method for reporting disparities in patient outcomes by patient race and ethnicity using indirect estimation. We use a single measure, the Hospital-Wide Readmission Measure (NQF #1789) as an example measure to test the new disparity methods for use with estimated patient race and ethnicity. However, the approach is general and can be applied to other imputed patient-level social factors and outcome measures.

2.2 Importance of Measuring Health Care Disparities

Although health equity has been a longstanding issue of concern for the American healthcare system, disparities in health outcomes persist.⁸⁻¹² The ASPE found a 10% to 31% higher odds of readmission for

Risk- Standardized Readmission Rate (RSRR) Following Elective Primary Total Hip Arthroplasty (THA) and/or Total Knee Arthroplasty (TKA) (NQF #1551) (THA/ TKA Readmission measure)

low-socioeconomic status (SES) patients compared to high-SES patients after accounting for patient comorbidities across conditions included in the HRRP.⁵ In addition, differences in odds of readmission between Black patients and White patients ranged from 9% to 20% depending on the condition examined.⁵ Health and healthcare disparities also impose considerable costs on the healthcare system. For instance, a study indicated that the economy loses an estimated \$309 billion per year due to the direct and indirect costs of health inequities along racial and ethnic lines.^{13,14} At the same time, the variation in disparities across providers is evidence that hospitals can reduce disparities.

Reporting disparities in outcomes through measure stratification can improve healthcare quality. Highlighting within-hospital disparities can encourage hospitals to improve outcomes for patients with social risks. At the same time, there is evidence that interventions can directly reduce healthcare disparities through multi-level efforts with patients and their caregivers, clinicians, and other important stakeholders.¹⁵⁻²⁰ These efforts include targeting patients with social risks during the initial admission; systematically screening health literacy of patients; and providing specific education and training for patients with social risk factors. Additional improvements can be made in improving communication with at-risk patients, their caregivers, and their clinicians as well as engaging local stakeholders to integrate community and healthcare resources in care coordination after discharge.

In summary, health equity measures are key to identifying and monitoring disparities in healthcare quality at individual hospitals, which can drive reductions in disparities of care and better inform patient choices. Reporting disparity measures could encourage hospitals to implement the aforementioned programs and thereby reduce the gap in outcomes between beneficiaries with and without social risk factors.

2.3 Overview of Two Disparity Methods

CMS previously developed two methods to assess healthcare quality for patients with social risk factors at a given hospital and illuminate potential disparities:

1. The *Within-Hospital Disparity Method* measures the difference in health outcomes between patients with and without a given social risk factor or demographic variable within a hospital.
 - The goal is to show whether two patients who are admitted to the same hospital with the same condition and medical history will have similar outcomes.
 - The method extends the model used in current risk-adjusted outcome measures by including a "disparity factor." This is used to calculate a rate difference (RD) for each hospital that reflects the difference in outcomes between patients at that hospital. This approach accounts for differences in patient characteristics such as age and medical conditions.
 - This method shows whether some hospitals are more successful at achieving similar outcomes across different race and ethnic groups of patients at their facility.
2. The *Across-Hospital Disparity Method* assesses hospitals' performance for only an identified group of patients with a social risk factor or who belong to a specific demographic group.
 - This method calculates a separate measure score for each racial or ethnic group at each hospital. This method also risk adjusts for patients' medical conditions to capture differences among hospitals rather than differences among patients so that hospitals

can be compared fairly. It is reported as a risk-standardized readmission rate (RSRR) for individual racial and ethnic groups at a hospital.

- This method shows whether some hospitals are more successful at achieving better outcomes for specific racial or ethnic groups compared to other hospitals.

Both methods are intended to provide information on hospital quality that will supplement the existing readmission measure results, which will continue to be publicly reported. By pairing these two disparity scores with the overall performance measure result, it will be evident if equity is achieved at a hospital by solely providing poor quality of care to all patients. For example, if a hospital has a low RD (near zero, indicating no difference in performance) between two patient groups they will score well on the Within-Hospital Method. However, if this is due to poor performance for both patient groups, they may receive a low RD while providing poor care to the vulnerable patient group. With these results, they would score well on the Within-Hospital Method, but the poor care for the vulnerable group will be reflected in the Across-Hospital Method.

2.4 Rationale for Measures Tested

In this methodology report, our primary analyses use the All-Cause Hospital-Wide Readmission Measure (HWR) as an example measure for reporting the CMS Disparity Methods using imputed race and ethnicity. CMS began publicly reporting the HWR measure in 2013 to provide broad assessment of the quality of care at hospitals. Results for this measure are posted on *Care Compare*, which CMS updates annually.

We chose the HWR measure as our primary test measure for several reasons. First, the measure covers a broad range of conditions, designated by five specialty cohorts: Medicine, Surgery/Gynecology, Cardiorespiratory, Cardiovascular, and Neurology. The use of a measure that covers so many conditions serves as an opportunity to test the methods across a similarly broad range of care settings. Furthermore, the HWR measure is large, including over 6 million index admissions from July 1, 2018 to June 30, 2019 alone.³⁴ The large size of the HWR cohort ensures that sample sizes are large enough to reliably calculate hospital performance using imputed race and ethnicity for as many hospitals as possible (for more details on sample size requirements for the two disparity methods, see [Section 5.3.1](#) and [Section 6.3.1](#)). In addition, higher overall outcome rates increase the likelihood of identifying meaningful disparities when stratifying by race and ethnicity.

While our primary application of indirect estimation was the HWR measure, we also tested this approach for six condition-specific readmission measures. These measures were chosen because of their long history of public reporting and use in the HRRP program.[†] See [Appendix B](#) for results of testing on the condition-specific readmission measures.³²

2.5 Rationale for Using Imputed Patient Race and Ethnicity

There are many different social determinants of health, including social risk factors and demographic variables, that have known associations with poorer health outcomes. However, data sources for large-

[†] As finalized in the FY 2022 Inpatient Prospective Payment System (IPPS)/Long-Term Care Hospital Prospective Payment System (LTCH PPS) final rule, the pneumonia readmission measure will be suppressed in FY 2023 HRRP calculations. We have completed testing on the measure as a proof of concept.

scale disparity reporting for patient social determinates of health are lacking. To date, CMS has focused disparity reporting on one social risk factor, DE for Medicare and Medicaid, as it has been found to be one of the most robust and available patient level indicators of social risk.⁵ Given the existing evidence of racial and ethnic disparities in hospital outcomes, including hospital readmission rates, reporting hospital outcomes stratified by race and ethnicity can support quality improvement efforts to reduce these inequities.

The gold standard for patient-level race and ethnicity is individually self-reported data. However, studies have shown that existing Medicare administrative race and ethnicity data contain inaccuracies, contributed to by limited historical collection classifications and antiquated race and ethnicity identification practices.⁶ For example, the original CMS administrative data on race and ethnicity are based on information reported to the Social Security Administration (SSA) using a form that required most Medicare beneficiaries (those whose SSA information was provided prior to 1980) to choose “Black,” “White,” or “Other.” For this reason, these data often (sometimes greater than 40% of the time) misclassify Asian or Pacific Islander (API) and Hispanic beneficiaries as “White” or “Other”. Using these potentially inaccurate sources for conducting equity stratification could result in the overestimation or underestimation of quality of care received by certain groups of beneficiaries.

Efforts to improve patient reported race and ethnic data sources are ongoing. However, to provide actionable information that is timely, alternative approaches have been developed to provide highly accurate estimations of the racial and ethnic makeup of a community. One method, called indirect estimation, or imputation, improves upon imperfect and incomplete data on race and ethnicity by using a combination of other data sources that are predictive of self-identified patient race and ethnicity, such as language preference, existing race and ethnicity data in claims, first and last names that match to validated lists of names correlated to specific national origin groups, or racial and ethnicity composition of surrounding neighborhoods identified through census self-report. This additional information can be used, in combination with the existing Medicare beneficiary information, to predict the likely self-reported race and ethnicity of beneficiaries. While this type of prediction should not be used to make inferences about individuals, it can be meaningfully used to make predictions about aggregated groups, an approach which has been used to supplement existing data sources or to provide estimations for use in disparity analysis, for example, by the CMS Office of Minority Health (OMH),²² and by CMS Medicare Advantage health plans.²³

2.6 Methods for Indirect Estimation of Race and Ethnicity

The MBISG method provides six predicted probabilities for each beneficiary; these are the probabilities that the beneficiary would self-report as: American Indian/Alaskan Native (AI/AN), API, Black, Hispanic, Multiracial, and non-Hispanic White (hereafter referred to as White). In our testing of the methods presented here we focused on the four largest groups, API, Black, Hispanic, and White. Though disparities involving other groups are equally important, the MBISG is not yet recommended for inference about the Multiracial group and total numbers for the AI/AN group were too small to reliably assess disparities. In addition, consistent with historic evidence of generally better healthcare for White beneficiaries, we chose to use the White group as the ‘reference’ group, measuring differences between the other three groups and the White group. We recognize that there is also interest in measuring differences between the non-White groups, as well as conditions or environments in which White

patients are not the correct choice of reference, and these methods can be used to compare any groups of interest or to compare all groups to the overall average.

2.7 Approach to Methods Development

The original development of the CMS Disparity Methods was completed in 2018. The methods were developed in consultation with clinical and measurement experts, key stakeholders, patients, families, and caregivers. They were designed to be applied to various quality measures that follow national guidelines for publicly reported outcome measures set by the National Quality Forum (NQF), CMS's Measure Management System, and the American Heart Association's scientific statement "Standards for Statistical Models Used for Public Reporting of Health Outcomes".^{24,25} For details on the development of the original methods and subsequent updates, please see the measure methodologies and annual updates on *QualityNet* at <https://qualitynet.cms.gov/inpatient/measures/disparity-methods/methodology>.

Throughout the development of the methods to incorporate patient race and ethnicity, we obtained stakeholder input via two mechanisms. First, CMS described our work in the proposed inpatient prospective payment system rule for fiscal year (FY) 2022.²⁶ The FY2022 rule presented CMS's intention to incorporate patient race and ethnicity into the CMS Disparity Reporting program by utilizing the MBISG, an imputation method designed for CMS by the RAND corporation which combines Medicare administrative data, first and surname matching, and geocoded residential address linked to the US Census to estimate the probability that a patient self identifies to six racial and ethnic groups^{27,28} and sought input via public comment.

Commenters noted the importance of measuring disparities in health care quality for racial and ethnic groups. Several commenters supported the use of indirect estimation by race and ethnicity, but recommended that methods be validated by recognized authorities such as NQF or expressed a preference for using patient reported data. Other comments reinforced the need to be wary of furthering stigmatization or measurement bias.

Second, we reconvened the technical expert panel (TEP) that provided input on the development of the original disparity methods. The TEP consists of members with diverse perspectives and backgrounds, including clinicians, hospitals, purchasers, consumers, and experts in quality improvement and healthcare disparities. Convening a TEP ensures transparency and helps method developers obtain balanced input from multiple stakeholders. During the TEP meeting, we received important input on the application of the MBISG model to the two disparity methods and how to display the results of the analyses.

3. Overview of Hospital-Wide Readmission Measure

We applied the CMS Disparity Methods to the HWR Measure (NQF #1789). The HWR measure is a claims-based, risk-adjusted measure, designed following similar readmission based measures, but offers a broader assessment of quality of care at hospitals. Below, we describe the key features of the HWR measure as it is currently calculated and used in CMS programs. For more details about the measure, see the 2021 Annual Updates and Specifications report on *QualityNet* at: <https://qualitynet.cms.gov/inpatient/measures/readmission/methodology>.

3.1 Cohort

Our analyses focus on the HWR measure cohort, which assesses hospitalizations to which the readmission outcome is attributed and includes admission for patients enrolled in Medicare Fee-For-Service (FFS) Part A for the 12 months prior to the date of admission and during the index admission:

- For Veterans Affairs (VA) beneficiaries hospitalized in VA hospitals, there are no Medicare FFS enrollment requirements;
- For VA beneficiaries hospitalized in non-VA hospitals, they must be concurrently enrolled in Medicare FFS Part A at the time of the index admission to be eligible for inclusion;
- Age 65 or over;
- Discharged alive from a non-federal short-term acute care hospital or VA hospital; and,
- Not transferred to another acute care facility.

The measure excludes admission for patients who are:

- Admitted to Prospective Payment System (PPS)-exempt cancer hospitals;
- Without at least 30 days of post-discharge enrollment in Medicare FFS (in the case of patients who are not VA beneficiaries);
- Discharged against medical advice;
- Admitted for primary psychiatric diagnoses;
- Admitted for rehabilitation; or
- Admitted for medical treatment of cancer.

Each eligible admission is assigned to one of five mutually exclusive specialty cohorts: Medicine, Surgery/Gynecology, Cardiorespiratory, Cardiovascular, and Neurology. The cohorts reflect how care for patients is organized within hospitals. To assign admissions to cohorts, admissions are first screened for the presence of an eligible Agency for Healthcare Research and Quality (AHRQ) Clinical Classifications Software (CCS) surgical procedure category or one of the defined singular International Classification of Disease Tenth Revision (ICD-10)- Procedure Coding System (PCS) codes listed in the 2021 HWR Measure Code Specifications supplemental file posted on *QualityNet*. Admissions with an eligible surgical procedure are assigned to the surgical cohort, regardless of the principal discharge diagnosis code of the admission. All remaining admissions are assigned to cohorts based on the AHRQ CCS diagnosis category of the principal discharge diagnosis.

