YALE NEW HAVEN HEALTH

Center for Outcomes Research and Evaluation (CORE)
1 Church Street, Suite 200
New Haven, Connecticut 06510-3330
Phone: 203-764-5700 Fax: 203-764-5653

MEMORANDUM

TO:	National Quality Forum (NQF) Admissions & Readmissions Standing Committee
FROM:	Theodore Long, MD, MHS, Karen Dorsey, MD, PhD, and Susannah Bernheim, MD, MHS, Yale New Haven Health Services Corporation – Center for Outcomes Research and Evaluation (YNHHSC/CORE)
THROUGH:	The Centers for Medicare and Medicaid Services (CMS) Lein Han, PhD
DATE:	Monday, February 22, 2016
SUBJECT:	Ad Hoc SDS Responses for NQF #0505 Hospital 30-day all-cause risk-standardized readmission rate (RSRR) following acute myocardial infarction (AMI) hospitalization

Admissions & Readmissions Ad Hoc SDS Trial Period Questions: AMI Readmission

1. Enter measure # and title

AMI Readmission Measure #: 0505

AMI Readmission Measure Title: Hospital 30-day all-cause risk-standardized readmission rate (RSRR) following acute myocardial infarction (AMI) hospitalization

2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?

"Sociodemographic status" incorporates socioeconomic variables as well as race into a single term. However, given the fact that socioeconomic risk factors are distinct from race and therefore should be interpreted differently, we have decided to keep "socioeconomic status" and "race" as separate terms.

We selected socioeconomic status (SES) and race variables to analyze after reviewing the literature and examining available national data sources. There is a large body of literature linking various SES factors and African-American race to worse health status and higher readmission risk (Blum et al., 2014; Eapen et al. 2015; Gilman et al., 2014; Hu et al., 2014; Joynt and Jha, 2013). Income, education, and occupational level are the most commonly examined variables. The literature directly examining how different SES factors or race might influence the likelihood of older, insured, Medicare patients of being readmitted within 30 days of an admission for AMI is limited. However studies indicate an association between SES or race and increased risk of AMI readmission (Bernheim et al., 2007; Damiani et al., 2015; Herrin et al., 2015; Joynt, Orav, and Jha 2011; Lindenauer et al., 2013). The causal pathways for SES and race variable selection are described below in Question #3.

Based on this review and the availability of data, the SES and race variables used for analysis were:

- Dual eligible status (meaning enrolled in both Medicare and Medicaid)
- African-American race
- Agency for Healthcare Research and Quality (AHRQ)-validated SES Index score (composite of 7 different variables found in census data: percentage of people in the labor force who are unemployed, percentage of people living below poverty level, median household income, median value of owner-occupied dwellings, percentage of people ≥25 years of age with less than a 12th-grade education, percentage of people ≥25 years of age completing ≥4 years of college, and percentage of households that average ≥1 people per room)

In selecting variables, our intent was to be responsive to the NQF guidelines for measure developers in the context of the Sociodemographic Status (SDS) Trial Period and identify variables that are feasible to test and use in the near term. We examined patient-level indicators of both SES and race or ethnicity that are reliably available for all Medicare beneficiaries. We aimed to select those variables that are most valid and available. We briefly describe the benefits and limitations to our selected variables below.

For race, studies examining the validity of data on patients' race and ethnicity collected by the Centers for Medicare and Medicaid Services (CMS) have shown that only the data identifying African-American beneficiaries have adequate sensitivity and specificity to be applied broadly in research or measures of quality. While using this variable is not ideal because it groups all non-African-American beneficiaries together, it is currently the only race variable available on all beneficiaries across the nation that is linkable to claims data. The NQF has mixed guidance on the consideration of race as a risk-adjustment variable. Our team felt it was important to include in analyses because it helps to highlight some of the causal pathways by which both race and SES influence outcomes.

We similarly recognize that Medicare-Medicaid dual eligibility has limitations as a proxy for patients' income or assets because it is a dichotomous variable. However, the threshold for over 65-year-old Medicare patients is valuable as it takes into account both income and assets and is consistently applied across states. For both our race and the dual-eligible variables, there is a body of literature demonstrating differential health care and health outcomes among beneficiaries (Trivedi et al., 2014; Hasnain-Wynia et al., 2007; Joynt et al., 2011; Bradley et al., 2004; Barnato et al., 2005; Hu et al., 2014) indicating that these variables, while not ideal, also allow us to examine some of the pathways of interest.

Finally, we selected the AHRQ SES Index score because it is a well-validated and widely-used variable that describes the average SES of people living in defined geographic areas (Bonito et al., 2008). Its value as a proxy for patient-level information is dependent on having the most granular level data with respect to communities that patients live in. Currently, the individual data elements used to calculate the score are available at the 5-digit zip code and census block levels only. In this submission, we present analysis using the 5-digit level. However, we are currently performing analysis at the census block level, the most granular level possible. We hope to present the results of the census block-level analysis to the committee.

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3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

The readmission measures are intended to assess important aspects of hospital quality of care. Decisions about which risk factors should be included in each measure's risk-adjustment model should be made on the basis of whether inclusion of such variables is likely to make the measures more successful at illuminating quality differences and motivating quality improvement. (This aim should be distinguished from decisions made in response to concerns about the impact of related payment programs on safety-net hospitals; concerns which can be addressed through other policy mechanisms.) The determination of whether inclusion of socioeconomic factors or race as patient-level, risk-adjustment variables improves or diminishes the readmission measures' assessment of hospital quality is controversial. This controversy arises because some aspects of disparities in outcomes may be attributed to hospital quality and other aspects attributed to factors outside the hospital's control. The measure developer's, Yale New Haven Health Services Corporation – Center for Outcomes Research and Evaluation's (YNHHSC/CORE's), perspective is that we are firmly committed to fairness in measurement, but we are also committed to ensuring that the measures do not reinforce a status quo in which poorer quality of care is provided to African American and poorer populations. The medical literature and our analyses consistently demonstrate that hospitals contribute to the disparities in outcomes for socioeconomically disadvantaged groups, and for that reason we do not believe the addition of patient-level risk adjustment for race or SES (as fixed effects in the model) is an appropriate solution for the readmission measures. Ongoing work within Health and Human Services and CORE will continue to evaluate alternative solutions that better reflect the balance of hospital- and patient-level influences on readmission risk for socioeconomically disadvantaged patients.

Since our first measures were implemented in the Hospital Inpatient Quality Reporting program, CORE has been committed to studying and monitoring disparities in patients' outcomes and the relationships among race, social, or economic disadvantage, and hospitals' performance on the 30-day readmission, mortality, complication, and payment measures. In response to the requirements of the SDS trial period we have additionally undertaken a comprehensive review of the literature examining the relationships among these factors and patients' outcomes across multiple conditions and procedures, and completed analyses recommended or requested by NQF or its committees to explore the impact of adding such factors to the measures' risk models. **The findings of this work, shown within this submission, have confirmed our long-held understanding that hospitals contribute in significant ways to persistent disparities in patients' outcomes; and that adjusting for race or for social and economic disadvantage could inappropriately obscure true signals of the quality of care such patients receive.** Additionally, because interpersonal and structural bias or discrimination within the healthcare system continue to play a significant role in the persistence of disparities (Trivedi et al., 2014), sociodemographic factors must be given special consideration. In contrast, there is no evidence of bias in the care of patients due to a diagnosis of diabetes or chronic obstructive pulmonary disease (COPD), two conditions that we do adjust for in the measures. Hospitals may provide differential care to patients with these diseases due to differences in providers' expertise or the availability of specialists or intensive care, but there is no evidence that interpersonal or structural bias targeted toward these patients plays any significant role. Incorporating risk adjustment for SES or race can diminish the ability of the measures to illuminate such quality issues. Concerns about the financial viability of the safety net do not need to be pitted against discussion of risk-adjustment as there are other policy mechanisms protecting safety-net hospitals and the patients they serve from undue financial penalties or loss of resources.

Decisions about whether to incorporate SES and race variables into outcome quality measure risk models are more complex and controversial than the decisions regarding the incorporation of clinical factors because any increased risk for worse outcomes following a hospitalization for historically socially disadvantaged patients may be due, in part, to bias or discrimination in provision of care. This can occur because such patients may have access to poorer quality providers or due to differences in care for such patients. There is a broad literature documenting the relationship between SES or race and health care quality (Blum et al., 2014; Gilman et al., 2014; Hu et al., 2014; Joynt and Jha, 2013) that does not exist to a similar degree for clinical factors. Therefore, within a risk model that accounts for differences in illness severity and comorbidities (through adjustment for risk factors), any remaining elevated risk for poor outcomes related to social disadvantage may be due to quality differences.

Given that the goal of the measures is to illuminate quality differences, and that socioeconomic factors and race are historically entangled with differential provision of high quality care, we maintain that adjustment for either should only be undertaken with care, and with clear evidence that risk differences are unrelated to differential quality of care.

Below we lay out a more complete conceptual model of pathways by which socioeconomic factors and race may influence readmission risk and the implications for risk-adjustment. We have identified analyses that aim to disentangle these pathways. The analyses demonstrate that differences among hospitals contribute substantially to increased risk for socially disadvantaged patients – that is, the effect of low SES on readmission can be attributed substantially to the hospitals where such patients are treated.

Below we describe our conceptual model.

To develop a conceptual model of the relationship between patient-level SES and race variables and the readmission outcome, we began by completing a literature search and conceptualizing four distinct causal pathways.

<u>Literature Review of Socioeconomic Status (SES) and Race Variables and AMI Readmission</u>

To examine the relationship between SES and race variables and hospital 30-day, all-cause, risk-standardized readmission rate (RSRR) following AMI hospitalization, a literature search was performed with the following exclusion criteria: international studies, articles published more than 10 years ago, articles without primary data, articles using Veterans Affairs databases as the primary data source, and articles not explicitly focused on SES or race and AMI readmission. Twenty-one studies were initially reviewed, and 16 studies were excluded from full-text review based on the above criteria. Studies indicated that SES and race variables were associated with increased risk of AMI readmission (Bernheim et al., 2007; Damiani et al., 2015; Herrin et al., 2015; Joynt, Orav, and Jha 2011; Lindenauer et al., 2013). Joynt et al. compared 30-day readmission risk in patient-level logistic regression models and found that black patients had higher readmission rates than white patients (odds ratio [OR]: 1.13; 95% confidence interval [CI]: 1.11-1.14; $p<0.001$) and that patients from minority-serving hospitals had higher readmission rates than those from non-minority-serving hospitals (OR: 1.23; 95% CI: 1.20-1.27; $p<0.001$). These findings were not explained by differences in hospitals' proportions of Medicaid patients or Disproportionate Share Indices. Lindenauer et al. compared 30-day readmission risk using hierarchical logistic regression models for Medicare patients and found that higher state-level income inequality was associated with increased AMI readmission risk (risk ratio: 1.09; 95% CI: 1.03-1.15). In a systematic literature review, Damiani et al. found race or ethnicity to be associated with increased short-term readmission risk among AMI patients. However, while studies have shown an association between patient-level variables and increased risk of readmission, others have found that there may not be a significant effect on hospital-level profiling (Blum et al., 2014).

Causal Pathways for Socioeconomic Status (SES) and Race

Although some recent literature evaluates the relationship between patient SES or race and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways. Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission.

The conceptual relationship, or potential causal pathways by which these possible SES risk factors influence the risk of readmission following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider.

1. **Relationship of SES factors or race to health at admission**. Patients who have lower income, lower education, lower literacy, or unstable housing may have a worse general health status and may present for their hospitalization or procedure with a greater severity of underlying illness that is not captured by claims data. These SES risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may contribute to worse health status at admission due to competing priorities (restrictions based on job, lack of childcare), lack of access to care (geographic, cultural, or financial), or lack of health insurance. Given that these risk factors all lead to worse general health status, this causal pathway should be largely accounted for by current clinical risk-adjustment**.**

In addition to SES risk factors, studies have shown that worse health status is more prevalent among African-American patients compared with white patients. The association between race and worse health is in part mediated by the association between race and SES risk factors such as poverty or disparate access to care associated with poverty or neighborhood.

2. **Use of low-quality hospitals**. Patients of lower income, lower education, or unstable housing have been shown not to have equitable access to high quality facilities because such facilities are less likely to be found in geographic areas with large populations of poor patients; thus patients with low income are more likely to be seen in lower quality hospitals, which can contribute to increased risk of readmission following hospitalization (Jha et al., 2011; Reames et al., 2014). Similarly African-American patients have been shown to have less access to high quality facilities compared with white patients (Skinner et al., 2005).

3. **Differential care within a hospital**. The third major pathway by which SES factors or race may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, African-American patients have been shown to experience differential, lower quality, or discriminatory care within a given facility (Trivedi et al., 2014). Alternatively, patients with SES risk factors such as lower education may require differentiated care – for example, provision of lower literacy information – that they do not receive.

4. **Influence of SES on readmission risk outside of hospital quality and health status**. Some SES risk factors, such as income or wealth, may affect the likelihood of readmission without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may have a worse outcome post-discharge due to competing economic priorities or a lack of access to care outside of the hospital.

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4. What were the statistical results of the analyses used to select risk factors?

Here we describe our general approach to selecting clinical risk factors and the results of that approach for the AMI readmission measure brought for endorsement maintenance. We sought to develop a model that included key variables that were clinically relevant and based on strong relationships with the outcome and that was parsimonious, using a grouper that is in the public domain for the 15,000+ International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes. The candidate variables for the model were derived from: the index admission, with comorbidities identified from the index admission secondary diagnoses (excluding potential complications); 12-month pre-index inpatient data (for any condition); outpatient hospital data; and Part B physician data. We developed candidate variables for the model from the claims codes.

We started with the 189 diagnostic groups included in the Hierarchical Condition Category (HCC) clinical classification system (Pope et al., 2000). The HCC clinical classification system was developed for CMS in preparation for all-encounter risk adjustment for Medicare Advantage (managed care) plans and represented a refinement of an earlier risk-adjustment method based solely on principal inpatient diagnosis. The HCC model makes use of all physician and hospital encounter diagnoses and was designed to predict a beneficiary's expenditures based on the total clinical profile represented by all of his/her assigned HCCs. Under the HCC algorithm, the 15,000+ ICD-9-CM diagnosis codes are first assigned to one of 804 mutually exclusive groupings ("DxGroups") and then subsequently aggregated into 189 condition categories (CCs) (Pope et al., 2000). We do not use the hierarchy and therefore refer to the CCs rather than HCCs.

To select candidate variables, a team of clinicians began with a review of all 189 CC variables. A total of 154 CCs determined to be clinically relevant to the readmission outcome were included for consideration. Some CCs were then combined into clinically coherent groupings of CCs. Our set of candidate variables therefore included 97 CC-based variables, two demographic variables (age and gender), two AMI location variables (anterior myocardial infarction [MI] and other location of MI), and two procedure codes relevant to readmission risk (history of percutaneous coronary intervention [PCI] and history of coronary artery bypass graft [CABG]). The final risk adjustment variables were selected by a team of clinicians and analysts primarily based on their clinical relevance but with knowledge of their strength of association with the readmission outcome.

To inform variable selection, a modified approach to stepwise logistic regression was performed. The developmental dataset was used to create 500 bootstrap samples. For each sample, we ran a logistic stepwise regression, with both backward and forward selection, that included the 103 candidate variables. The results were summarized to show the percentage of times that each of the candidate variables was significantly associated with readmission (at the $p<0.001$ level) in each of the 500 repeated samples (for example, 80 percent would mean that the candidate variable was selected as significant at $p<0.001$ in 80 percent of the estimations). We also assessed the direction and magnitude of the regression coefficients.

The clinician team reviewed these results and decided to retain all risk-adjustment variables above a 70% cutoff with the exception of obesity, which was excluded due to lack of clinical coherence. These 18 variables demonstrated a relatively strong association with readmission and were clinically relevant. Variables selected in less than 70% of the bootstrap samples were also included in the final model if:

1) They were markers for end of life/frailty:

- Decubitus ulcer
- Dementia and senility

- Protein-calorie Malnutrition
- Hemiplegia, Paraplegia, Paralysis, Functional Disability
- Metastatic Cancer and Acute Leukemia
- Stroke

2) They were on the same clinical spectrum as a variable above the 70% cutoff and were clinically important for AMI patients:

- Cerebrovascular Disease
- Acute Coronary Syndrome
- Angina pectoris, Old Myocardial Infarction
- History of PCI
- History of CABG
- Asthma

3) Certain hospitals might have a disproportionate share of patients with the condition:

- Cancer

This resulted in a final risk-adjustment model that included 31 variables.

Table 1 shows the final variables in the model with associated OR and 95% CI. For this analysis, we used data from the 2013 public reporting year. These were the same data used in the NQF application submitted in 2014.

- Years of data: July 1, 2009 – June 30, 2012
- Number of admissions: 534,341
- Patient Descriptive Characteristics: average age=78.9; % male=51.5
- Number of Measured Entities: 4,464

Table 1. Final AMI Readmission Model Variables

Variable	07/2009-06/2012 OR (95% CI)
Age minus 65 (years above 65, continuous)	1.01 (1.01 - 1.01)
Male (%)	0.91 (0.90 - 0.93)
History of Percutaneous Transluminal Coronary Angioplasty (PTCA) (ICD-9 codes V45.82, 00.66, 36.06, 36.07)	0.91 (0.89 - 0.93)
History of Coronary Artery Bypass Graft (CABG) surgery (ICD-9 codes V45.81, 36.10-36.16)	0.99 (0.97 - 1.02)
Congestive heart failure (CC 80)	1.24 (1.22 - 1.26)
Acute coronary syndrome (CC 81-82)	1.02 (1.01 - 1.04)
Anterior myocardial infarction (ICD-9 codes 410.00-410.12)	1.19 (1.16 - 1.23)
Other location of myocardial infarction (ICD-9 codes 410.20-410.62)	0.94 (0.92 - 0.96)
Angina pectoris/old myocardial infarction (CC 83)	1.01 (1.00 - 1.03)
Coronary atherosclerosis (CC 84)	0.95 (0.93 - 0.97)
Valvular or rheumatic heart disease (CC 86)	1.11 (1.09 - 1.13)
Specified arrhythmias and other heart rhythm disorders (CC 92-93)	1.08 (1.06 - 1.10)
History of infection (CC 1, 3-6)	1.05 (1.03 - 1.07)
Metastatic cancer or acute leukemia (CC 7)	1.20 (1.15 - 1.26)

Variable	07/2009-06/2012 OR (95% CI)
Cancer (CC 8-12)	1.03 (1.01 - 1.05)
Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)	1.20 (1.19 - 1.22)
Protein-calorie malnutrition (CC 21)	1.11 (1.08 - 1.14)
Disorders of fluid/electrolyte/acid-base (CC 22-23)	1.12 (1.10 - 1.14)
Iron deficiency or other unspecified anemias and blood disease (CC 47)	1.23 (1.21 - 1.24)
Dementia or other specified brain disorders (CC 49-50)	1.00 (0.98 - 1.02)
Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)	1.08 (1.05 - 1.12)
Stroke (CC 95-96)	1.04 (1.01 - 1.07)
Cerebrovascular disease (CC 97-99, 103)	1.05 (1.03 - 1.07)
Vascular or circulatory disease (CC 104-106)	1.09 (1.07 - 1.11)
Chronic obstructive pulmonary disease (COPD) (CC 108)	1.26 (1.24 - 1.28)
Asthma (CC 110)	1.01 (0.98 - 1.04)
Pneumonia (CC 111-113)	1.20 (1.18 - 1.22)
End-stage renal disease or dialysis (CC 129-130)	1.32 (1.27 - 1.37)
Renal failure (CC 131)	1.18 (1.15 - 1.20)
Other urinary tract disorders (CC 136)	1.08 (1.06 - 1.10)
Decubitus ulcer or chronic skin ulcer (CC 148-149)	1.10 (1.08 - 1.13)

References:

Pope G, Ellis R, Ash A, et al. Principal Inpatient Diagnostic Cost Group Models for Medicare Risk Adjustment. *Health Care Financing Review.* 2000;21(3):26.

5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).

Methods:

In order to analyze SES and race factors for potential inclusion we performed a number of analyses, in alignment with NQF guidance: variation in prevalence of the factor across measured entities, performance of providers by proportion of patients of low SES or racial minorities, empirical association with the outcome (bivariate), and the incremental effect of SES variables and race in a multivariable model, including examining the extent to which the addition of any one of these variables improved model performance or changed hospital results.

Finally, we aimed to assess the extent to which the effect of SES or race is at the patient or the hospital level. For example, social or economic disadvantage may increase the risk of readmission because patients have an individual higher risk or because such patients receive differential care within a hospital (patient-level effect). Alternatively, patients of low SES may be more frequently admitted to hospitals with higher overall readmission rates (hospital-level effect). Thus, as an additional step, we performed a decomposition analysis to assess the independent effects of the SES and race variables at the patient level and the hospital level. If, for example, all the elevated risk of readmission for patients of low SES was due to lower quality/higher readmission risk in hospitals with more patients of low SES, then a significant hospital-level effect would be expected with little-to-no patient-level effect. However, if the increased readmission risk was solely related to higher risk for patients of low SES, then a significant patient-level effect would be expected and a significant hospital-level effect would not be expected. Decomposition analysis is a standard technique that we utilized, with the consultation of analytic experts in the field of quality measurement, to evaluate the contributions of patient-level and hospital-level effects (Guarnizo-Herreno & Wehby 2012; Normand 2008; Shahian et al., 2012).

Specifically, we decomposed each of the SES and race variables as follows: Let X_{ij} be a binary indicator of the SES or race status of the i^{th} patient at the j^{th} hospital, and $\mathbf{X}_j$ the percent of patients at hospital j with $X_{ij} = 1$. Then we rewrote $X_{ij} = (X_{ij} - \mathbf{X}_j) + \mathbf{X}_j \equiv X_{patient} + X_{hospital}$. The first variable, $X_{patient}$, represents the effect of the risk factor at the patient level (sometimes called the "within" hospital effect), and the second, $X_{hospital}$, represents the effect at the hospital level (sometimes called the "between" hospital effect). By including both of these in the same model, we can assess whether these are independent effects, or whether only one of these effects contributes. This analysis allows us to simultaneously estimate the independent effects of: 1) hospitals with higher or lower proportions of low SES patients or African-American patients on the readmission rate of an average patient; and 2) a patient's SES or race on their own readmission rates when seen at an average hospital.

It is very important to note, however, that even in the presence of a significant patient-level effect and absence of a significant hospital-level effect, the increased risk could be partly or entirely due to the quality of care patients receive in the hospital. For example, biased or differential care provided within a hospital to low-income patients as compared to high-income patients would exert its impact at the level of individual patients, and therefore be a patient-level effect. It is also important to note that the patient-level and hospital-level coefficients cannot be quantitatively compared because the patient's SES circumstance or race in the model is binary whereas the hospitals' proportion of low SES patients or African-American patients is continuous.

Results:

Variation in prevalence of the factor across measured entities

The prevalence of SES factors and African-American patients in the AMI cohort varies across measured entities. The median percentage of dual eligible patients is 10.9% (interquartile range [IQR]: 7.0% – 16.9%). The median percentage of African-American patients is 3.8% (IQR: 0.9% – 10.9%). The median percentage of patients with an ARHQ SES Index score equal to or below 45.9 is 16.4% (IQR: 4.1% – 40.6%). Table 2 displays the risk-standardized readmission rates for hospitals with a high or low proportion of patients with these SES factors or of African-American race. Hospitals with a high proportion of these patients had slightly higher readmission rates than those with a low proportion.

Table 2. Variation in RSRRs across Measured Entities by Proportion of Minority/Low SES Patients

Data Element	Low proportion dual eligible patients (≤7.0%)	High proportion dual eligible patients (≥16.9%)	Low proportion African-American patients (≤0.9%)	High proportion African-American patients (≥10.9%)	Low proportion of patients equal to or below AHRQ SES Index score of 45.9 (≤4.1%)	High proportion of patients equal to or below AHRQ SES Index score of 45.9 (≥40.6%)
Number of Hospitals	581	582	582	582	581	581
Number of Patients	122,490	86,786	93,675	119,215	104,914	118,580
Maximum RSRR	20.7	20.5	20.3	20.4	20.7	20.6
90th percentile RSRR	18.3	18.6	18.0	18.7	18.0	18.7
75th percentile RSRR	17.6	18.0	17.3	18.1	17.4	18.0
Median (50th percentile) RSRR	16.9	17.2	16.7	17.4	16.8	17.2
25th percentile RSRR	16.3	16.6	16.2	16.7	16.3	16.5
10th percentile RSRR	15.6	16.1	15.5	16.2	15.7	16.0
Minimum RSRR	13.7	14.6	13.9	13.3	13.7	13.3

Empirical association with the outcome (univariate)

The patient-level observed AMI readmission rate is higher for dual eligible patients, 21.05%, compared with 16.43% for all other patients. The readmission rate for African-American patients was also higher at 21.24% compared with 16.61% for patients of all other races. Similarly, the readmission rate for patients with an AHRQ SES Index score equal to or below 45.9 was 18.05% compared with 16.62% for patients with an AHRQ SES Index score above 45.9.

Incremental effect of SES variables and race in a multivariable model

We examined the strength and significance of the SES variables and race in the context of a multivariable model. Consistent with the above findings, when we include any of these variables in a multivariate model that includes all of the claims-based clinical variables, the effect size of each of these variables is modest (Table 5). The c-statistic is unchanged with the addition of any of these variables into the model (Table 3). Furthermore, the addition of any of these variables into the model has little to no effect on hospital performance as evidenced by minimal change in hospitals' RSRRs with the addition of any of these variables.

The median absolute change in hospitals' RSRRs when adding a dual eligibility indicator is 0.0086% (IQR: -0.0201% – 0.0305%, minimum -0.3367% – maximum 0.1319%) with a correlation coefficient between RSRRs for each hospital with and without dual eligibility added of 0.9991. The median absolute change in hospitals' RSRRs when adding a race indicator is 0.0128% (IQR: -0.0423% – 0.0526%, minimum -0.7728% – maximum 0.1635%) with a correlation coefficient between RSRRs for each hospital with and without race added of 0.9980. The median absolute change in hospitals' RSRRs when adding an indicator for a low AHRQ SES Index score is 0.0215% (IQR: -0.0597% – 0.0812%, minimum -0.9867% – maximum 0.6295%) with a correlation coefficient between RSRRs for each hospital with and without an indicator for a low AHRQ SES Index score added of 0.9905.

Table 3. AMI Readmission C-Statistics for Each Model

AMI Readmission Model	C-Statistic
Original Model	0.650
Original Model + Dual Eligible	0.651
Original Model + Race	0.651
Original Model + AHRQ SES Index	0.651

As an additional step, a decomposition analysis was performed (as described above). The results are shown in Table 4.

Table 4. AMI Readmission Decomposition Analysis*

Parameter	Estimate (Standard Error)	P-value
Dual Eligible – Patient-Level	0.1133 (0.0115)	<.0001
Dual Eligible – Hospital-Level	0.3394 (0.0550)	<.0001
African American – Patient-Level	0.0706 (0.0147)	<.0001
African American – Hospital-Level	0.4223 (0.0410)	<.0001
AHRQ SES Index – Patient-Level	0.0229 (0.0105)	0.0283
AHRQ SES Index – Hospital-Level	0.1419 (0.0229)	<.0001

* The p-values represent the significance of the patient-level and hospital-level variables. It is important to note that the coefficients cannot be quantitatively compared because the patient-level variable is binary whereas the hospital-level variable is continuous.

The patient-level and hospital-level dual eligible, race, and low AHRQ SES Index effects were both significantly associated with AMI readmission in the decomposition analysis. If the dual eligible, race, or low AHRQ SES Index variables are used in the model to adjust for patient-level differences, then some of the differences in outcomes between hospitals would also be adjusted for, potentially obscuring a signal of hospital quality.

Given these findings and the complex pathways that could explain any relationship between SES or race with readmission, we did not incorporate SES variables or race into the measure.

References:

Guarnizo-Herreno CC, Wehby GL. Explaining racial/ethnic disparities in children's dental health: a decomposition analysis. *Am J Public Health.* 2012;102(5):859-866.

Normand SL. Some old and some new statistical tools for outcomes research. *Circulation.* 2008;118(8):872-884.

Shahian DM, Iezzoni LI, Meyer GS, Kirle L, Normand SL. Hospital-wide mortality as a quality metric: conceptual and methodological challenges. *American journal of medical quality : the official journal of the American College of Medical Quality.* 2012;27(2):112-123.

Table 5. AMI Readmission Risk Model Estimates

Parameter	Original Model		Original Model + Dual Eligible		Original Model + Race		Original Model + AHRQ SES Index	
	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value
Age minus 65 (years above 65, continuous)	0.011 (0.001)	<.0001	0.012 (0.001)	<.0001	0.012 (0.001)	<.0001	0.011 (0.001)	<.0001
Male	-0.092 (0.008)	<.0001	-0.088 (0.008)	<.0001	-0.088 (0.008)	<.0001	-0.092 (0.008)	<.0001
History of Coronary Artery Bypass Graft (CABG) surgery (ICD-9 codes V45.81, 36.10-36.16)	0.023 (0.012)	0.0455	0.025 (0.012)	0.0339	0.027(0.012)	0.0212	0.023 (0.012)	0.0444
History of Percutaneous Transluminal Coronary Angioplasty (PTCA) (ICD-9 codes V45.82, 00.66, 36.06, 36.07)	-0.075 (0.010)	<.0001	-0.073 (0.010)	<.0001	-0.074 (0.010)	<.0001	-0.075 (0.011)	<.0001
Angina pectoris/old myocardial infarction (CC 83)	0.043 (0.009)	<.0001	0.042 (0.009)	<.0001	0.043 (0.009)	<.0001	0.043 (0.009)	<.0001
Congestive heart failure (CC 80)	0.180 (0.010)	<.0001	0.177 (0.010)	<.0001	0.178 (0.010)	<.0001	0.181 (0.010)	<.0001
Coronary atherosclerosis (CC 84)	0.032 (0.012)	0.0082	0.035 (0.012)	0.0043	0.035 (0.012)	0.0041	0.033 (0.012)	0.0072
Acute coronary syndrome (CC 81-82)	0.001 (0.010)	0.9321	0.000 (0.010)	0.9926	0.001 (0.010)	0.9555	-0.003 (0.010)	0.7868
Specified arrhythmias and other heart rhythm disorders (CC 92-93)	0.090 (0.009)	<.0001	0.091 (0.009)	<.0001	0.092 (0.009)	<.0001	0.092 (0.009)	<.0001
Valvular or rheumatic heart disease (CC 86)	0.126 (0.008)	<.0001	0.128 (0.008)	<.0001	0.127 (0.008)	<.0001	0.125 (0.008)	<.0001
Cerebrovascular disease (CC 97-99, 103)	0.045 (0.010)	<.0001	0.047 (0.010)	<.0001	0.047 (0.010)	<.0001	0.046 (0.010)	<.0001
Stroke (CC 95-96)	0.024 (0.015)	0.0985	0.023 (0.015)	0.1129	0.021 (0.015)	0.1443	0.025 (0.015)	0.0847
Vascular or circulatory disease (CC 104-106)	0.107 (0.009)	<.0001	0.106 (0.009)	<.0001	0.106 (0.009)	<.0001	0.110 (0.009)	<.0001

Parameter	Original Model		Original Model + Dual Eligible		Original Model + Race		Original Model + AHRQ SES Index	
	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value
Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)	0.069 (0.015)	<.0001	0.064 (0.015)	<.0001	0.065 (0.015)	<.0001	0.070 (0.015)	<.0001
Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)	0.177 (0.008)	<.0001	0.174 (0.008)	<.0001	0.174 (0.008)	<.0001	0.174 (0.008)	<.0001
Renal failure (CC 131)	0.138 (0.010)	<.0001	0.137 (0.010)	<.0001	0.135 (0.010)	<.0001	0.138 (0.010)	<.0001
End-stage renal disease or dialysis (CC 129-130)	0.300 (0.018)	<.0001	0.296 (0.018)	<.0001	0.285 (0.019)	<.0001	0.301 (0.019)	<.0001
Other urinary tract disorders (CC 136)	0.080 (0.009)	<.0001	0.080 (0.009)	<.0001	0.079 (0.009)	<.0001	0.079 (0.009)	<.0001
Chronic obstructive pulmonary disease (COPD) (CC 108)	0.252 (0.008)	<.0001	0.247 (0.008)	<.0001	0.255 (0.008)	<.0001	0.252 (0.009)	<.0001
Pneumonia (CC 111-113)	0.149 (0.009)	<.0001	0.147 (0.009)	<.0001	0.150 (0.009)	<.0001	0.146 (0.009)	<.0001
Asthma (CC 110)	0.016 (0.014)	0.2561	0.016 (0.014)	0.2691	0.013 (0.014)	0.3736	0.018 (0.015)	0.2283
Disorders of fluid/electrolyte/acid-base (CC 22-23)	0.115 (0.010)	<.0001	0.114 (0.010)	<.0001	0.114 (0.010)	<.0001	0.113 (0.010)	<.0001
History of infection (CC 1, 3-6)	0.044 (0.009)	<.0001	0.041 (0.009)	<.0001	0.044 (0.009)	<.0001	0.046 (0.009)	<.0001
Metastatic cancer or acute leukemia (CC 7)	0.224 (0.025)	<.0001	0.225 (0.025)	<.0001	0.225 (0.025)	<.0001	0.229 (0.025)	<.0001
Cancer (CC 8-12)	0.024 (0.010)	0.0174	0.027 (0.010)	0.0065	0.023 (0.010)	0.0196	0.025 (0.010)	0.0138
Iron deficiency or other unspecified anemias and blood disease (CC 47)	0.289 (0.009)	<.0001	0.287 (0.009)	<.0001	0.288 (0.009)	<.0001	0.291 (0.009)	<.0001
Decubitus ulcer or chronic skin ulcer (CC 148-149)	0.088 (0.013)	<.0001	0.087 (0.013)	<.0001	0.089 (0.013)	<.0001	0.090 (0.013)	<.0001
Dementia or other specified brain disorders (CC 49-50)	0.017 (0.010)	0.0844	0.010 (0.010)	0.2892	0.014 (0.010)	0.1545	0.015 (0.010)	0.1305
Protein-calorie malnutrition (CC 21)	0.110 (0.014)	<.0001	0.108 (0.014)	<.0001	0.107 (0.014)	<.0001	0.108 (0.014)	<.0001

Parameter	Original Model		Original Model + Dual Eligible		Original Model + Race		Original Model + AHRQ SES Index	
	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value
Anterior myocardial infarction (ICD-9 codes 410.00-410.12)	0.209 (0.015)	<.0001	0.211 (0.015)	<.0001	0.211 (0.015)	<.0001	0.212 (0.016)	<.0001
Other location of myocardial infarction (ICD-9 codes 410.20-410.62)	-0.094 (0.014)	<.0001	-0.092 (0.014)	<.0001	-0.092 (0.014)	<.0001	-0.094 (0.014)	<.0001
Dual Eligibility	-	-	0.125 (0.011)	<.0001	-	-	-	-
African-American Race	-	-	-	-	0.122 (0.014)	<.0001	-	-
Low AHRQ SES Index	-	-	-	-	-	-	0.052 (0.009)	<.0001

6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).