3.2 Outcome

The outcome for the HWR measure is 30-day all-cause unplanned readmission. Readmission is defined as an unplanned re-hospitalization to any short-term acute care facility within 30 days of the discharge date from an eligible index admission.

The measure captures unplanned readmissions that arise for acute clinical events requiring urgent re-hospitalization within 30 days of discharge. This means that only an unplanned inpatient admission to a short-term acute care hospital can qualify as a readmission. Planned readmissions, which are generally not a signal of quality of care, are not considered readmissions in the measure's outcome. Planned readmissions are identified using the Planned Readmission Algorithm (version 4.0), a set of criteria for identifying admissions that are typically planned according to procedure and diagnostic codes. Details about the Planned Readmission Algorithm (version 4.0) are available in the measure's 2021 annual update report.²¹

The measure assigns a dichotomous yes/no outcome to each patient indicating whether that patient has an unplanned readmission within 30 days. If a patient has at least one unplanned readmission within 30 days of discharge from the index admission, then the readmission outcome is "yes" and the patient would be considered "readmitted." If the first readmission after discharge is planned, any subsequent unplanned readmission is not considered in the outcome for that index admission because the unplanned readmission could be related to care provided during the intervening planned readmission rather than during the index hospitalization.

3.3 Risk Adjustment Variables

Each of the 5 specialty cohorts are risk adjusted separately. To account for differences in case mix among hospitals, the measure includes an adjustment for factors such as age and comorbid diseases, which are clinically relevant and have relationships with the outcome. Case mix differences among hospitals are based on the clinical status of the patient at the time of the index admission. Accordingly, only comorbidities that convey information about the patient at the time of the index admission, or any time within the preceding 12 months, are included in risk adjustment. Complications that arise during the course of the hospitalization are not used in risk adjustment.

To account for differences in service mix among hospitals, the measure adjusts for the principal discharge diagnosis of the index admission (grouped into AHRQ CCS diagnosis categories). Thus, for the Cardiorespiratory, Cardiovascular, Neurology, and Medicine specialty cohorts, the AHRQ CCS diagnosis categories used for risk adjustment are the same as those used to define each of these cohorts (listed in the 2021 HWR Measure Code Specifications supplemental file posted here on *QualityNet*). For the Surgery/Gynecology cohort, which is defined by AHRQ CCS procedure categories and ICD-10-PCS codes, the AHRQ CCS diagnosis category used for risk adjustment is simply the AHRQ CCS diagnosis category that the principal discharge diagnosis for that surgical admission falls into.

For each patient, risk-adjustment variables are obtained from ICD-10 diagnosis codes in inpatient Medicare claims data extending 12 months prior to the index admission, and all ICD-10 secondary diagnosis codes from the index admission itself. For VA beneficiaries, the risk-adjustment variables are obtained from VA administrative data. ICD-10 codes are then mapped to the Condition Category (CC). Note that CC mappings to ICD-10-Clinical Modification (CM) codes are available on *QualityNet*.

The measure does not include an adjustment for social risk factors because the association between social risk factors and health outcomes can be due, in part, to differences in the quality of health care that groups of patients with varying social risk factors receive. The intent is for the measure to adjust for age and clinical characteristics while illuminating important quality differences. The NQF re-endorsed the measure without adjustment for patient-level social risk factors in the last endorsement maintenance submission prior to 2021.

Refer to the 2021 HWR Measure Code Specifications supplemental file posted on *QualityNet* for the list of comorbidity risk-adjustment variables used in the HWR measure and the list of potential complications that are excluded from risk adjustment if they occur during the index admission. These risk-adjustment variable specifications apply to all five specialty cohorts.

3.4 Measure Calculation

This section provides an overview on the calculation of the overall HWR measure (for more details, see [Appendix A](#)), or the measure methodology report available on *QualityNet*. We built on this model to calculate disparity scores using the Within-Hospital Disparity Method (for more details, see [Section 5.2](#)) and the Across-Hospital Disparity Method (for more details, see [Section 6.2](#)).

The hospital-level 30-day all-cause RSRR is constructed using hierarchical logistic regression models, with one model estimated for each of the five specialty cohorts. In brief, the approach simultaneously models data at the patient and hospital levels to account for variance in patient outcomes within and between hospitals.²⁹ At the patient level, it models the log-odds of hospital readmission within 30 days of discharge using age, selected clinical covariates, and a hospital-specific effect. At the hospital level, the approach models the hospital-specific effects as arising from a normal distribution. The hospital effect represents the underlying risk of a readmission at the hospital, after accounting for patient risk. The hospital-specific effects are given a distribution to account for the clustering (non-independence) of patients within the same hospital.⁸ If there were no differences among hospitals, then after adjusting for patient risk, the hospital effects should be identical across all hospitals.

After estimating the hierarchical model for each specialty cohort group, the standardized readmission ratio (SRR) is calculated as the ratio of the number of “predicted” readmissions to the number of “expected” readmissions at a given hospital. For each hospital and specialty cohort, the numerator of the ratio is the number of readmissions within 30 days predicted based on the hospital’s performance with its observed case mix and service mix; the denominator is the number of readmissions expected based on the nation’s performance with that hospital’s case mix and service mix. This approach is analogous to a ratio of “observed” to “expected” used in other types of statistical analyses. It conceptually allows a particular hospital’s performance, given its case mix and service mix, to be compared to an average hospital’s performance with the same case mix and service mix. Thus, a lower ratio indicates lower-than-expected readmission rates or better quality, while a higher ratio indicates higher-than-expected readmission rates or worse quality.

The specialty cohort SRRs are then pooled for each hospital using a volume-weighted geometric mean to create a hospital-wide combined SRR. The combined SRR is multiplied by the national observed readmission rate to produce the RSRR. The statistical modelling approach is described fully in [Appendix A](#) and in the methodology report posted on *QualityNet*.

3.5 Condition-Specific Readmission Measures

While our primary application of indirect estimation was the HWR measure, we also tested this approach for six condition-specific readmission measures:

1. *NQF #0505*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Acute Myocardial Infarction (AMI);
2. *NQF #1891*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Chronic Obstructive Pulmonary Disease (COPD);

3. *NQF #2515*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Coronary Artery Bypass Graft (CABG);
4. *NQF #1551*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Elective Primary Total Hip Arthroplasty and/or Total Knee Arthroplasty (THA/TKA);
5. *NQF #0330*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Heart Failure (HF); and,
6. *NQF #0506*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Pneumonia Hospitalization (Pneumonia).

These measures were chosen because of their long history of public reporting and use in the HRRP program.[‡] These six measures are similar in construct to the HWR measure, though include only a single model rather than five different models. Details on these measures can be found on *QualityNet* at the Hospital Readmission Reduction Program page.³⁵

See [Appendix B](#) for results of testing on the condition-specific readmission measures.

[‡] As finalized in the FY 2022 Inpatient Prospective Payment System (IPPS)/Long-Term Care Hospital Prospective Payment System (LTCH PPS) final rule, the pneumonia readmission measure will be suppressed in FY 2023 HRRP calculations. We have completed testing on the measure as a proof of concept.

4. Data Sources

4.1 Medicare Administrative Claims Data

The data sources used for our analyses are Medicare inpatient administrative claims and enrollment information for the year the results are reported on Care Compare (reporting year, or RY), in this case 2022, which includes patients with hospitalizations between July 1, 2020 to June 30, 2021 for HWR (July 1, 2018 to June 30, 2021 for condition-specific measures). The datasets also contain associated inpatient, outpatient, and physician Medicare administrative claims for the 12 months prior to the index admission and the one month subsequent to the index admission for patients admitted in this time period. Medicare claims data was used to identify critical access hospital status.

4.2 Medicare Bayesian Improved Surname Geocoding Method Dataset

MBISG version 2.1 is an algorithm developed for CMS that combines the original Social Security Administration linked Medicare administrative self-reported race and ethnicity variable with geographic, first name, surname, and additional demographic and Medicare coverage data to better estimate beneficiary race and ethnicity. The MBISG method is a Medicare-specific application of RAND's more general Bayesian Improved Surname Geocoding (BISG) approach.

The gold standard for gathering data on race and ethnicity is individual self-report. However, studies have shown that the original (SSA) Medicare administrative race and ethnicity variable, which is based on constrained self-report, is often inaccurate, especially in identifying API and Hispanic beneficiaries. Indirect estimation improves upon imperfect and incomplete data on race and ethnicity by drawing on other administrative variables that contain racial and ethnic information to better match what beneficiaries self-report when given a full set of self-report options. This section describes MBISG 2.1, an indirect estimation method that improves upon version 2.0.

The MBISG 2.1 method supplements the original (SSA) beneficiary-reported information on race and ethnicity with additional administrative information, in some cases by linking external information into the dataset. For example, beneficiary surnames are linked to the distribution of self-reported race and ethnicity by surname from the 2000/2010 Censuses, and beneficiary residential addresses are linked to the most recently available Census race and ethnicity data at the smallest geographic level that Census makes available, the block group, which corresponds to 12-digit FIPS codes. MBISG 2.1 combines this and other available administrative information reported by beneficiaries to CMS to create estimates of race and ethnicity that better match what Medicare beneficiaries themselves self-report.

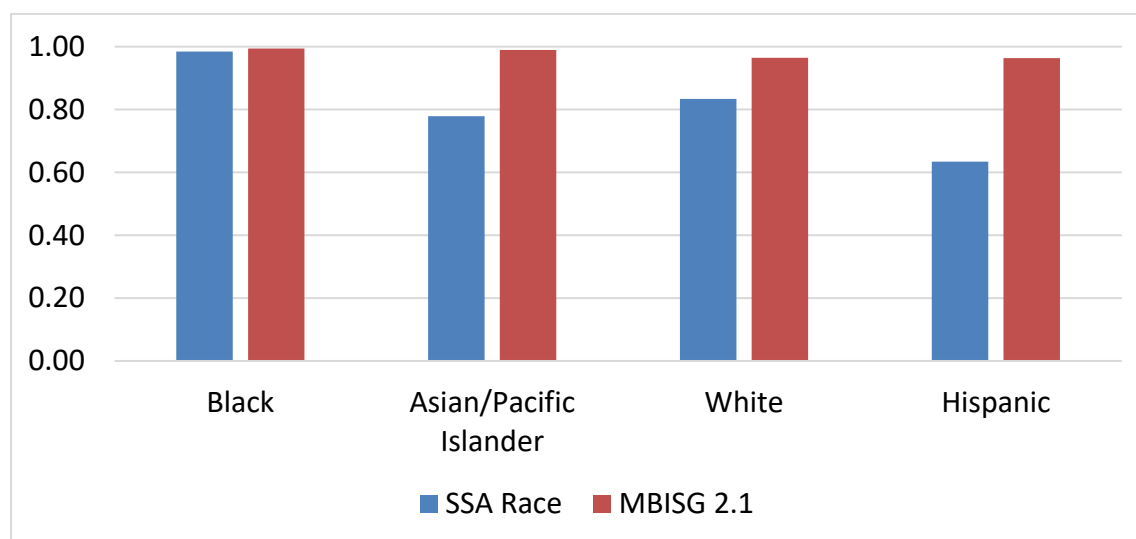
The MBISG 2.1 method does not assign a single race and ethnicity to individual beneficiaries; instead, it generates a set of six probabilities that the beneficiary would self-identify as each of six racial and ethnic groups: AI/AN, API, Black, Hispanic, Multiracial, and White. These categories correspond to those that Census uses in its surname list, which categorizes self-reported race and ethnicity based on a self-reported Hispanic ethnicity item and a check-all-that-apply race item. MBISG 2.1 probabilities reflect the uncertainty associated with each category for each person and are tools for making estimates about the racial and ethnic attributes of groups, not individuals. In no case should the estimated probabilities be used for making inferences about individual people; only self-reported data on race and ethnicity should be used for that purpose. However, in aggregate, these results can provide insight and accurate

information at the population level for aggregations such as the patients of a given hospital, or the members of a given plan.

The accuracy of the MBISG 2.1 method can be assessed by applying the method to data with known self-reported race and ethnicity. The concordance statistics shown in [Figure 1](#) are based on analyses that validated MBISG 2.1 against self-reported race and ethnicity data from the Medicare Consumer Assessment of Healthcare Providers and Systems (MCAHPS) Surveys. Respondents to the Medicare CAHPS surveys self-report their race and ethnicity using a full set of response options. Only 4% of survey respondents do not provide this information, and this low rate of not reporting varies little by race and ethnicity.³⁰ These self-reported race and ethnicity data were linked to the original self-reported SSA data and to the improved data generated by MBISG 2.1 to compare the concordance of each for different racial and ethnic groups.

As shown in [Figure 1](#), MBISG 2.1 has 96-99% concordance with what Medicare beneficiaries report when given a full set of response options with respect to API, Black, Hispanic, and White race/ethnicity.³³ This is a much higher concordance than what is achieved by the original self-reported SSA variable, also shown in [Figure 1](#). More recent analyses have also shown MBISG 2.1 to be a promising method for identifying AI/AN beneficiaries (not shown in Figure 1). However, because of the small number of patients (total probabilities) in this group they were not included in stratification or other analyses that follow.