We computed three summary statistics for assessing model performance (Harrell and Shih, 2001) for the cohorts:

Discrimination Statistics

(1) Area under the receiver operating characteristic (ROC) curve (the c-statistic [also called ROC curve] is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model is able to distinguish between a patient with and without an outcome)

(2) Predictive ability (discrimination in predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects. Therefore, we would hope to see a wide range between the lowest decile and highest decile)

Calibration Statistics

(3) Over-fitting indices (over-fitting refers to the phenomenon in which a model accurately describes the relationship between predictive variables and outcome in the development dataset but fails to provide valid predictions in new patients)

Results:

We tested the performance of the model for the 2013 public reporting cohort (described in our response to Question #4 above) and the 2006 development dataset:

- Dates of Data: January 1, 2006-December 31, 2006
- Number of Admissions: 100,465 (development sample); 100,285 (validation sample)
- Patient Descriptive Characteristics: average age = 78.77; %male = 49.40
- Number of Measured Entities: 4,383 (development sample); 4,416 (validation sample).

During initial measure development, we tested the performance of the model developed in a randomly selected half of the hospitalizations for AMI in 2006 compared with performance calculated from hospitalizations from the other half. As a part of measure reevaluation, we assessed temporal trends in model performance in the 2013 public reporting data. Below, we report the model performance only for the 3-year combined results.

Discrimination Statistics

For the 2006 development cohort, the results are summarized below:

- First half of randomly split development cohort: c-statistic = 0.63; predictive ability (lowest decile %, highest decile %) = (8.0, 33)
- Second half of randomly split development cohort: c-statistic = 0.62; predictive ability (lowest decile %, highest decile %) = (8.0, 33)

For the 2013 public reporting cohort, the results are summarized below:

- C-statistic = 0.64; predictive ability (lowest decile %, highest decile %) = (6.8, 32.1)

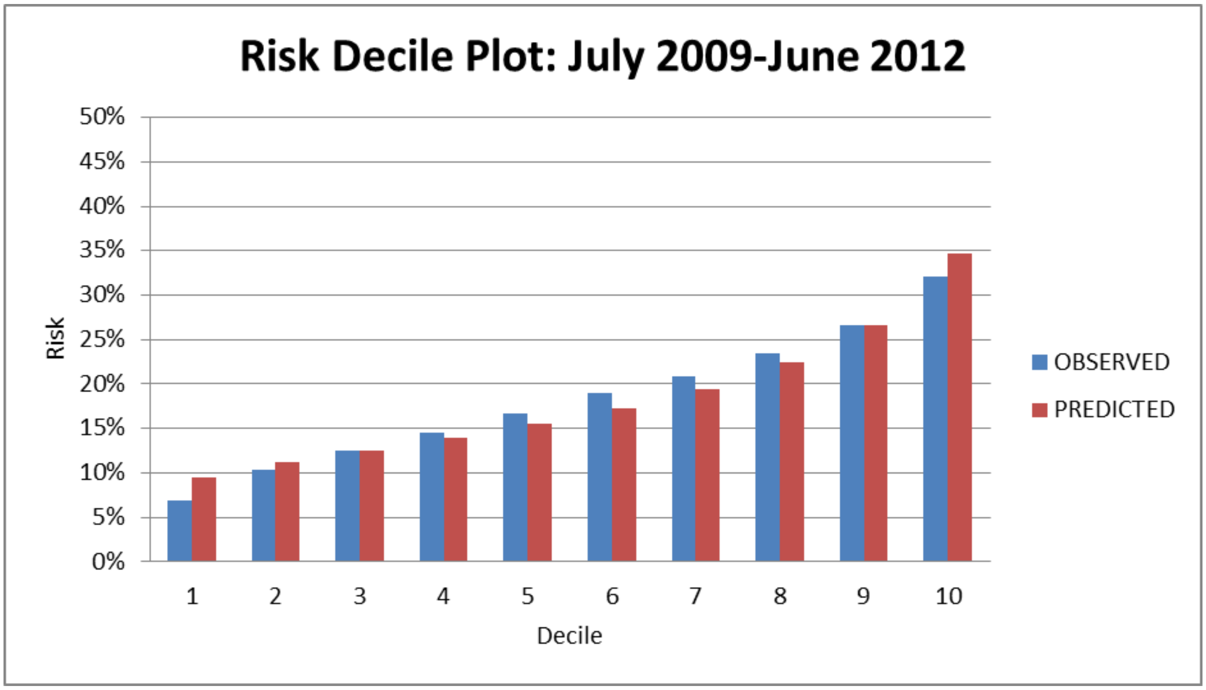
For comparison of model with and without inclusion of SDS factors, see Question #5.

Calibration Statistics

For the 2006 original measure development cohort, the results are summarized below:

- First half of split sample: Calibration: (0,1)
- Second half of split sample: Calibration: (0.015, 0.997)

The risk decile plot is a graphical depiction of the deciles calculated to measure predictive ability. Below, we present the risk decile plot showing the distributions for fee-for-service (FFS) Medicare data from July 2009 to June 2012. Plots for the development and validation samples were similar.



Reference:

F.E. Harrell and Y.C.T. Shih, Using full probability models to compute probabilities of actual interest to decision makers, *Int. J. Technol. Assess. Health Care* 17 (2001), pp. 17–26.

7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.

We did not identify any unintended consequences during measure development, model testing, or reevaluation. However, we are committed to ongoing monitoring of this measure's use and assessing potential unintended consequences over time, such as the inappropriate shifting of care, increased patient morbidity and mortality, and other negative unintended consequences for patients. We are aware of stakeholder concern that not adding patient-level SES or race variables into the readmission model might disproportionately penalize hospitals caring for a higher proportion of patients with low SES. Acknowledging this concern, we tested the effect of including SES or race variables into the measure, and additionally completed a decomposition analysis to understand whether the effect of the SES or race variables were at either the patient or the hospital level. The decomposition results suggest that the hospital-level effect is significant for both SES variables and the African-American race variables. If these variables are used to adjust for patient-level differences, then differences between hospitals would also be affected, which could potentially obscure a signal of hospital quality. While we do not recommend adjusting for SES or race in this measure, we do believe that there may be better pathways outside of patient-level risk adjustment to address stakeholder concerns about financial penalties.

8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.

N/A

9. Please enter the details of the final statistical risk model and variables here.

Our approach to risk adjustment is tailored to and appropriate for a publicly reported outcome measure, as articulated in the American Heart Association (AHA) Scientific Statement, "Standards for Statistical Models Used for Public Reporting of Health Outcomes" (Krumholz et al., 2006).

The measure employs a hierarchical logistic regression model to create a hospital-level 30-day, all-cause, RSRR. In brief, the approach simultaneously models data at the patient and hospital levels to account for the variance in patient outcomes within and between hospitals (Normand & Shahian, 2007). At the patient level, the model adjusts the log-odds of readmission within 30 days of discharge for age, gender, and selected clinical covariates. At the hospital level, the approach models the hospital-specific intercepts as arising from a normal distribution. The hospital intercept represents the underlying risk of readmission at the hospital, after accounting for patient risk. If there were no differences among hospitals, then after adjusting for patient risk, the hospital intercepts should be identical across all hospitals.

The final set of risk adjustment variables is:

<u>Demographics</u>

- Age minus 65 (years above 65, continuous)
- Male

<u>Comorbidities</u>

- History of Percutaneous Transluminal Coronary Angioplasty (PTCA) (ICD-9 codes V45.82, 00.66, 36.06, 36.07)
- History of Coronary Artery Bypass Graft (CABG) surgery (ICD-9 codes V45.81, 36.10-36.16)
- Congestive heart failure (CC 80)
- Acute coronary syndrome (CC 81-82)
- Anterior myocardial infarction (ICD-9 codes 410.00-410.12)
- Other location of myocardial infarction (ICD-9 codes 410.20-410.62)
- Angina pectoris/old myocardial infarction (CC 83)
- Coronary atherosclerosis (CC 84)
- Valvular or rheumatic heart disease (CC 86)
- Specified arrhythmias and other heart rhythm disorders (CC 92-93)
- History of infection (CC 1, 3-6)
- Metastatic cancer or acute leukemia (CC 7)
- Cancer (CC 8-12)
- Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)
- Protein-calorie malnutrition (CC 21)
- Disorders of fluid/electrolyte/acid-base (CC 22-23)
- Iron deficiency or other unspecified anemias and blood disease (CC 47)
- Dementia or other specified brain disorders (CC 49-50)
- Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)
- Stroke (CC 95-96)
- Cerebrovascular disease (CC 97-99, 103)
- Vascular or circulatory disease (CC 104-106)
- Chronic obstructive pulmonary disease (COPD) (CC 108)
- Asthma (CC 110)

- Pneumonia (CC 111-113)
- End-stage renal disease or dialysis (CC 129-130)
- Renal failure (CC 131)
- Other urinary tract disorders (CC 136)
- Decubitus ulcer or chronic skin ulcer (CC 148-149)

References:

Krumholz HM, Brindis RG, Brush JE, et al. 2006. 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 113: 456-462.

Normand S-LT, Shahian DM. 2007. Statistical and Clinical Aspects of Hospital Outcomes Profiling. Stat Sci 22 (2): 206-226.

Pope GC, et al. 2000. Principal Inpatient Diagnostic Cost Group Models for Medicare Risk Adjustment. Health Care Financing Review 21(3): 93-118.

10. Compare measure performance scores with and without SDS factors in the risk adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

As explained in Question #5, we examined the strength and significance of the SES and race variables in the context of a multivariable model. The addition of any of these variables into the model has little to no effect on hospital performance. We examined the change in hospitals' RSRRs with the addition of these variables.

The median absolute change in hospitals' RSRRs when adding a dual eligibility indicator is 0.0086% (IQR: -0.0201% – 0.0305%, minimum -0.3367% – maximum 0.1319%) with a correlation coefficient between RSRRs for each hospital with and without dual eligibility added of 0.9991. The median absolute change in hospitals' RSRRs when adding a race indicator is 0.0128% (IQR: -0.0423% – 0.0526%, minimum -0.7728% – maximum 0.1635%) with a correlation coefficient between RSRRs for each hospital with and without race added of 0.9980. The median absolute change in hospitals' RSRRs when adding an indicator for a low AHRQ SES Index score is 0.0215% (IQR: -0.0597% – 0.0812%, minimum -0.9867% – maximum 0.6295%) with a correlation coefficient between RSRRs for each hospital with and without an indicator for a low AHRQ SES Index score added of 0.9905.

11. Appendix (includes literature review, reference list, etc.)

N/A

MEMO
TO: NQF Admission – Readmission Project
From: Measure Developer, Measure #0695
RE: Sociodemographic Variable Trial Period
Date: February 29, 2016

[NQF] Admissions and Readmissions March 8 and May 13 SDS Webinar Developer Questions

1. Enter measure # and title.

Measure 0695: Hospital 30-Day Risk-Standardized Readmission Rates following Percutaneous Coronary Intervention (PCI)

2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?

Patient-level sociodemographic variables (SDS) available in the American College of Cardiology's CathPCI Registry dataset include: gender, race, Hispanic ethnicity, age, zip code, and insurance status.

Age and gender are viewed as clinical variables. For the purpose of this risk standardized model, we treated them as such and will not be discussed further in the evaluation of SDS variables.

Patient-level sociodemographic variables available in the Medicare Provider and Analysis Review (MEDPAR) dataset includes: gender, race, Hispanic ethnicity, age and zip code. For patients with dual eligibility status, CMS data provides income quintiles.

3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

The recommendation from the measure developer is to not include sociodemographic factors in the measure's final risk standardized model for Measure #0695 (Hospital 30-Day Risk-Standardized Readmission Rates following Percutaneous Coronary Intervention).

The socioeconomic status analyses included within the original NQF application for this measure provides the strongest evidence suggesting that these SDS factors do not exert a strong impact on hospital risk standardized readmission rates post percutaneous coronary interventions.

4. What were the statistical results of the analyses used to select risk factors?

During the development of the original measure we used logistic regression with stepwise selection (entry $p<0.05$; retention with $p<0.01$) for variable selection. We also assessed the direction and magnitude of the regression coefficients. This resulted in a final risk-adjusted readmission model that included 20 variables. There were variables for demographics (age and gender), history and risk factors, cardiac status (heart failure, symptoms present on admission), cath lab visits (ejection fraction percentage), and PCI procedure (PCI status, highest risk lesion, highest pre-procedure TIMI flow).

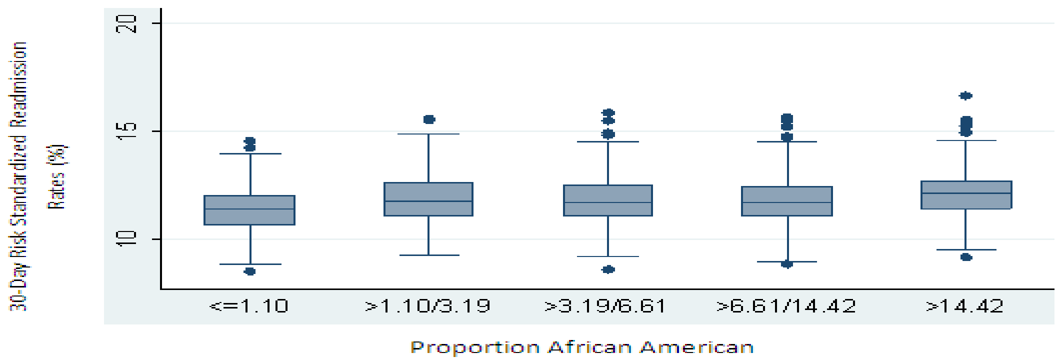
Based on the datasets available, race and dual eligibility were sociodemographic variables considered and analyzed. We used Medicare Provider Analysis and Review (MEDPAR) File for 2010 to calculate the percentage of African-American patients treated at each hospital, using all patients admitted to each hospital. We examined hospital-level RSRRs across hospitals grouped by quintile of the proportion of African-American patients. Overall, there were modest differences in the RSRRs by quintile. Specifically, the median RSRR for hospitals with the highest proportion of African-American patients was 12.4% compared with 11.2% for hospitals with the lowest proportion of African-American patients. In comparison to the registry average of 11.8%, hospitals with high proportions of African-American patients have modestly higher 30-day RSRRs.

We used the MEDPAR File for 2010 to calculate the percentage of patients 65 or older and eligible for both Medicare and Medicaid (dual eligible patients) treated at each hospital. The proportion of dual eligible patients was used as a marker for determining the SES status of hospitals' patients because this is a low income and vulnerable population. Similar to our analyses above, we examined hospital-level RSRRs across quintiles of dual eligible patients treated. There were no differences in RSRRs across income quintile. The median RSRR for hospitals in the top quintile of dual eligible patients was 12.3% compared with 11.6% for hospitals in the bottom quintile of dual eligible patients. In comparison to the registry average of 11.8%, hospitals that treat a high percentage of dual eligible patients have moderately higher 30-day RSRRs.

5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).

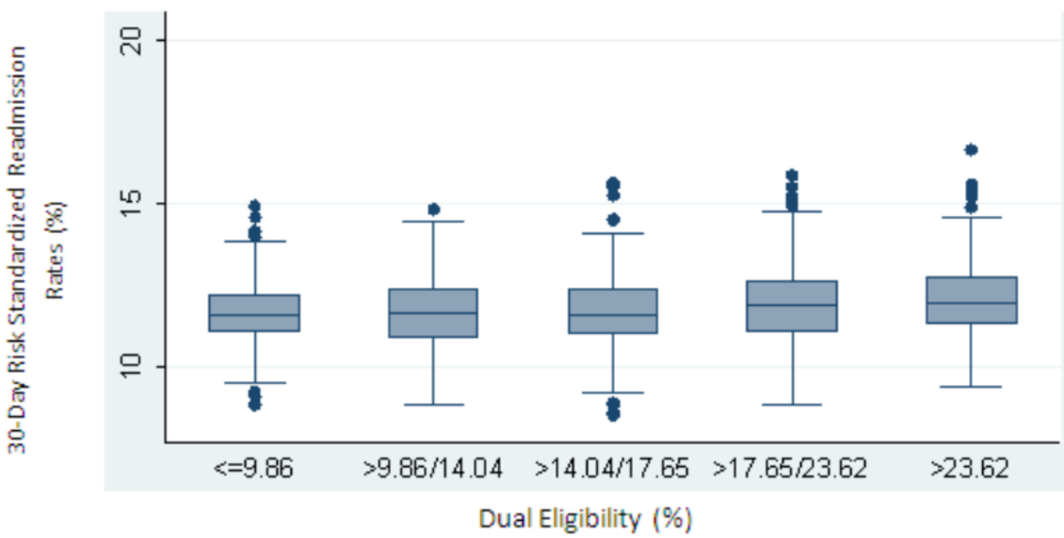
The analyses conducted using the MEDPAR file indicated that the distributions for the RSRRs by proportion of African Americans overlapped across hospital quintiles (Figure 1), and many hospitals caring for the highest percentage of African-American patients performed well on the measures.

Figure 1. Distributions of Hospital RSRRs by Proportion of African Americans



Additionally, the distributions for the RSRRs by proportion of dual eligible patients overlapped (Figure 2), and many hospitals in the highest quintile of dual eligible patients performed well on the measure.

Figure 2. Distributions of Hospital RSRRs by Proportion of Dual Eligible Patients



6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).

During measure development, we computed three summary statistics for assessing model performance for the development and validation cohort:[2]

Discrimination Statistics:

(1) Area under the receiver operating characteristic (ROC) curve (the c statistic (also called ROC) is the probability that predicting the outcome is better than chance, which is a measure of how

accurately a statistical model is able to distinguish between a patient with and without an outcome.)

(2) Predictive ability (discrimination in predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects. Therefore, we would hope to see a wide range between the lowest decile and highest decile)

Calibration Statistics:

(3) Over-fitting indices (over-fitting refers to the phenomenon in which a model accurately describes the relationship between predictive variables and outcome in the development dataset but fails to provide valid predictions in new patients)

We compared the model performance in the development sample with its performance in a similarly derived sample from patients discharged in 2006 who had undergone PCI. There were 117,375 cases discharged from the 618 hospitals in the 2006 validation dataset. This validation sample had a crude readmission rate of 10.7%. We also computed statistics (1) and (2) for the current measure cohort, which includes discharges from 2010-2011.

7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.

The goal of this measure is to improve patient outcomes by providing patients, physicians, and hospitals with information about hospital-level RSRRS following hospitalization for PCI. Measurement of patient outcomes allows for a broad view of quality of care that encompasses more than what can be captured by individual process-of-care measures. Complex and critical aspects of care, such as communication between providers, prevention of and response to complications, patient safety, and coordinated transitions to the outpatient environment, all contribute to patient outcomes but are difficult to measure by individual process measures. The goal of outcomes measurement is to risk-adjust for patients' conditions at the time of hospital admission and then evaluate patient outcomes. This measure was developed to identify institutions' whose performance is better or worse than would be expected based on their patient case mix, and therefore promote hospital quality improvement and better inform consumers about care quality.

This measure describes hospital-level readmission rates following PCI, with the overriding goal to reduce preventable readmissions to best-in-class (NPP 3.3) and reduce readmissions following hospitalization for relevant conditions to best-in-class (NPP 3.4). The expectation is that providing this information to hospitals, coupled with public reporting of hospitals' results, will drive internal hospital quality improvement efforts to focus efforts on reducing readmissions following hospitalization for PCI. This perspective may motivate hospitals to look for opportunities not only within the organization, but also to better coordinate the transition of care from the inpatient to the outpatient arena.

The routine inclusion of SDS into risk models has the potential to explain away meaningful and actionable differences in hospital performance. Analyses have shown that many hospitals caring for a higher proportion of disadvantaged patients perform extremely well on the measure. Furthermore, inclusion of SDS does not meaningfully change estimates of hospital performance.

Contractual relationships in place with the NCDR and hospitals require that 100% of patient's undergoing the PCI are submitted into the CathPCI Registry dataset. This implies that 100% of the patients would be asked for additional SDS related data elements. This is not feasible for hospitals as PCI is the most common cardiac intervention with more than 650,000 procedures across the country annually. Furthermore, given what is known about the willingess of individuals to provide this information, even a concerted attempt to collect this data point would likely result in rates of missing data that would render the variable useless. Information surrounding various SDS factors are not currently available in external data sources, (ie administrative claims data), and thus cannot be electronically mapped to patient records.

Finally, even if we agreed that adjusting for SDS is important and valid, we believe that it is not feasible due to the absence of an accepted manner of reliably capturing SDS including education, income, and other social stressors. The data constraints create insurmountable barriers to capturing sociodemographic data. While there is limited evidence suggesting that people may be more inclined to provide level of education information, over their household income, we would be challenged to validate that information.

8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.

Measure #0695 performs well as defined above without the inclusion of sociodemographic factors. The measure developer does not intend to incorporate SDS variables into the model's risk standardization. Thus, this question is not applicable.

9. Please enter the details of the final statistical risk model and variables here.

No changes have been made to the measure.

For the development cohort the results are summarized below:
C-statistic=0.665
Predictive ability (lowest decile %, highest decile %): 4.05%, 25.08%
Calibration: (0.00,1.00)

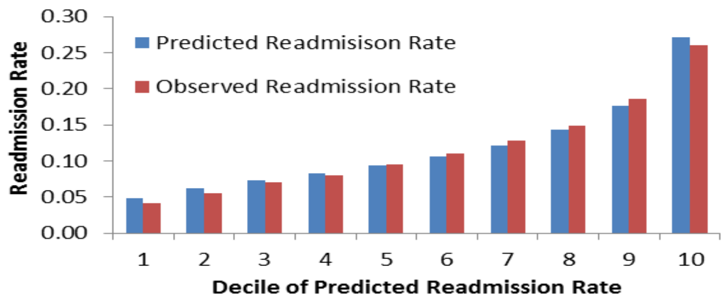
For the validation cohort the results are summarized below:
C statistic=0.663
Predictive ability (lowest decile %, highest decile %): 3.80%, 23.80%
Calibration: (-0.06, 0.99)

For the current measure cohort (combined data from 2010 and 2011) the results are summarized below:
C statistic=0.668

Predictive ability (lowest decile %, highest decile %): 4.2%, 26.1%
Calibration: (-0.004, 1.008)

The risk decile plot is a graphical depiction of the deciles calculated to measure predictive ability. Below, we present the risk decile plot showing the distributions for the current measure cohort.

Figure 3. Risk decile plot, 2010-2011 study sample.



Discrimination Statistics
The C-statistics of 0.665, 0.663 and 0.668 indicate good model discrimination. Readmission, as opposed to other outcomes such as mortality consistently has a lower c-statistic, even in medical record models. This is likely because readmission is less determined by patient comorbidities and more by health system factors. The model indicated a wide range between the lowest decile and highest decile, indicating the ability to distinguish high-risk patients from low-risk patients.
Calibration Statistics

Over-fitting (Calibration γ0, γ1)
If the γ0 in the validation samples are substantially far from zero and the γ1 is substantially far from 1, there is potential evidence of over-fitting. The calibration value close to 0 at one end and close to 1 on the other end indicates good calibration of the model.

Risk Decile Plots
Higher deciles of the predicted outcomes are associated with higher observed outcomes, which show a good calibration of the model. This plot indicates excellent discrimination of the model and good predictive ability.

Overall Interpretation
Interpreted together, our diagnostic results demonstrate the risk-adjustment model adequately controls for differences in patient characteristics (case mix).

Variables included:

(1) Age
(2) Female

(3) Body Mass Index
(4) Heart failure-previous history
(5) Previous valvular surgery
(6) Cerebrovascular Disease
(7) Peripheral Vascular Disease
(8) Chronic Lung Disease
(9) Diabetes
(10) Glomerular Filtration Rate
(11) Renal failure - dialysis
(12) Hypertension
(13) History of tobacco use
(14) Previous PCI
(15) Heart failure – current status
(16) Symptoms present on admission
(17) Ejection Fraction Percentage
(18) PCI status
(19) Highest risk lesion – location
(20) Highest pre-procedure TIMI flow

10. Compare measure performance scores with and without SDS factors in the risk adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

The measure developer does not intend to incorporate SDS variables into the model's risk standardization. This question is not applicable.

11. Appendix (includes literature review, reference list, etc.)

1. Normand S-LT, Shahian DM. 2007. Statistical and Clinical Aspects of Hospital Outcomes Profiling. Stat Sci 22(2): 206-226.

2. Harrell FE Jr., Shih YC. 2001. Using full probability models to compute probabilities of actual interest to decision makers. Int. J. Technol Assess Health Care 17(1):17-26.

NQF Measure #2393: Pediatric All-Condition Readmission Measure
Relationship Between Pediatric Hospital Readmissions and Sociodemographic Status
March 8 2016 Webinar Developer Question (due 2/22/16)

***1. Enter measure # and title**

Measure #2393: Pediatric All-Condition Readmission Measure

***2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?**

- Patient insurance (primary payer): Medicaid, Medicare, Private Insurance, Self-pay, Other
- Median income within patient's zip code
- Distribution of education level within patient's zip code: Less than High School, High School Graduate, Some College/Associate Degree, and Bachelor's Degree or Above

3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

Based on the relationship between these SDS factors and pediatric hospital readmissions and the performance of various candidate multivariate models in distinguishing who was readmitted or not readmitted, we recommend adding insurance as an adjuster to the existing all-condition model.

***4. What were the statistical results of the analyses used to select risk factors?**

We used comprehensive all payer New York data reporting system established in 1979 as a result of cooperation between the healthcare industry and government (SPARCS). This system was initially created to collect information on discharges from hospitals. SPARCS currently collects patient-level detail on patient characteristics, diagnoses and treatments, services, and charges for each hospital inpatient stay and outpatient (ambulatory surgery, emergency department, and outpatient services) visit; and each ambulatory surgery and outpatient services visit to a hospital extension clinic and diagnostic and treatment center licensed to provide ambulatory surgical services.

For this analysis, we selected discharges from inpatient visits in 2013. There were 136,357 eligible pediatric all-condition index admissions in 183 hospitals, and 6,206 (4.55%) were followed by ≥ 1 unplanned readmission within 30 days.

We assessed 2 different approaches for selection of risk factors: (1) significance of bivariate and multivariate analyses, and (2) goodness-of-fit using c-statistics of 8 different multivariate models.

A. BIVARIATE AND MULTIVARIATE ANALYSES

The New York data included 3 SDS variables: insurance, income, and education. Insurance was a patient-level variable while income and education were zip-code-level variables.

Insurance

Insurance was analyzed as a 5-level primary payer variable reflecting the patient's primary payer during the index admission: Medicaid, Medicare, Private Insurance, Self-pay, and Other. Insurance had a statistically significant association with 30-day readmission in both bivariate and multivariate analysis with p-value <0.001 (see Table 1). In bivariate analysis, compared with patients with Medicaid, those with Private Insurance, Self-pay, and Other insurance had significantly lower odds of readmission (OR 0.66 [95%CI 0.62,0.70]; 0.64, [0.52,0.79]; 0.67 [0.55,0.82], respectively) while those with Medicare had significantly higher odds of readmission (OR: 2.44 [95%CI 1.65,3.60]; p<0.001 for each comparison in, Table 1). In multivariate analysis, adjusting for income; education; and the core case-mix variables of age, gender, and chronic conditions, patients with Private Insurance, Self-pay, and Other insurance had 0.8 lower odds of readmission than those with Medicaid, while the difference in readmission risk for those with Medicare was no longer significant.

Table 1. Bivariate and Multivariate Results for Insurance

Individual Insurance Status	n (%)	Bivariate Analysis		Multivariate Analysis*	
		OR (95% CI)	p-value	OR (95% CI)	p-value
Medicaid	84,991 (62.3)	reference	--	reference	--
Medicare	256 (0.2)	2.44 (1.65,3.60)	<0.001	1.16 (0.75,1.80)	0.49
Private Insurance	45,112 (33.1)	0.66 (0.62,0.70)	<0.001	0.79 (0.74,0.85)	<0.001
Self-pay	3,185 (2.3)	0.64 (0.52,0.79)	<0.001	0.78 (0.62,0.97)	0.03
Other	2,809 (2.1)	0.67 (0.55,0.82)	<0.001	0.78 (0.63,0.96)	0.02

*Adjusting for income, education and core case-mix variables (age, gender, 17 Chronic Condition Indicators, CCI count)

Income

To serve as a proxy for family income, we used the median income within a patient's zip code, categorized into quartiles. In bivariate analysis, compared with patients who lived in a zip code with a median income in the lowest quartile, those who lived in a zip code with a median income in the highest quartile had a significantly lower risk of readmission (OR 0.83 [95%CI 0.76-0.90]; p <0.001, Table 2). However, this relationship was no longer significant after adjusting for insurance, education and the core case-mix variables.

Table 2. Bivariate and Multivariate Results for Zip Code Level Income

	n (%)	Bivariate Analysis		Multivariate Analysis*	
		OR (95% CI)	p-value	OR (95% CI)	p-value
1st quartile	36,945 (27.1)	reference	--	reference	--
2nd quartile	32,590 (23.9)	0.97 (0.90,1.05)	0.47	0.98 (0.90,1.06)	0.62
3rd quartile	32,226 (23.6)	1.03 (0.96,1.12)	0.39	1.05 (0.96,1.15)	0.27

4th quartile	30,040 (22.0)	0.83 (0.76,0.90)	<0.001	0.94 (0.84,1.06)	0.34

*Adjusting for insurance, education and core case-mix variables (age, gender, 17 CCIs, CCI count)

Education

To evaluate the relationship between education and readmission risk, we used 4 continuous variables that indicated the percentage of residents in the patient's zip code who had attained education levels of Less than High School, High School Graduate, Some College/Associate Degree, and Bachelor's Degree or Above. These variables are collinear, summing to 100%, so we used the variable for proportion of Bachelor's Degree or Above per patient zip code as the reference. In bivariate analysis, probability of readmission increased by 4 to 10% as the proportion of people with Less than High School, High School, and Some College/Associate Degree per neighborhood went up by one percentage from the mean (OR 1.08 [95%CI 1.04,1.13]; 1.04 [1.002,1.09]; 1.10 [1.06,1.15]; respectively) (see Table 3). That is, as the proportion of people with an education level of Less than High School in the neighborhood increased from 17.4% to 18.4%, the odds of readmissions increased by 1.08, while the proportions of people who were High School Graduates and had Some College/Associate Degree stayed constant, and proportion of people who have Bachelor's Degree or Above decreased from 13.3% to 12.3%. However, relationship between education and readmission risk was no longer significant after adjusting for insurance, income, and core case-mix variables.

Table 3. Bivariate and Multivariate Results for Zip Code Level Education

Education	Mean (SD)	Bivariate Analysis		Multivariate Analysis*	
		OR (95% CI)^	p-value	OR (95% CI)	p-value
Bachelor's Degree or Above	13.3 (10.1)	--	--	--	--
Less than High School	17.4 (9.5)	1.08 (1.04,1.13)	<0.001	1.02 (0.97,1.07)	0.44
High School Graduate	26.8 (7.9)	1.04 (1.002,1.09)	0.04	0.98 (0.94,1.03)	0.42
Some College/Associate Degree	42.5 (9.5)	1.10 (1.06,1.15)	<0.001	1.04 (0.997,1.09)	0.07

^Odds ratios indicate the difference in odds, relative to the mean, for each 1-point increase in the percentage of residents in the patient's zip code with the indicated education level while the percentage of Bachelor's Degree or Above (reference) decreases by 1-point and other education variables stay constant.
*Adjusting for insurance, income, and core case-mix variables (age, gender, 17 CCIs, CCI count)

B. GOODNESS-OF-FIT USING C-STATISTICS

We compared the c-statistics of 8 multivariate models: 1 model contained just the core case-mix variables, while the other 7 models included the core variables plus varying combinations of the 3 candidate SDS variables (insurance, income, and education). The model that included the core case-mix variables plus insurance had the highest c-statistic at 0.710 (Table 4).

Table 4. C-Statistics of All-Condition Multivariate Models

Multivariate Models	C-statistic
All-condition core case-mix model (age, gender, 17 CCIs, CCI count)	0.708
+ insurance, education, and income	0.709
+ insurance and education	0.709
+ insurance and income	0.709
+ education and income	0.708
+ insurance	0.710
+ education	0.708
+ income	0.707

***5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).**

We used the results of bivariate and multivariate analyses, together with the goodness of fit of the 8 candidate models as evaluated using c-statistics (Table 4), to select the SDS factors for the final multivariate model.

Insurance was the only SDS variable that was significantly associated with readmission risk in both bivariate and multivariate analyses. In addition, adding insurance to the original all-condition model increased the c-statistic from 0.708 to 0.710, while adding income and education to the original all-condition model did not improve the c-statistics.

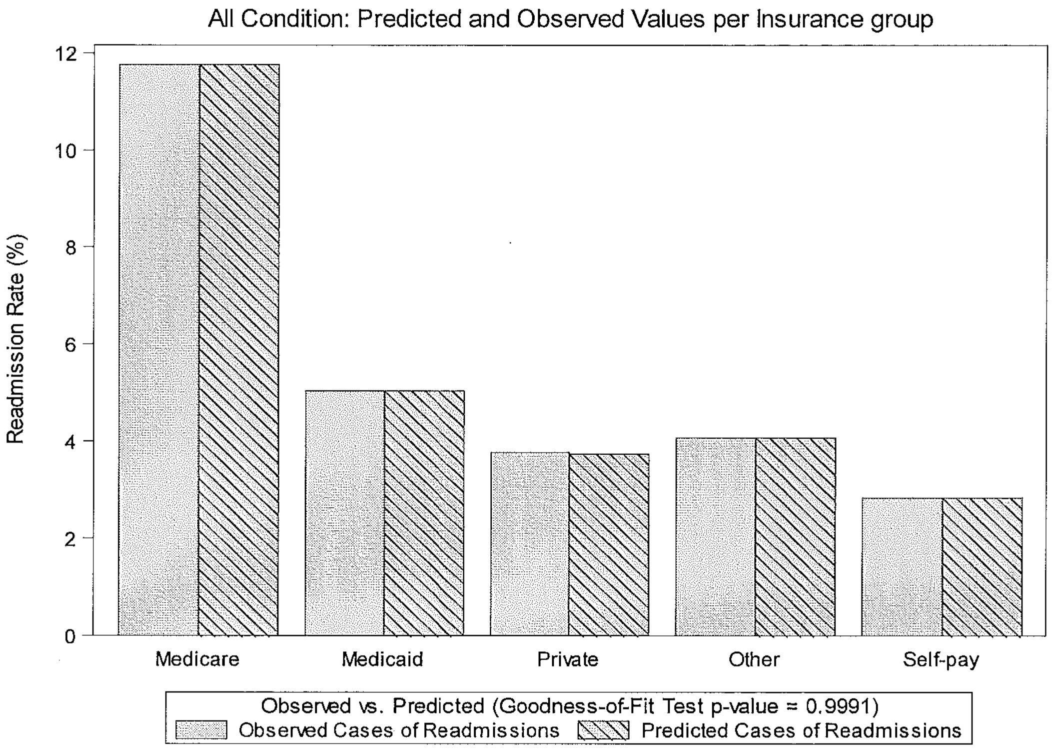
***6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).**

We assessed the discriminative ability of the model using the c-statistic.[1,2] Discrimination refers to how well the model distinguishes between subjects with and without the outcome (in this case, readmission).[1] The c-statistic is a unitless measure of the probability that a randomly selected subject who experienced readmission will have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission.[1]

We assessed model calibration with a chi-square goodness-of-fit test analogous to the Hosmer-Lemeshow test.[3] We used the test, which evaluates how well observed outcomes correspond to those predicted by the fitted logistic regression model,[3] to determine how well observed and predicted numbers of readmissions matched for the levels of the insurance variables in our model. The lack of a significant difference between observed and predicted values indicates good model calibration.

For the final model containing the core case-mix variables plus insurance, the c-statistic was 0.710, and the p-value for the chi-square goodness-of-fit test was 0.99, which indicated good model calibration.

Figure 1. Chi-Square Goodness-of-Fit Test for All-Condition Readmissions: Insurance



***7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.**

This measure is subject to the known general limitations of readmissions measures, which have been the subject of extensive discussion. In particular, a readmissions measure cannot conclusively distinguish between effects of hospital quality and quality of post-discharge services that might vary across hospital service areas. However, adjustment for insurance type should help to address this limitation, to the extent that quality of community services accessible to a patient is associated with the socioeconomic characteristics embodied in the insurance type measure.

One potential limitation is that we performed the analyses of SDS factors using data from a single (although large and diverse) state. In addition, insurance variables may have limitations: for example, data could be missing or incorrect. Variation in public insurance eligibility criteria across states may also affect how consistently insurance status reflects socioeconomic status.

While coefficients of adjustment models can be estimated in large states like New York, further study is required to determine whether results can be generalized nationally, or in groups of states, for a national implementation that includes states with smaller populations and therefore smaller samples.

***8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.**

We found that 95% of index admissions in the New York database were for patients who had Medicaid or Private Insurance. We therefore constructed a multivariate model containing the core case-mix variables, a binary indicator variable for whether a patient had Medicaid vs. Private Insurance, interaction terms between the core case-mix variables and the Medicaid vs. Private Insurance variable, and random coefficients for Medicaid and Private Insurance at the hospital level. The magnitude and significance of the interaction term provided insight about whether stratification of readmission rates by insurance status is necessary. In addition, measuring the correlation coefficient between random coefficients for Medicaid and Private Insurance quantified the relative quality of care received by patients with Medicaid or Private Insurance at a given hospital. A high correlation between random coefficients for Medicaid and Private Insurance would suggest that hospitals that provide good care to patients with Private Insurance are likely to provide good care to Medicaid-insured patients as well, and that hospitals that provide poor-quality care to patients with Private Insurance are likely to provide poor-quality care to Medicaid-insured patients. Conversely, a low correlation between random coefficients would suggest that hospitals do not provide the same quality of care for patients with Private Insurance and those with Medicaid.

We found that only a few of the interactions terms were significant (specifically, age, CCI count, CCI 2, and CCI 9), but the magnitude of other interaction terms was negligible even when the main effect was large. This result suggests retaining a simpler model without interaction terms would not hurt model performance substantially. The correlation coefficient between random coefficients for Medicaid and Private Insurance at the hospital level was 0.95, strongly suggesting that care quality for patients with Medicaid and Private Insurance was essentially equivalent. We therefore suggest that stratification of readmission rates by insurance type is not necessary. (Note that this is consistent with the existence of a difference of fixed magnitude on the logistic scale between readmission rates between Medicaid and other patients in each hospital.)

***9. Please enter the details of the final statistical risk model and variables here.**

A. ELEMENTS OF CASE-MIX AND INSURANCE ADJUSTMENT MODEL

The final model containing the core case-mix variables and insurance is a 2-level logistic regression model with fixed effect variables for patient case-mix at the first level and random intercepts for hospitals at the second level.

The model estimates 3 types of parameters. First, the coefficients of patient demographic and clinical characteristics represent the influence of these characteristics on predicted probabilities of readmission for an individual patient. Second, hospital-level random intercept estimates (evaluated for each hospital) represent the greater or lesser adjusted probability of readmission, not explained by patient-level fixed effects, for patients discharged from each hospital. Finally, variance estimates of the hospital random effects summarize the amount of variation among the intercepts for different hospitals and hence summarize the amount of variation in adjusted readmission rates across hospitals, at least some of which may be due to variation in health system quality.

The following case-mix variables, defined from the index admission, were included in the original pediatric all-condition model[4]:
• Age group
• Gender
• Presence of chronic conditions in each of 17 body systems (organ systems, disease categories, or other categories)
• Number of body systems affected by chronic conditions

In the final model, we have added a 5-level insurance variable that reflects the patient's primary payer during the index admission:

- Medicaid
- Medicare
- Private
- Self-pay
- Other (includes patients with no charge)

Note: One could consider alternative ways of categorizing the insurance variable.

Table 5. Coefficients of Core Case-Mix and Insurance Variables in the Final Multivariate Model

Case-Mix and Insurance Variables	OR	p-value
Age		
0 years	reference	-
1-4 years	0.96	0.28
5-7 years	0.81	<0.001
8-11 years	0.90	0.04
12-17 years	0.90	0.02
Gender		
Female	reference	-
Male	1.04	0.17
Chronic Condition Indicators (CCI)		
1. Infectious and parasitic disease	1.18	0.65
2. Neoplasms	2.51	<0.001

3. Endocrine, nutritional, and metabolic diseases and immunity disorders	1.30	<0.001
4. Diseases of blood and blood-forming organs	1.97	<0.001
5. Mental disorders	1.06	0.27
6. Diseases of the nervous system and sense organs	1.46	<0.001
7. Diseases of the circulatory system	1.46	<0.001
8. Diseases of the respiratory system	1.05	0.27
9. Diseases of the digestive system	1.74	<0.001
10. Diseases of the genitourinary system	1.76	<0.001
12. Diseases of the skin and subcutaneous tissue	1.08	0.57
13. Diseases of the musculoskeletal system	1.33	<0.001
14. Congenital anomalies	1.25	<0.001
15. Certain conditions originating in the perinatal period	0.55	0.05
16. Symptoms, signs, and ill-defined conditions	1.36	0.02
17. Injury and poisoning	1.20	0.41
18. Factors influencing health status and contact with health services	2.28	<0.001
CCI Count		
0 to 1 CCI	reference	-
2 CCIs	1.31	<0.001
3 CCIs	1.11	0.20
4 CCIs or more	0.87	0.24
Insurance		
Medicaid	reference	-
Medicare	1.17	0.48
Private Insurance	0.77	<0.001
Self-pay	0.75	0.01
Other	0.74	0.00

B. ADJUSTED HOSPITAL RATES

The hospital-specific readmission rate, adjusted for case-mix and insurance, is estimated through direct standardization using the entire dataset as the standard population. The resulting estimates represent the readmission rate that each hospital would have if it served a population with the same representative case-mix and distribution of insurance; the estimates are therefore conducive to comparisons among hospitals.

After adjusting for the core case-mix variables and insurance, the mean adjusted hospital readmission rate was 3.8%, and the median adjusted hospital rate was 3.6% (IQR 3.3%-4.1%).

***10. Compare measure performance scores with and without SDS factors in the risk**

adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

The final risk adjustment model was compared to the original case-mix adjustment model in 3 ways, as described below.

A. C-STATISTIC

The c-statistic for the new model (core case-mix variables + insurance) was 0.710, while the c-statistic for the original case-mix model was 0.708. This shows that by adding insurance to the core case-mix model, there was about 0.3% improvement in the probability that a randomly selected subject who was readmitted to the hospital would have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission.

B. KENDALL RANK CORRELATION

The Kendall rank correlation coefficient is a non-parametric statistic that quantifies the degree of similarity between rankings of the same subjects. The mean hospital readmission rate after adjusting for the core case-mix variables and insurance was 3.8%, and the median adjusted hospital rate was 3.6% (IQR 3.3%-4.1%). Adjusting for the core case-mix variables alone, the mean hospital readmission rate was 3.7%, and the median adjusted hospital rate was 3.6% (IQR 3.3%-4.0%). The Kendall correlation between the readmission rates adjusted for core case-mix variables plus insurance and those adjusted for core case-mix variables only was 0.93. This result indicates that the rankings of hospital readmission rates adjusted using these 2 models were highly correlated.

C. EXCESS READMISSION RATIOS

We identified hospitals with meaningfully different readmission performance based on their excess readmission ratio, calculated using NQF-endorsed methods. For each hospital, the numerator of the ratio, its number of adjusted actual readmissions, is calculated by estimating the probability of readmission for each patient at that hospital and adding the probabilities for all of the hospital's patients. The denominator of the ratio, its number of expected readmissions, is calculated by estimating the probability of readmission for each of the hospital's patients if he or she had been at an average hospital and then by adding the probabilities for all of the hospital's patients.[4]

Numerator ─ Adjusted Actual Readmissions

Each patient's predicted probability of readmission = $\dfrac{1}{1 + e^{-Z_a}}$

Z_a = hospital-specific effect + $X\beta$

where Xβ = intercept + case-mix adjustment coefficients

Denominator — *Expected Readmissions*
Each patient's predicted probability of readmission = $\frac{1}{1 + e^{-Ze}}$

$Z_e = X\beta$
where Xβ = intercept + case-mix adjustment coefficients

Using the original pediatric all-condition model, 73 hospitals of 183 hospitals (40%) had an excess readmission ratio >1, indicating that their number of adjusted actual readmissions was higher than would be expected at an average hospital. Using the new model with the core case-mix variables plus insurance, 5 additional hospitals had an excess readmission ratio >1—i.e., for 78 hospitals (43%), the number of adjusted actual readmissions was higher than the expected at an average hospital.

11. Appendix (includes literature review, reference list, etc.)

1. Austin PC, Steyerberg EW. Interpreting the concordance statistic of a logistic regression model: relation to the variance and odds ratio of a continuous explanatory variable. *BMC Med Res Methodol*. 2012;12:82. doi:10.1186/1471-2288-12-82.

2. Steyerberg EW, Vickers AJ, Cook NR, et al. Assessing the performance of prediction models: a framework for traditional and novel measures. *Epidemiology*. 2010;21(1):128-138. doi:10.1097/EDE.0b013e3181c30fb2.

3. Hosmer DW, Hosmer T, Le Cessie S, Lemeshow S. A Comparison of Goodness-of-Fit Tests for the Logistic Regression Model. *Stat Med*. 1997;16(9):965-980. doi:10.1002/(SICI)1097-0258(19970515)16:9<965::AID-SIM509>3.0.CO;2-O.

4. Center of Excellence for Pediatric Quality Measurement. *Measure 2393: Pediatric All-Condition Readmission Measure*. National Quality Forum; 2014.

NQF Measure #2414: Pediatric Lower Respiratory Infection Readmission Measure
Relationship Between Pediatric Hospital Readmissions and Sociodemographic Status
March 8 2016 Webinar Developer Question (due 2/22/16)

***1. Enter measure # and title**

Measure #2414: Pediatric Lower Respiratory Infection Readmission Measure

***2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?**

- Patient insurance (primary payer): Medicaid, Private Insurance, Self-pay, Other
- Median income within patient's zip code
- Distribution of education level within patient's zip code: Less than High School, High School Graduate, Some College/Associate Degree, and Bachelor's Degree or Above

3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

Based on the relationship between these SDS factors and pediatric lower respiratory infection (LRI) hospital readmissions and the performance of various candidate multivariate models in distinguishing who was readmitted or not readmitted, we recommend adding insurance as an adjuster to the existing LRI model.

***4. What were the statistical results of the analyses used to select risk factors?**

We used comprehensive all payer New York data reporting system established in 1979 as a result of cooperation between the healthcare industry and government (SPARCS). This system was initially created to collect information on discharges from hospitals. SPARCS currently collects patient-level detail on patient characteristics, diagnoses and treatments, services, and charges for each hospital inpatient stay and outpatient (ambulatory surgery, emergency department, and outpatient services) visit; and each ambulatory surgery and outpatient services visit to a hospital extension clinic and diagnostic and treatment center licensed to provide ambulatory surgical services.

For this analysis, we selected discharges from inpatient visits in 2013. There were 17,039 eligible pediatric LRI index admissions in 126 hospitals and 747 (4.4%) were followed by ≥1 unplanned readmission within 30 days.

We assessed 2 different approaches for selection of risk factors: (1) significance of bivariate and multivariate analyses, and (2) goodness-of-fit using c-statistics of 8 different multivariate models.

A. BIVARIATE AND MULTIVARIATE ANALYSES

The New York data included 3 SDS variables: insurance, income, and education. Insurance was a patient-level variable while income and education were zip-code-level variables.

Insurance

Insurance was categorized as a 4-level primary payer variable: Medicaid, Private Insurance, Self-pay, and Other. There were only 19 LRI index admissions insured with Medicare and none of these admissions had a readmission. Therefore, Medicare-insured index admissions were combined with Other to avoid model fitting issue. Insurance had a statistically significant association with 30-day readmission in bivariate analysis with p-value <0.001 (see Table 1). In bivariate analysis, compared with patients with Medicaid, those with Private Insurance, Self-pay, and Other insurance had significantly lower odds of readmission (OR 0.67 [95%CI 0.55, 0.82]; 1.02 [0.62,1.68]; 0.95 [0.52, 1.76], respectively). In multivariate analysis, adjusting for insurance and the core case-mix variables of age, gender, and chronic conditions, directions of all of the odds ratios stayed the same, but insurance was no longer significant.

Table 1. Bivariate and Multivariate Results for Insurance

Individual Insurance Status	**n (%)**	**Bivariate Analysis**		**Multivariate Analysis***	
		OR (95% CI)	p-value	OR (95% CI)	p-value
Medicaid	12,277 (72.1)	reference	--	reference	--
Private Insurance	4,064 (23.9)	0.67 (0.55, 0.82)	<0.001	0.85 (0.70, 1.03)	0.10
Self-pay	383 (2.3)	1.02 (0.62,1.68)	0.94	1.27(0.77, 2.09)	0.35
Other	315 (1.9)	0.95 (0.52, 1.76)	0.88	0.96(0.52, 1.77)	0.89

*Adjusting for core case-mix variables (age, gender, 16 Chronic Condition Indicators, CCI count); CCI 15 was excluded from multivariate models because of 0 cases of observed readmissions.

Income

To serve as a proxy for family income, we used the median income within a patient's zip code, categorized into quartiles. In bivariate analysis, income did not show a significant association with 30-day readmission (overall p-value=0.16) although the 2nd quartile of the income variable was associated with decreased odds of readmission (see Table 2). Due to lack of statistical significance in bivariate analysis, we did not test for association between income and readmission in multivariate analysis.

Table 2. Bivariate and Multivariate Results for Zip Code Level Income

Income	**n (%)**	**Bivariate Analysis**	
		OR (95% CI)	p-value
1st quartile	5,566 (32.7)	reference	--
2nd quartile	4,465 (26.2)	0.79 (0.64, 0.98)	0.03
3rd quartile	3,793 (22.3)	0.96 (0.78, 1.18)	0.68
4th quartile	2,950 (17.3)	0.89 (0.70, 1.13)	0.33

Education
To evaluate the relationship between education and readmission risk, we used 4 continuous variables that indicated the percentage of residents in the patient's zip code who had attained education levels of Less than High School, High School Graduate, Some College/Associate Degree, and Bachelor's Degree or Above. These variables are collinear, summing to 100%, so we used the variable for proportion of Bachelor's Degree or Above per patient zip code as the reference. In bivariate analysis, all of the three education variables did not show significant associations with 30-day readmission rates (see Table 3). Since education was not significantly associated with odds of readmission in bivariate analysis, we did not test for association between education and readmission in multivariate analysis.

Table 3. Bivariate and Multivariate Results for Zip Code Level Education

Education	Mean (SD)	Bivariate Analysis	
		OR (95% CI)^	p-value
Bachelor's Degree or Above	12.0 (9.5)	--	--
Less than High School	19.1 (9.7)	1.01 (1.00, 1.02)	0.22
High School Graduate	27.3 (7.7)	1.00 (0.99, 1.01)	0.73
Some College/Associate Degree	41.7 (9.2)	1.01 (1.00, 1.02)	0.28

^Odds ratios indicate the difference in odds, relative to the mean, for each 1-point increase in the percentage of residents in the patient's zip code with the indicated education level while the percentage of Bachelor's Degree or Above (reference) decreases by 1-point and other education variables stay constant.

B. GOODNESS OF FIT USING C-STATISTICS

Since insurance was the only SDS variable that was significant in bivariate analysis, insurance was selected as a potential SDS variable to include in the multivariate model. We compared between the c-statistics of the LRI core case-mix model (age, gender, 16 CCIs, CCI count) and the LRI multivariate model with insurance as an additional adjuster. The LRI multivariate model with core case-mix variables and insurance had a higher c-statistic than the LRI core case-mix model (0.701 vs 0.699; see Table 4).

Table 4. C-Statistics of LRI Multivariate Models

Multivariate Models	C-statistic
LRI core case-mix model (age, gender, 16 CCIs, CCI count)*	0.699
+ insurance	0.701

*CCI 15 was excluded from multivariate models because of 0 cases of observed readmissions.

***5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).**

We used the results of bivariate and multivariate analyses, together with the goodness of fit of the 8 candidate models as evaluated using c-statistics (Table 4), to select the SDS factors for the final multivariate model.

Insurance was the only SDS variable that was significant in bivariate analysis. Although insurance was not significantly associated with readmission in the multivariate model, adding insurance to the current LRI model increased the model accuracy (c-statistic from 0.699 to 0.701).

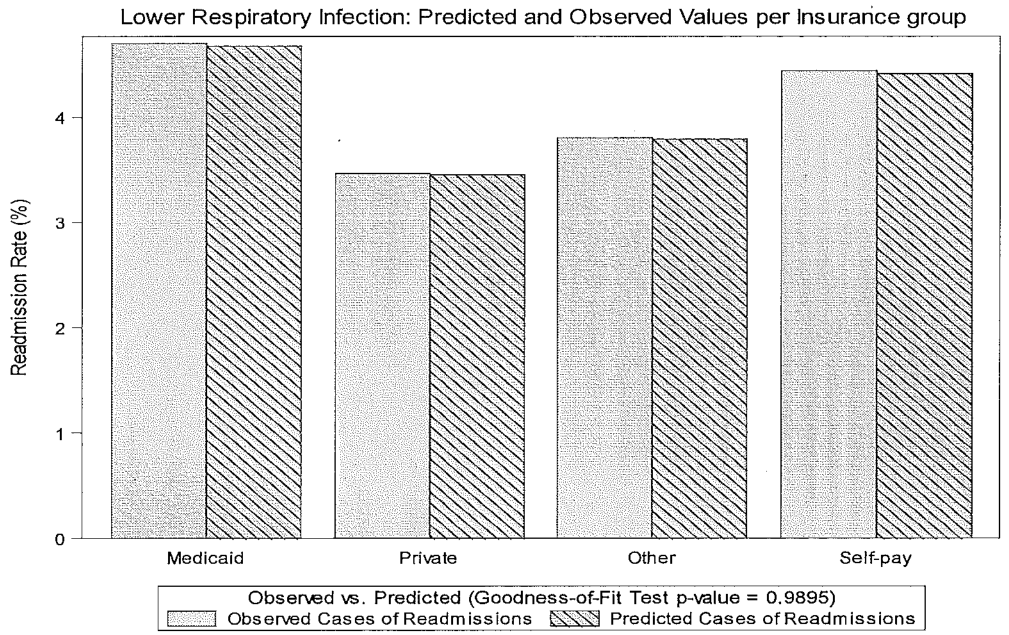
***6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).**

We assessed the discriminative ability of the model using the c-statistic.[1,2] Discrimination refers to how well the model distinguishes between subjects with and without the outcome (in this case, readmission).[1] The c-statistic is a unitless measure of the probability that a randomly selected subject who experienced readmission will have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission.[1]

We assessed model calibration with a chi-square goodness-of-fit test analogous to the Hosmer-Lemeshow test.[3] We used the test, which evaluates how well observed outcomes correspond to those predicted by the fitted logistic regression model,[3] to determine how well observed and predicted numbers of readmissions matched for the levels of the insurance variables in our model. The lack of a significant difference between observed and predicted values indicates good model calibration.

For the final LRI model containing the core case-mix variables plus insurance, the c-statistic was 0.701 and the p-value for the chi-square goodness-of-fit test was 0.99, which indicated good model calibration.

Figure 1. Chi-Square Goodness-of-Fit Test for LRI Readmissions: Insurance



***7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.**

This measure is subject to the known general limitations of readmissions measures, which have been the subject of extensive discussion. In particular, a readmissions measure cannot conclusively distinguish between effects of hospital quality and quality of post-discharge services that might vary across hospital service areas. However, adjustment for insurance type should help to address this limitation, to the extent that quality of community services accessible to a patient is associated with the socioeconomic characteristics embodied in the insurance type measure.

One potential limitation is that we performed the analyses of SDS factors using data from a single (although large and diverse) state. In addition, insurance variables may have limitations: for example, data could be missing or incorrect. Variation in public insurance eligibility criteria across states may also affect how consistently insurance status reflects socioeconomic status.

While coefficients of adjustment models can be estimated in large states like New York, further study is required to determine whether results can be generalized nationally, or in groups of states, for a national implementation that includes states with smaller populations and therefore smaller samples.

***8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value**

sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.

We found that 96% of the LRI index admissions in the New York database were for patients who had Medicaid or Private Insurance. We therefore constructed a multivariate model containing the core case-mix variables, a binary indicator variable for whether a patient had Medicaid vs. Private Insurance, interaction terms between the core case-mix variables and the Medicaid vs. Private Insurance variable, and random coefficients for Medicaid and Private Insurance at the hospital level. The magnitude and significance of the interaction term provided insight about whether stratification of readmission rates by insurance status is necessary. In addition, measuring the correlation coefficient between random coefficients for Medicaid and Private Insurance quantified the relative quality of care received by patients with Medicaid or Private Insurance at a given hospital. A high correlation between random coefficients for Medicaid and Private Insurance would suggest that hospitals that provide good care to patients with Private Insurance are likely to provide good care to Medicaid-insured patients as well, and that hospitals that provide poor-quality care to patients with Private Insurance are likely to provide poor-quality care to Medicaid-insured patients. Conversely, a low correlation between random coefficients would suggest that hospitals do not provide the same quality of care for patients with Private Insurance and those with Medicaid.

Due to model fitting issues, we only included statistically significant core case-mix variables (age, CCI count, CCI2, CCI4, CCI 10, CCI13, CCI14, and CCI18); insurance type (Medicaid vs. Private Insurance); and interaction terms between the selected core case-mix variables and Medicaid vs. Private Insurance in addition to random coefficients.

None of the interaction terms were significant. This suggests that simplifying the model by dropping interactions would not hurt, but might improve the accuracy of the model. This result suggests retaining a simpler model without interaction terms would not hurt model performance substantially. The correlation coefficient between random coefficients for Medicaid and Private Insurance at the hospital level was 0.99, strongly suggesting that care quality for patients with Medicaid and Private Insurance was essentially equivalent. We therefore suggest that stratification of readmission rates by insurance type is not necessary. (Note that this is consistent with the existence of a difference of fixed magnitude on the logistic scale between readmission rates between Medicaid and other patients in each hospital.)

***9. Please enter the details of the final statistical risk model and variables here.**

A. ELEMENTS OF CASE-MIX AND INSURANCE ADJUSTMENT MODEL

The final model containing the core case-mix variables and insurance is a 2-level logistic regression model with fixed effect variables for patient case-mix at the first level and random intercepts for hospitals at the second level.

The model estimates 3 types of parameters. First, the coefficients of patient demographic and clinical characteristics represent the influence of these characteristics on predicted probabilities of readmission for an individual patient. Second, hospital-level random intercept estimates (evaluated for each hospital) represent the greater or lesser adjusted probability of readmission, not explained by patient-level fixed effects, for patients discharged from each hospital. Finally, variance estimates of the hospital random effects summarize the amount of variation among the intercepts for different hospitals and hence summarize the amount of variation in adjusted readmission rates across hospitals, at least some of which may be due to variation in health system quality.

The following case-mix variables, defined from the index admission, were included in the original pediatric LRI model[4]:
• Age group
• Gender
• Presence of chronic conditions in each of 17 body systems (organ systems, disease categories, or other categories)
• Number of body systems affected by chronic conditions

In the final model, we have added a 4-level insurance variable that reflects the patient's primary payer during the index admission:

- Medicaid
- Private
- Self-pay
- Other (includes patients with no charge)

Note: One could consider alternative ways of categorizing the insurance variable.

Table 5. Coefficients of Core Case-Mix and Insurance Variables in the Final Multivariate Model

Case-Mix and Insurance Variables	OR	p-value
Age		
0 years	reference	-
1-4 years	0.62	<0.001
5-7 years	0.55	0.00
8-11 years	0.41	<0.001
12-17 years	0.50	0.00
Gender		
Female	reference	-
Male	1.14	0.09
Chronic Condition Indicators (CCI)		
1. Infectious and parasitic disease	2.90	0.38
2. Neoplasms	4.76	<0.001
3. Endocrine, nutritional, and metabolic diseases and immunity disorders	1.26	0.14

4. Diseases of blood and blood-forming organs	1.40	0.04
5. Mental disorders	1.22	0.23
6. Diseases of the nervous system and sense organs	1.26	0.19
7. Diseases of the circulatory system	1.15	0.39
8. Diseases of the respiratory system	1.12	0.26
9. Diseases of the digestive system	1.29	0.08
10. Diseases of the genitourinary system	2.44	0.01
12. Diseases of the skin and subcutaneous tissue	1.08	0.81
13. Diseases of the musculoskeletal system	2.18	0.00
14. Congenital anomalies	1.88	<0.001
16. Symptoms, signs, and ill-defined conditions	0.42	0.27
17. Injury and poisoning	2.63	0.26
18. Factors influencing health status and contact with health services	2.15	<0.001
CCI Count		
0 to 1 CCI	reference	-
2 CCIs	1.28	0.14
3 CCIs	1.89	0.01
4 CCIs or more	1.23	0.58
Insurance		
Medicaid	reference	-
Private Insurance	0.85	0.10
Self-pay	1.27	0.35
Other	0.96	0.89

B. ADJUSTED HOSPITAL RATES

The hospital-specific readmission rate, adjusted for case-mix and insurance, is estimated through direct standardization using the entire dataset as the standard population. The resulting estimates represent the readmission rate that each hospital would have if it served a population with the same representative case-mix and distribution of insurance; the estimates are therefore conducive to comparisons among hospitals.

After adjusting for the core case-mix variables and insurance, the mean adjusted hospital readmission rate was 4.3% and the median adjusted hospital rate was 4.2% (IQR 4.2%-4.3%).

***10. Compare measure performance scores with and without SDS factors in the risk adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an**

interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

The final risk adjustment model was compared to the original case-mix adjustment model in 3 ways, as described below.

A. C-STATISTIC

The c-statistic for the new model (core case-mix variables + insurance) was 0.702, while the c-statistic for the original case-mix model was 0.699. This shows that by adding insurance to the core case-mix model, there was about 0.3% improvement in the probability that a randomly selected subject who was readmitted to the hospital would have a higher predicted probability of having been readmitted than a randomly selected subject who did not experience readmission.

B. KENDALL RANK CORRELATION

The Kendall rank correlation coefficient is a non-parametric statistic that quantifies the degree of similarity between rankings of the same subjects. The mean hospital readmission rate after adjusting for the core case-mix variables and insurance was 4.3%, and the median adjusted hospital rate was 4.2% (IQR 4.2%-4.3%). Adjusting for the core case-mix variables alone, the mean hospital readmission rate was 4.3%, and the median adjusted hospital rate was 4.3% (IQR 4.2%-4.3%). The Kendall correlation between the readmission rates adjusted for core case-mix variables plus insurance and those adjusted for core case-mix variables only was 0.99. This result indicates that the rankings of hospital readmission rates adjusted using these 2 models were highly correlated.

C. EXCESS READMISSION RATIOS

We identified hospitals with meaningfully different readmission performance based on their excess readmission ratio, calculated using NQF-endorsed methods. For each hospital, the numerator of the ratio, its number of adjusted actual readmissions, is calculated by estimating the probability of readmission for each patient at that hospital and adding the probabilities for all of the hospital's patients. The denominator of the ratio, its number of expected readmissions, is calculated by estimating the probability of readmission for each of the hospital's patients if he or she had been at an average hospital and then by adding the probabilities for all of the hospital's patients.[4]

Numerator ─ Adjusted Actual Readmissions

Each patient's predicted probability of readmission = $\frac{1}{1 + e^{-Z_a}}$

Z_a = hospital-specific effect + $X\beta$

where $X\beta$ = intercept + case-mix adjustment coefficients

Denominator ─ Expected Readmissions

Each patient's predicted probability of readmission = $\dfrac{1}{1 + e^{-Z_e}}$

$Z_e = X\beta$

where $X\beta$ = intercept + case-mix adjustment coefficients

Using the original LRI model, 41 hospitals of 126 hospitals (32.5%) had an excess readmission ratio >1, indicating that their number of adjusted actual readmissions was higher than would be expected at an average hospital. The proportion of hospitals with an excess readmission ratio >1 did not change using the new model with the core case-mix variables plus insurance.

11. Appendix (includes literature review, reference list, etc.)

1. Austin PC, Steyerberg EW. Interpreting the concordance statistic of a logistic regression model: relation to the variance and odds ratio of a continuous explanatory variable. *BMC Med Res Methodol*. 2012;12:82. doi:10.1186/1471-2288-12-82.

2. Steyerberg EW, Vickers AJ, Cook NR, et al. Assessing the performance of prediction models: a framework for traditional and novel measures. *Epidemiology*. 2010;21(1):128-138. doi:10.1097/EDE.0b013e3181c30fb2.

3. Hosmer DW, Hosmer T, Le Cessie S, Lemeshow S. A Comparison of Goodness-of-Fit Tests for the Logistic Regression Model. *Stat Med*. 1997;16(9):965-980. doi:10.1002/(SICI)1097-0258(19970515)16:9<965::AID-SIM509>3.0.CO;2-O.

4. Center of Excellence for Pediatric Quality Measurement. *Measure 2414: Pediatric Lower Respiratory Infection Readmission Measure*. National Quality Forum; 2014.

Admissions and Readmissions 3/8/16

SDS Webinar Developer Questions

1. Measure # and title

NQF #2514 – Risk-Adjusted Coronary Artery Bypass Graft (CABG) Readmission Rate

2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?

The SDS factors that we analyzed were race/ethnicity and payor information.

For race/ethnicity, we defined a few mutually exclusive groups for the regression analysis:

1. Black/African American (including Hispanic Black/African American and multiracial patients with Black/African American as one of races that they checked)
2. Hispanic (including all patients of Hispanic ethnicity who did not identify as Black/African American)
3. Asian
4. American Indian/Alaskan Native
5. Native Hawaiian/Pacific Islander
6. White
7. Other

For payor, we defined three mutually exclusive categories. By the study sample definition, all patients have Medicare as one of the payors.

1. Medicare and Medicaid
2. Medicare and commercial insurance without Medicaid
3. Other (including mostly of patients with Medicare as the sole payor)

3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

The results of our analysis demonstrated that, overall, readmission measure results with and without SDS adjustment were highly correlated. In reclassification analyses, addition of SDS factors resulted in a change of one performance category (better or worse) for only 0.9% of programs. These were generally due to very small changes in standardized readmission rates for programs that initially were just slightly to one side or another of the border between two categories, and which moved slightly to the other side with adjustment for SDS. In these cases, higher than average proportions of Black or Hispanic race patients resulted in an improvement in performance category when results were risk adjusted; conversely, higher than average proportions of Medicare plus commercial insurance patients resulted in lower performance categories when adjusted for payor status.

We recommend that measure results be presented in two different ways – 1. Results stratified by race and payor using the currently endorsed model; 2. Risk-adjusted results using a model that includes SDS factors.