Figure 1: Concordance statistics for SSA Race Variable and MBISG 2.1 (compared to self-report)



Estimates from MBISG 2.1 in these applications are similar to what would result if beneficiaries had all been permitted to self-report race and ethnicity with a full set of response options. However, despite the high accuracy of MBISG 2.1 and widespread use of similar algorithms, there remains some degree of public sensitivity regarding use of algorithms to infer demographic information. CMS continues to work with Federal and private partners to improve collection and standardization of interoperable social and demographic information, including data from electronic health records (EHRs), to improve our understanding of how these variables can be better measured in order to close the equity gap. However, these initiatives often take substantial time to materialize, and there is a pressing need to

better explore racial and ethnic disparities in the Medicare program. The MBISG 2.1 method provides an accurate means to assess and improve equity as these data accumulate.

5. The Within-Hospital Disparity Method

5.1 Goal

The goal of the Within-Hospital Disparity Method is to illuminate within-hospital disparities between patient groups for a given performance measure. It answers the question: “Will two patients who differ only with respect to their race or ethnicity have different outcomes at a given hospital?”

In other words, this method is intended to illuminate whether patients admitted to the same hospital but identifying as a different racial or ethnic group experience different outcomes following discharge. This method allows us to measure the gap, or the disparity effect, across hospitals to assess whether some hospitals have a greater gap compared to others.

5.2 Modeling Strategy

We originally developed the Within-Hospital Disparity Method to directly measure the differences between subgroups of patients to be applied to a dichotomous indicator of social risk. This approach built on the model used in currently implemented readmission measures and incorporates two additional factors: 1) a patient-level indicator, generally an indicator of social risk or a demographic variable; and, 2) a hospital-level variable representing the proportion of patients at that hospital with the indicator. We add both variables to the original model; specifically, the original model is modified to include:

1. **A patient-level indicator as a “random effect”**; that is, an effect, like the overall quality effect included in the overall hospital measure, that can vary from hospital to hospital. This is the “hospital-specific disparity effect” or simply the “hospital disparity effect”; and,
2. **A hospital-level variable representing the proportion of patients with the risk factor in that hospital as a “fixed effect”**; that is, an effect that is constant across hospitals.

The coefficient for the patient-level indicator captures the within-hospital disparity directly and represents the differential impact of the factor on readmissions within each hospital. This coefficient is the “hospital disparity effect”; it is the critical component for evaluating differences in readmission rates among subgroups of patients within a hospital. Because it is allowed to vary across hospitals, it provides an estimate of the effect of the social risk factor or demographic variable for each hospital. The key advantages of this approach are that, consistent with the principles we established, it sets the same standards for all patients. It then assesses the impact of social risk on readmission risk within each hospital. The random effect directly estimates the disparity between patients with and without the social risk factor.

The coefficient for the proportion of patients at the hospital with the social risk factor reflects the difference in readmission rates between hospitals with different proportions of such patients. It is added to the model to reduce bias in estimating the patient-level effect and to ensure that we correctly interpret the hospital-specific random coefficient (i.e., the hospital disparity effect). In order to simplify interpretation of the model results, we center all risk factors around their means, except for the social risk factors or demographic variables which are centered on their hospital means.

5.2.1 Statistical Models

This section describes the original HWR risk model used for each specialty cohort, the original Within-Hospital Disparity Method for dichotomous social risk factors, and adaptation of the Within-Disparity Method model used to measure disparity based on imputed race and ethnic groups.

Original Readmission Model

Assume that we have a total number of I hospitals and the hospital i has n_i cases, $i = 1, \dots, I$. Let Y_{ij} represent the outcome for the j -th case treated at the i -th hospital. The outcome Y_{ij} is binary (1 = readmitted, 0 = not readmitted) variables, $i = 1, \dots, I; j = 1, \dots, n_i$. Denote the current (original) p -dimensional vector of risk factors by $\{X_{ij1}, X_{ij2}, \dots, X_{ijp}\}$, $i = 1, \dots, I; j = 1, \dots, n_i$.

A hierarchical generalized linear model (HGLM) is currently used to adjust for the original risk factors for CMS measures, which has a form of

$$\text{logit}(p_{ij}) = \beta_0 + \beta_1 X_{ij1} + \dots + \beta_p X_{ijp} + \epsilon_{0i} \quad (1)$$

where $p_{ij} = \Pr \{Y_{ij} = 1\}$ and ϵ_{0i} is the random intercept for each hospital that follows a normal distribution $N(0, \sigma_0^2)$.

Within-Hospital Disparity Method for Dichotomous Social Risk Factors

To evaluate the within-hospital disparity for each hospital associated with a dichotomous social risk factor (SR), we modified model (1) and estimate instead the following HGLM

$$\begin{aligned} \text{logit}(p_{ij}) = & \beta_0 + \beta_1(X_{ij1} - X_{..1}) + \dots + \beta_p(X_{ijp} - X_{..p}) + \epsilon_{0i} + \beta_{p+1}(SR_{ij} - SR_{i.}) \\ & + \beta_{p+2}(SR_{i.} - SR_{..}) + \epsilon_{1i}(SR_{ij} - SR_{i.}) \end{aligned} \quad (2)$$

where

- $X_{..k} = \frac{1}{\sum_{i=1}^I n_i} \sum_{i=1}^I \sum_{j=1}^{n_i} X_{ijk}$ for $k=1, \dots, p$;
- SR_{ij} is the social risk indicator (1=Yes, 0=No) for case j at hospital i ;
- $SR_{i.} = \frac{1}{n_i} \sum_{j=1}^{n_i} SR_{ij}$ is the proportion of cases with the social risk factor in hospital i , and $SR_{..} = \frac{1}{I} \sum_{i=1}^I SR_{i.}$ is the average of all hospitals proportion of cases with the social risk factor;
- $(\epsilon_{0i}, \epsilon_{1i})' \sim N_2(0, \Sigma)$ with $\Sigma = \begin{pmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{01} & \sigma_1^2 \end{pmatrix}$.

In this model, the fixed effect β_{p+2} reflects overall disparity, which is the average disparity effect across all hospitals. The random slope ϵ_{1i} reflects hospital i 's hospital-specific disparity effect, which is the degree to which the disparity in outcomes in hospital i differs from the average disparity. By combining these two, we can estimate the disparity effect at a given hospital.

Once model (2) is estimated, RD is calculated from model (2) by predicting the probability of a positive outcome under two different assumptions and calculating the difference. In both cases, we assume $\mathbf{X} = \text{mean}(\mathbf{X}_{ij})$, the average value of all risk factors over the population, and include the hospital-specific quality effect ϵ_{0i} and hospital-specific disparity ϵ_{1i} . For one, we assume $SR_j = 0$, that the hypothetical patient has no disparity risk factor, and for the other we assume $SR_j = 1$, that the hypothetical average patient has the disparity risk factor. The difference between these two predicted probabilities is the RD,

which can be intuitively interpreted as the difference in outcome rates for “average patients” treated at that hospital with and without the social risk factor, in symbols.

$$RD_i = \text{logit}^{-1}[\beta_0 + \epsilon_{0i} + \beta_{p+1}(1 - SR_{i\cdot}) + \beta_{p+2}(SR_{i\cdot} - SR_{\cdot\cdot}) + \epsilon_{1i}(1 - SR_{i\cdot})] \\ - \text{logit}^{-1}[\beta_0 + \epsilon_{0i} - \beta_{p+1}SR_{i\cdot} + \beta_{p+2}(SR_{i\cdot} - SR_{\cdot\cdot}) - \epsilon_{1i}SR_{i\cdot}], \quad (3)$$

For hospitals $i = 1, \dots, I$

This is calculated separately for each hospital i , with confidence intervals constructed using conventional or parametric bootstrapping.

Indirect Estimation of the Within-Hospital Disparity Method using imputed Race and ethnicity data

When using imputed race and ethnicity data from the MBISG, each patient has not one stratification factor but several, one for each race and ethnicity group. Specifically, each beneficiary has probabilities p_w , p_B , p_H , and p_A estimating the probability that the beneficiary would self-identify as White (W), Black (B), Hispanic (H) or Asian and Pacific Islander (A) respectively. Though the MBISG assigns probabilities for AI/AN and Multiracial groups, these had very low total probability and were not used. Note that this exclusion applies only to the probability assignments, not the patients. In order to estimate disparities using these 4 probabilities, we use the following modelling approach, which is applied separately for each of the 5 specialty cohorts in the HWR measure.

1. Expand the dataset so each observation (an eligible admission) has 4 rows, $r=1, \dots, 4$.
2. Create 4 indicators, B, H, A, and W, one for each R/E group.
3. Set
 - B=1 for row 1, B= 0 for the other rows
 - H=1 for row 2, H=0 for the other rows
 - A=1 for row 3, A=0 for the other rows
 - W=1 for row 4, W=0 for the other rows
4. Assign weight p_B to row 1, p_H to row 2, p_A to row 3 and p_W to row 4.

Using this constructed dataset, estimate the following model, which generalizes model (2) to include 3 social risk factors:

$$\text{logit}(p_{ij}) = \beta_0 + \beta_1(X_{ij1} - X_{\cdot 1}) + \dots + \beta_p(X_{ijp} - X_{\cdot p}) + \epsilon_{0i} \\ + \gamma_{10}(B_{ij} - B_{i\cdot}) + \gamma_{11}(B_{i\cdot} - B_{\cdot\cdot}) + \epsilon_{1i}(B - B_{i\cdot}) \quad (4) \\ + \gamma_{20}(H_{ij} - H_{i\cdot}) + \gamma_{21}(H_{i\cdot} - H_{\cdot\cdot}) + \epsilon_{2i}(H_{ij} - H_{i\cdot}) \\ + \gamma_{30}(A_{ij} - A_{i\cdot}) + \gamma_{31}(A_{i\cdot} - A_{\cdot\cdot}) + \epsilon_{3i}(A_{ij} - A_{i\cdot})$$

where

- $X_{\cdot k} = \frac{1}{\sum_{i=1}^I n_i} \sum_{i=1}^I \sum_{j=1}^{n_i} X_{ijk}$ for $k=1, \dots, p$;
- B_{ij} , H_{ij} , A_{ij} are indicators for group = B,H,A, for case j at hospital i

- $B_{i\cdot} = \frac{1}{n_i} \sum_{j=1}^{n_i} B_{ij}$ and $B_{\cdot\cdot} = \frac{1}{I} \sum_{i=1}^I B_{i\cdot}$; and same for H and A
- $(\epsilon_{0i}, \epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i})' \sim N_2(0, \Sigma)$ are random intercept + 3 random slopes; Σ diagonal
- The fixed effects $\gamma_{10}, \gamma_{20}, \gamma_{30}$ reflect overall B, H, and A disparities
- The random slopes $\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}$ reflects hospital i's specific B, H, and A disparity effects.

Indirect estimation is accomplished by estimating model (4) using weighted estimation, where each observation is weighted by the MBISG probabilities as noted above.

For each race or ethnicity group, we then estimate the risk difference using a modified version of (3) which is expanded to include terms for the other groups. For example, to compare B to W we use

$$RD[BW]_i = \text{logit}^{-1}[\beta_{0c} + \epsilon_{0i} + \gamma_{10}(\mathbf{1} - \mathbf{B}_{i\cdot}) + \gamma_{11}(B_{i\cdot} - B_{\cdot\cdot}) + \epsilon_{1ic}(1 - B_{i\cdot}) - \gamma_{20}(H_{i\cdot}) + \gamma_{21}(H_{i\cdot} - H_{\cdot\cdot}) - \epsilon_{2i}(H_{i\cdot}) - \gamma_{30}(A_{i\cdot}) + \gamma_{31}(A_{i\cdot} - A_{\cdot\cdot}) - \epsilon_{3i}(A_{i\cdot})] - \text{logit}^{-1}[\beta_0 + \epsilon_{0i} - \gamma_{10}\mathbf{B}_{i\cdot} + \gamma_{11}(B_{i\cdot} - B_{\cdot\cdot}) - \epsilon_{1i}B_{i\cdot} - \gamma_{20}(H_{i\cdot}) + \gamma_{21}(H_{i\cdot} - H_{\cdot\cdot}) - \epsilon_{2ic}(H_{i\cdot}) - \gamma_{30}(A_{i\cdot}) + \gamma_{31}(A_{i\cdot} - A_{\cdot\cdot}) - \epsilon_{3ic}(A_{i\cdot})] \quad (5)$$

and other RDs constructed similarly to compare H and A to W. To calculate a summary RD for HWR, a weighted average of each addend in (5) across specialty cohorts is calculated using the volume of the relevant race and ethnicity group.

For the six condition-specific readmission measures, we applied the same model, but to the single cohort.

5.3 Reporting Within-Hospital Disparities

5.3.1 Sample Size Considerations

Our current overall quality measures are typically reliable for sample sizes of 25 or more patients, and are therefore only publicly reported for hospitals with 25 or more patients. This is consistent with the HWR measure. If a hospital has fewer than 25 eligible cases readmission rates and interval estimates will not be publicly reported for the measure.

For the Within-Hospital Disparity Method, we similarly plan to report risk differences for hospitals with at least 25 patients overall and 12 patients in each patient subgroup. Because subgroups are determined by probabilities, we used the sum of the probabilities for each race/ethnicity category to arrive at a nominal samples size; these will be calculated and applied separately for each comparison (e.g., Black vs White). This sample size is aligned with the overall measure, and allows us to report results for as many hospitals as possible, but will limit reporting on hospitals where results may be less reliable and less meaningful.