4. What were the statistical results of the analyses used to select risk factors?

The performance measure was implemented as a random effect logistic regression model with a list of patient-level risk factors and a provider-level normally distributed random intercept.

Patient-level risk factors included:

- Ejection faction
- Preoperative atrial fibrillation
- Myocardial infarction
- Age
- Unstable angina
- Congestive heart failure
- Renal function
- Operative status
- Gender
- Whether the operation was a reoperation
- Chronic lung disease
- Diabetes
- Preoperative IABP or inotropes
- Immunosuppressive treatment
- Peripheral vascular disease
- Body surface area
- Cardiovascular disease
- Hypertension
- Percutaneous coronary intervention within 6 hours of operation
- Left main disease
- Surgery date

<u>Methods</u>
The goals of the risk factor selection process were to identify factors strongly associated with readmission and to assess the consistency of variable selection across adjacent calendar years. We split the study sample by the calendar year when the admissions ended. For each yearly sample:

1. In the entire sample, we performed marginal logistic regression model with stepwise variable selection (significant level = 0.05 for both entry and removal).
2. We then drew bootstrap samples of the entire sample, repeated the stepwise selection routine on each bootstrap sample, and summarized the frequency each variable was selected across all bootstrap samples.

We planned to review the results and include in the final model any predictors deemed important by one or both analyses, or by expert knowledge.

Please note that the variable selection method is also described in detail in the published Circulation article (link provided in section 11 below).

<u>Results</u>

NATIONAL QUALITY FORUM

After reviewing the results, the group decided to include all covariates that were either selected at the 0.05 level in the original sample for one or more calendar years, or were selected at least 50% of bootstrap samples at the 0.05 level for at least one calendar year.

The table below summarizes the results of the variable selection analysis. The second, third, and fourth column list the estimated coefficients from the entire sample stepwise models (analysis #1). Empty cells indicate that the variable was not selected. The fifth, sixth and the seventh columns list the frequency the variables were selected among 1000 bootstrap replicates (analysis #2).

	Estimated coefficients if selected at 0.05 level in the entire yearly sample			Percentage of times selected among 1000 bootstrap replicates		
	2008	2009	2010	2008	2009	2010
Ejection fraction	-0.0086	-0.0063	-0.0053	100.0	97.5	87.8
Preoperative A-fib	0.3321	0.3370	0.2437	100.0	100.0	100.0
Unstable angina (no MI < 8days)	0.0868		0.0727	86.0	5.4	69.8
CHD & NYHA class (vs. no CHF)	-	-	-	-	-	-
CHF NYHA I-IV	0.1711	0.1864	0.1112	99.8	100.0	91.6
CHF NYHA IV				7.9	6.8	5.1
Age	0.0304	0.0326	0.0297	100.0	100.0	100.0
Dialysis	0.7878	0.5785	0.7634	100.0	98.6	100.0
Creatinine				15.7	10.9	32.6
Creatinine change of slope at 1.0	0.5013	0.4222	0.5292	85.6	93.6	67.7
Creatinine change of slope at 1.5	-0.3688	-0.2706	-0.3381	92.4	76.0	79.0
Status (vs. elective)	-	-	-	-	-	-
Urgent/Emergent/Emergent Salvage	0.0780	0.1009	0.0758	87.5	96.3	80.9
Emergent/Emergent Salvage		0.1461		23.6	50.5	31.3
Emergent+resuscitation/Emergent Salvage				15.3	6.3	17.9
Female vs. male (at BSA=1.8)	0.3116	0.2910	0.2433	100.0	100.0	100.0
Reop (vs No previous operation)	-	-	-	-	-	-
1 or more previous operations				21.5	33.3	34.4
2 or more previous operations	0.3909			53.6	41.1	44.2
Chronic lung disease (vs. none)						
Mild-Severe	0.1892	0.1966	0.2035	100.0	100.0	100.0
Moderate-Severe		0.1338	0.1243	23.4	76.6	68.3
Severe	0.2187	0.1444	0.1295	88.4	65.8	58.4
Diabetes (vs. no diabetes)	-	-	-	-	-	-
Diabetes (any)	0.1159	0.0988	0.1021	98.5	95.6	94.2
Insulin diabetes	0.2979	0.2658	0.2497	100.0	100.0	100.0
Pre-op IABP or Inotrope	0.1121		0.0953	78.8	20.4	45.8
Immunosuppressive treatment	0.3043	0.3189	0.3608	99.7	99.9	100.0
Aortic insufficiency (>= moderate)				16.0	39.4	4.3
Mitral insufficiency (>= moderate)				23.3	8.6	32.0
Tricuspid insufficiency (>= moderate)				25.5	47.1	10.0
Aortic stenosis				26.0	19.0	51.8
PVD	0.1680	0.2069	0.1921	100.0	100.0	100.0
MI (vs. MI > 21 days or no MI)	-	-	-	-	-	-
<21 days	0.1226	0.1361	0.1505	95.6	98.8	98.7

<=24 hours				6.7	13.7	10.9
<=6 hours			0.2213	7.5	38.6	41.4
BSA	-0.3739	-0.3455	-0.6516	81.6	73.8	99.9
BSA Squared	1.2498	1.0977	1.6661	100.0	99.9	100.0
BSA x female	0.7214	0.6676	1.0025	99.2	98.3	100.0
BSA Squared x female				8.2	7.6	11.9
Surgery date (Days past 12/31/2003)	-0.0002	-0.0001	-0.0001	100.0	100.0	100.0
CVD/CVA (vs. No CVD)	-	-	-	-	-	-
CVD	0.1244	0.1046	0.1799	70.1	55.4	99.7
CVD w/ CVA				44.1	49.3	5.8
Hypertension		0.0799		39.1	58.7	35.2
Number Diseased Vessels				6.9	29.9	14.7
Shock				7.2	6.2	11.3
PCI < 6 hours		0.2508		17.9	53.0	8.0
Left main disease		-0.0549		18.3	62.7	17.7
Age x reoperation		0.0019	0.0022	20.4	38.3	42.3
Age x emergent status				20.6	21.0	21.4

5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).

SDS factors were not considered for inclusion in our original measure risk model, in keeping with NQF policy at the time of measure development. For the purposes of this exercise, we studied the variation of SDS factors and the potential impact of adding the SDS factors to the STS CABG readmission rate model.

We first summarized provider-level variation of a few selected SDS factors among CABG patients in 2008-2010. Those included were Medicare-eligible patients in the US who were successfully linked to the STS Adult Cardiac Surgery Database. We then assessed the association between the SDS factors and 30-day all-cause readmission. Finally, we evaluated the impact of adding these factors to the STS CABG readmission rate model, which again, did not originally include any SDS covariates.

<u>Average readmission rates by SDS categories</u>

We calculated the average readmission rates in different race/ethnicity and payor groups.

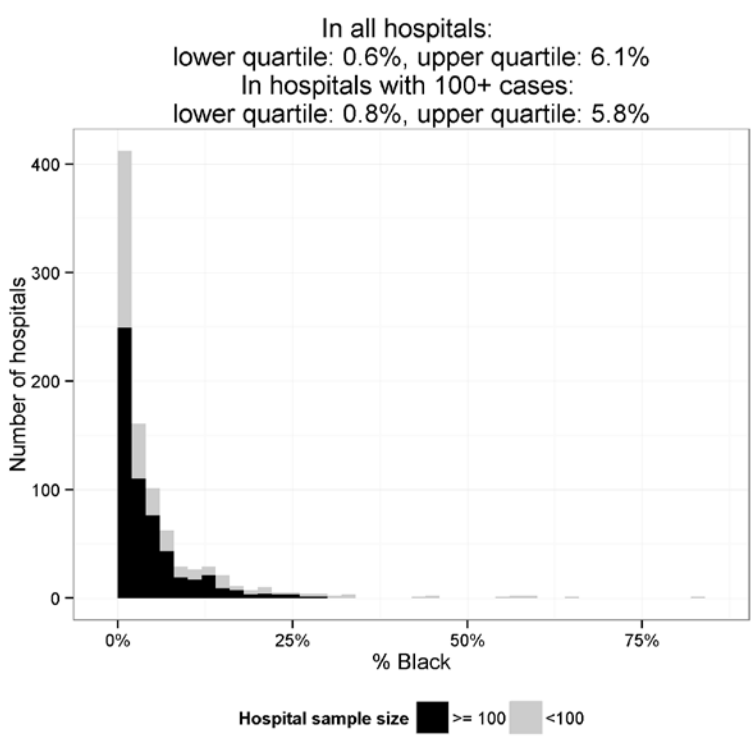
	Number of readmissions	*Readmission rate*	*Number of patients*
Ethnicity			
Non-Hispanic	26,042	16.7%	155,780
Hispanic	1,143	19.1%	5,982
Race categories			
1 - Black	1,576	20.2%	7,792
2 - Asian	410	18.0%	2,277
3 - Native American	94	20.5%	459
4 - Pacific Islander	39	16.6%	235
5 - Other	627	17.6%	3,554
6 - Caucasian	24,287	16.6%	146,625
7 - Multiracial	152	18.5%	820

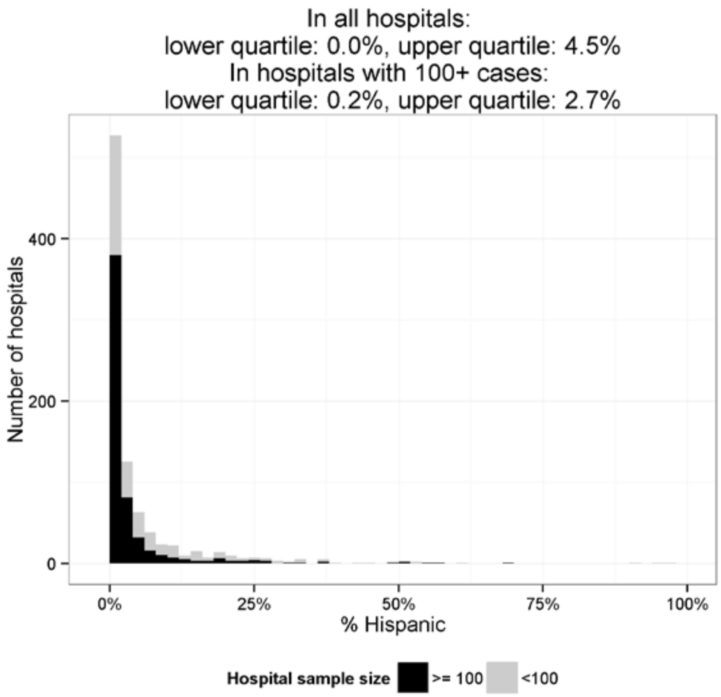
Payor categories			
1 - Medicare+Medicaid dual eligible	2,143	22.9%	9,347
2 - Medicare+Commercial without Medicaid	12,885	15.9%	80,966
3 - Medicare without Medicaid/Commercial	12,157	17.0%	71,449
Overall	27,185	16.8%	161,762

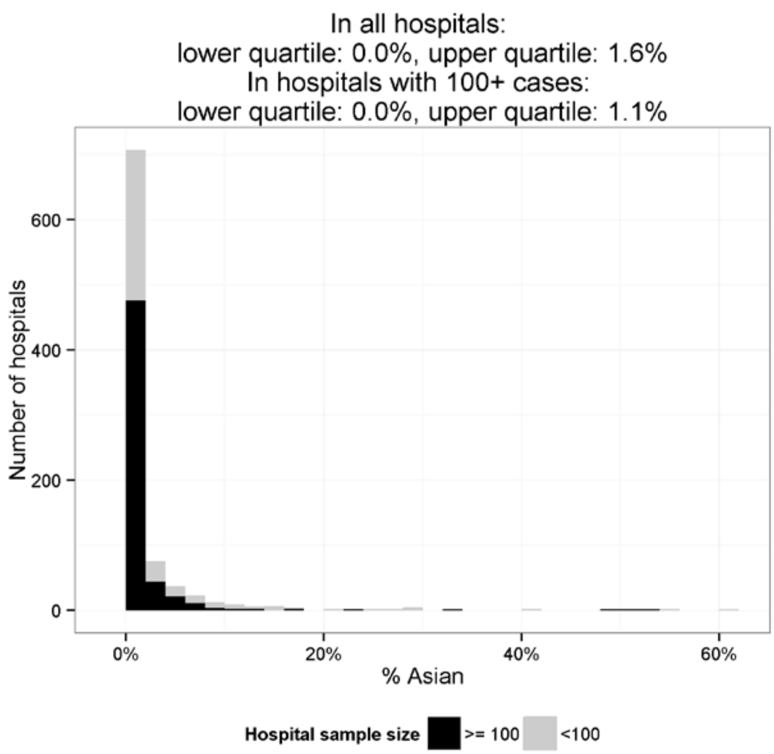
Hispanic patients on average had a higher readmission rate than non-Hispanic patients. Among different race groups, Native Americans had the highest readmission rate with blacks being a close second, while the Pacific islanders and Caucasians had the lowest. Among payor groups, those with commercial insurance (but no Medicaid benefit) had the lowest aggregated readmission rate, while Medicare and Medicaid dual eligible patients had the highest rate.

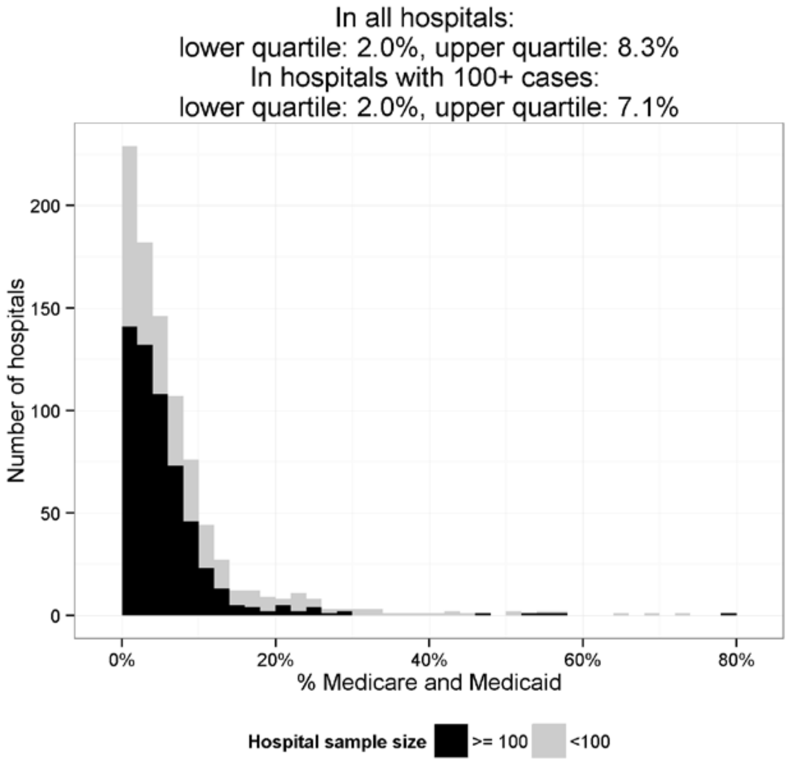
Variation in SDS across hospitals

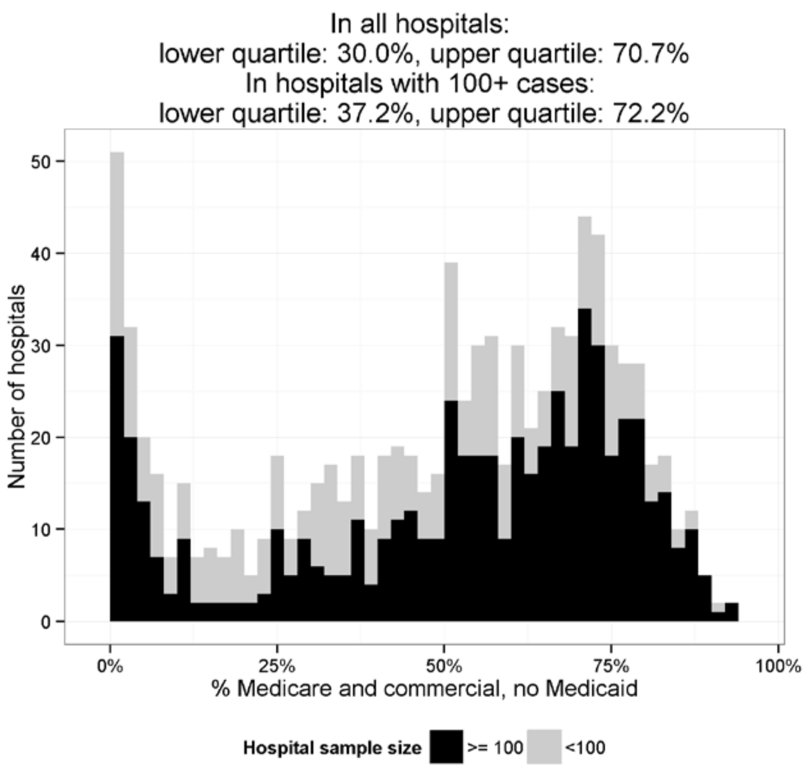
We calculated the hospital-specific proportions of patients that belonged to each of the race and payor groups. The distributions of the hospital-specific proportions were summarized graphically. In the graphs, we made the distinction between relatively large hospitals (≥ 100 cases) and relatively small hospitals (< 100 cases). On average the proportions calculated for the large hospitals were closer to the true demographics that the hospitals served.




In all hospitals:
lower quartile: 0.0%, upper quartile: 4.5%
In hospitals with 100+ cases:
lower quartile: 0.2%, upper quartile: 2.7%
Number of hospitals
400
200
0
0%
25%
50%
75%
100%
% Hispanic
Hospital sample size
>= 100
<100


In all hospitals:
lower quartile: 0.0%, upper quartile: 1.6%
In hospitals with 100+ cases:
lower quartile: 0.0%, upper quartile: 1.1%
Number of hospitals
600
400
200
0
0%
20%
40%
60%
% Asian
Hospital sample size
>= 100
<100


In all hospitals:
lower quartile: 2.0%, upper quartile: 8.3%
In hospitals with 100+ cases:
lower quartile: 2.0%, upper quartile: 7.1%
Number of hospitals
% Medicare and Medicaid
Hospital sample size
>= 100
<100


In all hospitals:
lower quartile: 30.0%, upper quartile: 70.7%
In hospitals with 100+ cases:
lower quartile: 37.2%, upper quartile: 72.2%
Number of hospitals
% Medicare and commercial, no Medicaid
Hospital sample size
>= 100
<100

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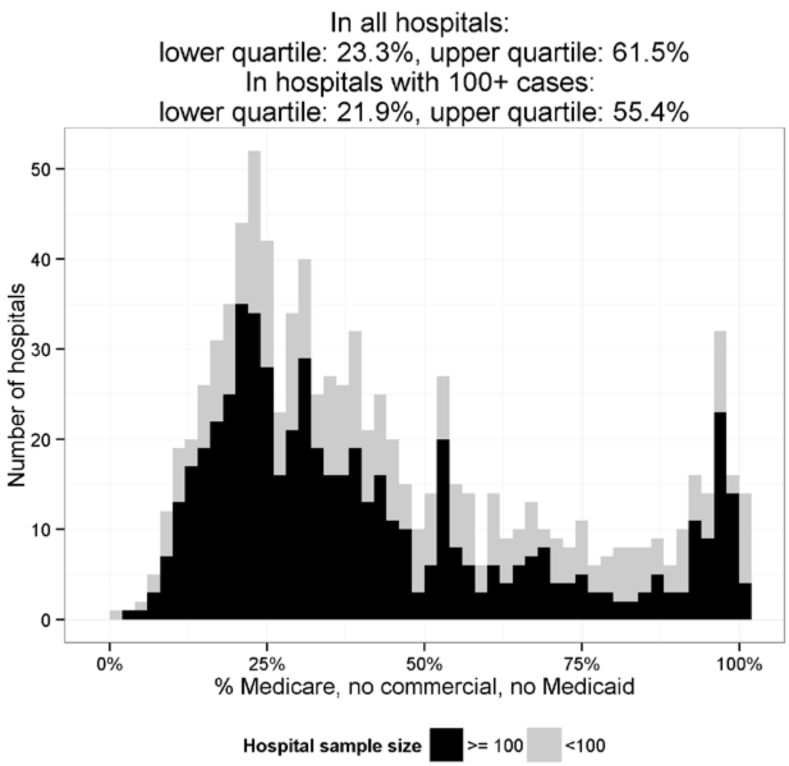


Risk-adjusted odds ratios among race and payor groups

We added the race/ethnicity and payor categories to the STS readmission rate case-mix adjustment model and estimated the odds ratios between the categories. The odds ratios were estimated with a random effect logistic regression model with a hospital-level normally distributed random intercept.

Effect	*Estimated OR (95% CI)**	*P-value*
Race/ethnicity		
Black vs White	1.06 (1.00, 1.13)	0.053
Hispanic vs White	1.10 (1.02, 1.18)	0.015
Asian vs White	1.04 (0.93, 1.17)	0.48
Native American vs White	1.07 (0.85, 1.36)	0.55
Pacific islander vs White	0.93 (0.68, 1.28)	0.66
Other vs White	1.13 (1.00, 1.26)	0.041
Payor		
Medicare and Medicaid dual eligible vs Medicare only	1.27 (1.20, 1.34)	<.0001
Medicare and commercial (no Medicaid) vs Medicare only	0.95 (0.92, 0.98)	0.0003

* Model also included a list of patient risk factors as detailed in attached document

<u>Comparison of estimated risk-adjusted odds ratios between a random effect model and a conditional logistic model</u>

There were variations in SDS variables across hospitals. Hospitals also had different performance in terms of reducing readmissions. It was plausible that hospitals admitting more patients from a certain SDS group were indeed better (or worse) than the other hospitals. If this were true, then the estimated association between SDS and readmission could be (in part) attributable to hospital performance differences. This made it important to separate SDS' association with readmission and hospital's association with readmission.

One way to get this was to fit a conditional logistic regression model stratified by hospitals. In such a model, outcomes in patients of different groups were only compared within hospitals and not across them. The estimated associations could therefore be considered independent of hospital variations in performance.

We fitted the conditional logistic regression model and compared the estimated odds ratios with those from the random effect logistic regression model.

Effect	*Estimated OR (95% CI) from Random Effect Model*	*Estimated OR (95% CI) from Conditional Logistic Model*
Race/ethnicity		
Black vs White	1.06 (1.00, 1.13)	1.04 (0.97, 1.10)
Hispanic vs White	1.10 (1.02, 1.18)	1.12 (1.03, 1.21)
Asian vs White	1.04 (0.93, 1.17)	1.07 (0.95, 1.21)
Native American vs White	1.07 (0.85, 1.36)	1.03 (0.81, 1.32)
Pacific islander vs White	0.93 (0.68, 1.28)	1.00 (0.72, 1.38)
Other vs White	1.13 (1.00, 1.26)	1.10 (0.98, 1.24)
Payor		
Medicare and Medicaid dual eligible vs Medicare only	1.27 (1.20, 1.34)	1.28 (1.21, 1.36)
Medicare and commercial (no Medicaid) vs Medicare only	0.95 (0.92, 0.98)	0.94 (0.91, 0.97)

In the conditional logistic model, we saw a very small reduction in the association between black patients and readmission rate and a small increase for the non-black Hispanic group.

6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).

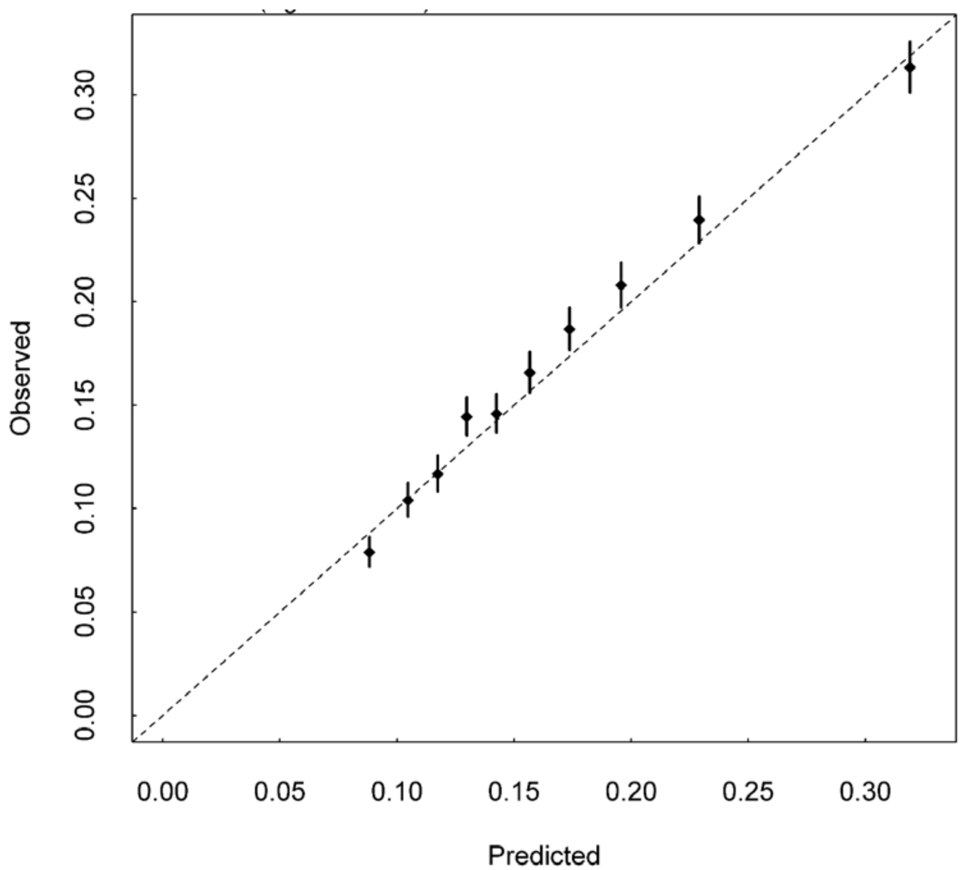
<u>Methods</u>

To assess the adequacy of model with the selected list of patient risk factors, we fitted the final model using only 2008 data and validated the estimated coefficients using 2009 data. C-index was calculated to assess discrimination. To assess calibration, we graphically depicted the observed versus expected all-cause 30-day readmission rates within patient deciles divided by predicted risk.

<u>Results</u>

The c-index was 0.631. At the time of the model development, there was rarely any readmission model with a c-index of exceeding 0.68. The range that we found of similar models was 0.60-0.68.

The agreement between predicted and observed readmission rates across predicted risk deciles was excellent (figure below).



7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.

Our analyses were limited to the SDS data elements available in the STS Adult Cardiac Surgery Database. Had more robust SDS measures been available, more substantial effects of adjustment for these factors may have been observed.

8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.

The performance measure does not include SDS variables. For an analysis of the potential impact of including specific SDS variables in the measure, please refer to other sections of this form.

9. **Please enter the details of the final statistical risk model and variables here.**

Please see below for covariate definitions and estimated odds ratios from the risk adjustment model.

Please note the model is a hierarchical logistic regression with hospital-specific intercepts (random effects). Coefficients are re-estimated on the current sample each time the measure is calculated.

The model was also described in the published article:
Shahian, D.M., He, X., O'Brien, S., Grover, F.L., Jacobs, J.P., Edwards, F.H., Welke, K.F., Suter, L.G., Drye, E., Shewan, C.M. and Han, L., 2014. Development of a clinical registry-based 30-day readmission measure for coronary artery bypass grafting surgery. Circulation, pp.CIRCULATIONAHA-113.
URL: http://circ.ahajournals.org/content/130/5/399.short

The table below lists all the patient level predictors included in the final case-mix adjustment model

Predictor	Coding
Ejection Fraction	Linear (value > 50 mapped to 50)
Preoperative Atrial Fibrillation	Yes/No
Unstable Angina (no MI <= 7 days)	Yes/No
Myocardial Infarction	(1) No recent (2) 1-21 days (3) 6-24 hours (4) <= 6 hours
Age	Linear
Chronic Heart Disease	Yes/No
Renal Function	(1) On dialysis (2) for patients not on dialysis: model by two creatinine level variables: (a) linear with value <1.0 mapped to 1.0 (2) linear with value <1.5 mapped to 1.5
Status	(1) Elective (2) Urgent (3) Emergent
Gender	Female/Male
Reoperation	Yes/No
Chronic Lung Disease	(1) None (2) Mild (3) Moderate (4) Severe
Diabetes	(1) No (2) non-insulin (3) insulin
Preoperative IAPB or Inotrope	Yes/No
Immunosuppressive Treatment	Yes/No
PVD	Yes/No
Body Square Area	Four variables: (1) linear (2) quadratic (3) linear * female (4) quadratic * female
CVD	Yes/No
Hypertension	Yes/No
PCI <= 6 hours	Yes/No
Left Main Disease	Yes/No
Surgery Date	Linear

The following table summarizes the estimated odds ratios from a random effect logistic regression model. The model included all factors in the table above and a normally distributed provider level random intercept.

Effect	*Estimated odds ratio (95% confidence interval)*
EF - per 10 unit descrease	1.06 (1.05, 1.08)
Preop Afib	1.36 (1.30, 1.42)
Unstable angina (no MI <= 7 days)	1.06 (1.03, 1.10)
CHF NYHA I-IV	1.18 (1.14, 1.22)
per 10 year increase	1.36 (1.33, 1.39)
Dialysis and Creatinine	
Dialysis vs No Dialysis & Creatinine <= 1.0	2.01 (1.86, 2.17)
Creatinine 1.5 vs 1.0	1.28 (1.23, 1.33)
Creatinine 2.0 vs 1.0	1.38 (1.32, 1.43)
Creatinine 2.5 vs 1.0	1.49 (1.41, 1.57)
Status (vs. elective)*	
Urgent	1.09 (1.05, 1.12)
Emergent/Emergent Salvage	1.16 (1.06, 1.26)
Female (at BSA=1.8) vs. Male (at BSA=2.0)	1.38 (1.33, 1.43)
Reop (vs No previous operation)	
1 or more previous operations	1.14 (1.07, 1.21)
Chronic lung disease (vs. none)	
Mild	1.22 (1.18, 1.27)
Moderate	1.36 (1.29, 1.43)
Severe	1.61 (1.52, 1.71)
Diabetes (vs. no diabetes)	
Non-insulin diabetes	1.10 (1.07, 1.14)
Insulin diabetes	1.45 (1.39, 1.51)
Pre-op IABP or Inotrope	1.08 (1.02, 1.14)
Immunosuppressive treatment	1.38 (1.29, 1.49)
PVD	1.20 (1.16, 1.24)
MI (vs. MI > 21 days or no MI)	
1-21 days	1.15 (1.11, 1.20)
6-24 hrs	1.13 (1.03, 1.24)
<=6 hrs	1.27 (1.12, 1.44)
BSA	
1.6 vs 2.0 in male	1.21 (1.13, 1.29)
1.8 vs 2.0 in male	1.04 (1.01, 1.07)
2.2 vs 2.0 in male	1.07 (1.06, 1.09)
1.6 vs 1.8 in female	0.99 (0.96, 1.01)
2.0 vs 1.8 in female	1.13 (1.10, 1.16)
2.2 vs 1.8 in female	1.44 (1.34, 1.53)
Surgery data per half-year increase	0.99 (0.98, 0.99)
CVD	1.14 (1.11, 1.18)
Hypertension	1.07 (1.02, 1.12)
PCI < 6 hours	1.10 (0.95, 1.28)

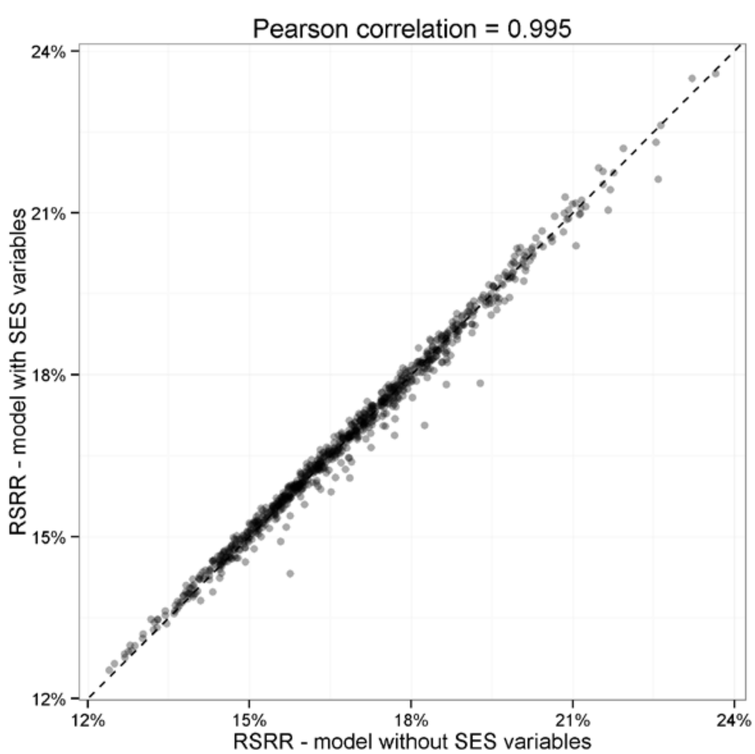
Left main disease	0.96 (0.94, 0.99)

10. Compare measure performance scores with and without SDS factors in the risk adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

<u>Comparison of risk-adjusted readmission rate (RSRR) from the current STS readmission model and a model with SDS variables added</u>

We calculated the hospital RSRR by incorporating the SDS covariates into the STS readmission case-mix adjustment model. This was to assess the impact of hospital performance rating by including the SDS variables in the model. The RSRRs were compared to those calculated with the current STS readmission model that does not include any SDS factors. To be consistent with previously published material, we estimated the model and the RSRRs with all hospitals; however, in the comparison we only included hospitals with 90% of more CMS admissions linked to the STS Adult Cardiac Surgery Database and more than 30 eligible admissions.

The point estimates of the RSRRs were compared in the scatter plot below. Overall, the Pearson correlation and Spearman's rank correlation between the two sets of RSRRs were 0.995 and 0.995, respectively.



We also derived the 95% interval estimates of the RSRR (by bootstrapping), which were used to define performance outliers. The table below summarizes the cross-classification of the outlier status based on the model without and the model with SDS factors.

		Model with SDS factors (race/ethnicity and payor)		
		Better than expected	**As Expected**	**Worse than expected**
Model without SDS factors	**Better than expected**	20	3	0
	As expected	2	795	2
	Worse than expected	0	1	23

Better than expected = 95% interval estimate of RSRR entirely below population aggregated rate
Worse than expected = 95% interval estimate of RSRR entirely above population aggregated rate
As expected = 95% interval estimate of RSRR neither entirely above nor entirely below population aggregated rate

The outlier status based on the two models agreed for 99.1% (838/846) of all hospitals.

To shed light on the eight centers that were classified into different performance groups by the two models, we summarized their properties below. Instead of using RSRR, we showed the point and interval estimates of the Standardized Readmission Ratio (SRR) below. Note that RSRR = SRR*Overall readmission rate.

SRRs are calculated as the ratio of the predicted number of readmissions to the expected number of readmissions. An SRR of 1 indicates that the hospital's performance is of the overall average performance. The 95% interval estimate of SRR, obtained by bootstrapping, is compared with 1 and if the interval lies above 1, the center is labeled 'worse than expected'. If the interval lies below 1, the center is labeled 'better than expected'. Otherwise, the center is labeled 'as expected'.

	Model without SES		**Model with SES**			**Distribution of SES factors, center level %**				
Center	**SRR**	**SRR Interval**	**SRR**	**SRR Interval**	**Change of Group: W/o SES -> w/ SES[1]**	**Hispanic Ethnicity**	**Black**	**Medicare And Medicaid**	**Medicare And Commercial without Medicaid**	**Center Sample Size**
1	0.830	0.685 - 1.000	0.845	0.697 - 1.016	3 -> 2	3.3	0.2	3.8	86.4	350-450
2	0.824	0.681 - 0.994	0.83	0.685 - 1.000	3 -> 2	0.5	0.2	6.8	70.9	350-450
3	0.823	0.679 - 0.982	0.839	0.692 - 1.001	3 -> 2	0.4	0.0	3.2	86.5	450-550
4	1.240	0.997 - 1.504	1.249	1.008 - 1.516	2 -> 1	1.2	1.2	4.4	62.7	150-250
5	1.209	0.990 - 1.453	1.222	1.004 - 1.464	2 -> 1	1.6	2.6	3.1	71.0	150-250
6	0.839	0.691 - 1.017	0.822	0.679 - 0.999	2 -> 3	25.5	1.0	21.2	62.3	250-350
7	0.831	0.684 - 1.004	0.826	0.684 - 0.999	2 -> 3	0.2	8.6	8.9	37.8	450-550
8	1.227	1.002 - 1.486	1.218	0.997 - 1.468	1 -> 2	6.8	4.2	5.7	37.1	250-350
All included Linked patients[2]	-	-	-	-	-	**3.7**	**4.8**	**5.8**	**50.1**	-

[1] 1 ="Worse than expected"; 2 = "As expected"; 3 = "Better than expected"

[2] Percentages were calculated in all linked CMS patients included in the study

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11. Appendix (includes literature review, reference list, etc.)

Shahian, D.M., He, X., O'Brien, S., Grover, F.L., Jacobs, J.P., Edwards, F.H., Welke, K.F., Suter, L.G., Drye, E., Shewan, C.M. and Han, L., 2014. Development of a clinical registry-based 30-day readmission measure for coronary artery bypass grafting surgery. Circulation, pp.CIRCULATIONAHA-113.
URL: http://circ.ahajournals.org/content/130/5/399.short

Center for Outcomes Research and Evaluation (CORE)
1 Church Street, Suite 200
New Haven, Connecticut 06510-3330
Phone: 203-764-5700 Fax: 203-764-5653

MEMORANDUM

TO: National Quality Forum (NQF) Admissions & Readmissions Standing Committee
FROM: Theodore Long, MD, MHS, Karen Dorsey, MD, PhD, and Susannah Bernheim, MD, MHS, Yale New Haven Health Services Corporation – Center for Outcomes Research and Evaluation (YNHHSC/CORE)
THROUGH: The Centers for Medicare and Medicaid Services (CMS)
Lein Han, PhD
DATE: Monday, February 22, 2016
SUBJECT: Ad Hoc SDS Responses for NQF #2515 Hospital 30-day, all-cause, unplanned, risk-standardized readmission rate (RSRR) following coronary artery bypass graft (CABG) surgery

Admissions & Readmissions Ad Hoc SDS Trial Period Questions: CABG Readmission

1. Enter measure # and title

CABG Readmission Measure #: 2515

CABG Readmission Measure Title: Hospital 30-day, all-cause, unplanned, risk-standardized readmission rate (RSRR) following coronary artery bypass graft (CABG) surgery

2. What were the patient-level sociodemographic variables that were available and analyzed during measure development?

"Sociodemographic status" incorporates socioeconomic variables as well as race into a single term. However, given the fact that socioeconomic risk factors are distinct from race and therefore should be interpreted differently, we have decided to keep "socioeconomic status" and "race" as separate terms.

We selected socioeconomic status (SES) and race variables to analyze after reviewing the literature and examining available national data sources. There is a large body of literature linking various SES factors and African-American race to worse health status and higher readmission risk (Blum et al., 2014; Eapen et al. 2015; Gilman et al., 2014; Hu et al., 2014; Joynt and Jha, 2013). Income, education, and occupational level are the most commonly examined variables. The literature directly examining how different SES factors or race might influence the likelihood of older, insured, Medicare patients of being readmitted within 30 days of CABG surgery is limited. There are insufficient results to indicate a consistent effect on risk of readmission (Chou, Deily, and Li 2014; Murphy et al. 2008). The causal pathways for SES and race variable selection are described below in Question #3.

Based on this review and the availability of data, the SES and race variables used for analysis were:

- Dual eligible status (meaning enrolled in both Medicare and Medicaid)
- African-American race
- Agency for Healthcare Research and Quality (AHRQ)-validated SES Index score (composite of 7 different variables found in census data: percentage of people in the labor force who are unemployed, percentage of people living below poverty level, median household income, median value of owner-occupied dwellings, percentage of people ≥25 years of age with less than a 12th-grade education, percentage of people ≥25 years of age completing ≥4 years of college, and percentage of households that average ≥1 people per room)

In selecting variables, our intent was to be responsive to the NQF guidelines for measure developers in the context of the Sociodemographic Status (SDS) Trial Period and identify variables that are feasible to test and use in the near term. We examined patient-level indicators of both SES and race or ethnicity that are reliably available for all Medicare beneficiaries. We aimed to select those variables that are most valid and available. We briefly describe the benefits and limitations to our selected variables below.

For race, studies examining the validity of data on patients' race and ethnicity collected by the Centers for Medicare and Medicaid Services (CMS) have shown that only the data identifying African-American beneficiaries have adequate sensitivity and specificity to be applied broadly in research or measures of quality. While using this variable is not ideal because it groups all non-African-American beneficiaries together, it is currently the only race variable available on all beneficiaries across the nation that is linkable to claims data. The NQF has mixed guidance on the consideration of race as a risk-adjustment variable. Our team felt it was important to include in analyses because it helps to highlight some of the causal pathways by which both race and SES influence outcomes.

We similarly recognize that Medicare-Medicaid dual eligibility has limitations as a proxy for patients' income or assets because it is a dichotomous variable. However, the threshold for over 65-year-old Medicare patients is valuable as it takes into account both income and assets and is consistently applied across states. For both our race and the dual-eligible variables, there is a body of literature demonstrating differential health care and health outcomes among beneficiaries (Trivedi et al., 2014; Hasnain-Wynia et al., 2007; Joynt et al., 2011; Bradley et al., 2004; Barnato et al., 2005; Hu et al., 2014) indicating that these variables, while not ideal, also allow us to examine some of the pathways of interest.

Finally, we selected the AHRQ SES Index score because it is a well-validated and widely-used variable that describes the average SES of people living in defined geographic areas (Bonito et al., 2008). Its value as a proxy for patient-level information is dependent on having the most granular level data with respect to communities that patients live in. Currently, the individual data elements used to calculate the score are available at the 5-digit zip code and census block levels only. In this submission, we present analysis using the 5-digit level. However, we are currently performing analysis at the census block level, the most granular level possible. We hope to present the results of the census block-level analysis to the committee.

<u>References:</u>

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3. From the measure developer perspective, what is your recommendation for the Standing Committee to consider on whether SDS factors should be included in the measure's final risk adjustment model?

The readmission measures are intended to assess important aspects of hospital quality of care. Decisions about which risk factors should be included in each measure's risk-adjustment model should be made on the basis of whether inclusion of such variables is likely to make the measures more successful at illuminating quality differences and motivating quality improvement. (This aim should be distinguished from decisions made in response to concerns about the impact of related payment programs on safety-net hospitals; concerns which can be addressed through other policy mechanisms.) The determination of whether inclusion of socioeconomic factors or race as patient-level, risk-adjustment variables improves or diminishes the readmission measures' assessment of hospital quality is controversial. This controversy arises because some aspects of disparities in outcomes may be attributed to hospital quality and other aspects attributed to factors outside the hospital's control. The measure developer's, Yale New Haven Health Services Corporation – Center for Outcomes Research and Evaluation's (YNHHSC/CORE's), perspective is that we are firmly committed to fairness in measurement, but we are also committed to ensuring that the measures do not reinforce a status quo in which poorer quality of care is provided to African American and poorer populations. The medical literature and our analyses consistently demonstrate that hospitals contribute to the disparities in outcomes for socioeconomically disadvantaged groups, and for that reason we do not believe the addition of patient-level risk adjustment for race or SES (as fixed effects in the model) is an appropriate solution for the readmission measures. Ongoing work within Health and Human Services and CORE will continue to evaluate alternative solutions that better reflect the balance of hospital- and patient-level influences on readmission risk for socioeconomically disadvantaged patients.

Since our first measures were implemented in the Hospital Inpatient Quality Reporting program, CORE has been committed to studying and monitoring disparities in patients' outcomes and the relationships among race, social, or economic disadvantage, and hospitals' performance on the 30-day readmission, mortality, complication, and payment measures. In response to the requirements of the SDS trial period we have additionally undertaken a comprehensive review of the literature examining the relationships among these factors and patients' outcomes across multiple conditions and procedures, and completed analyses recommended or requested by NQF or its committees to explore the impact of adding such factors to the measures' risk models. **The findings of this work, shown within this submission, have confirmed our long-held understanding that hospitals contribute in significant ways to persistent disparities in patients' outcomes; and that adjusting for race or for social and economic disadvantage could inappropriately obscure true signals of the quality of care such patients receive.** Additionally, because interpersonal and structural bias or discrimination within the healthcare system continue to play a significant role in the persistence of disparities (Trivedi et al., 2014), sociodemographic factors must be given special consideration. In contrast, there is no evidence of bias in the care of patients due to a diagnosis of diabetes or chronic obstructive pulmonary disease (COPD), two conditions that we do adjust for in the measures. Hospitals may provide differential care to patients with these diseases due to differences in providers' expertise or the availability of specialists or intensive care, but there is no evidence that interpersonal or structural bias targeted toward these patients plays any significant role. Incorporating risk adjustment for SES or race can diminish the ability of the measures to illuminate such quality issues. Concerns about the financial viability of the safety net do not need to be pitted against discussion of risk-adjustment as there are other policy mechanisms protecting safety-net hospitals and the patients they serve from undue financial penalties or loss of resources.

Decisions about whether to incorporate SES and race variables into outcome quality measure risk models are more complex and controversial than the decisions regarding the incorporation of clinical factors because any increased risk for worse outcomes following a hospitalization for historically socially disadvantaged patients may be due, in part, to bias or discrimination in provision of care. This can occur because such patients may have access to poorer quality providers or due to differences in care for such patients. There is a broad literature documenting the relationship between SES or race and health care quality (Blum et al., 2014; Gilman et al., 2014; Hu et al., 2014; Joynt and Jha, 2013) that does not exist to a similar degree for clinical factors. Therefore, within a risk model that accounts for differences in illness severity and comorbidities (through adjustment for risk factors), any remaining elevated risk for poor outcomes related to social disadvantage may be due to quality differences.

Given that the goal of the measures is to illuminate quality differences, and that socioeconomic factors and race are historically entangled with differential provision of high quality care, we maintain that adjustment for either should only be undertaken with care, and with clear evidence that risk differences are unrelated to differential quality of care.

Below we lay out a more complete conceptual model of pathways by which socioeconomic factors and race may influence readmission risk and the implications for risk-adjustment. We have identified analyses that aim to disentangle these pathways. The analyses demonstrate that differences among hospitals contribute substantially to increased risk for socially disadvantaged patients – that is, the effect of low SES on readmission can be attributed substantially to the hospitals where such patients are treated.

Below we describe our conceptual model.

To develop a conceptual model of the relationship between patient-level SES and race variables and the readmission outcome, we began by completing a literature search and conceptualizing four distinct causal pathways.

Literature Review of Socioeconomic Status (SES) and Race Variables and CABG Readmission

To examine the relationship between SES and race variables and hospital 30-day, all-cause, risk-standardized readmission rate (RSRR) following CABG surgery, a literature search was performed with the following exclusion criteria: international studies, articles published more than 10 years ago, articles without primary data, articles using Veterans Affairs databases as the primary data source, and articles not explicitly focused on SES or race and CABG readmission. Nine studies were initially reviewed, and seven studies were excluded from full-text review based on the above criteria. Studies have been limited, and those that have been conducted have used travel distance and living alone as variables (Chou, Deily, and Li 2014; Murphy et al. 2008), with results being too limited to indicate a consistent effect.

Causal Pathways for Socioeconomic Status (SES) and Race

Although some recent literature evaluates the relationship between patient SES or race and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways. Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission.

The conceptual relationship, or potential causal pathways by which these possible SES risk factors influence the risk of readmission following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider.

1. **Relationship of SES factors or race to health at admission**. Patients who have lower income, lower education, lower literacy, or unstable housing may have a worse general health status and may present for their hospitalization or procedure with a greater severity of underlying illness that is not captured by claims data. These SES risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may contribute to worse health status at admission due to competing priorities (restrictions based on job, lack of childcare), lack of access to care (geographic, cultural, or financial), or lack of health insurance. Given that these risk factors all lead to worse general health status, this causal pathway should be largely accounted for by current clinical risk-adjustment**.**

In addition to SES risk factors, studies have shown that worse health status is more prevalent among African-American patients compared with white patients. The association between race and worse health is in part mediated by the association between race and SES risk factors such as poverty or disparate access to care associated with poverty or neighborhood.

2. **Use of low-quality hospitals**. Patients of lower income, lower education, or unstable housing have been shown not to have equitable access to high quality facilities because such facilities are less likely to be found in geographic areas with large populations of poor patients; thus patients with low income are more likely to be seen in lower quality hospitals, which can contribute to increased risk of readmission following hospitalization (Jha et al., 2011; Reames et al., 2014). Similarly African-American patients have been shown to have less access to high quality facilities compared with white patients (Skinner et al., 2005).

3. **Differential care within a hospital**. The third major pathway by which SES factors or race may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, African-American patients have been shown to experience differential, lower quality, or discriminatory care within a given facility (Trivedi et al., 2014). Alternatively, patients with SES risk factors such as lower education may require differentiated care – for example, provision of lower literacy information – that they do not receive.

4. **Influence of SES on readmission risk outside of hospital quality and health status**. Some SES risk factors, such as income or wealth, may affect the likelihood of readmission without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may have a worse outcome post-discharge due to competing economic priorities or a lack of access to care outside of the hospital.

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4. What were the statistical results of the analyses used to select risk factors?

Here we describe our general approach to selecting clinical risk factors and the results of that approach for the CABG readmission measure brought for initial endorsement. We sought to develop a model that included key variables that were clinically relevant and based on strong relationships with the outcome and that was parsimonious, using a grouper that is in the public domain for the 15,000+ International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes. The candidate variables for the model were derived from: the index admission, with comorbidities identified from the index admission secondary diagnoses (excluding potential complications); 12-month pre-index inpatient data (for any condition); outpatient hospital data; and Part B physician data. We developed candidate variables for the model from the claims codes.

We started with the 189 diagnostic groups included in the Hierarchical Condition Category (HCC) clinical classification system (Pope et al., 2000). The HCC clinical classification system was developed for CMS in preparation for all-encounter risk adjustment for Medicare Advantage (managed care) plans and represented a refinement of an earlier risk-adjustment method based solely on principal inpatient diagnosis. The HCC model makes use of all physician and hospital encounter diagnoses and was designed to predict a beneficiary's expenditures based on the total clinical profile represented by all of his/her assigned HCCs. Under the HCC algorithm, the 15,000+ ICD-9-CM diagnosis codes are first assigned to one of 804 mutually exclusive groupings ("DxGroups") and then subsequently aggregated into 189 condition categories (CCs) (Pope et al., 2000). We do not use the hierarchy and therefore refer to the CCs rather than HCCs.

To select candidate variables, a team of clinicians reviewed all 189 CCs and excluded those that were not relevant to the Medicare population or that were not clinically relevant to the readmission outcome (for example, attention deficit disorder, female infertility). Clinically relevant CCs were selected as candidate variables and some of those CCs were then combined into clinically coherent CC groupings. Other candidate variables included age, gender, and cardiogenic shock. Gender was included in risk adjustment due to the fact that women have smaller caliber vessels and thus represent more technically challenging CABG procedures compared to men (O'Connor et al., 1996).

To inform final variable selection, a modified approach to stepwise logistic regression was performed. The development sample was used to create 1,000 "bootstrap" samples. For each sample, we ran a logistic stepwise regression that included the candidate variables. The results were summarized to show the percentage of times that each of the candidate variables was significantly associated with readmission ($p<0.001$) in each of the 1,000 repeated samples (for example, 90 percent would mean that the candidate variable was selected as significant at $p<0.001$ in 90 percent of the estimations). We also assessed the direction and magnitude of the regression coefficients.

The clinician team reviewed these results and decided to retain all risk-adjustment variables above a 70% cutoff, because they demonstrated a relatively strong and stable association with risk for readmission and were clinically relevant. Additionally, specific variables with particular clinical relevance to the risk of readmission were forced into the model (regardless of percent selection) to ensure appropriate risk adjustment for CABG. These included:

1) Clinical variables associated with CABG:
    - History of Prior CABG or Valve Surgery
2) Markers for end of life/frailty:
    - Decubitus Ulcer or Chronic Skin Ulcer
    - Dementia and Senility

- Metastatic Cancer and Acute Leukemia
- Protein-calorie Malnutrition
- Hemiplegia, Paraplegia, Paralysis, Functional Disability
- Stroke

3) Diagnoses with potential asymmetry among hospitals that would impact the validity of the model:

- Lung, Upper Digestive Tract, and Other Severe Cancers
- Lymphatic, Head and Neck, Brain, and Other Major Cancers; Breast, Prostate, Colorectal and Other Cancers and Tumors; Other Respiratory and heart Neoplasms
- Other Digestive and Urinary Neoplasms

This resulted in a final risk-adjustment model that included 26 variables.

Table 1 shows the final variables in the model with associated odds ratios (OR) and 95% confidence intervals (CI). For this analysis, we used data from January 2009 through September 2011. These were the same data used in the NQF application submitted in 2014.

- Years of data: January 1, 2009 – September 30, 2011
- Number of admissions: 150,900
- Patient Descriptive Characteristics: average age=73.9; % male=69.0
- Number of Measured Entities: 1,195

Table 1. Final CABG Readmission Model Variables

Variable	01/01/2009-09/30/2011 OR (95% CI)
Age minus 65 (years above 65, continuous)	1.03 (1.02 – 1.03)
Male	0.77 (0.75 – 0.79)
History of prior CABG or valve surgery (ICD-9 Diagnosis Codes: V42.2, V43.3, V45.81, 414.02, 414.03, 414.04, 414.05, 414.06, 414.07, 996.02, 996.03 ; ICD-9 Procedure Codes: 39.61)	1.05 (0.99 – 1.11)
Cardiogenic shock (ICD-9 Code 785.51)	1.33 (1.24 – 1.41)
Chronic obstructive pulmonary disease (COPD) (CC 108)	1.29 (1.25 – 1.33)
Renal failure (CC 131)	1.29 (1.24 – 1.34)
Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)	1.15 (1.12 – 1.19)
Other endocrine/metabolic/nutritional disorders (CC 24)	0.85 (0.82 – 0.89)
Congestive heart failure (CC 80)	1.21 (1.17 – 1.26)
Specified arrhythmias and other heart rhythm disorders (CC 92-93)	1.12 (1.09 – 1.16)
Other lung disorders (CC 115)	1.06 (1.03 – 1.10)
Major psychiatric disorders (CC 54-56)	1.22 (1.14 – 1.30)
Vascular or circulatory disease (CC 104-106)	1.11 (1.07 – 1.14)
Disorders of fluid/electrolyte/acid-base (CC 22-23)	1.19 (1.15 – 1.24)
Pneumonia (CC 111-113)	1.16 (1.11 – 1.21)
Cerebrovascular disease (CC 97-99, 103)	0.95 (0.92 – 0.98)
Polyneuropathy (CC 71)	1.20 (1.14 – 1.26)
Protein-calorie malnutrition (CC 21)	1.26 (1.18 – 1.34)
Severe hematological disorders (CC 44)	1.38 (1.23 – 1.54)

Variable	01/01/2009-09/30/2011 OR (95% CI)
Fibrosis of lung or other chronic lung disorders (CC 109)	1.10 (1.03 – 1.17)
Decubitus ulcer or chronic skin ulcer (CC 148-149)	1.30 (1.21 – 1.39)
Dialysis status (CC 130)	1.36 (1.23 – 1.50)
Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)	1.12 (1.04 – 1.21)
Stroke (CC 95-96)	1.07 (1.00 – 1.14)
Dementia or other specified brain disorders (CC 49-50)	1.16 (1.09 – 1.23)
Cancer (CC 7-12)	0.99 (0.95 – 1.02)

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5. Describe the analyses and interpretation resulting in the decision to select SDS factors (e.g. prevalence of the factor across measured entities, empirical association with the outcome, contribution of unique variation in the outcome, assessment of between-unit effects and within-unit effects).

Methods:

In order to analyze SES and race factors for potential inclusion we performed a number of analyses, in alignment with NQF guidance: variation in prevalence of the factor across measured entities, performance of providers by proportion of patients of low SES or racial minorities, empirical association with the outcome (bivariate), and the incremental effect of SES variables and race in a multivariable model, including examining the extent to which the addition of any one of these variables improved model performance or changed hospital results.

Finally, we aimed to assess the extent to which the effect of SES or race is at the patient or the hospital level. For example, social or economic disadvantage may increase the risk of readmission because patients have an individual higher risk or because such patients receive differential care within a hospital (patient-level effect). Alternatively, patients of low SES may be more frequently admitted to hospitals with higher overall readmission rates (hospital-level effect). Thus, as an additional step, we performed a decomposition analysis to assess the independent effects of the SES and race variables at the patient level and the hospital level. If, for example, all the elevated risk of readmission for patients of low SES was due to lower quality/higher readmission risk in hospitals with more patients of low SES, then a significant hospital-level effect would be expected with little-to-no patient-level effect. However, if the increased readmission risk was solely related to higher risk for patients of low SES, then a significant patient-level effect would be expected and a significant hospital-level effect would not be expected. Decomposition analysis is a standard technique that we utilized, with the consultation of analytic experts in the field of quality measurement, to evaluate the contributions of patient-level and hospital-level effects (Guarnizo-Herreno & Wehby 2012; Normand 2008; Shahian et al., 2012).

Specifically, we decomposed each of the SES and race variables as follows: Let X_{ij} be a binary indicator of the SES or race status of the i^{th} patient at the j^{th} hospital, and $\mathbf{X}_j$ the percent of patients at hospital j with $X_{ij} = 1$. Then we rewrote $X_{ij} = (X_{ij} - \mathbf{X}_j) + \mathbf{X}_j \equiv X_{patient} + X_{hospital}$. The first variable, $X_{patient}$, represents the effect of the risk factor at the patient level (sometimes called the "within" hospital effect), and the second, $X_{hospital}$, represents the effect at the hospital level (sometimes called the "between" hospital effect). By including both of these in the same model, we can assess whether these are independent effects, or whether only one of these effects contributes. This analysis allows us to simultaneously estimate the independent effects of: 1) hospitals with higher or lower proportions of low SES patients or African-American patients on the readmission rate of an average patient; and 2) a patient's SES or race on their own readmission rates when seen at an average hospital.

It is very important to note, however, that even in the presence of a significant patient-level effect and absence of a significant hospital-level effect, the increased risk could be partly or entirely due to the quality of care patients receive in the hospital. For example, biased or differential care provided within a hospital to low-income patients as compared to high-income patients would exert its impact at the level of individual patients, and therefore be a patient-level effect. It is also important to note that the patient-level and hospital-level coefficients cannot be quantitatively compared because the patient's SES circumstance or race in the model is binary whereas the hospitals' proportion of low SES patients or African-American patients is continuous.

Results:

Variation in prevalence of the factor across measured entities

The prevalence of SES factors and African-American patients in the CABG cohort varies across measured entities. The median percentage of dual eligible patients is 7.1% (interquartile range [IQR]: 4.4% – 11.0%). The median percentage of African-American patients is 2.7% (IQR: 0.8% – 7.0%). The median percentage of patients with an AHRQ SES Index score equal to or below 46.0 is 18.5% (IQR: 7.5% – 37.2%). Table 2 displays the risk-standardized readmission rates for hospitals with a high or low proportion of patients with these SES factors or of African-American race. Hospitals with a high proportion of these patients had slightly higher readmission rates than those with a low proportion.

Table 2. Variation in RSRRs across Measured Entities by Proportion of Minority/Low SES Patients

Data Element	Low proportion dual eligible patients (≤4.4%)	High proportion dual eligible patients (≥11.0%)	Low proportion African-American patients (≤0.8%)	High proportion African-American patients (≥7.0%)	Low proportion of patients equal to or below AHRQ SES Index score of 46.0 (≤7.5%)	High proportion of patients equal to or below AHRQ SES Index score of 46.0 (≥37.2%)
Number of Hospitals	265	264	265	263	264	264
Number of Patients	32,793	25,503	28,260	34,065	33,873	34,618
Maximum RSRR	19.8	21.0	18.0	19.3	18.6	19.8
90th percentile RSRR	16.4	16.7	16.6	16.8	16.5	17.0
75th percentile RSRR	15.5	15.9	15.7	15.9	15.6	16.1
Median (50th percentile) RSRR	14.7	15.0	14.5	14.9	14.7	15.2
25th percentile RSRR	14.1	14.3	13.9	14.2	13.9	14.4
10th percentile RSRR	13.3	13.8	13.1	13.6	13.1	13.7
Minimum RSRR	11.5	12.0	11.6	12.0	11.9	12.0

Empirical association with the outcome (univariate)

The patient-level observed CABG readmission rate is higher for dual eligible patients, 19.53%, compared with 14.53% for all other patients. The readmission rate for African-American patients was also higher at 17.93% compared with 14.78% for patients of all other races. Similarly the readmission rate for patients with an AHRQ SES Index score equal to or below 46.0 was 16.10% compared with 14.57% for patients with an AHRQ SES Index score above 46.0.

Incremental effect of SES variables and race in a multivariable model

We then examined the strength and significance of the SES variables and race in the context of a multivariable model. Consistent with the above findings, when we include any of these variables in a multivariate model that includes all of the claims-based clinical variables, the effect size of each of these variables is modest (Table 5). The c-statistic is unchanged with the addition of any of these variables into the model (Table 3). Furthermore the addition of any of these variables into the model has little to no effect on hospital performance. We examined the change in hospitals' RSRRs with the addition of any of these variables.

The median absolute change in hospitals' RSRRs when adding a dual eligibility indicator is 0.010% (IQR: -0.018% – 0.030%, minimum -0.316% – maximum 0.103%) with a correlation coefficient between RSRRs for each hospital with and without dual eligibility added of 0.99928. The median absolute change in hospitals' RSRRs when adding a race indicator is 0.003% (IQR: -0.003% – 0.007%, minimum -0.089% – maximum 0.018%) with a correlation coefficient between RSRRs for each hospital with and without race added of 0.99995. The median absolute change in hospitals' RSRRs when adding an indicator for a low AHRQ SES Index score is 0.030% (IQR: -0.051% – 0.091%, minimum -1.158% – maximum 0.365%) with a correlation coefficient between RSRRs for each hospital with and without an indicator for a low AHRQ SES Index score added of 0.99205.

Table 3. CABG Readmission C-Statistics for Each Model

CABG Readmission Model	C-Statistic
Original Model	0.633
Original Model + Dual Eligible	0.633
Original Model + Race	0.633
Original Model + AHRQ SES Index	0.633

As an additional step, a decomposition analysis was performed. The results are shown in Table 4.

Table 4. CABG Readmission Decomposition Analysis*

Parameter	Estimate (Standard Error)	P-value
Dual Eligible – Patient-Level	0.1705 (0.0269)	<.0001
Dual Eligible – Hospital-Level	0.3400 (0.1467)	0.0205
African American – Patient-Level	0.0067 (0.0347)	0.8472
African American – Hospital-Level	0.5452 (0.1403)	0.0001
AHRQ SES Index – Patient-Level	0.0357 (0.0202)	0.0777
AHRQ SES Index – Hospital-Level	0.2185 (0.0512)	<.0001

* The p-values represent the significance of the patient-level and hospital-level variables. It is important to note that the coefficients cannot be quantitatively compared because the patient-level variable is binary whereas the hospital-level variable is continuous.

Both the patient-level and hospital-level dual eligible effects were significantly associated with CABG readmission in the decomposition analysis. The patient-level race and low AHRQ SES Index effects were not appreciably different from zero, though the hospital-level race and low AHRQ SES effects were significant. If the dual eligible variable is used in the model to adjust for patient-level differences, then some of the differences between hospitals would also be adjusted for, potentially obscuring a signal of hospital quality. If race or low AHRQ SES Index are used as risk-adjustment variables, they will primarily capture an effect of the hospital on the outcome, not the effect of intrinsic characteristics of patients or of how they are treated.

Given these findings and the complex pathways that could explain any relationship between SES or race with readmission, we did not incorporate SES variables or race into the measure.

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Table 5. CABG Readmission Risk Model Estimates

Parameter	Original Model		Original Model + Dual Eligible		Original Model + Race		Original Model + AHRQ SES Index	
	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value
Age minus 65 (years above 65, continuous)	0.027 (0.001)	<.0001	0.028 (0.001)	<.0001	0.028 (0.001)	<.0001	0.028 (0.001)	<.0001
Male	-0.269 (0.016)	<.0001	-0.262 (0.017)	<.0001	-0.268 (0.017)	<.0001	-0.275 (0.017)	<.0001
History of prior CABG or valve surgery (ICD-9 Diagnosis Codes: V42.2, V43.3, V45.81, 414.02, 414.03, 414.04, 414.05, 414.06, 414.07, 996.02, 996.03 ; ICD-9 Procedure Codes: 39.61)	0.010 (0.033)	0.7596	0.012 (0.033)	0.7182	0.011 (0.033)	0.750	0.008 (0.034)	0.8047
Cardiogenic shock (ICD-9 Code 785.51)	0.319 (0.033)	<.0001	0.319 (0.033)	<.0001	0.318 (0.033)	<.0001	0.313 (0.033)	<.0001
Chronic obstructive pulmonary disease (COPD) (CC 108)	0.298 (0.017)	<.0001	0.290 (0.017)	<.0001	0.298 (0.017)	<.0001	0.296 (0.018)	<.0001
Renal failure (CC 131)	0.244 (0.021)	<.0001	0.241 (0.021)	<.0001	0.243 (0.021)	<.0001	0.243 (0.021)	<.0001
Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)	0.146 (0.016)	<.0001	0.141 (0.016)	<.0001	0.145 (0.016)	<.0001	0.141 (0.016)	<.0001
Other endocrine/metabolic/nutritional disorders (CC 24)	-0.038 (0.032)	0.2394	-0.035 (0.032)	0.2854	-0.038 (0.032)	0.2434	-0.037 (0.033)	0.2565
Congestive heart failure (CC 80)	0.176 (0.020)	<.0001	0.173 (0.020)	<.0001	0.176 (0.020)	<.0001	0.176 (0.020)	<.0001
Specified arrhythmias and other heart rhythm disorders (CC 92-93)	0.109 (0.017)	<.0001	0.111 (0.017)	<.0001	0.110 (0.017)	<.0001	0.107 (0.018)	<.0001
Other lung disorders (CC 115)	0.072 (0.017)	<.0001	0.071 (0.017)	<.0001	0.072 (0.017)	<.0001	0.071 (0.017)	<.0001
Major psychiatric disorders (CC 54-56)	0.165 (0.034)	<.0001	0.157 (0.034)	<.0001	0.166 (0.034)	<.0001	0.165 (0.034)	<.0001
Vascular or circulatory disease (CC 104-106)	0.113 (0.017)	<.0001	0.111 (0.017)	<.0001	0.113 (0.017)	<.0001	0.114 (0.017)	<.0001

Parameter	Original Model		Original Model + Dual Eligible		Original Model + Race		Original Model + AHRQ SES Index	
	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value	GLMM Estimate (Standard Error)	P value
Disorders of fluid/electrolyte/acid-base (CC 22-23)	0.081 (0.021)	0.0001	0.080 (0.021)	0.0001	0.081 (0.021)	0.0001	0.086 (0.021)	<.0001
Pneumonia (CC 111-113)	0.172 (0.022)	<.0001	0.168 (0.022)	<.0001	0.172 (0.022)	<.0001	0.166 (0.023)	<.0001
Cerebrovascular disease (CC 97-99, 103)	-0.042 (0.018)	0.0207	-0.041 (0.018)	0.0237	-0.041 (0.018)	0.022	-0.040 (0.018)	0.0269
Polyneuropathy (CC 71)	0.171 (0.024)	<.0001	0.171 (0.024)	<.0001	0.171 (0.024)	<.0001	0.167 (0.024)	<.0001
Protein-calorie malnutrition (CC 21)	0.274 (0.033)	<.0001	0.270 (0.033)	<.0001	0.274 (0.033)	<.0001	0.274 (0.033)	<.0001
Severe hematological disorders (CC 44)	0.351 (0.078)	<.0001	0.350 (0.078)	<.0001	0.350 (0.078)	<.0001	0.361 (0.078)	<.0001
Fibrosis of lung or other chronic lung disorders (CC 109)	0.056 (0.035)	0.1127	0.058 (0.035)	0.0978	0.056 (0.035)	0.109	0.062 (0.035)	0.0799
Decubitus ulcer or chronic skin ulcer (CC 148-149)	0.276 (0.037)	<.0001	0.273 (0.037)	<.0001	0.276 (0.037)	<.0001	0.282 (0.037)	<.0001
Dialysis status (CC 130)	0.368 (0.048)	<.0001	0.356 (0.048)	<.0001	0.362 (0.049)	<.0001	0.363 (0.049)	<.0001
Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)	0.042 (0.040)	0.3033	0.033 (0.041)	0.4182	0.041 (0.040)	0.314	0.045 (0.041)	0.2748
Stroke (CC 95-96)	0.043 (0.036)	0.232	0.042 (0.036)	0.2435	0.042 (0.036)	0.238	0.032 (0.036)	0.3851
Dementia or other specified brain disorders (CC 49-50)	0.118 (0.031)	<.0001	0.113 (0.031)	0.0003	0.117 (0.031)	0.0001	0.117 (0.031)	0.0002
Cancer (CC 7-12)	0.029 (0.019)	0.1384	0.032 (0.019)	0.0993	0.028 (0.019)	0.142	0.028 (0.020)	0.1572
Dual Eligible	-	-	0.182 (0.026)	<.0001	-	-	-	-
African-American Race	-	-	-	-	0.040 (0.034)	0.2354	-	-
Low AHRQ SES Index	-	-	-	-	-	-	0.070 (0.019)	0.0002

6. Describe the method of testing/analysis used to develop and validate the adequacy of the statistical model or stratification approach (describe the steps—do not just name a method; what statistical analysis was used).