5.3.2 Evaluating the Within-Hospital Disparity Method.

We applied the Within-Hospital Disparity Method to the HWR measure using data from RY 2022, which includes admissions from July 1, 2020 to June 30, 2021. First, we summarized the unadjusted RD for each subgroup, and report the mean odds ratios from the five specialty cohort models ([Table 1](#)). We reported the distribution of the RDs in readmission across hospitals, for each cohort and overall ([Table 2](#)), constructed histograms of each distribution ([Figure 2](#)), and reported the distributions of the HWR

specialty cohorts ([Table 3](#)). We then summarized the total probabilities for each race and ethnic group and each specialty cohort and the percent of hospitals meeting reporting threshold ([Table 4](#)).

5.4 Results

5.4.1 Unadjusted and Adjusted Difference in Overall Readmission Rates between Race and Ethnic Groups

The mean unadjusted readmission rate for White beneficiaries was 14.5%. When compared to the White group, the Black group (readmission rate = 18.9%, mean RD = 4.3%), Hispanic group (readmission rate = 16.5%, mean RD = 2.0%) and API group (readmission rate = 15.4%, mean RD = 0.9%) had overall higher readmission rates.

The adjusted difference in readmission rate between patient groups at the national level accounts for patients' comorbidities adjusted for in the HWR measure methodology. The results show that the difference in overall readmission rates between patient groups in terms of odds of readmission is greater than one for all specialty cohort/racial and ethnic group combination except for the Medicine specialty cohort for the White-API comparison. An odds ratio greater than one indicates that nationally, Black, Hispanic, and API groups are more likely to get readmitted than the White group after adjusting for case mix ([Table 1](#)).

5.4.2 Variance of the Hospital-Specific Disparity Effect

We tested whether the variance of the hospital-specific disparity effect is significant ([Table 1](#)). Results show that the variance of the hospital-specific disparity effect is zero for two of the specialty cohort and race and ethnicity group comparison combinations, <0.0005 for eight, and greater than zero for the remaining seven. When the variance of the hospital-specific disparity effect is zero (or very close), there is no meaningful difference in the level of disparity between hospitals. This does not indicate no disparity, however, only that the measured disparity (shown by the RD) is consistent across hospitals.

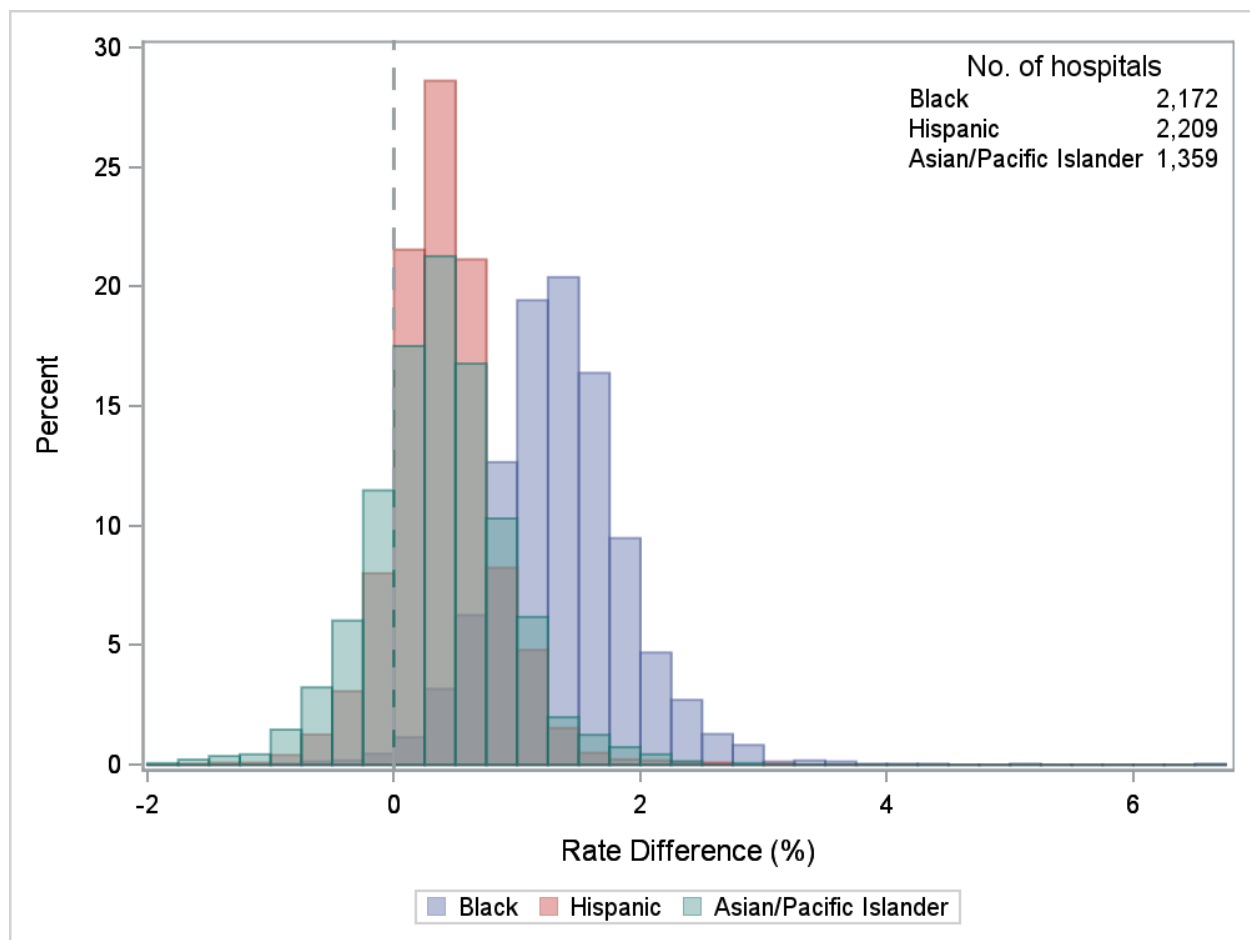
5.4.3 Hospital Rate Differences between Patient Groups Identified by the MBISG

[Figure 2](#) displays the overall distribution of hospital RD in hospital- wide readmission between White and Black, Hispanic, and API as identified by the MBISG. Only reporting hospitals (hospitals that meet the case minimum for the Within-Hospital Method) are included in the histogram. The cohort of patients identified as likely to be White were used as the comparison group. For the Black patient group, nearly all hospitals have an estimated RD greater than zero, indicating that this patient group has a higher rate of readmission than the White patient group. The Hispanic and API groups have similar distribution of RDs, with majority of hospitals also having greater than zero. This indicates higher rate of readmission than the White patient group. See [Table 1](#) for distributions.

Table 1: Within-Hospital Disparity Method Results

Cohort	Group (compared to White)	N (non-white readmissions)	Unadjusted Rate Difference	Mean Adjusted Rate Difference for Reporting Hospitals as an Odds Ratio (SD)	Mean Hospital Rate Difference (SD)	Variance of Random Hospital Disparity Effect (SE)
Medicine	Black	50942	3.55	1.06 (0.01)	0.76 (0.14)	0.051 (0.017)
	Hispanic	26802	1.60	1.01 (0.01)	0.08 (0.16)	<0.0005 (0.017)
	API	10742	0.32	0.99 (0.01)	-0.20 (0.10)	0
Surgery/ Gynecology	Black	11300	4.37	1.07 (0.01)	0.65 (0.10)	<0.0005 (0.038)
	Hispanic	7651	2.03	1.03 (0.00)	0.25 (0.01)	<0.0005 (0.000)
	API	3023	0.96	1.01 (0.00)	0.06 (0.02)	0
Cardio-respiratory	Black	8356	3.48	1.11 (0.03)	1.53 (0.41)	<0.0005 (0.059)
	Hispanic	3864	1.51	1.04 (0.01)	0.63 (0.12)	<0.0005 (0.000)
	API	1592	1.24	1.06 (0.06)	0.86 (0.74)	0.011 (0.000)
Cardio-vascular	Black	6150	4.19	1.09 (0.02)	0.96 (0.26)	0.098 (0.052)
	Hispanic	3678	1.94	1.04 (0.01)	0.43 (0.11)	0.001 (0.041)
	API	1509	1.04	1.04 (0.06)	0.34 (0.62)	0.005 (0.076)
Neurology	Black	5740	3.84	1.16 (0.00)	1.62 (0.13)	0.001 (0.072)
	Hispanic	2552	1.22	1.01 (0.01)	0.15 (0.07)	<0.0005 (0.000)
	API	1303	0.94	1.08 (0.02)	0.83 (0.24)	<0.0005 (0.089)
Hospital-wide (Full Cohort)	Black	82488	4.34	N/A	1.35 (0.57)	N/A
	Hispanic	44548	1.97	N/A	0.40 (0.42)	N/A
	API	18169	0.88	N/A	0.36 (0.56)	N/A

Figure 2: Distribution of Rate Difference in Readmission between Racial and Ethnic Groups (reference group: White)



[Table 2](#) shows the distribution of the RD in readmission between patient cohorts identified using the MBISG model across hospitals for the full HWR measure cohort. Of 3,859 eligible hospitals, 43.72%, 42.76%, and 64.78%, of hospitals had too few cases to allow reporting for the Black to White, Hispanic to White, and API to White comparisons.

Table 2: Distribution of Hospital Results on the Within-Hospital Disparity Method for the Full Hospital-wide Readmission Cohort

Comparison Groups	Total Number of Eligible Hospitals*	Total Number of Reporting Hospitals**	Rate Difference (%) among reporting hospitals								Number of Cases Too Small (% of eligible hospitals)
			Min	10 th	25 th	Med	75 th	90 th	Max	Mean	
Black	3,859	2172	-0.77	0.71	1.01	1.32	1.65	2.01	6.73	1.35	43.72
Hispanic		2209	-1.63	-0.06	0.16	0.39	0.62	0.89	3.12	0.40	42.76
API		1359	-1.77	-0.31	0.02	0.35	0.68	1.03	2.79	0.36	64.78

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

[Table 3](#) shows the distribution of the RD in readmission between patient cohorts identified using the MBISG model within hospitals. Within-hospital results are shown as a RD between White and Black, Hispanic, and API groups individually.

[Table 3](#) also shows the number of eligible hospitals for each specialty cohort/racial and ethnic group combination. Hospitals were only eligible for disparity analysis if they had at least one White and one Black, Hispanic, or API (depending on the comparison being made) patient. For results to be reported the hospital must have seen at least 25 patients, including at least 12 for each compared group. The percent of eligible hospitals with too few cases for reporting for subcohort comparisons ranged from 48.18% of eligible hospitals to 95.40%.

Table 3: Distribution of Hospital Results on the Within-Hospital Disparity Method for the Hospital-Wide Readmission Specialty Cohorts

	Comparison Groups	Total Number of Eligible Hospitals*	Total Number of Reporting Hospitals**	Rate Difference (%) among reporting hospitals								Number of Cases Too Small (% of eligible hospitals)
				Min	10 th	25 th	Med	75 th	90 th	Max	Mean	
Medicine	Black	3682	1908	-0.04	0.61	0.68	0.75	0.83	0.92	1.43	0.76	48.18
	Hispanic	3682	1740	-1.18	-0.11	-0.01	0.10	0.18	0.25	0.51	0.08	52.74
	API	3682	949	-0.91	-0.34	-0.26	-0.19	-0.13	-0.07	0.09	-0.20	74.23
Surgery/ Gynecology	Black	2866	1118	0.24	0.53	0.58	0.65	0.71	0.77	1.04	0.65	60.99
	Hispanic	2866	1058	0.21	0.24	0.24	0.25	0.25	0.26	0.30	0.25	63.08
	API	2866	458	-0.01	0.03	0.05	0.06	0.08	0.09	0.14	0.06	84.02

Cardio-respiratory	Black	2829	832	-1.34	1.03	1.31	1.59	1.79	1.97	2.68	1.53	70.59
	Hispanic	2829	396	-0.05	0.48	0.56	0.65	0.72	0.76	0.92	0.63	86.00
	API	2829	130	-2.23	-0.04	0.44	0.84	1.37	1.76	2.77	0.86	95.40
Cardio-vascular	Black	2359	745	0.12	0.66	0.80	0.94	1.10	1.30	2.40	0.96	68.42
	Hispanic	2359	481	-0.25	0.32	0.38	0.45	0.51	0.55	0.64	0.43	79.61
	API	2359	208	-3.05	-0.38	-0.01	0.42	0.77	1.07	1.67	0.34	91.18
Neurology	Black	2283	730	1.19	1.46	1.52	1.61	1.70	1.78	2.26	1.62	68.02
	Hispanic	2283	391	-0.21	0.07	0.11	0.15	0.19	0.22	0.32	0.15	82.87
	API	2283	180	0.21	0.55	0.71	0.83	0.99	1.13	1.65	0.83	92.12

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

5.4.4 Patient Representation (Within-Hospital Disparity Method)

We examined patient representation in reporting and non-reporting hospitals to better understand the usability of these methods for the HWR measure.