We computed three summary statistics for assessing model performance (Harrell and Shih, 2001) for the cohorts:

Discrimination Statistics

(1) Area under the receiver operating characteristic (ROC) curve (the c-statistic [also called ROC curve] is the probability that predicting the outcome is better than chance, which is a measure of how accurately a statistical model is able to distinguish between a patient with and without an outcome)

(2) Predictive ability (discrimination in predictive ability measures the ability to distinguish high-risk subjects from low-risk subjects. Therefore, we would hope to see a wide range between the lowest decile and highest decile)

Calibration Statistics

(3) Over-fitting indices (over-fitting refers to the phenomenon in which a model accurately describes the relationship between predictive variables and outcome in the development dataset but fails to provide valid predictions in new patients)

Results:

We tested the performance of the model for the 2008-2010 development dataset.

- Dates of Data: January 1, 2008 – December 30, 2010
- Number of Admissions: 62,811 (2008 cohort); 58,676 (2009 cohort); 54,404 (2010 cohort)
- Number of Measured Entities: 1,163 (2008 cohort); 1,160 (2009 cohort); 1,164 (2010 cohort)

During initial measure development, we tested the performance of the model developed in the hospitalizations for CABG in 2009 compared with performance calculated from hospitalizations 2008 and 2010.

Discrimination Statistics

For the 2008-2010 development dataset, the results are summarized below:

- 2009 development cohort: c-statistic = 0.62; predictive ability (lowest decile %, highest decile %) = (8.7, 29.8)
- 2008 validation cohort: c-statistic = 0.63; predictive ability (lowest decile %, highest decile %) = (8.8, 30.5)
- 2010 validation cohort: c-statistic = 0.63; predictive ability (lowest decile %, highest decile %) = (8.4, 30.3)

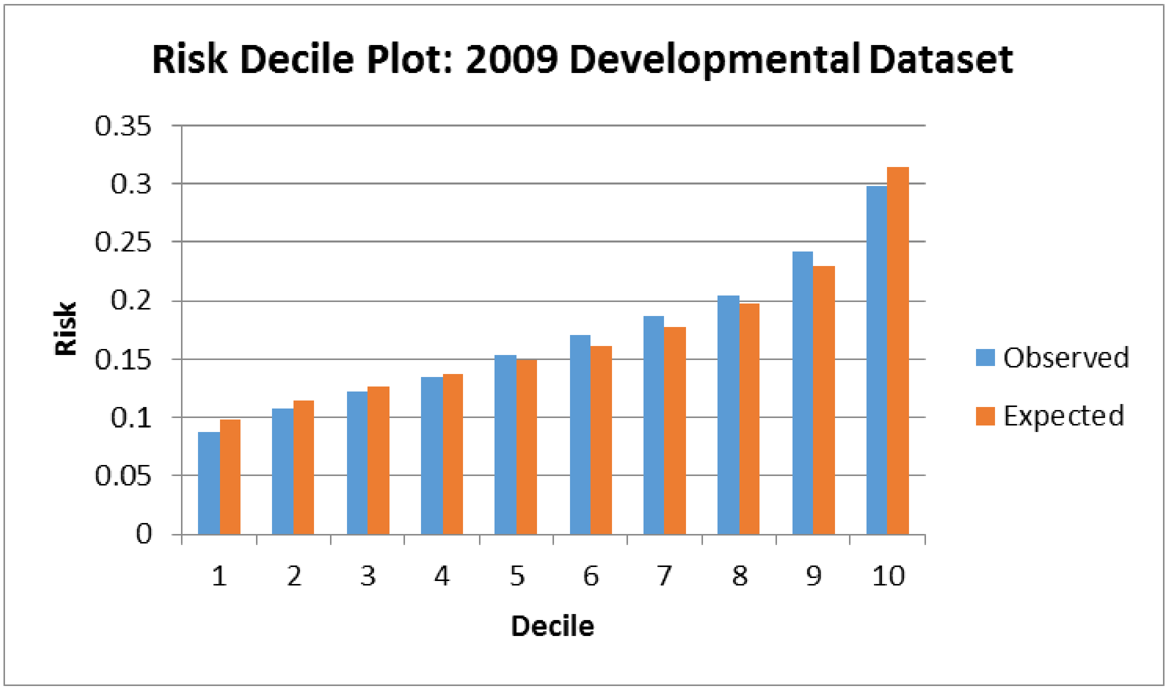
For comparison of model with and without inclusion of SDS factors, see Question #5.

Calibration Statistics

For the 2008-2010 original measure development dataset, the results are summarized below:

- 2009 development cohort: Calibration: (0,1)
- 2008 validation cohort: Calibration: (0.02, 1.01)
- 2010 validation cohort: Calibration: (-0.03, 1.00)

The risk decile plot is a graphical depiction of the deciles calculated to measure predictive ability. Below, we present the risk decile plot showing the distributions for fee-for-service (FFS) Medicare data for the 2009 development cohort, which is representative of the risk decile plots for all other datasets.



<u>Reference:</u>

F.E. Harrell and Y.C.T. Shih, Using full probability models to compute probabilities of actual interest to decision makers, *Int. J. Technol. Assess. Health Care* 17 (2001), pp. 17–26.

7. Discuss the risks for misuse of the specified performance measure. This discussion could include information on the known limitations of the performance measure that could impact its use in accountability programs.

We did not identify any unintended consequences during measure development, model testing, or reevaluation. However, we are committed to ongoing monitoring of this measure's use and assessing potential unintended consequences over time, such as the inappropriate shifting of care, increased patient morbidity and mortality, and other negative unintended consequences for patients. We are aware of stakeholder concern that not adding patient-level SES or race variables into the readmission model might disproportionately penalize hospitals caring for a higher proportion of patients with low SES. Acknowledging this concern, we tested the effect of including SES or race variables into the measure, and additionally completed a decomposition analysis to understand whether the effect of the SES or race variables were at either the patient or the hospital level. The decomposition results suggest that the hospital-level effect is significant for both SES variables and the African-American race variables. If these variables are used to adjust for patient-level differences, then differences between hospitals would also be affected, which could potentially obscure a signal of hospital quality. While we do not recommend adjusting for SES or race in this measure, we do believe that there may be better pathways outside of patient-level risk adjustment to address stakeholder concerns about financial penalties.

8. If a performance measure includes SDS variables in its risk adjustment model, the measure developer should provide the information required to stratify a clinically-adjusted only version of the measure results for those SDS variables. This information may include the stratification variables, definitions, specific data collection items/responses, code/value sets, and the risk-model covariates and coefficients for the clinically-adjusted version of the measure when appropriate.

N/A

9. Please enter the details of the final statistical risk model and variables here.

Our approach to risk adjustment is tailored to and appropriate for a publicly reported outcome measure, as articulated in the American Heart Association (AHA) Scientific Statement, "Standards for Statistical Models Used for Public Reporting of Health Outcomes" (Krumholz et al., 2006).

The measure employs a hierarchical logistic regression model to create a hospital-level 30-day, all-cause, RSRR. In brief, the approach simultaneously models data at the patient and hospital levels to account for the variance in patient outcomes within and between hospitals (Normand & Shahian, 2007). At the patient level, the model adjusts the log-odds of readmission within 30 days of discharge for age, gender, and selected clinical covariates. At the hospital level, the approach models the hospital-specific intercepts as arising from a normal distribution. The hospital intercept represents the underlying risk of readmission at the hospital, after accounting for patient risk. If there were no differences among hospitals, then after adjusting for patient risk, the hospital intercepts should be identical across all hospitals.

The final set of risk adjustment variables is:

<u>Demographics</u>

- Age minus 65 (years above 65, continuous)
- Male

<u>Comorbidities</u>

- History of prior CABG or valve surgery (ICD-9 Diagnosis Codes: V42.2, V43.3, V45.81, 414.02, 414.03, 414.04, 414.05, 414.06, 414.07, 996.02, 996.03 ; ICD-9 Procedure Codes: 39.61)
- Cardiogenic shock (ICD-9 Code 785.51)
- Chronic obstructive pulmonary disease (COPD) (CC 108)
- Renal failure (CC 131)
- Diabetes mellitus (DM) or DM complications (CC 15-20, 119-120)
- Other endocrine/metabolic/nutritional disorders (CC 24)
- Congestive heart failure (CC 80)
- Specified arrhythmias and other heart rhythm disorders (CC 92-93)
- Other lung disorders (CC 115)
- Major psychiatric disorders (CC 54-56)
- Vascular or circulatory disease (CC 104-106)
- Disorders of fluid/electrolyte/acid-base (CC 22-23)
- Pneumonia (CC 111-113)
- Cerebrovascular disease (CC 97-99, 103)
- Polyneuropathy (CC 71)
- Protein-calorie malnutrition (CC 21)
- Severe hematological disorders (CC 44)
- Fibrosis of lung or other chronic lung disorders (CC 109)
- Decubitus ulcer or chronic skin ulcer (CC 148-149)
- Dialysis status (CC 130)
- Hemiplegia, paraplegia, paralysis, functional disability (CC 67-69, 100-102, 177-178)
- Stroke (CC 95-96)
- Dementia or other specified brain disorders (CC 49-50)
- Cancer (CC 7-12)

References:

Krumholz HM, Brindis RG, Brush JE, et al. 2006. 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 113: 456-462.

Normand S-LT, Shahian DM. 2007. Statistical and Clinical Aspects of Hospital Outcomes Profiling. Stat Sci 22 (2): 206-226.

Pope GC, et al. 2000. Principal Inpatient Diagnostic Cost Group Models for Medicare Risk Adjustment. Health Care Financing Review 21(3): 93-118.

10. Compare measure performance scores with and without SDS factors in the risk adjustment model. Include the method of testing conducted to compare performance scores with and without SDS factors in the risk adjustment model for the same entities, the statistical results from testing the differences in the performance scores with and without SDS factors in the risk adjustment model. (e.g., correlation, rank order) and provide an interpretation of your results in terms of the differences in performance scores with and without SDS factors in the risk adjustment model for the same entities.

As explained in Question #5, we examined the strength and significance of the SES and race variables in the context of a multivariable model. The addition of any of these variables into the model has little to no effect on hospital performance. We examined the change in hospitals' RSRRs with the addition of these variables.

The median absolute change in hospitals' RSRRs when adding a dual eligibility indicator is 0.010% (IQR: -0.018% – 0.030%, minimum -0.316% – maximum 0.103%) with a correlation coefficient between RSRRs for each hospital with and without dual eligibility added of 0.99928. The median absolute change in hospitals' RSRRs when adding a race indicator is 0.003% (IQR: -0.003% – 0.007%, minimum -0.089% – maximum 0.018%) with a correlation coefficient between RSRRs for each hospital with and without race added of 0.99995. The median absolute change in hospitals' RSRRs when adding an indicator for a low AHRQ SES Index score is 0.030% (IQR: -0.051% – 0.091%, minimum -1.158% – maximum 0.365%) with a correlation coefficient between RSRRs for each hospital with and without an indicator for a low AHRQ SES Index score added of 0.99205.

11. Appendix (includes literature review, reference list, etc.)

N/A

Developer Responses: Readmissions SDS Trial Webinar #1

Measure: NQF #0505 Hospital 30-day all-cause risk-standardized readmission rate (RSRR) following acute myocardial infarction (AMI) hospitalization

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

A variety of sociodemographic status (SDS) risk factors may influence readmission risk following a hospital visit for acute myocardial infarction (AMI). Although some recent literature evaluates the relationship between patient SDS and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways. With respect to AMI, several factors including race/ethnicity, income, marital status, and education status have been looked at, but the associations have been inconclusive [1]. Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission. The risk factors that have been examined in the SDS readmission literature can be categorized into three domains: (1) patient-level variables, (2) neighborhood/community-level variables, and (3) hospital- level variables. Patient-level variables describe characteristics of individual patients, and range from the race or ethnicity of the patient to the patient's income or education level [2, 3]. Neighborhood/community-level variables use information from sources such as the American Community Survey (ACS) as either a proxy for individual patient-level data or to measure environmental factors. Studies using these variables use one dimensional measures such as median household income or composite measures such as the Agency for Healthcare Research and Quality (AHRQ)- validated SES index score [4]. Hospital-level variables measure attributes of the hospital which may be related to patient risk. Examples of hospital-level variables used in studies are ZIP code characteristics aggregated to the hospital level or the proportion of Medicaid patient days [5, 6].

The conceptual relationship, or potential causal pathways by which these possible SDS risk factors influence the risk of return to the hospital following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider. We briefly describe them here and comment on their implications for the hospital readmission measures.

1. Relationship of SDS to health at admission. Sociodemographic disadvantage often leads to worse general health status and therefore patients who have lower income/education/literacy or unstable

housing may present for their hospitalization or procedure with a greater severity of underlying illness. These SDS risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may also contribute to worse health status at admission due to patients failing to respond to early symptoms and presenting for treatment later in their disease progression. This causal pathway should be largely accounted for by current clinical risk- adjustment.

However, while studies have shown that variables such as race are associated with worse health status, race itself may not directly affect health status at hospital admission. Rather, the association of race with worse health is likely mediated through the association between race and other sociodemographic factors such as poverty or disparate access to high quality care.

2. Use of low-quality hospitals. SDS risk factors may be associated with access to quality healthcare providers because of the distribution of providers and prohibitive costs. In particular, SDS factors can influence the likelihood that patients access high quality care. Patients of lower income, lower education, or unstable housing may not have access to high quality facilities because such facilities are less likely to be found in lower SDS geographic areas. Poor and minority patients are more likely to be seen in lower quality hospitals, which can contribute to the likelihood of hospital readmission [7-9]. To the extent that the relationship between SDS and readmission is driven by clustering of low SDS patients within lower quality facilities, traditional patient-level risk adjustment for SDS would be inappropriate.

3. Differential care within a hospital. The third major pathway by which SDS factors may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, patients of low income or minority race may experience differential, lower quality, or discriminatory care within a given facility [10]. Alternatively, patients with SDS risk factors may require differentiated care – e.g. provision of lower literacy information – that they do not receive. That is to say, hospitals may provide the same care for all populations (e.g. the same discharge instructions) and this may represent substandard care for patients for whom the standard approach is not effective (e.g. due to low literacy). By failing to actively address the unique needs of patients with SDS risk factors, institutions may be providing lower quality care to these patients. Again, in such circumstances, patient-level risk adjustment for SDS is problematic as it would essentially adjust for a characteristic of the care provided rather than for a patient risk factor.

4. Influence of SDS on readmission risk outside of hospital quality and health status. Some SDS risk factors, such as income or wealth, may affect the likelihood of hospital readmission without directly affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and

education, a lower-income patient may be less likely to follow prescribed care (e.g. refill a prescription or keep a follow-up visit with a primary care provider) because limited resources create competing priorities for the patient or their community may have a limited supply of primary care providers. These kinds of pathways present more complex questions about appropriate risk-adjustment decisions.

References:

1. Damiani G, Salvatori E, Silvestrini G, et al. Influence of socioeconomic factors on hospital readmissions for heart failure and acute myocardial infarction in patients 65 years and older: evidence from a systematic review. Clinical interventions in aging. 2015;10:237-245.

2. Hu J, Gonsahn MD, Nerenz DR. Socioeconomic status and readmissions: evidence from an urban teaching hospital. Health affairs (Project Hope). 2014;33(5):778-785.

3. Eapen ZJ, McCoy LA, Fonarow GC, Yancy CW, Miranda ML, Peterson ED, Califf RM, Hernandez AF. Utility of socioeconomic status in predicting 30-day outcomes after heart failure hospitalization.

Circ Heart Fail. 2015 May;8(3):473-80.

4. Blum AB; Egorova NN; Sosunov EA; Gelijns AC; DuPree E; Moskowitz AJ; Federman AD; Ascheim DD; Keyhani S. Impact of socioeconomic status measures on hospital profiling in New York City. Circ Cardiovasc Qual Outcomes. 7(3):391-7, 2014 May.

5. Joynt KE, Jha AK. Characteristics of hospitals receiving penalties under the Hospital Readmissions Reduction Program. JAMA. 2013 Jan 23;309(4):342-3.

6. Gilman M, Adams EK, Hockenberry JM, Wilson IB, Milstein AS, Becker ER. California safety-net hospitals likely to be penalized by ACA value, readmission, and meaningful-use programs.

Health Aff (Millwood). 2014 Aug;33(8):1314-22.

7. Jha AK, Orav EJ, Epstein AM. Low-quality, high-cost hospitals, mainly in South, care for sharply higher shares of elderly black, Hispanic, and Medicaid patients. Health affairs (Project Hope). Oct 2011;30(10):1904-1911.

8. Reames BN, Birkmeyer NJ, Dimick JB, Ghaferi AA. Socioeconomic disparities in mortality after cancer surgery: failure to rescue. JAMA surgery. May 2014;149(5):475-481.

9. Skinner J, Chandra A, Staiger D, Lee J, McClellan M. Mortality After Acute Myocardial Infarction in Hospitals That Disproportionately Treat Black Patients. Circulation. 2005;112(17):2634-2641.

10. Trivedi AN, Nsa W, Hausmann LRM, et al. Quality and Equity of Care in U.S. Hospitals. New England Journal of Medicine. 2014;371(24):2298-2308.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

Since these measures have been developed and implemented using national-level data, there is substantial variation in SDS risk factors across hospitals. Two variables we have presented in our NQF applications provide empirical evidence that this variation exists. For the AMI Readmission measure, the percentage of patients who are black ranges from 0% to 96.0% across hospitals, with a median of 4.0% (interquartile range [IQR] 1.2%-11.1%). The percentage of patients who are Medicaid beneficiaries ranges from 0% to 76.1% across hospitals, with a median of 18.3% (IQR 13.4%- 22.8%). This information was based on the most current data for reporting.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The variables that are available within or that can be linked directly to Medicare administrative claims data used for these measures include the following:

1. Race (black, white, other). Data source: Medicare claims, enrollment database.
2. Medicaid dual-eligible status. Data source: Medicare claims, enrollment database.
3. Neighborhood SES factors as proxies for patient-level SES [1]. Data source: Enrollment database and Census data (American Community Survey).

References:

1. Creation of New Race-Ethnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries: Final Report. August 2012. Agency for Healthcare Research and Quality, Rockville, MD. http://archive.ahrq.gov/research/findings/final-reports/medicareindicators/index.html

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

SDS is a multifaceted phenomenon (more so than clinical factors) and therefore it is unlikely that a single SDS factor will fully and consistently capture the aspects of SDS which affect the risk of readmission through the causal pathways described above.

Dual-eligible status: For our readmission measures, which include Medicare fee-for-service (FFS) beneficiaries aged 65 years and older, dual-status is a good indicator of current assets and income and dual-eligibility criteria are consistent across most states (though cost of living varies) [1]. We think this is, therefore, a reasonable patient-level variable to assess the relationship between SDS and readmission in that it provides a reliably-obtained indication of patients with low income/assets. There are two important caveats: first, dual-eligible status is a dichotomous variable and thus provides less gradation of SDS; and second, for some patients dual-eligibility is the result of a “spending down” to obtain coverage for nursing care. For such patients, it is difficult to differentiate between those who may have faced a lifetime of low SDS and associated challenges versus those who have had more resources earlier in life and only recently became classified as low income.

Race: The particular case of race as a predictor of health outcomes illuminates the complexity of the role SDS variables play in assessing hospital performance. Racial identity itself confers no differential risk of mortality or readmission following hospitalization. The evidence suggests that a greater prevalence of risk factors in combination with the effects of bias and discrimination account for differential outcomes observed among certain racial groups. This is not to say that there are no meaningful biological variations among groups whose genetic ancestry can be traced to different geographic regions of the world. However, these variations are quite specific and narrowly defined and have not been shown confer broad health risks across groups absent specific genetic markers. Nevertheless, numerous studies have demonstrated greater disease burden, lack of access to health care services, and bias in application of medical intervention among racial minorities, particularly black patients seeking care for a variety of medical and surgical conditions.

In risk-adjusted statistical models of readmission following hospitalization, race is a marker for other SDS factors, such as poverty or social support; however, we often find that the association between race and readmission is greater and more robust or consistent than that of economic factors. The absence of any biologically defined causal pathway suggests that this stronger association may result from exposure to broad societal racial bias. We can determine the specific health outcome-related effects of exposure to societal racial bias through quality measurement, as the health outcome is relatively consistent across exposed individuals. Poverty may have more nuanced effects dependent on unmeasured factors such as the surrounding community, familial support, and others.

Whether we should we include a risk variable to adjust for the presence of this bias depends on whether or not the risk conferred through bias is attributable to factors within or beyond the hospitals' control. The evidence that blacks receive differential care across a variety of medical and surgical conditions suggests that, even as this bias exists broadly throughout the institutions of society, hospitals and providers also contribute to it [2]. If so, this contribution of the hospital – the effect of treatment bias – should not be included in risk adjusted models of hospital performance as to do so would, in effect, be giving hospitals credit for more disparate or discriminatory care.

ZIP Code-level SDS indicators: The American Community Survey (ACS) provides a number of SDS indicators that are available at the ZIP code level. We are in the process of developing an approach to linking these data to at the 9-digit ZIP code level, which will allow for a more granular perspective on local SDS. We propose to analyze an Agency for Healthcare Research and Quality (AHRQ)-validated composite index of SES which has been used and tested among Medicare beneficiaries [3]. This index is a composite of seven different variables found in the Census data which may capture SDS better than any single variable. The variables are: (1) median household income, (2) percentage of persons living below the federal poverty level, (3) percentage of persons who are aged >16 years and in the labor force but not employed, (4) median value of owner-occupied homes, (5) percentage of persons aged >25 years who completed at least a 12th grade education, (6) percentage of persons aged >25 years who completed at least four years of college, and (7) percentage of households that average one or more persons per room. This is a neighborhood-level variable, which we would use as a proxy for patient-level SDS factors.

References:

1. Medicaid.gov. "Seniors & Medicare and Medicaid Enrollees." Centers for Medicare & Medicaid Services. http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Population/Medicare-Medicaid-Enrollees-Dual- Eligibles/Seniors-and-Medicare-and-Medicaid-Enrollees.html. Accessed August 24, 2015.

2. Barnato AE, Lucas FL, Staiger D, Wennberg DE, Chandra A. Hospital-level Racial Disparities in Acute Myocardial Infarction Treatment and Outcomes. Medical care. 2005;43(4):308-319.

3. Creation of New Race-Ethnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries: Final Report. August 2012. Agency for Healthcare Research and Quality, Rockville, MD. http://archive.ahrq.gov/research/findings/final-reports/medicareindicators/index.html. Accessed August 24, 2015.

Measure: NQF # 0695 Hospital 30-Day Risk-Standardized Readmission Rates following Percutaneous Coronary Intervention (PCI)

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

[Repeating original response] Studies have suggested that across a number of conditions and procedures, patients' risk of readmission varies by sociodemographic status. However, there is limited scientific literature that links sociodemographic factors to hospital-level risk standardized readmission rates (RSRR).

This readmission post PCI measure is mapped to Medicare claims data, thus requiring the patient population evaluated be covered with CMS insurance. Our measure includes variables for gender and age. Race and ethnicity are captured within the registry dataset. Consistent with the previous recommendation to exclude socioeconomic status and race from statistical risk models, these variables were not included in the PCI readmission measure.

The preponderance of data suggests that hospital related factors, specifically detailed discharge planning and post discharge follow up, exert a stronger influence on readmission rates. A 2011 systematic review of 43 studies, 16 of which were randomized trials, found that the strategies employed in successful studies involved several simultaneous interventions, including patient-centered discharge instructions and a post discharge telephone call. A 2012 systematic review identified several interventions (including medication reconciliation, structured electronic discharge summaries, discharge planning, and facilitated communication between hospital and community providers) that favorably influenced readmission rates (Hesselink, 2012).

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the

measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

[Repeating original response] The socioeconomic status analyses included within the NQF application for this measures provides the strongest evidence suggesting that these SDS factors do not exert a strong impact on hospital RSRR.

We analyzed whether disparities in performance on this measure exist at the hospital level. To identify potential disparities, we examined the relationship between hospital-level RSRR and hospital proportion of African- American patients among all hospitals grouped by quintile of the proportion of African-American patients. We used the Medicare Provider Analysis and Review (MEDPAR) File for 2010 to calculate the proportion of African-American patients treated at each hospital, using all patients admitted to each hospital. There were 277,439 admissions to 1,195 hospitals.

Our analyses demonstrated that there were modest differences in the RSRRs by quintile. Specifically, the median RSRR for hospitals with the highest proportion of African-American patients was 12.4% compared with 11.2% for hospitals with the lowest proportion of African-American patients. In comparison to the registry average of 11.8%, hospitals with high proportions of African-American patients have modestly higher 30-day RSRRs. However, the distributions for the RSRRs overlapped across hospital quintiles, and many hospitals caring for the highest percentage of African-American patients performed well on the measures.

Similarly, to identify potential disparities related socoioeconomic status, we examined the relationship between RSRR and hospital proportion of dual eligible patients. We used the MEDPAR File for 2010 to calculate the percentage of patients 65 or older and eligible for both Medicare and Medicaid (dual eligible patients) treated at each hospital. There were 277,439 admissions to 1,195 hospitals. The proportion of dual eligible patients was used as a marker for determining the SES status of hospitals' patients because this is a low income and vulnerable population. Similar to the analysis above, we examined hospital-level RSRRs across quintiles of the proportion of dual eligible patients.

There were no differences in RSRRs across income quintile. Analyses demonstrated that the median RSRR for hospitals in the top quintile of dual eligible patients was 12.3% compared with 11.6% for hospitals in the bottom quintile of dual eligible patients. In comparison to the registry average of 11.8%, hospitals that treat a high percentage of dual eligible patients have moderately higher 30-day RSRRs. However, the distributions for the RSRRs overlapped, and many hospitals in the highest quintile of dual eligible patients performed well on the measure.

Aside from our own analysis, an exhaustive review of the literature found only one, single center study that identified a possible link between sociodemographic factors and readmissions post PCI. Khawaja and colleagues reported on a review of over 15,000 patients who underwent (both urgent and non-urgent) PCI between 1998 and 2008, the 30-day readmission rate was 9.4 percent (Khawaja, 2012). The author's intent was to identify factors associated with 30-day readmission rates. Demographic variables, including age and sex, were collected from the Mayo Clinic PCI registry.

Additional demographic variables were collected from Mayo Clinic administrative databases and merged with the PCI registry. These variables included marital status (single, married, divorced, separated, or widowed), education level (eighth grade or less, some high school, high school graduate or equivalent, some college, college graduate, postgraduate studies, or unknown), miles traveled to Mayo Clinic, and insurance type (Medicare, Medicaid, uninsured, or privately insured). Clinical variables were also evaluated. After their multivariable analysis, the following factors were found to be associated with an increased risk of readmission: female sex, Medicare insurance, having less than a high school education, unstable angina, cerebrovascular accident or transient ischemic attack, moderate to severe renal disease, chronic obstructive pulmonary disease, peptic ulcer disease, metastatic cancer, and a length of stay of more than three days (Khawaja, 2012).

While patient's level of education had a weak association, it is one isolated sociodemographic risk factor that has been identified to influence readmission rates throughout the literature. Wasfy et al. (2013), provided evidence from a 5573 patients during 2007 -2011 in a single center study, identifying that the largest proportion of readmissions after PCI is due to symptoms that prompt concern for angina. The overwhelming majority of which (90.0%) do not require repeat revascularization (Wasfy, 2013). Feasible suggestions to reduce readmission rates derived from this study suggested that hospitals may be able to minimize 30-day readmission rates after PCI substantially by postponing non-urgent, non- coronary procedures after PCI. Transferring the evaluation of low-risk chest pain to the outpatient setting or to emergency department observation units could dramatically reduce 30 day readmission rates after PCI (Wasfy, 2013). These suggestions to reduce the rate of readmission are actionable, feasible and do not add additional burden to the hospitals. Requiring hospitals to query each patient for their level of education, would increase data collection burden and demands on the hospitals for minimal gains.

The NQF Technical Report (2014, p. 40) clearly states that "data constraints may be the biggest barrier to adjustment for sociodemographicfactors and will require further initiatives to define standards and to implement datacollection". The National Committee on Vital and Health Statistics proposed that education (i.e., years of schooling) should be

considered a core health data element that should be standardized in healthcare and healthcare information fields (NCVHSR, 1996). Despite this recommendation nearly two decades ago, education is not widely collected in healthcare. The NQF Technical Report references work by Kirst et al, (2013) to support the concept that “education may be easier to collect from patients with fewer refusals” than elements such as household income (NQF Technical Panel Report, p.41). In the original article Kirst explains what was required to attain a response rate of only 2.9%.

“… A public opinion and market research firm was employed to administer the survey… 72,216 calls were attempted.

…. After excluding, answering machines, calls with no answer, language barriers, ill or incapable respondents, and no eligible respondent being available, a total of 15,976 people were asked to participate in the survey. Of these .. 1,306 [qualified] as eligible and completed the interview. This represents a response rate of 2.9%, with 8.2% of persons asked to complete the survey doing so.

Willingness to participate in the survey was taken to imply consent, and no personal identifiers were collected. Surveys were conducted in English and French…” (Kirst, 2013).

While potentially feasible from a clinical trial with the ability to finance a public opinion and market research firm to capture the level of educate data, this is not feasible at a hospital level.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

Datasets used to develop this measure include the CathPCI Registry and the Medicare Provider and Analysis Review (MEDPAR) file.

Patient-level sociodemographic variables available in the CathPCI Registry dataset include: gender, race, Hispanic ethnicity, age, zip code, and insurance status.

Patient-level sociodemographic variables available in the MEDPAR dataset includes: gender, race, Hispanic ethnicity, age and zip code.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

SDS Variable #1: African American Race

As described above, the empirical analyses conducted during measure development demonstrates that there were modest differences in the RSRRs by quintile. Specifically, the median RSRR for hospitals with the highest proportion of African-American patients was 12.4% compared with 11.2% for hospitals with the lowest proportion of African-American patients. In comparison to the registry average of 11.8%, hospitals with high proportions of African-American patients have modestly higher 30-day RSRRs. However, the distributions for the RSRRs overlapped across hospital quintiles, and many hospitals caring for the highest percentage of African-American patients performed well on the measures.

SDS Variable #2: Income

There were no differences in RSRRs across income quintile. Analyses demonstrated that the median RSRR for hospitals in the top quintile of dual eligible patients was 12.3% compared with 11.6% for hospitals in the bottom quintile of dual eligible patients. In comparison to the registry average of 11.8%, hospitals that treat a high percentage of dual eligible patients have moderately higher 30-day RSRRs. However, the distributions for the RSRRs overlapped, and many hospitals in the highest quintile of dual eligible patients performed well on the measure.

In conclusion, empirical analysis for variables of African American race and income included within this measure suggest that SDS factors feasible for analysis do not exert a strong impact on hospital RSRR.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

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Measure: NQF #2375, PointRight® Pro 30™

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The literature on ethnic disparities in care in SNFs is scarce overall, with only two articles focusing on ethnic differences in rehospitalization rates. A Medline search of racial disparities in SNFs only yields 37 articles of which a fifth address issues related to ethnic disparities in access to SNF services. Of the remaining articles most address disparities in long term care but not for residents receiving short post-acute care services. Two articles focus on ethnic disparities related to hospitalizations (Li, 2011; Grunier, 2008). In the first study using national MDS data from 2008, the authors found that the 30 day rehospitalization rates were 14.3% for white patients (n = 865,993) and 18.6% for black patients (n = 94,651). Both patient and admitting facility characteristics accounted for a considerable portion of overall racial disparities, but disparities persisted after multivariable adjustments overall and in patient subgroups (Li, 2011). However, this study did not compare within-facility and between-facility disparities. Within-facility disparities are those where disparities exist between blacks and whites in the same facilities and between-facility disparities are those that exist between facilities with different racial composition (i.e. facilities with higher minority populations have poorer care quality than facilities with mostly white populations). Based on previous research related to racial disparities in SNFs, it is expected that disparities in rehospitalization would exist between facilities.