- Black group vs White group comparison – Of 3,859 eligible hospitals, 2,172 (56.28%) met the reporting threshold. Reporting hospitals include 98.79% of admissions attributed to the Black group, and 99.00% of readmissions attributed to the Black group.
- Hispanic group vs White group comparison – Of 3,859 eligible hospitals, 2,209 (57.24%) met the reporting threshold. Reporting hospitals included 96.90% of admissions attributed to the Hispanic group, and 97.18% of readmissions attributed to the Hispanic group.
- API group vs White group comparison – Of 3,859 eligible hospitals, 1,359 (35.21%) met the reporting threshold. Reporting hospitals included 94.18% of admissions attributed to the API group, and 94.64% of readmissions attributed to the API group.

Table 4: Comparison of Reporting and Non-Reporting Hospitals for the Hospital-Wide Readmission Full Cohort (Within-Hospital Method)

Group	Encounter Type	Total included in eligible hospitals [n]	Total included in reporting hospitals [n (%)]
Black	Admissions	437196	431901 (98.8)
	Readmissions	82488	81660 (99.0)
Hispanic	Admissions	270014	261655 (97.0)
	Readmissions	44548	43290 (97.2)
API	Admissions	117963	111099 (94.2)
	Readmissions	18169	17195 (94.6)

6. The Across Hospital Disparity Method

6.1 Goal

The goal of the Across-Hospital Disparity Method is to measure and compare hospital performance for the subgroups of patients with a social or demographic factor. In contrast to the Within-Hospital Disparity Method, this method does not quantify the disparity in readmission between groups of patients, but instead calculates a RSRR for only patients with the risk factor or who belong to the measured group for each hospital. This method answers the question: “How does Hospital A perform for their patients with this risk factor or demographic status when compared to Hospital B?”

6.2 Modelling Strategy

The original Across-Hospital Disparity Method model applies the model used in currently implemented measures to the subset of patients with a social risk factor to calculate RSRRs for each hospital. The outcome and risk-adjustment model are the same as in the currently reported 30-day readmission measures. However, the cohort is a subset of the overall measure cohort with the social risk factor or demographic variable being measured. This means that the model used to calculate the Across-Hospital Disparity RSRRs adjusts for the same comorbidities as the model that includes all eligible Medicare patients, but the coefficients for comorbidities may be different.

For indirect estimation, we no longer have subgroups of patients with a specific risk factor; instead, we have a set of probabilities for each patient indicating the likelihood that they would have self-identified as one of the racial and ethnic groups included in the MBISG model. Thus, we modify this approach by estimating a single model using all patients, and then summing up the predicted and expected outcomes using the MBISG probabilities as weights.

6.2.1 Statistical Models

Original Statistical Model

For the original HWR measure, we estimate RSRRs using HGLMs applied to each specialty cohort. This strategy accounts for within-hospital correlation of the observed readmission rate and accommodates the assumption that underlying differences in quality across hospitals lead to systematic differences in outcomes. We model the probability of readmission p_{ij} as a function of patient age and clinically relevant comorbidities with an intercept ϵ_{0i} for the hospital-specific random effect.

$$\text{logit}(p_{ij}) = \beta_0 + \beta_1 X_{ij1} + \dots + \beta_p X_{ijp} + \epsilon_{0i} \quad (7)$$

where $\epsilon_{0i} \sim N(0, \sigma^2)$ and other notations are defined identically as in model (1).

Across-Hospital Disparity Method for Dichotomous Social Risk Factors

The Across-Hospital method for dichotomous factors simply replicates the original model (7) using only patients with the risk factor.

For the original Across-Hospital Disparity Method, the results of these cohort models are used to construct a SRR for each cohort. The SRR for each cohort is calculated as the ratio of the number of “predicted” readmissions to the number of “expected” readmissions at a given hospital.

$$SRR_i = \frac{\sum \text{logit}^{-1}[\beta_0 + \beta_1 X_{ij1} + \dots + \beta_p X_{ijp} + \epsilon_{0i}]}{\sum \text{logit}^{-1}[\beta_0 + \beta_{1c} X_{ij1} + \dots + \beta_{pc} X_{ijp}]} \quad (8)$$

For each hospital, the numerator of the ratio is the number of readmissions within 30 days, predicted based on the hospital's performance with its observed case mix for patients with a social risk factor or demographic variable, and the denominator is the number of readmissions expected based on the nation's performance with that hospital's case mix for patients with a social risk factor or demographic variable. This approach is analogous to a ratio of "observed" to "expected" used in other types of statistical analyses. The SRRs are pooled across cohorts for each hospital using geometric mean, weighted by volume. Then this final SRR is multiplied by the overall national raw readmission rate for all patients in all cohorts to produce the RSRR.

$$RSRR_j = SRR_j \times \bar{y}$$

This approach conceptually allows a particular hospital's performance, given its case mix, to be compared to an average hospital's performance with the same case mix.

Indirect Estimation of Across-Hospital Disparity Method using imputed race and ethnicity

To calculate the Across Method using imputed race and ethnicity probabilities, we estimate the model (7) using *all* patients in the cohort. We estimate the model separately for B, H and A subgroups, applying the corresponding weight in each case.

Using the results of model (7), we then calculate the SRR for each cohort as in (8), but 3 different times, using different weights each time. Specifically, to calculate SRR[B] for Black patients, we weight each observation by p_B ; we then pool these across the 5 specialty cohorts using the $\sum p_B$ in each category to weight the SRR. We replicate this to construct SRR[H] and SRR[A] in a similar fashion. These SRRs are then multiplied by the overall weighted average readmission rate for the corresponding group to produce a "risk-standardized readmission rate" or RSRR for B, H and A patients.

6.3 Reporting Across-Hospital Disparities

6.3.1 Sample Size Considerations

Our current overall quality measures are typically reliable for sample sizes of 25 or more patients. For the Across-Hospital Method, we would report results only for hospitals with at least 25 patients in the race or ethnicity subgroup. There was increasing probabilities of higher degree of noise when a sample size was small, and we thus use 25 patients to balance the tradeoff between the number of reporting hospitals and the results' reliability. This sample size allows us to report results for as many hospitals as possible, but will limit reporting on hospitals where results may be less reliable and less meaningful.

6.3.2 Evaluating the Across-Hospital Disparity Method

We applied the Across-Hospital Disparity Method to the HWR measure using data from July 1, 2020 to June 30, 2021.

We examined the mean unadjusted and adjusted 30-day readmission rate for the HWR cohort at the national level. Then we reported whether there is significant variation among hospitals by reporting the across-hospital variance ([Table 5](#)). We also reported the mean and the distribution of the race/ethnicity specific RSRRs for the overall HWR measure ([Table 6](#) and [Figure 3](#)). We also report the mean and distribution of the race and ethnicity specific RSRRs for each specialty cohort in the HWR measure ([Table 7](#)). Finally, we summarized the number of hospitalizations, the percent of patients from each race and ethnicity group and cohort, and the percent of hospitals in the HWR specialty cohorts ([Table 8](#)).

6.4 Results

To be included in the cohort, hospitals must have at least one patient for the specific race or ethnicity being considered patient. For potential future public reporting, we would require hospitals to have at least 25 patients in each group. Using this cut-off, we could report RSRRs for 1,802 (58.45%), 1720 (47.94%), and 884 (33.33%) of hospitals eligible for the across-hospital disparity method for the Black, Hispanic, and API groups respectively.

6.4.1 Unadjusted and Adjusted Readmission Rates

The mean unadjusted readmission rate within 30 days of index discharge for all included hospitalizations is 18.88%, 16.51%, 15.42% for the full HWR measure for the Black, Hispanic, and API patient groups respectively.

The adjusted mean readmission rates for each group are consistent with the unadjusted rates, with the mean group-specific RSRRs being 18.89%, 16.48%, and 15.39% for the Black, Hispanic, and API groups. The distribution of group specific RSRRs for the overall HWR measure is described in [Table 6](#) and [Figure 3](#).

6.4.2 Across-Hospital Variance

We assessed the variance in risk of readmission across hospitals, which is captured by the random intercept term. Across-hospital variance is zero for seven of the specialty cohort/racial and ethnic groups, indicating no variation in hospital performance for the combination tested, while the remaining eight specialty cohort/racial and ethnic group combinations show some variation. A latent variance that is zero or close to 0 indicates that performance for the subcohort measured is similar across hospitals.

Table 5: Across-Hospital Disparity Results

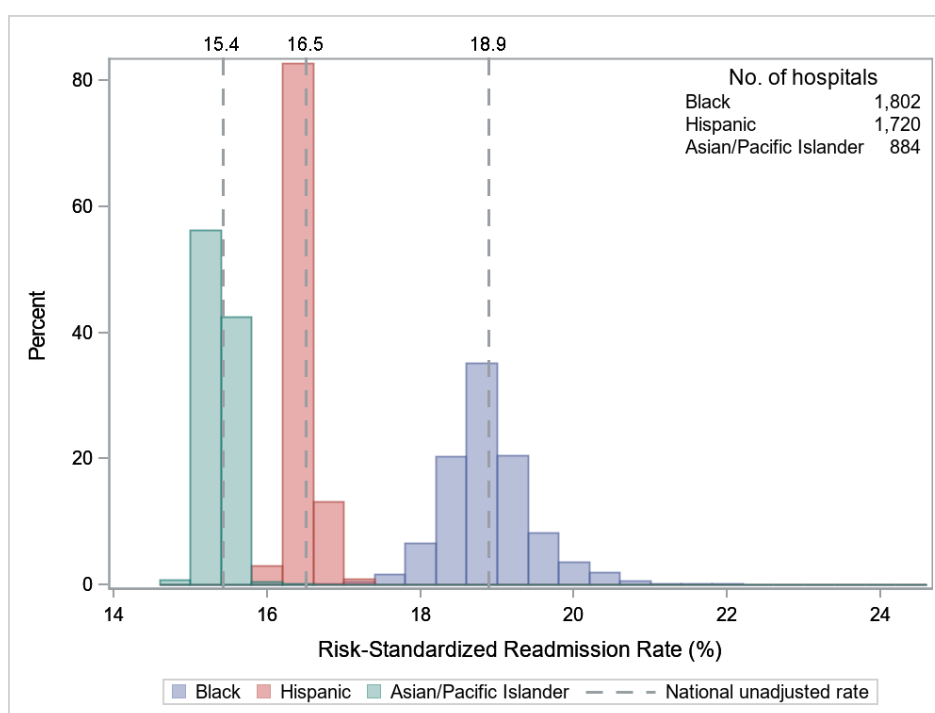
Cohort	Group	Mean Unadjusted Group-Specific Readmission Rate	Mean Group-Specific RSRR (SE)	Variance of Random Intercept (SE)
Medicine	Black	20.26	20.27 (0.83)	0.019 (0.002)
	Hispanic	18.30	18.29 (0.22)	0.007 (0.002)
	API	17.04	17.02 (0.14)	0.006 (0.004)
Surgery/Gynecology	Black	15.20	15.18 (0.03)	0.001 (0.004)
	Hispanic	12.86	12.83 (0.00)	0
	API	11.80	11.76 (0.06)	0.005 (0.008)
Cardio-respiratory	Black	21.42	21.34 (0.45)	0.018 (0.007)
	Hispanic	19.41	19.29 (0.00)	0
	API	19.13	19.07 (0.00)	0
Cardio-vascular	Black	16.94	16.93 (0.82)	0.043 (0.010)
	Hispanic	14.68	14.67 (0.00)	0
	API	13.76	13.77 (0.00)	0

Neurology	Black	16.06	16.02 (0.27)	0.014 (0.008)
	Hispanic	13.46	13.40 (0.00)	0
	API	13.17	13.09 (0.00)	0
Hospital-wide (Full Cohort)	Black	18.88	18.87 (0.49)	N/A
	Hispanic	16.51	16.48 (0.11)	N/A
	API	15.42	15.39 (0.08)	N/A

6.4.3 Distribution of Hospital Performance

[Figure 3](#) shows the distribution of RSRR across hospitals for the Black, Hispanic, and API groups. The median RSRR is 15.39%, 16.48%, and 18.89% for the API, Hispanic, and Black groups.

Figure 3: Across-Hospital Distribution of Risk Standardized Readmission Rates Using MBISG Results



[Table 6](#) shows the distribution of group-specific RSRRs across hospitals. The results show that the RSRRs for the interquartile range to be within 1% for each group, ranging from 0.13% to 0.81%. However, outliers exist on each side of the IQR indicating some variation. [Table 7](#) also shows the total number of eligible and reporting hospitals for each group identified by the MBISG. Of eligible hospitals, 41.55%, 52.06%, and 66.67% of eligible hospitals reported too few cases to receive disparity results.

Table 6: Distribution of Hospital Results on the Across-Hospital Disparity Method for the Full Hospital-Wide Readmission Cohort

Groups			RSRR (%) among reporting hospitals	# of Cases Too Small
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	Total Eligible Hospitals*	Total Reporting Hospitals**	Min	10 th	25 th	Med	75 th	90 th	Max	Mean	(% of eligible hospitals)
Black	3083	1802	16.44	18.23	18.55	18.83	19.14	19.64	24.41	18.89	41.55
Hispanic	3588	1720	15.66	16.33	16.41	16.47	16.54	16.64	17.91	16.48	52.06
API	2652	884	14.73	15.27	15.33	15.39	15.45	15.52	16.26	15.39	66.67

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

[Table 7](#) shows the distribution of the RD in readmission between patient cohorts identified using the MBISG model across hospitals for the HWR specialty cohorts. Across-hospital results are shown as a RSRR for the Black, Hispanic, and API groups individually.