In the second article, hospitalization rates for long stay residents on Medicaid were examined (short stay residents were not included) (Grunier, 2008). In this study, using MDS data to look at long stay residents, 18.5% of white and 24.1% of black residents were hospitalized. Residents in nursing homes with high concentrations of blacks had 20% higher odds (95 percent confidence interval [CI]=1.15-1.25) of hospitalization than residents in nursing homes with no blacks. Ten- dollar increments in Medicaid rates reduced the odds of hospitalization by 4 percent (95% CI=0.93-1.00) for white residents and 22 percent (95% CI=0.69-0.87) for black residents.

Multiple studies in the past twenty years have examined racial disparities in the care of SNF residents and have consistently found poorer care in facilities with high minority populations (Fennell et al., 2000; Mor et al., 2004; Smith et al., 2007). Work on disparities in quality of care between elderly white and black residents within SNFs has shown clearly that nursing homes remain relatively segregated, and that nursing home care can be described as a tiered system in which blacks are concentrated in marginal-quality homes (Mor et al., 2004). Such homes tend to have serious deficiencies in staffing ratios, performance, and are more financially vulnerable (Smith et al, 2007; Chisholm et al., 2013). Based on a review of the SNF disparities literature, Konetzka and Werner (2009) concluded that disparities in care are likely related to racial and socioeconomic segregation as opposed to within-provider discrimination. This conclusion is supported, for example, by Grunier and colleagues who found that as the proportion of black residents in the nursing home increased the risk of hospitalization among all residents, regardless of race, also increased (Grunier et al., 2008). Rehospitalization risk likely also increases as the proportion of black residents increases, indicating that the best measure of racial disparities in rates of rehospitalization is one that measures rehospitalization at the facility level. Cai, S., Mukamel, D., & Temkin-Greener, H. (2010). Pressure ulcer prevalence among black and white nursing home residents in New York state: Evidence of racial disparity? Medical Care 48(3), 233-239.

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QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

To describe the relationship between the SDS risk factor(s) and the measured unit, we plan to analyze the quantitative effect of including or omitting the SDS characteristics (individually and collectively) on the risk adjustment model in terms of these four questions:

- What is the correlation between the SDS risk adjustor at each level of aggregation and the rehospitalization rate (controlling for the non-SDS risk adjustors) or rehospitalization indicator?
- What is the most appropriate level of aggregation at which to include each SDS risk adjustor? Should it be included at the facility-level, regional-level, or patient-level?
- Having chosen an appropriate set of SDS risk adjustors to include, and having decided the best level at which to include each of them into the model, what is the marginal improvement in the performance of the risk adjustment model when SDS adjustors are included? We will evaluate discrimination using C-statistics and R-squared statistics, and we will evaluate calibration using percentile plots percentile plots.

Disparity between the groups that are defined by the different levels of the SDS factor might be the result of differential care within a nursing home. This will be tested by exploring and adding into the model interaction terms of the SDS with other factors. Alternatively, it is possible that the disparity between the groups is rather due to differences resulting from the unequal quality of care across facilities. We will assess the effect of an SDS factor, avoiding confounding issues associated with quality of care, by fitting a model that further adjusts for the fixed effects of the nursing homes.

Correlation between the SDS risk adjustor and the rehospitalization rate/indicator. We will measure the correlation between the SDS characteristic at each level of aggregation, and the risk adjusted rehospitalization rate (regional and provider levels) or the rehospitalization indicator with the non-SDS risk adjustment model applied to it (patient level). It is important to do this net of the effects of the non-SDS risk adjustors already incorporated into the measure so that we do not focus on SDS characteristics that have already been accounted for by proxy, through the non-SDS clinical adjustors. By examining the correlations, we will understand the relative importance of each adjustor and can form a final shortlist for the SDS trial period project.

Levels of aggregation. We see three natural levels of analysis for including or omitting each SDS characteristic into the risk adjustment model: between-region variance in rehospitalization rates, within-region provider variance in rehospitalization rates, and within-facility patient variance in rehospitalization rates. Between-region variance reflects systematic differences in rehospitalization rates between one region and the next. Within-region provider variance reflects systematic differences in rehospitalization rates between the providers within a region. Within-provider variance reflects systematic differences in rehospitalization rates between the patients of a given provider.

We are still working to understand exactly how these different levels interact with the appropriateness of including or omitting SDS characteristics, but our preliminary understanding is that explaining variance at one level using an SDS characteristic may be desirable, where explaining variance at a different level for that characteristic may be undesirable. For example, adjusting for income differentials across regions, or between the providers of a region, may appropriately recognize that some providers serve poorer, higher-risk populations, but adjusting for differentials in income for patients within a provider may generate perverse patient selection incentives. We need to understand these contrasts in order to avoid causing perverse provider incentives.

Marginal improvement of revised risk adjustment model. For each expanded version of the risk adjustment model, we will re-test the performance of the risk adjustment model. This will parallel the same testing performed in the original NQF measure application. We will evaluate discrimination using C-statistics and R-squared statistics, and will evaluate calibration using percentile plots (actual rehospitalization rates grouped into quantiles vs mean expected rehospitalization rates).

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

Below are the patient-level sociodemographic variables that are available in the MDS.

Person characteristics:

- Race
- Age (already included in RA model)
- Sex (already included in RA model)
- Marital status (possibly crossed with age and sex)
- Language
- Gender
- Dual eligibility/state buy-in

Additionally, in the analysis phase we would like to explore the following variables as a proxy for individual level data.

- Facility characteristics:

- Percent of patients by race
- Percent of patients by age category
- Percent of patients by sex
- Percent of patients by gender
- Percent of patients by marital status
- Percent of patients by language
- Percent of patients by state buy-in indicator
- Percent of the facility's census that is receiving post-acute care (i.e., admitted from a hospital in the prior 30 days)
- Percent of the facility's census that is covered by Medicare FFS
- Percent of facility's residents with Medicaid benefits interacted with three levels of liberality of Medicaid eligibility, and three levels of liberality of per diem Medicaid SNF reimbursement
- The number of beds in the facility
- The ownership of the facility (nonprofit, for profit individual, for profit chain, public)

Regional characteristics (County or CBSA of SNF):

- Median household income
- Percent of households >= 133% of Federal poverty level
- Percent of adults eligible for Medicaid (according to state standards)
- Percent of persons >= 65 with private insurance
- Percent of persons >= 65 with Medicaid
- Percent of persons >= 65 with Medicare FFS
- Percent of persons >= 65 with Medicare Advantage
- Percent of persons in the labor force >= 25 who are unemployed
- Percent of persons >= 18 who are homeless
- Percent of persons aged >= 30 with a graduate degree; percent of persons aged >= 25 with a college degree
- Percent of persons >= 30 who live in rented dwellings
- Percent of people in the geographical region and the same demographic category who are poor

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

The available patient-level SDS variables of race and language well represent the issue of racial disparity. As noted above, studies have found poorer care in facilities with high minority populations (Fennell et al., 2000; Mor et al., 2004; Smith et al., 2007).

QUESTION 5: Appendix (includes literature review, reference list, etc.)

None.

Measure: NQF #2380: Rehospitalization during the First 30 days of Home Health

Measure: NQF #2505: Emergency Department (ED) Use without Hospital Readmission during the First 30 Days of Home Health

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

While a recent scoping review (Goodridge et al. 2012) found general agreement that persons of lower socioeconomic status are not disadvantaged in terms of HH care services, there is a well-documented socioeconomic gradient seen with primary and acute care services. Findings from the literature support a linkage between proposed SDS factors and ED use and hospital readmission. Individuals with lower social economic status (SES) are more likely to use EDs for primary health care services. In the home health setting, the 30-day period for re-hospitalization occurs while the patient is living in their own home, increasing the likelihood that non-medical factors, including geographic location and economic resources, will have an impact on acute care use. More specific findings regarding the documented relationship between socio-demographic factors, readmission and ED use are described below.

- A recent study of 30-day hospital readmission of elderly patients with initial discharge destination of HH care found race to be a significant predictor of readmission (Richmond, 2013).
- One study of 1375 patients examining differential use of EDs by various racial and ethnic groups found confounding impact by other SDS variables and concluded that programs to reduce inappropriate ED use must be sensitive to an array of complex socioeconomic issues and may necessitate a substantial paradigm shift in how acute care is provided in low SES communities. Research has also shown that ED wait time is also linked to factors related to race/ethnicity, with black patients having longer wait times than non-black patients (Hong et al. 2007).
- Even after adjustment for potential confounding factors, lower income is a positive predictor of readmission risk of patients for heart failure (Philbin et al. 2001).
- A study of community-dwelling elders with Medicare coverage discharged to home found that living alone and lower levels of education were significant predictors of readmission (Arbaje et al. 2008).
- Significant disparities have been found in visits to the ED for conditions sensitive to ambulatory care by race/ethnicity, insurance status, age group, and socioeconomic status (Johnson et al. 2012).

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

Several socio-demographic factors were used to stratify the population level outcomes of rehospitalization and ED use in our original submission to NQF, using all HH stays beginning between July 1, 2010 and June 30, 2013. These results support the decision to include age, sex, and disability status in the existing risk adjustment model and also show that both race/ethnicity and Medicaid Status vary and are correlated with different outcome rates. In previous measure development work, our team also examined the impact of urban or rural location on Acute Care Hospitalization (NQF 0171) and ED Use without Hospitalization (NQF 0173) measured during the first 60 days of HH care. Rural beneficiaries with home health stays starting between July 2010 and June 2011 had higher rates of 60 day ED Use and Acute Care Hospitalization than did urban beneficiaries. This measure development work also found that both Rural location and Medicaid Status were significant predictors of hospitalization and ED visits even after controlling for age, sex, and clinical risk factors. Please refer to tables 1 and 2 provided in previous memo to NQF for empirical data.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The current risk adjustment model for NQF 2380 and 2505 relies on five categories of risk factors:

- Prior Care Setting including: acute care received in 30 days prior to HH, acute care received in 6 months prior to HH, and length of index hospitalization
- Age and sex interactions
- Health Status as measures by: Hierarchical Condition Categories (HCCs) based on past 6 months of Medicare claims, Diagnosis-Related Grouping (DRGs) on index hospitalization, and activities of daily living indicators, as captured on HH claims
- Medicare Enrollment Status, which identifies beneficiaries who are eligible for Medicare due to End-Stage Renal Disease (ESRD) or who were originally eligible due to disability
- Additional interactions between HHCs and Medicare Enrollment Status

The current model already includes demographic characteristics of age and sex. Additionally, the prior care setting risk factors likely account for some of the impact that additional SDS factors have on acute care utilization. Finally, both the age categories and the Medicare Enrollment Status indicators identify beneficiaries who are disabled and disability may act as both a clinical risk factor and a socio-demographic factor, due to correlation with income or employment.

Our team has identified several additional socio-demographic factors that can be reliably and feasibly captured using existing data sources. These include:

- Race/Ethnicity – included in Medicare Enrollment Database (EDB)
- Medicaid Status – included in EDB
- Rural location – determined from beneficiary address, as captured in EDB
- Neighborhood characteristics – determined from beneficiary address linked to survey data, such as the American Community Survey, and potentially including median income, employment rate, and crime rate

CMS is also proposing to pursue additional indicators of SDS for evaluation of use in the measures, such as the Area Deprivation Index.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

As previously mentioned, the results from our original submission to NQF support the decision to include age, sex, and disability status in the existing risk adjustment model and also show that both race/ethnicity and Medicaid Status vary and are correlated with different outcome rates. In addition, measure development work found that both Rural location and Medicaid Status were significant predictors of hospitalization and ED visits even after controlling for age, sex, and clinical risk factors.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

Reference List

1. Arbaje AI, Wolff JL, Yu Q, Powe NR, Anderson GF, Boult C. Postdischarge environmental and socioeconomic factors and the likelihood of early hospital readmission among community-dwelling Medicare beneficiaries. Gerontologist. 2008 Aug; 48(4):495-504.
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Measure: NQF #2393: Pediatric All-Condition Readmission Measure

Measure: NQF #2414: Pediatric Lower Respiratory Infection Readmission Measure

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

Multiple factors within and outside of health systems contribute to a patient's health status after hospital discharge and thus influence the risk of readmission [1-3]. An important set of factors consists of patients' and families' social and economic conditions, which comprise both individual resources and community resources such as access to transportation and paid family leave [3-8]. Sociodemographic status (SDS) can affect health directly, as well as indirectly by having an impact on self-management, adherence to recommendations, and access to care [9–11]. Nearly 21% of children live in poverty—a rate almost double that for adults—making effects of SDS on health especially relevant to pediatrics [12].

To examine the impact of SDS on pediatric all-condition hospital readmissions, we evaluated the relationship between readmission risk and insurance status.

Evidence in the Literature

We chose to focus on insurance status because multiple studies in the literature have demonstrated that public insurance is associated with higher pediatric readmission rates [13-18]. For example, an analysis of community (non- children's) hospitals in the 2007 AHRQ Healthcare Cost and Utilization Project (HCUP) State Inpatient Databases for Arizona, Nebraska, and South Carolina found that the unadjusted 30-day all-condition readmission rate for pediatric Medicaid beneficiaries (ages 0 to 20 years old, including newborns but excluding obstetric patients) was 3.1%, compared with 2.0% for privately insured children ($p < 0.05$) [17]. Within the full sample of Medicaid-insured adult and pediatric patients, readmission rates were higher than for privately insured patients except for the subcategory of 13- to 20-year-old females admitted for obstetric care [17].

Readmissions at children's hospitals are likewise more frequent in publicly insured children than in patients with other insurance statuses. A study of recurrent all-condition readmissions at 37 freestanding children's hospitals found that as a patient's annual readmission frequency increased from 0 to ≥ 4 readmissions, the rate at which patients were publicly insured correspondingly increased from 40.9% (0 readmissions) to 56.3% (≥ 4 readmissions) ($p < .001$) [16]. Public (versus commercial) insurance remained significantly associated with readmission risk in multivariate analysis (odds ratio [OR] 1.36, 95% CI 1.33-1.40) [16]. Similarly, in an analysis of all-condition readmissions at 72 freestanding and non-freestanding children's hospitals, the unadjusted readmission rate was highest for publicly insured patients (6.9%), followed by those who had other insurance (6.2%), private insurance (5.9%), and no insurance (4.5%) ($p < .001$) [19]. Public (versus private) insurance was a significant risk factor for readmission in multivariate analysis (OR 1.12, 95% CI 1.09-1.15) [19].

Given their higher risk of readmission, publicly insured children are a vulnerable population for whom targeted interventions to reduce readmissions are critical. The percentage of pediatric hospitalizations for which Medicaid is the primary payer is substantial and increasing: Medicaid is the single largest payer for hospitalized children and accounted for 44% of pediatric admissions in 2007, up from 36% in 2000 [20, 21].

Interventions that reduce hospital readmissions by improving hospital discharge, transition, and post-discharge care, as well as disease management should be beneficial to all patients, including those insured by Medicaid. Interventions that specifically address the complex needs of Medicaid-insured patients, such as limited resources for healthcare and barriers to accessing care, may be particularly effective in reducing readmission rates in this group. Successful interventions to prevent readmissions in Medicaid-insured patients are described in the literature.

The Care Transitions Innovation (i.e., C-Train) is a low-cost, multi-component transitional care intervention that has decreased readmission rates in uninsured and Medicaid-insured adult populations [22]. The intervention helps remove financial barriers to care by providing inpatient pharmacy consultation, a 30-day supply of medications for use after discharge, payment for medical homes for uninsured patients who lack access to outpatient care, and access to a transitional care nurse to bridge care between the inpatient and outpatient settings. This low-cost intervention illustrates how investing a relatively small amount of resources upfront could potentially avert the much greater cost of hospital readmission.

North Carolina has demonstrated that interventions implemented via a Medicaid program can be highly effective in reducing readmissions. Its state-wide initiative focused on comprehensive transitional care for Medicaid beneficiaries of any age with complex chronic medical conditions, with the intensity of the intervention tailored to patients' readmission risk [23]. Patients who received the intervention were 20% less likely to experience a readmission during the subsequent year than clinically similar patients who received routine care. Additionally, patients who received the transitional care were less likely than routine-care patients to experience multiple readmissions. These findings suggest that transitional care interventions targeted to address the particular needs of Medicaid-insured patients can reduce hospital readmissions among this high-risk population. The Pediatric All-Condition Readmission Measure could be used to track the impact of similar interventions in Medicaid-insured children.

Empirical Data

We assessed disparities in readmission risk associated with insurance status using our Pediatric All-Condition Readmission Measure. We performed multivariate analysis for community and children's hospitals in 2005-2009 AHRQ HCUP State Inpatient Databases with Revisit Data for New York and Nebraska. We found that compared with

Medicaid-insured patients, the odds of readmission were significantly lower for those who had private insurance (AOR 0.76, 95% CI [0.75 - 0.78]), other types of insurance (such as Medicare or other government-sponsored insurance) (AOR 0.85, 95% CI [0.78-0.92]), or self-pay status (AOR 0.73, 95% CI [0.69-0.78]). Medicaid insurance was a risk factor independent of patient age, gender, and chronic conditions and of index admission hospital.

Using the same data, we also evaluated whether a given hospital's readmission performance tends to correlate among patients with different insurance statuses. We fitted the measure case-mix model, adding a random slope indicator variable for Medicaid, private insurance, and self-pay statuses (we were unable to include an indicator variable for other types of insurance because the model would not converge, perhaps due to low numbers of observations in this category at some hospitals). We found that the regression coefficients were highly correlated among different insurance statuses. Correlations were 0.84 for Medicaid and self-pay, 0.92 for Medicaid and private insurance, and 0.90 for private insurance and self-pay. This finding indicates that readmission rates tend to vary in parallel for all insurance categories, which suggests that a hospital's adjusted readmission rate is a valid measure of performance (relative to other hospitals) for children with all insurance statuses.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the

measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

The percentage of admissions that are for Medicaid-insured patients varies across hospitals and is substantially greater in some hospitals than others [24]. We found in 2005-2009 AHRQ HCUP State Inpatient Databases with Revisit Data

for New York and Nebraska that the overall percentage of pediatric all-condition index hospitalizations at community and children's hospitals for which Medicaid was the primary payer was 47.7%. Because hospitals with very low pediatric volume might be outliers, we did not rely on observed sample hospital-level percentages to assess variation across hospitals. We instead estimated a random effects logistic regression to model the distribution of Medicaid rates at the hospital level. We found that the mean percentage of Medicaid hospitalizations was 41.8%; the percentage was 59.6% for hospitals 1 standard deviation above the mean and 26.0% for hospitals 1 standard deviation below the mean.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The only sociodemographic variable available in the datasets we used to develop this measure was insurance status in the 2009 AHRQ HCUP State Inpatient Databases with Revisit Data for New York and Nebraska. In addition, we plan to use the New York State 2013 Medicaid and all payer datasets that include the following variables: (1) individual-level insurance status and (2) census tract data to allow for determining neighborhood-level income and education.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

Insurance status, income, and education represent the underlying conceptual relationship identified. As stated above, SDS as measured by these variables can affect health directly, as well as indirectly by having an impact on self- management, adherence to recommendations, and access to care.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

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Measure: NQF #2496 - Standardized Readmission Ratio (SRR) for dialysis facilities

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The Standardized Readmission Ratio, as a systematic measure of the rate of unplanned readmissions at dialysis facilities, can help to improve coordinated care and provide cost-effective health care for the end stage renal patients. There has been increasing interest in exploring the relation of hospital readmissions for dialysis patients with patient characteristics such as income, education, insurance status, race, and employment status. However, many existing studies of this set of relationships were conducted in other health care situations, such as in nursing homes, hospitals. Among the few studies on readmissions in the dialysis facility setting, patient level SDS factors are either not included in the analyses, or they are included as basic controls without any conceptual pathway describing the relationship between these factors and readmissions. For example, the focus of the analysis by Erikson et al (2014) is to examine frequency of physician visits, subsequent to a discharge, and the impact on preventing readmissions. While the analysis included race and sex in the descriptive statistics and models, these were considered as basic patient level controls. It may not be appropriate to extrapolate about the empirical relationship between these SDS patient-level factors and readmissions on the basis of this study.

In addition, much of the work on socio-demographic (SDS) factors and readmissions has been done at the geographic level, as opposed to the individual patient level. For example, Philbin et al. (2001) found substantially higher risks of readmission for persons residing in low income ZIP codes. These results held after controlling for comorbidities, location of care, and a fairly full set of other SDS characteristics, including age, sex, race and insurance, as measured at the ZIP code level. All SDS characteristics in the model were also associated with odds of readmission.

Foster et al. (2014) applied the Community Need Index (CNI) developed by Truven Health Analytics to analyze variation in all-cause hospital readmission, with and without adjustment for socioeconomic (SES) characteristics and race. The CNI is calculated at the ZIP code level and reflects potential barriers to effective health care, including income, ethnicity, education, insurance and housing quality. The results show that standardizing for SES characteristics and race reduces the variation in readmission across hospitals, potentially resulting in a fairer comparison of readmission rates.

Singh has developed the Area Deprivation Index (ADI) with colleagues at the University of Wisconsin. Like the CNI, the ADI reflects a full set of SES and demographic characteristics, measured at the ZIP code level. Singh (2003) has applied the index in a variety of contexts, including analysis of county-level mortality rates. He found area differences in mortality associated with low SDS. Over the period studied, mortality differences widened because of slower mortality reductions in more deprived areas. Very recently, the ADI has been applied to the calculation of risk-adjusted rates of hospital readmission.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

The studies mentioned in our response to Question #2 have provided evidence that, at least at a conceptual level, patient SDS characteristics may affect the likelihood of hospital readmission among dialysis patients. To further explore this hypothesis, we conducted preliminary analyses of the relationships between select SDS characteristics and the Standardized Readmission Ratio (SRR) for dialysis facilities, using the 2012 national ESRD database, which comprises Medicare claims, CROWN data, CMS' ESRD Medical evidence form, CMS' Death Notification Form and UNOS transplant data, among other data sources. The database comprises more than 600,000 patients from 6,000+ facilities.

Relationship between patients' estimated income and SRR

As a proxy for patients' estimated income, we used the median income for each discharged patient's ZIP code of residence on the discharge date. In the model, income was categorized by quartiles. The estimated odds ratio of readmission was found to decrease slightly but steadily as the estimated income level increases. Compared with the first quartile (i.e., the lowest income level), the odds ratios were 0.995 ($p>0.05$), 0.975 ($p<0.01$) and 0.95 ($p<0.001$) for quartiles 2, 3 and 4, respectively. Thus, there is some indication that patients who reside in ZIP codes with higher median income have somewhat lower readmission rates than those living in ZIP codes with lower median income, although the effect is somewhat modest.

Using 2012 data, we compare the SRRs computed with and without adjustment for median income and examine the median SRR of facilities, by quintiles according to the facility average income of hospitalized patients in the facility. First, we note the non-SDS-adjusted and SDS-adjusted SRRs, respectively, are very comparable (Q1: 1.00 vs 0.99; QUESTION 1: 0.99 vs 0.99; QUESTION 2: 0.98 vs 0.98; QUESTION 3: 1.00 vs 1.00; QUESTION 4: 1.01 vs 1.02). Second, the relative consistency of these values across quintiles suggests there is no systematic change of SRRs over the range of average incomes in the population. This suggests there is no clear evidence that patients with lower economic status would tend to be treated in facilities with poorer (or better) readmission rates.

Relationship between race and ethnicity and SRR

We first studied the within-facility effects of race and ethnicity on readmission by including race and ethnicity as risk- adjusters in a mixed effects logistic regression model for readmission. We found that, within the same facilities, black patients have an odds ratio of 0.9993 for readmission compared to the non-black patients. Similarly, within the facilities, Hispanic patients have an odds ratio of 0.98 for readmission compared to those who are identified as non-Hispanic.

Both results suggest that race and ethnicity do not have a strong effect on readmissions within the same facility.

We next studied how facility-level racial and ethnic composition would affect SRR. Specifically, we examined the median SRR by facilities grouped in quintiles by their percentage of black patients and also by their percentage of Hispanic patients. First, we saw no systematic differences between the SRRs for facilities with varying percentages of Hispanic patients—when comparing the ethnicity-adjusted SRR with the non-ethnicity-adjusted SRR, the median SRR was the same for each quintile except Q5, with an unadjusted median SRR of 1.00 and an adjusted median SRR of 1.01. On the other hand, there is an obvious upward trend in the SRR among facilities with increasing proportions of black patients (median SRRs for Q1: 0.92 [unadjusted] v. 0.93 [adjusted]; median SRRs for QUESTION 4: 1.04 [unadjusted] v. 1.03 [adjusted]). This indicates that, even having accounted for the within-facility differences in readmissions between black and non- black patients, facilities with higher proportions of black patients have higher readmission rates than those with lower proportion of black patients. We plan to explore these relationships of race and readmissions further.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

We plan to examine four patient-level sociodemographic variables: Patient's unemployment status six months prior to onset of ESRD; whether the patient was dually eligible for Medicare and Medicaid at index discharge (indicator of lower income); whether the patient had Medicare as secondary insurance coverage at index discharge (indicator of higher income); and patient's race.

We recognize that one or more of these patient-level SDS factors are likely associated with one another particularly if they are collectively considered as constituent characteristics of area-level SDS factors. Based on studies and related literature cited here, there has been an observed interrelationship between area-level structural factors such as neighborhood-level poverty concentration, history of discrimination, crime levels, and racial segregation, that adversely impact access to care and health promoting resources (e.g., proximity to healthy foods, pharmacies, safe outside areas for activity) and in turn high comorbidity and poorer health outcomes such as higher readmissions for those populations living in high poverty or segregated areas. Often these populations are from historically disadvantaged racial and ethnic groups. Both patient- level and area-level variables are assumed to be independently and jointly associated with readmissions. For example, Kind et al found that “patients in the most disadvantaged neighborhoods were more likely to be black, on Medicaid, and had greater rates of comorbidities” (Kind et al Annals Int Med 2014, p769).

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

Race, income, and relatedly unemployment and insurance status may be associated with readmissions. However it is important to recognize one or more of these patient-level SDS factors likely shares an association with one another, such as race and income. For example, an observed relationship of race and higher readmissions could also be reflecting in part the unmeasured influence of a higher portion of patients in a specific race or ethnic group with lower income, Medicaid/dual eligible status, or unemployment. Similarly, there is interplay between area level structural factors (neighborhood poverty; history of discrimination) that impact access to care, leading to poorer health for those populations living in high poverty areas, and who are from historically disadvantaged racial and ethnic groups, and in turn experience higher readmissions. For example, Kind et al found that “patients in the most disadvantaged neighborhoods were more likely to be black, on Medicaid, and had greater rates of comorbidities” (Kind et al Annals Int Med 2014, p769). With that said we describe the conceptual relationship between each patient-level SDS factor and readmissions.

Unemployment status six months prior to ESRD-onset: This could adversely impact patients’ ability to have access to sufficient pre-ESRD care, and in turn increase their risk of an emergent dialysis start, and have higher or greater acuity of their comorbidity burden that may result in frequent re-hospitalizations due to their rapidly declining health. We also acknowledge unemployment status is likely associated with other SDS factors, such as income and insurance coverage.

Lower income status (dual Medicare/Medicaid eligibility status at index discharge): In the general population lower income patients tend to have higher readmission rates (MedPAC Chapter 4, June 2013). It is anticipated this would be more pronounced for the ESRD population given their typically higher comorbidity burden. Lower income indicates lower available resources to obtain primary care or have access to other care, medications, and so forth that could help prevent readmissions after discharge.

Higher income status (Medicare as Secondary Payer at index discharge): Conversely, while lower income patients tend to have higher readmission rates, as a by-product of less access to care and limited resources, we expect that patients with Medicare secondary payer status are those who have private insurance (either as employees, or through a spouse or parent) and have necessary resources to receive adequate care subsequent to their hospital discharge. They likely have access to a primary care provider, medications, and other health care resources post-discharge that can reduce the risk of a subsequent readmission.

Patient Race: The impact of patient race (black race) on readmissions has been observed in the general population (e.g., Kind et al 2014). It is possible this may also reflect confounding related to other SDS factors, therefore race per se may not be the primary risk factor but could reflect the outcome of care in facilities with a higher percent of poor

patients that are black. Poorer patients likely have poorer health status and face access to care obstacles. After a discharge they may be more vulnerable to readmission in the absence of sufficient follow-up care and access or resources for medications, and other post-follow-up care. Race could also reflect a real disparity in care where historical or cultural and societal barriers reify the provision of care. For example, facilities may also be in impoverished and racially segregated areas that have been found to be associated with higher readmissions (Williams and Collins 2001).

We caveat that adjusting for the above patient-level SDS factors has the potential to lower the standard of care for patients based on race, (lower) income status, and unemployment status if care is not taken to disentangle factors modifiable (discrimination and disparate care delivery) and non-modifiable (higher comorbidity burden) by dialysis facilities.

Finally, the four variables listed in our response to Question #4 represent many of the broad SDS categories (e.g., income, insurance coverage, cultural barriers). In an effort to examine SDS categories not represented by these four available patient-level adjustors (e.g., education, housing barriers), we plan to examine ZIP code-level variables available from Census data.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

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Measure: NQF #2510: Skilled Nursing Facility 30-Day All-Cause Readmission Measure (SNFRM)

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or

neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The potential relationship between SDS risk factors and the outcome of hospital readmissions for Skilled Nursing Facility (SNF) patients is plausible; however, the literature on such relationships specific to this setting is not extensive. Research has found that racial and socio-demographic disparities exist both in the quality of nursing facilities as well as in hospital readmission rates. Any discussion of disparities in hospitalization or hospital readmission rates should acknowledge the potential influence of differences in preferences for intensity of intervention by patient subgroups.

Additionally, previous studies suggest that these disparities arise from vulnerable populations being admitted disproportionately into poorer quality homes, rather than patients or residents receiving care at different levels of quality by race within the same facility (Mor et al., 2004; Cai, Mukamel, Temkin-Greener 2010). Studies have suggested that a contributing factor to systematically poorer quality care among facilities providing services to disproportionately more low socio-demographic residents or patients is the lack of resources to dedicate to quality improvement (Mor et al., 2004).

Multiple studies have found that nursing facilities with higher proportions of minority and low socio-economic status residents tend to have poorer results on quality of care indicators, and that African-Americans have higher rates of hospital readmission (Howard et al., 2002; Mor et al., 2004; Grabowski 2004; Silverstein et al., 2008; Jencks, Williams, and Coleman 2009). Prior research has shown that racial disparities exist in care provided to nursing home residents with respect to occurrence of pressure sores (Li, Yue, et al., 2011a) and provision of influenza and pneumococcal vaccination (Li, Yue, Mukamel, 2010), and data indicate that these racial disparities persist for hospital readmissions. Using data from a large health maintenance organization and fee-for-service Medicare claims for patients with a stroke occurring in the 2-year period 1998-2000, African-American race was a significant predictor of experiencing at least one complicated transition defined as moving from a less to a more intense care setting after hospital discharge. Patients who had had multiple complicated transitions were 38 percent more likely to be African-American (Kind et al., 2008).

Another study analyzing hospital readmission rates using Medicare claims data from 2003-2004 found that African- Americans had a nearly 6 percent higher risk of rehospitalization within 30 days of hospital discharge than those of other races (Jencks, Williams & Coleman, 2009).

Among studies specifically of hospital readmissions for patients in SNFs, one national study using MDS data found that the unadjusted 30-day readmission rate was 18.6 percent for African-American patients and 14.3 percent for White patients, resulting in an odds ratio of 1.37 (Li et al., 2011b). These differences were more marked when analyzing the 90-day readmission rate: the readmission rate for African-American patients was 29.5 percent compared to 22.1 percent for White patients, with an odds ratio of 1.48.

Recently published literature has focused on the potential relationship between unplanned readmissions and community or neighborhood-level socioeconomic characteristics that can serve as a proxy for individual-level factors. A small number of studies (Herrin et al, 2014; Kind et al, 2014; McHugh and Ma, 2013) have shown a relationship between county-level measures of low SDS (based on factors such as income, employment rate, education level, rate of home ownership and literacy) and increased rates of hospital readmission. This conceptual rationale—that neighborhood and community characteristics and general access to resources within the community influence the likelihood of readmission—will be used by the RTI team to identify potential county-level SDS factors for inclusion in the analysis.

The Medicare County Code variable specifies county of residence and has been shown to be a more reliable geographical identifier for Medicare beneficiaries than zipcode, and as such, we will focus on county-level measures of SDS for testing.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

The literature suggests that race and socio-economic status are possible patient-level risk factors that should be tested. Next, we summarize the results of our testing of these risk factors, as included in section 1b.4 of our Measure Submission Form. Our testing was limited by the availability of these variables in our data sources (Medicare claims and administrative data). As such, we tested race (White, Black, and Other which includes the following codes: unknown, other, Asian, Hispanic, and North American native) and a proxy for low-income status (the dual eligibility indicator, a variable indicating that the patient is enrolled in both Medicare and Medicaid) in our readmission models. We conducted analyses to assess the potential impact on facilities based on their proportion of patients that were Non-White or had the dual eligibility indicator. Results of these analyses are summarized below and included in Appendix Tables 1-2 at the end of this memo.

Analyses of the distribution of patients by race shows that non-White populations are not evenly distributed across facilities. When the total number of SNFs is broken down by the percentage of patients who are non-White, there are a large proportion of facilities that have non-White populations smaller than the national average (16.5% of US population 60 and older). Under 30 percent (27.1%) of facilities have more than 16.5 percent of their patients who are non-White. 10 percent of facilities have over 40 percent non-White patients. Approximately7 percent of facilities have a majority non-White patients.

When examining whether facilities with higher percentages of non-White patients have systematically different performance scores for the SNFRM, the data suggest that the RSRR increases slightly as the percentage of non-White patients increases (see Appendix Table 1). This is consistent with prior literature showing that hospitals deemed as "minority serving" (defined as over 30% of patient served are minority) had higher readmission rates (25.5% readmitted within 30 days) than those that were "non-minority serving" (22.0% readmitted within 30 days) (Joynt 2011). Our data showed results that are less pronounced, with patients in facilities with over 30 percent non-White patients having readmission rates of 23.2 percent, versus facilities with less than 30 percent non-White patients having rates between 21.7-22.6 percent. The clustering of patients by race in facilities makes it difficult to argue for taking steps like reporting stratified measures because many facilities have very small minority populations. Prior literature examining other health outcomes has suggested that disparities in outcomes are due to differential access to quality care facilities, rather than differences in care being received by residents of different races in the same facility (Li, Yue, et al. 2011a; Li, Yue, Mukamel, 2010).