[Table 7](#) also shows the number of eligible hospitals for each specialty cohort/racial and ethnic group. Hospitals were only eligible if they had at least 25 patients assigned to the racial or ethnic group by the MBISG. The percent of eligible hospitals with too few cases for reporting for specialty cohort/race and ethnic group combination comparisons ranged from 48.77% to 95.98%.

Table 7: Categorized Distribution of Hospital Results on the Across-Hospital Disparity Method

	Comparison Groups	Total Number of Eligible Hospitals*	Total Number of Reporting Hospitals**	RSRR (%) among reporting hospitals								Number of Cases Too Small (% of eligible hospitals)
				Min	10 th	25 th	Med	75 th	90 th	Max	Mean	
Medicine	Black	2920	1496	16.74	19.11	19.61	20.18	20.85	21.68	28.69	20.30	48.77
	Hispanic	3416	1228	16.75	17.93	18.12	18.27	18.46	18.72	20.76	18.30	64.05
	API	2443	556	15.96	16.73	16.88	17.01	17.15	17.32	18.64	17.02	77.24
Surgery/ Gynecology	Black	2282	739	14.97	15.13	15.16	15.18	15.21	15.24	15.35	15.18	67.62
	Hispanic	2678	623	12.83	12.83	12.83	12.83	12.83	12.83	12.83	12.83	76.74
	API	1888	235	11.14	11.63	11.69	11.75	11.81	11.92	12.32	11.76	87.55
Cardio-respiratory	Black	2156	445	19.10	20.43	20.90	21.32	21.86	22.40	24.77	21.39	79.36
	Hispanic	2403	170	19.29	19.29	19.29	19.29	19.29	19.29	19.29	19.29	92.93
	API	1369	55	19.07	19.07	19.07	19.07	19.07	19.07	19.07	19.07	95.98
	Black	1893	413	12.81	15.39	16.04	16.79	17.83	18.85	24.03	17.00	78.18

Cardio-vascular	Hispanic	2092	247	14.67	14.67	14.67	14.67	14.67	14.67	14.67	14.67	88.19
	API	1386	85	13.77	13.77	13.77	13.77	13.77	13.77	13.77	13.77	93.87
Neurology	Black	1847	424	14.48	15.49	15.75	16.01	16.29	16.68	19.20	16.04	77.04
	Hispanic	1912	180	13.40	13.40	13.40	13.40	13.40	13.40	13.40	13.40	90.59
	API	1317	82	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	93.77

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

6.4.4 Patient Representation (Across-Hospital Disparity Method)

We examined patient representation in reporting and non-reporting hospitals to better understand the usability of these methods for the HWR measure.

- Black group – Of 3,083 eligible hospitals, 1,802 (58.45%) met the reporting threshold. Within these hospitals, 97.60% of admissions for this group were captured and 97.95% of readmissions were captured.
- Hispanic group – Of 3,588 eligible hospitals, 1,720 (47.94%) met the reporting threshold. Within these hospitals, 94.55% of admissions for this group were captured and 95.30% of readmissions were captured.
- API group – Of 2,652 eligible hospitals, 884 (33.33%) met the reporting threshold. Within these hospitals, 88.24% of admissions for this group were captured and 88.74% of readmissions were captured.

Table 8: Comparison of Reporting and Non-Reporting Hospitals for the Hospital-Wide Readmission Measure Full Cohort (Across-Hospital Method)

Group	Encounter Type	Total included in eligible hospitals [n]	Total included in reporting hospitals [n (%)]
Black	Admissions	436927	426419 (97.60)
	Readmissions	82511	80818 (97.95)
Hispanic	Admissions	270586	255802 (94.54)
	Readmissions	44662	42565 (95.30)
API	Admissions	116829	103088 (88.24)
	Readmissions	18016	15987 (88.74)

7. Conclusion

7.1 Summary

The aims of examining quality for patients with prior evidence of inequitable care are to illuminate disparities, incentivize quality improvement for vulnerable populations, and allow consumers to make informed choices. To this end, we developed two complementary methods that assess disparities in outcomes of care:

1. The Within-Hospital Disparity Method illuminates differences in outcomes for patient groups based on social risk factor or demographic variables within a hospital.
2. The Across-Hospital Disparity Method allows for comparison of performance in care based on the existence of a social risk factor or demographic variable across hospitals.

Both disparity methods are designed to be reported in conjunction with overall hospital performance measures, since both disparity results and overall performance measures provide important but distinct information. Moreover, both can be applied to a wide set of patient-level factors, such as socioeconomic status, race, ethnicity, and gender.

In this report, we show how these methods can be adapted to construct disparity metrics for patient race and ethnicity that are imputed using the Medicare Bayesian Improved Surname Geocoding Method Version 2.1 (MBISG). The MBISG incorporates self-reported information, surnames, and geocoded data to estimate a set of probabilities for each patient, representing the likelihood that they would self-identify as one of six different race and ethnicity groups. These probabilities were used to impute disparity methods for the Hospital-wide All-Cause Unplanned Readmission Measure.

Results for the Within-Hospital Disparity Method indicate a disparity in outcomes based on patient's estimated race using the MBISG. On average, Black, Hispanic, and API patients have a greater risk of readmission than White patients. Importantly, results show that within-hospital disparities in readmission rates vary across hospitals. The mean RD in readmission between the White patient group and Black patient group, the White patient group and the Hispanic patient group, and the White patient group and the API patient group is 1.4%, 0.4%, and 0.4% respectively. In some hospitals, the RD is as large as 6.7%, 3.1%, and 2.8% respectively, even after accounting for differences in patients' severity of illness and prior medical history (comorbidities). Notably, while only between 35.2% to 57.2% of hospitals met the reporting threshold to receive disparity results for these estimated racial and ethnic groups, reportable facilities include most patients in the Black, Hispanic, API groups, specifically 94.2% to 98.8% of admissions, and 94.6% to 99.0% of readmissions. Prior disparity analyses focused on measuring reporting percentage of hospitals, but these results show mirror coverage of patients.

Similarly, results for the Across-Hospital Method showed that readmission rates for each racial and ethnic group vary across hospitals. The mean (range) RSRR for the Black patient group was 18.9% (16.4% to 24.4%), the Hispanic patient group was 16.5% (15.7% to 17.9%) , and the API patient group is 15.4% (14.7% to 16.3%). The range of RSRRs for these groups indicating variation across hospitals suggests opportunities for improvement. Similar to the Within-Hospital Method, the percent of patients included in reportable hospitals is much greater than the percent of reportable hospitals themselves. For the Black group, 97.6% of admissions were included in reporting hospitals, while 97.9% of readmissions were included in reporting hospitals. For the Hispanic group, these were 94.5% and 95.3%, and for the API group, 88.2% and 88.7%.

7.2 Limitations

The outlined disparity methods have certain limitations. First, the use of estimated patient race and ethnicity was prompted by incomplete data in CMS claims. Due to these inconsistencies, our ability to validate the disparity methods results against patient reported self-identified race and ethnicity was not possible.

Another limitation relates to the small sample sizes associated with specific cohorts. The examination of healthcare quality for subgroups of patients naturally results in smaller sample sizes. To ensure reliability of results we propose a minimum threshold of patients for reporting disparity results, though this means we cannot report results for all hospitals.

There are also limitations to using imputed race and ethnicity data. The gold standard for race and ethnicity is self-report, and the imputed probabilities used here, while validated against self-reported survey data, may be subject to unknown confounding when used to assess quality of care. However, we do not use these imputed probabilities to make inferences about any individuals, and know that the MBISG probabilities have high sensitivity and specificity for the four race and ethnicity groups analyzed here.

Finally, these methods do not account for overlap between demographic variables, such as patient race and ethnicity, and other demographic or social risk factors. Neither through calculation of HWR measure results, or through the application of the Disparity Methods for patient race and ethnicity are other social risk factors adjusted for, thus some overlap between social risk factors that are more prevalent in some populations than others may be captured when applying the methods to patient race and ethnicity. The aspiration of reporting on disparities is that the measures will illuminate important differences in quality which can then lead to further investigation by hospitals into the particular unique characteristics of their patient population as a means of finding solutions.

7.3 Implications

Taken together, our results show that the application of the Within-Hospital Disparity Method and the Across-Hospital Disparity Method to imputed race and ethnicity is technically feasible. The methods reveal variation across hospitals for both within- and across-hospital disparities. This suggests an opportunity for improvement of hospital performance for patients of different racial and ethnic groups could be incentivized by reporting hospitals' calculated disparities and race/ethnicity-specific readmission rates. As patient-reported race and ethnicity data become more available, these methods offer a meaningful way to stratify results to support historically marginalized populations.

8. References

1. Cruz-Flores, S., Rabinstein, A., Biller, J., Elkind, M. S., Griffith, P., Gorelick, P. B., ... & Valderrama, A. L. (2011). Racial-ethnic disparities in stroke care: the American experience: a statement for healthcare professionals from the American Heart Association/American Stroke Association. *Stroke*, 42(7), 2091-2116.
2. Molina, Y., Silva, A., & Rauscher, G. H. (2015). Racial/ethnic disparities in time to a breast cancer diagnosis: the mediating effects of healthcare facility factors. *Medical care*, 53(10), 872.
3. Canedo, J. R., Miller, S. T., Schlundt, D., Fadden, M. K., & Sanderson, M. (2018). Racial/ethnic disparities in diabetes quality of care: the role of healthcare access and socioeconomic status. *Journal of racial and ethnic health disparities*, 5(1), 7-14.
4. Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHS/CORE). Methodology Report: Assessing Hospital Disparities for Dual Eligible Patients: Thirty-Day All-Cause Unplanned Readmission Following Pneumonia Hospitalization Measure. 2018; <https://qualitynet.cms.gov/inpatient/measures/disparity-methods/methodology>. Accessed February 15, 2022.
5. Assistant Secretary for Planning and Evaluation (ASPE). Report to Congress: Social Risk Factors and Performance Under Medicare's Value-Based Purchasing Programs. 2016; <https://aspe.hhs.gov/pdf-report/report-congress-social-risk-factors-and-performance-under-medicares-value-based-purchasing-programs>. Accessed June 21, 2018.
6. Zaslavsky AM, Ayanian JZ, Zaboriski LB. The validity of racial and ethnic codes in enrollment data for Medicare beneficiaries. *Health Services Research*, 2012 Jun (47) (3 Pt 2): 1300–21.
7. Haas, A., Elliott, M. N., Dembosky, J. W., Adams, J. L., Wilson-Frederick, S. M., Mallett, J. S., Gaillot, S., Haffer, S. C., & Haviland, A. M. (2019). Imputation of race/ethnicity to enable measurement of HEDIS performance by race/ethnicity. *Health services research*, 54(1), 13–23. <https://doi.org/10.1111/1475-6773.13099>
8. Buntin MB, Ayanian JZ. Social Risk Factors and Equity in Medicare Payment. *New England Journal of Medicine*. 2017;376(6):507-510.
9. Joynt KE, Orav E, Jha AK. Thirty-Day Readmission Rates for Medicare Beneficiaries by Race and Site of Care. *JAMA*. 2011;305(7):675-681.
10. Dickman SL, Himmelstein DU, Woolhandler S. Inequality and the Health-Care System in the USA. *The Lancet*. 2017;389(10077):1431-1441.
11. Institute of Medicine. *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. Washington DC: 2002 by the National Academy of Sciences; 2003.
12. Institute of Medicine. *How Far Have We Come in Reducing Health Disparities? Progress Since 2000: Workshop Summary*. Washington DC: National Academy of Sciences; 2012.
13. Ayanian JZ. The Costs of Racial Disparities in Health Care. 2016; <https://catalyst.nejm.org/the-costs-of-racial-disparities-in-health-care/>. Accessed July 2, 2018.
14. Kaiser Family Foundation. Focus on Health Care Disparities: Key Facts. 2012; <https://kaiserfamilyfoundation.files.wordpress.com/2013/01/8396.pdf>. Accessed July 2, 2018
15. The National Academies of Sciences E, and Medicine,. *Accounting for Social Risk Factors in Medicare Payment: Identifying Social Risk Factors*. Washington DC: The National Academies Press; 2016.
16. Finding Answers: Solving Disparities Through Payment and Delivery System Reform 2017; <http://www.solvingdisparities.org/>. Accessed July 2, 2018.
17. Chin MH, Clarke AR, Nocon RS, et al. A Roadmap and Best Practices For Organizations to Reduce Racial and Ethnic Disparities in Health Care. *J Gen Intern Med*. 2012;27(8):992-1000.

18. Chin MH, Walters AE, Cook SC, Huang ES. Interventions to Reduce Racial and Ethnic Disparities in Health Care. *Medical Care Research and Review*. 2007;64(5_suppl):7S-28S.
19. Schlotthauer AE, Badler A, Cook SC, Perez DJ, Chin MH. Evaluating Interventions to Reduce Health Care Disparities: An RWJF Program. *Health Aff (Millwood)*. 2008;27(2):568-573.
20. The National Academies of Sciences E, and Medicine,. *Systems Practices for the Care of Socially At-Risk Populations*. Washington DC: National Academies Press; 2016.
21. Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHS/CORE). 2020 Readmission Measures Updates and Specifications Reports. 2020; <https://qualitynet.cms.gov/inpatient/measures/readmission/resources#tab3>. Accessed February 15, 2022.
22. Centers for Medicare & Medicaid Services (CMS) Office of Minority Health (OMH). Stratified Reporting. 2022; <https://www.cms.gov/About-CMS/Agency-Information/OMH/research-and-data/statistics-and-data/stratified-reporting>. Accessed February 14, 2022.
23. Agniel D, Martino SC, Burkhart Q, Hambarsoomian K, Orr N, Beckett MK, James C, Scholle SH, Wilson-Frederick S, Ng J, Elliott MN. (2021). Incentivizing excellent care to at-risk groups with a health equity summary score. *Journal of General Internal Medicine*, 36, 1847-1857.
24. Krumholz HM, Brindis RG, Brush JE, et al. Standards for Statistical Models Used for Public Reporting of Health Outcomes: An American Heart Association Scientific Statement from the Quality of Care and Outcomes Research Interdisciplinary Writing Group: Cosponsored by the Council on Epidemiology and Prevention and the Stroke Council Endorsed by the American College of Cardiology Foundation. . *Circulation*. 2006;113(3):456-462.
25. National Quality Forum (NQF). Measure Evaluation Criteria and Guidance for Evaluating Measures for Endorsement. 2016; https://www.qualityforum.org/Projects/i-m/Measure_Evaluation_Guidance/Measure_Evaluation_Guidance.aspx. Accessed July 2, 2018.
26. Medicare Program; Hospital Inpatient Prospective Payment Systems for Acute Care Hospitals and the Long-Term Care Hospital Prospective Payment System and Policy Changes and Fiscal Year 2022 Rates; Quality Programs and Medicare Promoting Interoperability Program Requirements for Eligible Hospitals and Critical Access Hospitals; Changes to Medicaid Provider Enrollment; and Changes to the Medicare Shared Savings Program 86 FR 44774 (Oct 1, 2021) to be codified at 42 C.F.R. pts. 412, 413, 425, 455 & 495).
27. Haas, A., Elliott, M. et al (2018). Imputation of race/ethnicity to enable measurement of HEDIS performance by race/ethnicity. *Health Services Research*, 54:13–23.
28. Bonito AJ, Bann C, Eicheldinger C, Carpenter L. Creation of New RaceEthnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries. Final Report, Sub-Task 2. (Prepared by RTI International for the Centers for Medicare and Medicaid Services through an interagency agreement with the Agency for Healthcare Research and Policy, under Contract No. 500–00–0024, Task No. 21) AHRQ Publication No. 08–0029–EF. Rockville, MD, Agency for Healthcare Research and Quality. January 2008. Available at: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6338295/pdf/HESR-54-13.pdf>.
29. Normand S-LT, Shahian DM. Statistical and clinical aspects of hospital outcomes profiling. *Statist. Sci*. 2007;22(2):206-226.
30. Dembosky JW, Haviland AM, Haas A, Hambarsoomian K, Weech-Maldonado R, Wilson-Frederick SM, Gaillot S, Elliott MN. (2018) Indirect estimation of race/ethnicity for survey respondents who do not report race/ethnicity. *Medical Care*, 57, e28-e33.
31. Health Services Advisory Group. (2021). Medicare Advantage and Prescription Drug Plan CAHPS Survey (website). Last updated August 11, 2021. Available at: <https://ma-pdpcahps.org/>

32. Centers for Medicare & Medicaid Services. Readmission Measures Overview.
<https://qualitynet.cms.gov/inpatient/measures/readmission>. Accessed February 25, 2022.
33. Martino, SC, Elliott, MN, Dembosky, JW, Hambarsoomian, K, Klein, DJ, Gildner, J, and Haviland, AM. Racial, Ethnic, and Gender Disparities in Health Care in Medicare Advantage. Baltimore, MD; CMS Office of Minority Health. 2021. Available at <https://www.cms.gov/About-CMS/Agency-Information/OMH/research-and-data/statistics-and-data/stratified-reporting>
34. Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation (YNHHS/CORE). 2021 Disparity Measures Updates and Specifications Report. 2021; <https://qualitynet.cms.gov/inpatient/measures/disparity-methods/methodology>. Accessed February 15, 2022.
35. Centers for Medicare & Medicaid Services. Payment Reduction Methodology.
<https://qualitynet.cms.gov/inpatient/hrrp/methodology>. Accessed February 25, 2022.

9. Appendices

9.1 Appendix A: Statistical Model for the Hospital-Wide Readmission Measure

The HWR measure uses hierarchical generalized linear models (HGLMs) to estimate RSRRs for hospitals. This modeling approach accounts for the within-hospital correlation of the observed outcome, and accommodates the assumption that underlying differences in quality across hospitals lead to systematic differences in outcomes.

For each of the five specialty cohorts in the HWR measure, a separate HGLM model is estimated. Then for each hospital, an SRR is calculated for each of the specialty cohorts with at least one index admission. Finally, a combined SRR for each hospital is created by calculating a volume weighted geometric mean of the specialty cohort SRRs for that hospital. The RSRR is calculated by multiplying the combined SRR for each hospital by the national observed readmission rate.

9.1.1 Hierarchical Generalized Linear Model

For each specialty cohort, we fit an HGLM, which accounts for clustering of observations within hospitals. We assume the outcome has a known exponential family distribution and relates linearly to the covariates via a known link function, h . Specifically, we assume a binomial distribution and a logit link function. Further, we account for the clustering within hospitals by estimating a hospital-specific effect, α_i , which we assume follows a normal distribution with a mean μ and variance τ^2 , the between-hospital variance component. The following equation defines the HGLM:

$$h(\Pr(Y_{ij} = 1 | \mathbf{Z}_{ij}, \omega_i)) = \log \left(\frac{\Pr(Y_{ij}=1 | \mathbf{Z}_{ij}, \omega_i)}{1 - \Pr(Y_{ij}=1 | \mathbf{Z}_{ij}, \omega_i)} \right) = \alpha_i + \boldsymbol{\beta} \mathbf{Z}_{ij} \quad (1)$$

$$\text{where } \alpha_i = \mu + \omega_i; \omega_i \sim N(0, \tau^2)$$

$$i=1, \dots, l; j=1, \dots, n_i$$

where Y_{ij} denotes the outcome (equal to 1 if the patient is readmitted within 30 days of discharge, 0 otherwise) for the j -th patient in the specialty cohort at the i -th hospital; $\mathbf{Z}_{ij} = (Z_{ij1}, Z_{ij2}, \dots, Z_{ijp})^T$ is a set of p patient-specific covariates derived from the data; and l denotes the total number of hospitals and n_i denotes the number of index admissions at hospital i in each specialty cohort. The hospital-specific intercept of the i -th hospital, α_i , defined above, comprises μ , the adjusted average intercept over all hospitals in the sample, and ω_i , the hospital-specific intercept deviation from μ .¹¹

We estimate the HGLMs using the SAS software system (GLIMMIX procedure).

9.1.2 Standardized Risk Ratio for Each Specialty Cohort

For each specialty cohort, we use the HGLM defined by Equation (1), to obtain the parameter estimates $\hat{\mu}$, $\{\hat{\alpha}_1, \hat{\alpha}_2, \dots, \hat{\alpha}_l\}$, $\hat{\boldsymbol{\beta}}$, and $\hat{\tau}^2$. We calculate an SRR, \hat{s}_i , for each hospital by computing the ratio of the number of predicted readmissions to the number of expected readmissions. Specifically, we calculate:

$$\text{Predicted Value: } \hat{p}_{ij} = h^{-1}(\hat{\alpha}_i + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij}) = \frac{\exp(\hat{\alpha}_i + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij})}{\exp(\hat{\alpha}_i + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij}) + 1} \quad (2)$$

$$\text{Expected Value: } \hat{e}_{ij} = h^{-1}(\hat{\mu} + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij}) = \frac{\exp(\hat{\mu} + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij})}{\exp(\hat{\mu} + \hat{\boldsymbol{\beta}} \mathbf{Z}_{ij}) + 1} \quad (3)$$

$$\text{Standardized Risk Ratio: } \hat{s}_i = \frac{\sum_{j=1}^{n_i} \hat{p}_{ij}}{\sum_{j=1}^{n_i} \hat{e}_{ij}} \quad (4)$$

9.1.3 Combined Standardized Risk Ratio and Risk Standardized Readmission Rate

For each hospital, we obtain the parameter estimate \hat{s}_i from Equation (4). To report a single readmission score, the specialty cohort SRRs are combined into a combined SRR, \hat{t}_i . The combined SRR is the volume-weighted geometric mean of the specialty cohort SRRs where $k=1, \dots, 5$ indicates the k -th specialty cohort:

$$\text{Combined Standardized Risk Ratio: } \hat{t}_i = \left(\prod_{k=1}^5 \hat{s}_{ik}^{n_{ik}} \right)^{\frac{1}{\sum_{k=1}^5 n_{ik}}} = \exp \left(\frac{\sum_{k=1}^5 n_{ik} \log \hat{s}_{ik}}{\sum_{k=1}^5 n_{ik}} \right) \quad (5)$$

We calculate an RSRR, \widehat{RSRR}_i , for each hospital by using the estimate from Equation (5) and multiplying by the national observed readmission rate, denoted by \bar{y} . Specifically, we calculate:

$$\text{Risk-Standardized Readmission Rate: } \widehat{RSRR}_i = \hat{t}_i \times \bar{y} \quad (6)$$

9.2 Appendix B: Condition-Specific Readmission Measure Disparity Results

The CMS Disparity Methods using estimated patient race and ethnicity were also applied to six condition-specific readmission measures. The results of the Within- and Across-Hospital Disparity Methods are presented in [Table 9](#) and [Table 10](#).

1. *NQF #0505*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Acute Myocardial Infarction (AMI)
2. *NQF #1891*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Chronic Obstructive Pulmonary Disease (COPD)
3. *NQF #2515*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Coronary Artery Bypass Graft (CABG)
4. *NQF #1551*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Elective Primary Total Hip Arthroplasty and/or Total Knee Arthroplasty (THA/TKA)
5. *NQF #0330*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Heart Failure (HF)
6. *NQF #0506*: Hospital 30-Day, All-Cause, Risk Standardized Readmission Rate Following Pneumonia Hospitalization (Pneumonia)

Table 9: Within-Hospital Condition-Specific Readmission Measure Disparity Results using Estimated Patient Race and ethnicity

Measure	Group (compared to White)	# of Eligible Facilities*	# of Reporting Facilities **	Within-Hospital Condition-Specific Rate Difference (%) by Percentile								% of hospitals with too few cases to report
				Min	10 th	25 th	Median	75 th	90 th	Max	Mean	
AMI	Black	2032	508	-0.47	-0.10	0.05	0.30	0.55	0.80	1.85	0.32	75.00
	Hispanic	2032	347	0.68	0.76	0.78	0.80	0.82	0.84	0.88	0.80	82.92
	API	2032	149	0.14	0.28	0.32	0.39	0.43	0.48	0.66	0.38	92.67
COPD	Black	2779	764	0.22	0.99	1.12	1.24	1.33	1.42	1.69	1.22	72.51
	Hispanic	2779	284	-0.19	-0.18	-0.18	-0.18	-0.18	-0.18	-0.17	-0.18	89.78
	API	2779	71	-2.21	-1.85	-1.40	-1.01	-0.73	-0.51	-0.15	-1.09	97.45
CABG	Black	893	87	-1.06	-0.53	-0.26	0.05	0.47	1.06	3.04	0.18	90.26
	Hispanic	893	71	-0.33	0.30	0.46	0.62	0.73	0.78	1.02	0.57	92.05
	API	893	31	-0.12	0.13	0.26	0.39	0.61	0.85	1.05	0.42	96.53
THA/TKA	Black	2374	555	-0.19	0.01	0.07	0.12	0.15	0.18	0.30	0.11	76.62
	Hispanic	2374	375	-0.21	-0.17	-0.16	-0.15	-0.14	-0.13	-0.06	-0.15	84.20
	API	2374	129	-0.39	-0.31	-0.27	-0.20	-0.11	-0.03	0.30	-0.18	94.57

HF	Black	3099	1360	-0.66	0.46	0.70	0.91	1.13	1.30	1.88	0.90	56.11
	Hispanic	3099	928	-0.17	0.22	0.29	0.34	0.40	0.45	0.59	0.34	70.05
	API	3099	383	-0.19	-0.13	-0.12	-0.10	-0.08	-0.06	-0.02	-0.10	87.64
Pneumo nia	Black	3317	1204	1.60	1.72	1.75	1.79	1.82	1.86	2.00	1.79	63.70
	Hispanic	3317	834	0.06	0.21	0.25	0.30	0.36	0.42	0.98	0.31	74.86
	API	3317	387	0.96	1.10	1.13	1.17	1.22	1.26	1.52	1.17	88.33

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

Figure 4: Within-Hospital Condition-Specific Readmission Measure Disparity Results using Estimated Patient Race and Ethnicity

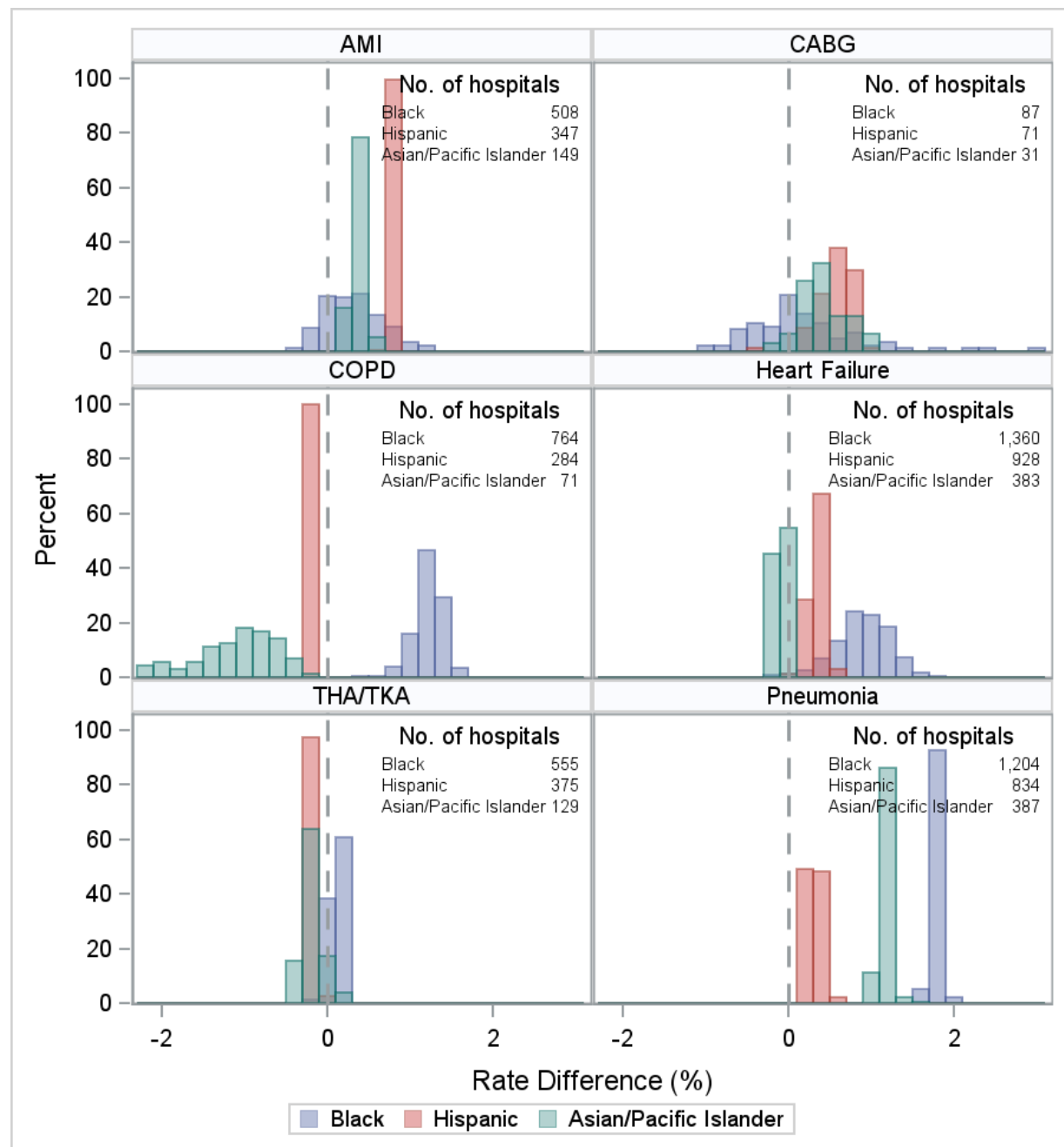


Table 10: Across-Hospital Condition-Specific Readmission Measure Disparity Results using Estimated Patient Race and ethnicity

Measure	Group	# of Eligible Facilities*	# of Reporting Facilities**	Across-Hospital Condition-Specific RSRR (%) by Percentile								% of hospitals with too few cases to report
				Min	10 th	25 th	Median	75 th	90 th	Max	Mean	
AMI	Black	2920	247	17.37	18.17	18.62	19.00	19.46	19.99	20.77	19.03	84.53
	Hispanic	3416	157	17.65	17.65	17.65	17.65	17.65	17.65	17.65	17.65	91.14
	API	2443	58	16.53	16.53	16.53	16.53	16.53	16.53	16.53	16.53	95.19
COPD	Black	2282	405	20.90	21.91	22.35	22.87	23.36	23.88	25.72	22.89	80.72
	Hispanic	2678	100	20.38	20.45	20.48	20.52	20.55	20.60	21.03	20.53	95.72
	API	1888	23	18.20	18.20	18.20	18.20	18.20	18.20	18.20	18.20	97.86
CABG	Black	2156	20	11.19	11.47	12.11	12.90	14.69	17.34	17.91	13.60	96.49
	Hispanic	2403	21	13.65	13.65	13.65	13.65	13.65	13.65	13.65	13.65	97.26
	API	1369	8	12.69	12.69	12.69	12.69	12.69	12.69	12.69	12.69	98.49
THA/TKA	Black	1893	272	4.12	4.48	4.54	4.63	4.74	4.84	5.08	4.64	84.59
	Hispanic	2092	159	3.95	3.95	3.95	3.95	3.95	3.95	3.95	3.95	92.48
	API	1386	53	3.48	3.48	3.48	3.48	3.48	3.48	3.48	3.48	95.59
HF	Black	1847	985	21.78	23.31	23.57	23.90	24.25	24.63	25.91	23.93	60.94
	Hispanic	1912	525	22.78	22.86	22.88	22.89	22.91	22.93	23.13	22.89	81.09
	API	1317	187	20.16	21.00	21.13	21.34	21.58	21.82	22.53	21.36	89.80
Pneumonia	Black	3083	766	20.42	20.82	20.88	20.95	21.03	21.11	21.42	20.96	69.78
	Hispanic	3588	472	18.11	18.11	18.11	18.11	18.11	18.11	18.11	18.11	84.22
	API	2652	193	16.08	17.69	17.90	18.09	18.30	18.49	19.36	18.08	89.80

*Eligible hospitals have 1+ White and 1+ Black, Hispanic, or API

**Reporting hospitals 12+ White, 12+ non-White, and 25+ total patients

Figure 5: Across-Hospital Condition-Specific Readmission Measure Disparity Results using Estimated Patient Race and Ethnicity

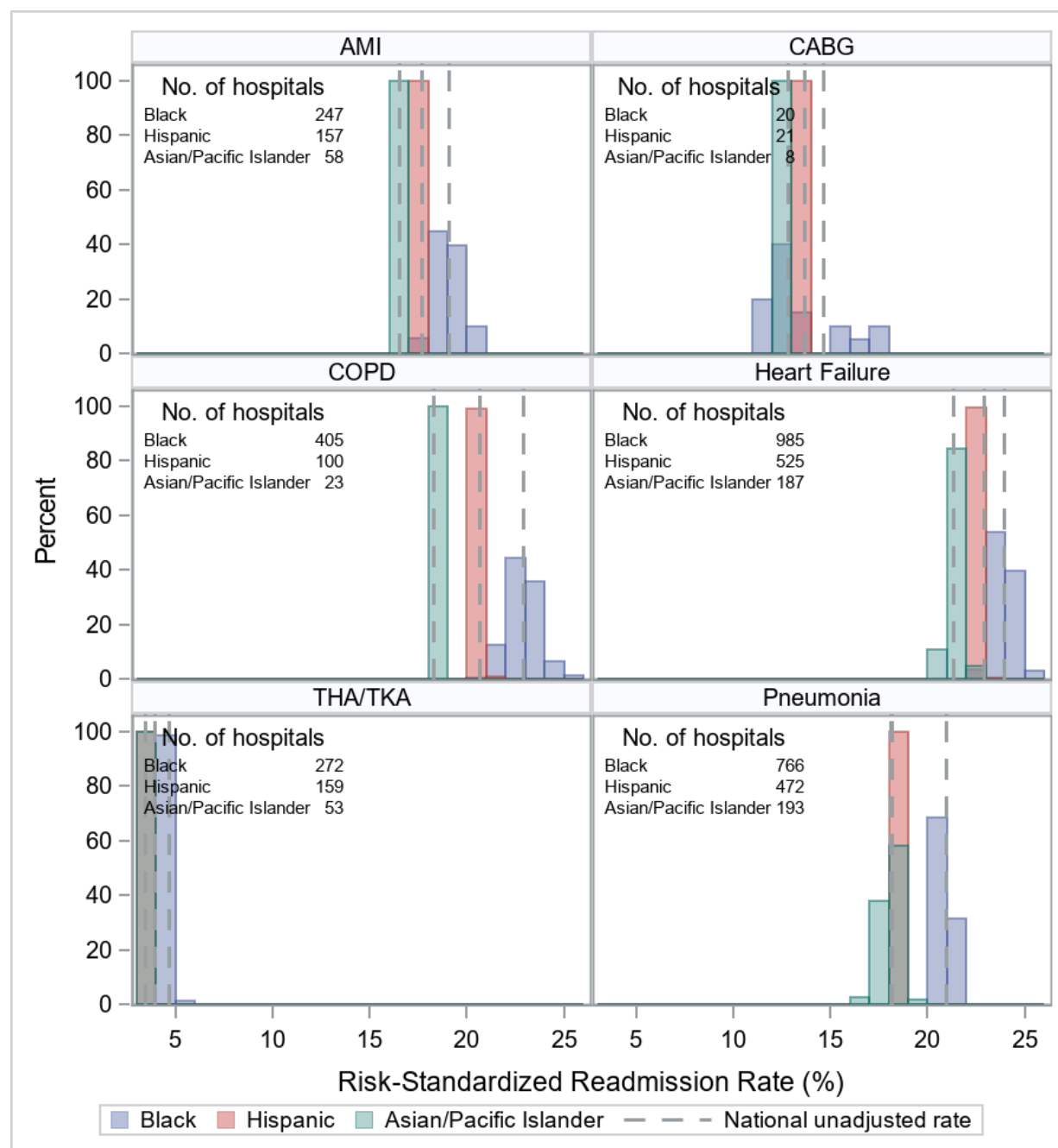


Table 11: Comparison of Reporting and Non-Reporting Hospitals for the Condition-Specific Measure Cohorts (Within-Hospital Method)

Measure	Group (compared to White)	Eligible hospitals (n)	Reporting hospitals (n)	Total non-white admissions (n)	Non-white admissions among reporting hospitals (n)	Non-white admissions among reporting hospitals (%)	Non-white readmissions (n)	Non-white readmissions among reporting hospitals (n)	Non-white readmissions among reporting hospitals (%)
AMI	Black	2032	508	21552	15829	73.4	4088	2991	73.2
	Hispanic	2032	347	17487	10544	60.3	3066	1905	62.2
	API	2032	149	7991	3957	49.5	1324	660	49.9
CD	Black	2779	764	34626	26983	77.9	7910	6227	78.7
	Hispanic	2779	284	16228	7470	46.0	3350	1619	48.3
	API	2779	71	5170	1591	30.8	945	297	31.4
CABG	Black	893	87	4083	1836	45.0	593	257	43.4
	Hispanic	893	71	4480	1702	38.0	609	231	37.9
	API	893	31	2436	681	28.0	309	78	25.3
HK	Black	2374	555	24891	19056	76.6	1149	845	73.6
	Hispanic	2374	375	18980	11259	59.3	747	415	55.6
	API	2374	129	7774	3880	49.9	272	117	42.9
HF	Black	3099	1360	104716	96965	92.6	25050	23165	92.5
	Hispanic	3099	928	51022	41025	80.4	11661	9514	81.6
	API	3099	383	20697	14038	67.8	4421	3035	68.6
PN	Black	3317	1204	63072	55461	87.9	13220	11728	88.7
	Hispanic	3317	834	46571	36080	77.5	8439	6673	79.1
	API	3317	387	21635	15267	70.6	3918	2843	72.6

Table 12: Comparison of Reporting and Non-Reporting Hospitals for the Condition-Specific Measure Cohorts (Across-Hospital Method)

Measure	Group	Eligible hospitals (n)	Reporting hospitals (n)	Total non-white admissions (n)	Non-white admissions among reporting hospitals (n)	Non-white admissions among reporting hospitals (%)	Non-white readmissions (n)	Non-white readmissions among reporting hospitals (n)	Non-white readmissions among reporting hospitals (%)
AMI	Black	1597	247	21617	11645	53.9	4117	2211	53.7
	Hispanic	1773	157	17620	7969	45.2	3114	1473	47.3
	API	1206	58	7842	2552	32.5	1297	410	31.6
CD	Black	2101	405	34722	21440	61.7	7960	4999	62.8
	Hispanic	2336	100	16170	5005	30.9	3343	1087	32.5
	API	1073	23	4885	936	19.2	892	160	18.0
CABG	Black	570	20	3984	714	17.9	583	79	13.5
	Hispanic	766	21	4494	839	18.7	614	120	19.5
	API	529	8	2357	285	12.1	301	26	8.8
HK	Black	1765	272	24883	14168	56.9	1157	595	51.5
	Hispanic	2114	159	18996	7871	41.4	747	298	39.9
	API	1202	53	7538	2620	34.8	258	68	26.4
HF	Black	2522	985	104932	92037	87.7	25111	22073	87.9
	Hispanic	2777	525	51215	35041	68.4	11741	8196	69.8
	API	1834	187	20413	11172	54.7	4357	2434	55.9
PN	Black	2535	766	63002	48262	76.6	13213	10253	77.6
	Hispanic	2991	472	46676	30305	64.9	8477	5676	67.0
	API	1892	193	21411	12166	56.8	3876	2278	58.8