For dual eligible patients, the results were similar, in that the RSRR was higher for facilities with larger percentages of Medicaid enrollees. However, differences were small (ranging from 20.8% for facilities with the lowest percentage of dual eligible patients, to 21.6% for facilities with the highest percentage). The results are presented in Appendix Table 2.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The patient-level sociodemographic variables that are available in the Medicare claims data are Age, Sex, and the Race and the Dual Eligibility Indicator variables described in questions 1 and 2. The Dual Status Indicator is a categorical variable in the Master Beneficiary Summary File that indicates what category of dual eligibility the patient is classified

as, based on varying levels of income and assistance received . Also available is the Original Reason for Entitlement variable, which states the reason the beneficiary qualified for Medicare benefits and may allow us to adjust for beneficiaries that qualified for Medicare on the basis of disability. The MedPAR records also include a variable to note whether the patient receives Supplemental Security Income (SSI), which is an indicator of lower income. In addition, the Minimum Data Set (MDS), a standardized, primary screening and assessment tool of health status used in the SNF setting, contains a patient-level measure of marital status at time of admission and preferred language, which will also be considered for SDS adjustment.

As discussed in question 1, county-level sociodemographic variables that may be relevant to readmissions will be identified for testing. These regional variables will function as proxies for a patient's sociodemographic status and capture aspects of a patient's access to resources in his or her community. Some potential county-level variables that are available and could reflect a patient's SDS status include the median household income, employment rate, degree of urbanization, median education level and the availability of primary care providers; a panel of county-level variables will be tested for risk adjustment, both separately and as an aggregated index, during the trial period. These may be extracted from a variety of data sources, including the U.S. Census data, the Health Professional Shortage Area designation database, and other publicly available sources of county-level variables.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

As evidenced from the tables provided in the Appendix below, the patient-level SDS variables that were tested (Race and Medicaid Buy-In indicator) are indicative of a difference in readmission rate based on these factors. This suggests that these variables do capture the underlying conceptual relationship at the patient level reliably, and are likely candidates for inclusion in the SDS risk-adjustment for this measure during the trial period. Determining the degree to which disparities in care are responsible for the effect of race in particular must be investigated.

Empirical analyses have not been conducted for any county-level variables that are being considered for inclusion for SDS risk adjustment. As the trial period moves forward, RTI and CMS will identify and obtain data for the regional characteristics that represent the underlying conceptual relationship for inclusion in the risk adjustment model based on existing literature, NQF guidance and expert opinion, and we will conduct empirical analyses using these variables accordingly.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

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Measure: NQF #2512 All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Long-Term Care Hospitals (LTCHs)

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The potential relationship between SDS risk factors and the outcome of readmissions post-discharge from Long-Term Care Hospitals (LTCHs) is plausible; however, there is a lack of literature on this topic specific to this setting. Evidence from readmission rates following acute-care discharge have shown disparities by race with Black beneficiaries having the highest 30-day readmission rates for acute myocardial infarction, heart failure, and pneumonia (Joynt, Orav, and Jha, 2011). Though this evidence is not specific to LTCHs, it suggests that race is one possible patient-level risk factor relevant to post-discharge readmissions that should be tested.

We included results of our testing of two SDS risk factors in section 1b.4 of our Measure Submission Form and summarize those results here. Our testing was limited by the availability of SDS variables in our data sources (Medicare claims and administrative data). As such, we tested race (White, Black, and Other which includes the following codes: unknown, other, Asian, Hispanic, and North American native) and a proxy for low-income status (Medicaid Buy-In) in our readmission models. The Buy-In variable is an indicator that a state is paying Part B premiums and/or cost sharing for beneficiaries because of low income. Buy-In policies vary by state, so although not perfect it is a reasonable measure for the effect of low-income.

Seventy-three percent of the LTCH sample was White, and the unadjusted, unplanned readmission rate was lowest for this group (22.6%) compared to the 20 percent of the sample in the Black race category which had the highest readmission rate (26.0%). Beneficiaries coded as Other for race—7.1 percent of the sample—had a higher readmission rate (24.6%) than White, but lower than Black beneficiaries. There is a high proportion of the LTCH sample with the Buy-In indicator code (41.1%), and the unadjusted, unplanned readmission rate was slightly higher than the national average.

Next, odds ratios were estimated from the logistic regression model including both race and Buy-In as risk-adjusters. In our risk-adjustment models, Black beneficiaries had about 6 percent higher odds of readmission relative to White beneficiaries, but there was no significant difference between beneficiaries in the Other race group compared to Whites. The odds of readmission for LTCH beneficiaries with the Buy-In indicator were 12 percent higher relative to those with no Buy-In indicator for an unplanned readmission. Please refer to Appendix Tables 1-2 at the end of this memo for the results described above.

Recently published literature has focused on the potential relationship between unplanned readmissions and community or neighborhood-level socioeconomic characteristics that can serve as a proxy for individual-level factors. A small number of studies (Herrin et al, 2014; Kind et al, 2014; McHugh and Ma, 2013) have shown a relationship between county-level measures of low SDS (based on factors such as income, employment rate, education level, rate of home ownership and literacy) and increased rates of hospital readmission. This conceptual rationale—that neighborhood and community characteristics and general access to resources within the community influence the likelihood of readmission—will be used by the RTI team to identify potential county-level SDS factors for inclusion in the analysis.

The Medicare County Code variable specifies county of residence and has been shown to be a more reliable geographical identifier for Medicare beneficiaries than zipcode, and as such, we will focus on county-level measures of SDS for testing.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

In addition to analyzing the effect of including race and SES in the readmission models at the patient level, we also conducted analyses to assess the potential impact on LTCHs' readmissions rates based on their percentage of patients that were Non-White or had the Buy-In indicator. Results of these analyses are summarized below and included in Appendix Tables 3-4 at the end of this memo, as reported in section 1.b.4 of our Measure Submission Form.

Analyses of the distribution of LTCH patients by race show that Non-White populations are not evenly distributed across facilities. There were small differences in comparing LTCHs' performance on the RSRR based on facility percentages of Non-White patients. For example, LTCHs with 0 to 12 percent Non-White patients had a mean RSRR of 23.5 percent and a median of 23.5 percent compared to LTCHs with 35 percent or more Non-White patients in which the mean and median RSRRs were higher, 25.2 and 24.8 percent, respectively. These results suggest that facilities' RSRRs increase slightly as the percentage of Non-White LTCH patients increases.

For LTCH patients with the Buy-In indicator, the results were similar. There were slight increases in the RSRRs as the percentage of LTCH patients with Buy-In increased within LTCHs. For example, based on models that did not adjust for race or Buy-In, LTCHs with 0 to 30 percent Buy-In patients had a mean RSRR of 23.4 percent and a median of 23.3 percent compared to LTCHs with 47 percent or more Buy-In patients in which the mean and median RSRRs were higher, 25.1 and 24.9 percent, respectively. In both cases it is not clear whether quality of care is a factor or some underlying factor not measured.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The patient-level sociodemographic variables that are available in the Medicare claims data are Age, Sex, and the Race and Dual Eligibility Indicator variables described in questions 1 and 2. The Dual Status Indicator is a categorical variable in the Master Beneficiary Summary File that indicates what category of dual eligibility the patient is classified as, based on varying levels of income and assistance received . Also available is the Original Reason for Entitlement variable, which states the reason the beneficiary qualified for Medicare benefits and may allow us to adjust for beneficiaries that qualified for Medicare on the basis of disability. In addition, the Long-Term Care Hospital (LTCH) Continuity Assessment Record & Evaluation (CARE) Data Set, a standardized, primary assessment tool of health status used in the LTCH setting, contains a patient-level measure of marital status at time of admission and preferred language, which will also be considered for SDS adjustment.

As discussed in question 1, county-level sociodemographic variables that may be relevant to readmissions will be identified for testing. These regional variables will function as proxies for a patient's sociodemographic status and capture aspects of a patient's access to resources in his or her community. Some potential county-level variables that are available and could reflect a patient's SDS status include the median household income, employment rate, degree of urbanization, median education level and the availability of primary care providers; a panel of county-level variables will be tested for risk adjustment, both separately and as an aggregated index, during the trial period. These may be extracted from a variety of data sources, including the U.S. Census data, the Health Professional Shortage Area designation database, and other publicly available sources of county-level variables.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

As evidenced from the tables provided in the Appendix below, the patient-level SDS variables that were tested (Race and Medicaid Buy-In indicator) are indicative of a difference in readmission rate based on these factors. This suggests that these variables do capture the underlying conceptual relationship at the patient level reliably, and are likely candidates for inclusion in the SDS risk-adjustment for this measure during the trial period. Determining the degree to which disparities in care are responsible for the effect of race in particular must be investigated.

Empirical analyses have not been conducted for any county-level variables that are being considered for inclusion for SDS risk adjustment. As the trial period moves forward, RTI and CMS will identify and obtain data for the regional characteristics that represent the underlying conceptual relationship for inclusion in the risk adjustment model based on existing literature, NQF guidance and expert opinion, and we will conduct empirical analyses using these variables accordingly.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

Herrin, J., St. Andre, J., Kenward, K., Joshi, M. S., Audet, A.-M. J. and Hines, S. C. (2015), Community Factors and Hospital Readmission Rates. Health Services Research, 50: 20–39.

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Appendix Tables Table A-1

Sample Descriptives for Race and SES Risk-Adjusters LTCH Post Discharge 2010/2011 Readmission Model (n=212,018)
Risk-Adjuster % sample with covariate % with unplanned readmission White 72.9 22.6
Black 20.0 26.0
Other 7.1 24.6
Medicaid Buy-In 41.1 25.6
Source: RTI International analysis of Medicare claims data, 2007-2012. (RTI program reference: lc35)

Table A-2

Odds Ratios for Race and SES Risk-Adjusters
LTCH Post-Discharge 2010/2011 Readmission Model Risk-Adjuster Odds Ratio 95% Confidence Interval
White REF REF
Black 1.06 1.03-1.09
Other 0.98 0.94-1.02
Medicaid Buy-In Indicator 1.12 1.09-1.14 Note: Full set of risk-adjusters not shown.
Source: RTI International analysis of Medicare claims data, 2007-2012. (RTI program reference: lc35)

Table A-3
Race: Distribution of Risk-Standardized Readmission Rate (%) by Facility Proportion Non-White Patients, 2010/2011
% of Facility Patients that are Non-White N Obs (LTCHs) Mean Minimum 25th Pctl Median 75th

Pctl Maximum
0 to <12% 116 23.5 18.1 21.8 23.5 25.1 30.6
12 to <22% 105 24.2 18.9 23.0 24.1 25.4 29.0
22 to <35% 115 24.3 17.9 23.0 24.3 25.8 28.5
35% or more 111 25.2 20.2 23.6 24.8 26.8 30.8
Total LTCHs 447 24.3 17.9 22.9 24.2 25.8 30.8
Note: The Risk-Standardized Readmission Rates reported are based on models that do not include race or Buy-In. LTCH=Long-Term Care Hospital; Obs=Observations; Pctl=Percentile.

Source: RTI analysis of Medicare claims data, 2007-2012. (RTI program references: lc38)

Table A-4

SES: Distribution of Risk-Standardized Readmission Rate (%) by Facility Proportion of Patients with Buy-In, 2010/2011
% of Facility Patients with State Buy-In during 2010/2011 N Obs (LTCHs) Mean Minimum 25th Pctl Median 75th
Pctl Maximum
0 to <30% 106 23.4 17.9 21.6 23.3 24.9 29.9
30 to <38% 121 24.3 19.5 23.0 24.1 25.4 30.1
38 to <47% 110 24.4 18.4 23.0 24.1 25.7 30.6
47% or more 110 25.1 21.2 23.9 24.9 26.4 30.8
Total LTCHs 447 24.3 17.9 22.9 24.2 25.8 30.8
Note: The Risk-Standardized Readmission Rates reported are based on models that do not include race or Buy-In. LTCH=Long-Term Care Hospital; Obs=Observations; Pctl=Percentile.

Source: RTI analysis of Medicare claims data, 2007-2012. (RTI program references: lc38)

Measure: NQF #2502 All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Inpatient Rehabilitation Facilities (IRFs)

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The potential relationship between SDS risk factors and the outcome of readmissions post-discharge from Inpatient Rehabilitation Facilities (IRFs) is plausible; however, the literature on such relationships specific to this setting is limited.

Readmission rates among patients recovering specifically from stroke were most frequently examined, and the evidence on disparities was mixed. Some studies showed no differences. For example, separately developed hierarchical models have shown that neither sex nor race is a significant predictor for either three-month (Ottenbacher et al., 2012) or six-month (Dossa, Glickman, & Berlowitz, 2011) acute rehospitalization from inpatient rehabilitation facilities. However, the former study, Ottenbacher et al. (2012), found that an interaction term between minority and depressive symptoms was significant in predicting hospital readmissions. One study of readmissions among stroke patients found differences by ethnicity suggesting certain ethnic patient populations had better readmission outcomes. In developing classification models assessing 80-180 day risk of hospital readmission post-IRF discharge for stroke patients, Hispanic men and Asian men had the lowest risk of rehospitalization compared to non-Hispanic white and African-American men (Ottenbacher et al., 2001). This finding was also identified in a study looking at 6-month hospital readmissions among older adults receiving inpatient rehabilitation after hip fracture (Ottenbacher et al., 2003). This hip fracture study found that 18.1 percent of non-Hispanic white males and 16.8 percent of African American males were rehospitalized compared to 10.1 percent of Hispanic males (Ottenbacher, et al., 2003).

Finally, a national study analyzing Medicare claims data from 2006-2011 for post-acute patients discharged from IRFs to the community for selected impairment categories found that readmission rates were highest among men and non-Hispanic blacks (Ottenbacher et al., 2014). This study also found higher readmission rates for dual eligible beneficiaries, suggesting a disparity by socio-economic status.

The literature suggests that race and socio-economic status are possible patient-level risk factors that should be tested.

Next, we summarize the results of our testing of these risk factors, as included in section 1b.4 of our Measure Submission Form. Our testing was limited by the availability of these variables in our data sources (Medicare claims and administrative data). As such, we tested race (White, Black, Other which includes the following codes: unknown, other, Asian, Hispanic, and North American native) and a proxy for low-income status (Medicaid Buy-In) in our readmission models.

About 10 percent of our sample was Black and we found that the unadjusted, unplanned readmission rate for this group was highest (15.5%). Eighty-five percent of the IRF sample included in the 2010/2011 model was White, and the unadjusted, unplanned readmission rate for this group was 13.4 percent. The remaining five percent of the sample included beneficiaries with race included in the Other category; the unadjusted, unplanned readmission rate for Other was similar to that of Whites (13.7%). Less than 19 percent of the IRF sample had the indicator for state (Medicaid) Buy-In of Medicare Part B, though the unadjusted, unplanned readmission rate was slightly higher among that group (16.0%).

In our risk-adjustment models, however, the odds of readmission for Black beneficiaries did not differ from White beneficiaries; however, there were reduced odds of readmissions for the Other race category relative to White beneficiaries. There was a significant increase in odds of readmission among beneficiaries with the Buy-In indicator— about 14 percent higher—relative to beneficiaries with no Buy-In indicator. Please refer to Appendix Tables 1-2 at the end of this memo for the results described above.

Recently published literature has focused on the potential relationship between unplanned readmissions and community or neighborhood-level socioeconomic characteristics that can serve as a proxy for individual-level factors. A small number of studies (Herrin et al, 2014; Kind et al, 2014; McHugh and Ma, 2013) have shown a relationship between county-level measures of low SDS (based on factors such as income, employment rate, education level, rate of home ownership and literacy) and increased rates of hospital readmission. This conceptual rationale—that neighborhood and community characteristics and general access to resources within the community influence the likelihood of readmission—will be used by the RTI team to identify potential county-level SDS factors for inclusion in the analysis.

The Medicare County Code variable specifies county of residence and has been shown to be a more reliable geographical identifier for Medicare beneficiaries than zipcode, and as such, we will focus on county-level measures of SDS for testing.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

In addition to analyzing the effect of including race and SES in the readmission models at the patient level, we also conducted analyses to assess the potential impact on facilities' scores based on the proportion of patients that were Non-White or had the Buy-In indicator. Results of these analyses are summarized below and included in Appendix Tables 3-4 at the end of this memo, as reported in section 1.b.4 of our Measure Submission Form. Analyses of the distribution of IRF patients by race shows that Non-White populations are not evenly distributed across facilities.

However, there were no differences in comparing IRFs' RSRRs based on facility percentages of Non-White patients. The mean RSRRs were similar, and there were only very small differences in the median RSRRs as IRFs' percentages of Non-White patients increased. Next, for IRF patients with the Buy-In indicator, a proxy for low-income status or SES, the results were similar. There were no differences in the RSRRs for facilities based on the proportion of patients with Buy-In. Note the RSRRs estimated for these analyses are based on risk-adjustment models that did not include either race or Buy-In. In both cases it is not clear whether quality of care is a factor or some underlying factor not measured.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The patient-level sociodemographic variables that are available in the Medicare claims data are Age, Sex, and the Race and Dual Eligibility Indicator variables described in questions 1 and 2. The Dual Status Indicator is a categorical variable in the Master Beneficiary Summary File that indicates what category of dual eligibility the patient is classified as, based on varying levels of income and assistance received . Also available is the Original Reason for Entitlement variable, which states the reason the beneficiary qualified for Medicare benefits and may allow us to adjust for beneficiaries that qualified for Medicare on the basis of disability. In addition, the IRF Patient Assessment Instrument (IRF-PAI), a standardized assessment tool of physical, cognitive, functional, and psychosocial status of patients, contains a patient-level measure of marital status at time of admission, which will also be considered for SDS adjustment.

As discussed in question 1, county-level sociodemographic variables that may be relevant to readmissions will be identified for testing. These regional variables will function as proxies for a patient's sociodemographic status and capture aspects of a patient's access to resources in his or her community.

Some potential county-level variables that are available and could reflect a patient's SDS status include the median household income, employment rate, degree of urbanization, median education level and the availability of primary care providers; a panel of county-level variables will be tested for risk adjustment, both separately and as an aggregated index, during the trial period. These may be extracted from a variety of data sources, including the U.S. Census data, the Health Professional Shortage Area designation database, and other publicly available sources of county-level variables.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

As evidenced from the tables provided in the Appendix below, the patient-level SDS variables that were tested (Race and Medicaid Buy-In indicator) are indicative of a difference in readmission rate based on these factors. This suggests that these variables do capture the underlying conceptual relationship at the patient level reliably, and are likely candidates for inclusion in the SDS risk-adjustment for this measure during the trial period. Determining the degree to which disparities in care are responsible for the effect of race in particular must be investigated.

Empirical analyses have not been conducted for any county-level variables that are being considered for inclusion for SDS risk adjustment. As the trial period moves forward, RTI and CMS will identify and obtain data for the regional characteristics that represent the underlying conceptual relationship for inclusion in the risk adjustment model based on existing literature, NQF guidance and expert opinion, and we will conduct empirical analyses using these variables accordingly.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

References:

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Kind, A. J., Jencks, S., Brock, J., Yu, M., Bartels, C., Ehlenbach, W., Greenberg, C & Smith, M. (2014). Neighborhood socioeconomic disadvantage and 30-day rehospitalization: a retrospective cohort study. Annals of internal medicine, 161(11), 765-774.

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Appendix Tables Table A-1

Sample Descriptives for Race and SES Risk-Adjusters
IRF Post-Discharge 2010/2011 Readmission Model Sample Unadjusted Rates
(n=590,120)
Risk-Adjuster % sample with covariate % with unplanned readmission White 85.2 13.4
Black 10.2 15.5
Other 4.6 13.7
Medicaid Buy-In 18.7 16.0
SOURCE: RTI International analysis of Medicare claims data, 2007-2012. (RTI program reference: lc35)

Table A-2
Odds Ratios for Race and SES Risk-Adjusters
IRF Post-Discharge 2010/2011 Readmission Model Risk-Adjuster Odds Ratio 95% Confidence Interval
White REF REF
Black 0.99 0.96-1.01
Other 0.91 0.88-0.95
Medicaid Buy-In Indicator 1.14 1.11-1.16 NOTE: Full set of risk-adjusters not shown.
SOURCE: RTI International analysis of Medicare claims data, 2007-2012. (RTI program reference: lc35)

Table A-3
Race: Distribution of Risk-Standardized Readmission Rate (%) by Facility Proportion Non-White Patients, 2010/2011
% of Facility Patients that are Non-White N Obs (IRFs) Mean Minimum 25th Pctl Median 75th
Pctl Maximum
0 to <5% 313 13.4 11.7 13.0 13.4 13.9 16.1
5 to <10% 271 13.4 11.2 13.0 13.4 13.8 15.5
10 to <20% 285 13.6 11.1 13.1 13.5 14.1 15.7
20% or more 302 13.5 11.8 13.1 13.6 13.9 15.6

Total IRFs 1,171 13.5 11.1 13.0 13.5 13.9 16.1
NOTE: The Risk-Standardized Readmission Rates reported are based on models that do not include race or Buy-In. IRF=Inpatient rehabilitation facility; Obs=Observations; Pctl=Percentile.
SOURCE: RTI analysis of Medicare claims data, 2007-2012. (RTI program references: lc38) Table A-4 SES: Distribution of Risk-Standardized Readmission Rate (%) by Facility Proportion of Patients with Buy-In, 2010/2011

% of Facility Patients with State Buy-In during 2010/2011 N Obs (IRFs) Mean Minimum 25th Pctl Median 75th Pctl Maximum
0 to <12% 288 13.4 11.5 13.0 13.4 13.8 15.5
12 to <17% 305 13.4 11.2 12.9 13.3 13.8 15.7
17 to <24% 291 13.5 11.1 13.1 13.5 14.0 16.1
24% or more 287 13.6 11.8 13.2 13.6 14.0 15.5
Total IRFs 1,171 13.5 11.1 13.0 13.5 13.9 16.1
NOTE: The Risk-Standardized Readmission Rates reported are based on models that do not include race or Buy-In. IRF=Inpatient rehabilitation facility; Obs=Observations; Pctl=Percentile.

SOURCE: RTI analysis of Medicare claims data, 2007-2012. (RTI program references: lc38)

Measure: NQF#2503 Hospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries

Measure: NQF#2504: 30-day Rehospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

The readmissions/1000 measure describes the readmission experience of a population of fee-for-service (FFS) Medicare beneficiaries; members of the population are defined by the geography of where they live. The measure is intended to track change in readmissions over time for a geographic region, and the SDS composition of a region's population are unlikely to change quickly, therefore we are using this measure without adjusting for the SDS of individual members. The readmissions/1000 measure probably reflects the influence of neighborhood contextual factors however, many of which are likely to be strongly correlated with socio-demographic (SD) determinants, or with personal SD factors that are often grouped into neighborhoods. What is unclear, and should be tested further, is whether or not neighborhoods of concentrated deprivation have more or less capacity to change, as many improvement initiatives focus efforts on such neighborhoods.

Published research has associated neighborhood of residence with health behaviors,[1] access to food[2,3] and safety,[4] and outcomes such as mortality,[1,5,6,7,8,9] birthweight[10] and rehospitalization risk for heart failure.[11] In addition, there is evidence that health indicators improve with moving persons to areas of less concentrated poverty.[12,13] Previous studies of child health and mental health outcomes have established that neighborhood disadvantage is a separate risk factor beyond individual personal disadvantage, with worse health and social outcomes for persons who live in both poor families and poor neighborhoods than for persons living in poor families in less poor neighborhoods.[12,14]

We have recently demonstrated that a composite measure of neighborhood deprivation, based on 2000 Census data, was associated with 30-day readmission risk after hospitalizations from 2004 - 2009 for heart failure, myocardial infarction or pneumonia, and remained so after adjustment for usual patient-level socioeconomic (SE) variables such as income and dual eligibility.[15]

We calculated the deprivation index from 17 US Census variables using methods developed by Gopal Singh, PhD, MS, MSc.16 Census variables used to calculate the ADI include:

- Percent of the population aged 25 and older with less than 9 years of education
- Percent of the population aged 25 and older with at least a high school diploma
- Percent employed persons aged 16 and older in white-collar occupations
- Median family income in US dollars
- Income disparity
- Median home value in US dollars
- Median gross rent in US dollars
- Median monthly mortgage in US dollars
- Percent of owner-occupied housing units
- Percent of civilian labor force population aged 16 years and older who are unemployed
- Percent of families below federal poverty level
- Percent of the population below 150% of the federal poverty threshold
- Percent of single-parent households with children less than 18 years of age
- Percent of households without a motor vehicle
- Percent of households without a telephone
- Percent of occupied housing units without complete plumbing
- Percent of households with more than 1 person per room

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1 Lantz PM, House JS, Lepkowski JM, Williams DR, Mero RP, Chen J. Socioeconomic factors, health behaviors, and mortality: results from a nationally representative prospective study of U.S. adults. JAMA. 1998;279:1703-8. [PMID: 9624022]

2 Moore LV, Diez Roux AV. Associations of neighborhood characteristics with the location and type of food stores. Am J Public Health. 2006;96:325-31. [PMID: 16380567]

3 Franco M, Diez Roux AV, Glass TA, Caballero B, Brancati FL. Neighborhood characteristics and availability of healthy foods in Baltimore. Am J Prev Med. 2008;35:561-7. [PMID: 18842389] doi:10.1016/j.amepre.2008.07.003

4 Hsieh CC, Pugh MD. Poverty, income inequality, and violent crime: a meta-analysis of recent aggregate data studies. Criminal Justice Review. 1993;18: 182-202.

5 Robert SA. Socioeconomic position and health: the independent contribution of community socioeconomic context. Annual Review of Sociology. 1999: 489-516.

6 House JS, Lepkowski JM, Kinney AM, Mero RP, Kessler RC, Herzog AR. The social stratification of aging and health. J Health Soc Behav. 1994;35:21334. [PMID: 7983335]

7 Joynt KE, Orav EJ, Jha AK. Thirty-day readmission rates for Medicare beneficiaries by race and site of care. JAMA. 2011;305:675-81. [PMID: 21325183] doi:10.1001/jama.2011.123

8 Joynt KE, Jha AK. Characteristics of hospitals receiving penalties under the Hospital Readmissions Reduction Program. JAMA. 2013;309:342-3. [PMID: 23340629] doi:10.1001/jama.2012.94856

9 Rau J. Hospitals treating the poor hardest hit by readmissions penalties. Kaiser Health News. 13 August 2012. Accessed at www.kaiserhealthnews.org /stories/2012/august/13/hospitals-treating-poor-hardest-hit-readmissions -penalties.aspx on 2 October 2014.
10 Blumenshine P, Egerter S, Barclay CJ, Cubbin C, Braveman PA. Socioeconomic disparities in adverse birth outcomes: a systematic review. Am J Prev Med. 2010;39:263-72. [PMID: 20709259] doi:10.1016/j.amepre.2010.05.012
11 Foraker RE, Rose KM, Suchindran CM, Chang PP, McNeill AM, Rosamond WD. Socioeconomic status, Medicaid coverage, clinical comorbidity, and rehospitalization or death after an incident heart failure hospitalization: Atherosclerosis Risk in Communities cohort (1987 to 2004). Circ Heart Fail. 2011;4: 308-16. [PMID: 21430286]doi:10.1161/ CIRCHEARTFAILURE.110.959031
12 Ludwig J, Duncan GJ, Gennetian LA, Katz LF, Kessler RC, Kling JR, et al. Neighborhoodeffectsonthelong-termwell-beingoflow-incomeadults.Science. 2012;337:1505-10. [PMID: 22997331]
13 Ludwig J, Sanbonmatsu L, Gennetian L, Adam E, Duncan GJ, Katz LF, et al. Neighborhoods, obesity, and diabetes—a randomized social experiment. N Engl J Med. 2011;365:1509-19. [PMID: 22010917] doi:10.1056 /NEJMsa1103216

Although neighborhood deprivation may be partially a proxy for personal SDS, we believe that it is an easier and therefore more practical approach to adjusting a regional population's readmission experience, without compromising validity.

Risk factors derived from Census data are unassociated with the effects of healthcare providers or the characteristics of the care provided. They measure slowly changing characteristics of the communities in which Medicare beneficiaries live and are present and stable from the beginning of a treatment episode and throughout that episode. They are also available in the public domain, freeing providers from having to capture these data themselves, and allowing them to fully engage in initiatives designed to address patterns of readmissions in their service areas.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

The geographic units at which both the outcome measure and the SDS adjustment factor are calculated can be set to any desired regional division. The US Census aggregates the variables used to calculate the ADI at the census tract level, and readmissions/1000 rates could be similarly assigned census tracts. Alternatively, ZIP+4 codes are the easiest method for aggregating admissions and readmissions rates, based on information from the Medicare enrollment file, and there are a number of publicly available software packages designed to translate ZIP+4 into census tracts which could be used to match census-derived ADI scores to ZIP+4 defined readmission rates.

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14 Acevedo-Garcia D, Osypuk TL, McArdle N, Williams DR. Toward a policy-relevant analysis of geographic and racial/ethnic disparities in child health. Health Aff (Millwood). 2008;27:321-33. [PMID: 18332486] doi:10.1377 /hlthaff.27.2.321
15 Kind AJ, Jencks S, Brock J, Yu M, Bartels C, Ehlenbach W, et al. Neighborhood Socioeconomic Disadvantage and 30-Day Rehospitalization: A Retrospective Cohort Study. Ann Intern Med. 2014;161:765-774. doi:10.7326/M13-2946
16 Singh GK. Area deprivation and widening inequalities in U.S. mortality, 1969-1998. Am J Public Health. 2003;93:1137-43. [PMID: 12835199]

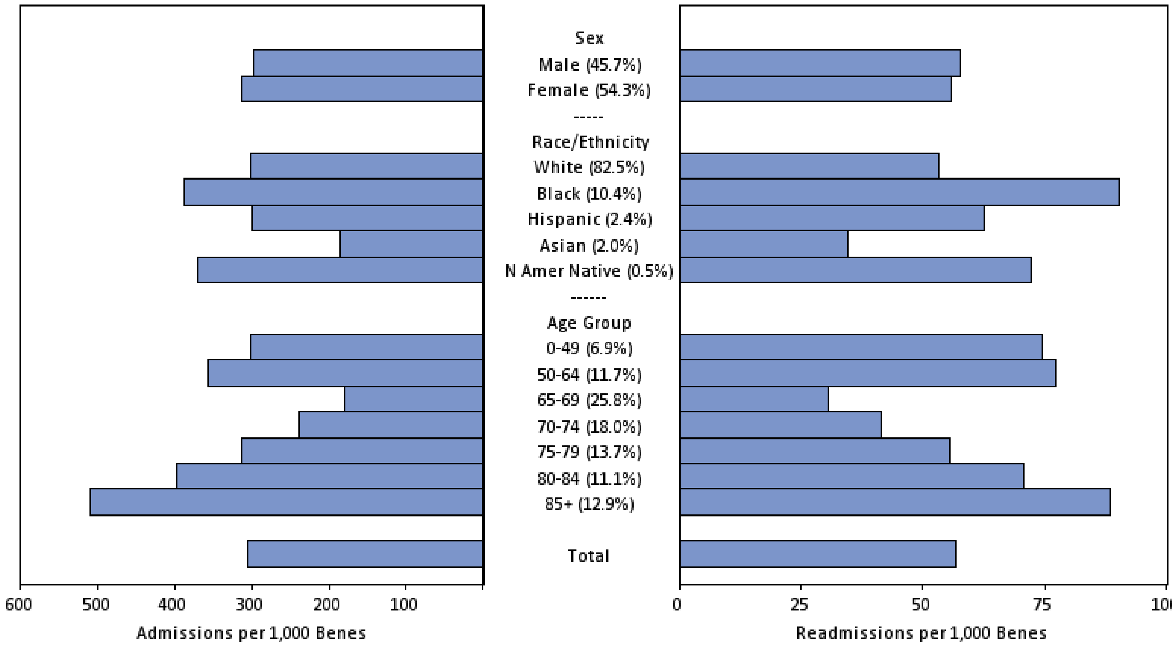
The variation in readmissions/discharges among patients hospitalized with heart failure, myocardial infarction and pneumonia varied from 21% to 27% in the published paper, with a sharp increase, or threshold, starting with the 15th percentile of most deprived neighborhoods. Geographically defined measures of readmission could be adjusted by the ADI metric as a binomial variable (significant neighborhood deprivation vs. no significant deprivation).

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

- Sex
- Race/ethnicity (not viewed as reliable enough)
- Age Group

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

Please see the graph below that represents admissions and readmission by demographic characteristics for Calendar Year 2011 for underlying conceptual relationship with the outcomes. However, while we do not believe race/ethnicity and/or sex distributions change over time, the age distribution may. We will be exploring if the age distribution changes over time during this trial period.


Sex
Male (45.7%)
Female (54.3%)

Race/Ethnicity
White (82.5%)
Black (10.4%)
Hispanic (2.4%)
Asian (2.0%)
N Amer Native (0.5%)

Age Group
0-49 (6.9%)
50-64 (11.7%)
65-69 (25.8%)
70-74 (18.0%)
75-79 (13.7%)
80-84 (11.1%)
85+ (12.9%)
Total
600
500
400
300
200
100
Admissions per 1,000 Benes
0
25
50
75
100
Readmissions per 1,000 Benes

Measure: NQF #2514: Risk-Adjusted Coronary Artery Bypass Graft (CABG) Readmission Rate

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

Current NQF policy suggests that the conditions for inclusion of SDS factors exist under the following circumstances [1]:

"Recommendation 1: When there is a conceptual relationship (i.e., logical rationale or theory) between sociodemographic factors and outcomes or processes of care and empirical evidence (e.g., statistical analysis) that sociodemographic factors affect an outcome or process of care reflected in a performance measure…those sociodemographic factors should be included in risk adjustment of the performance score (using accepted guidelines for selecting risk factors) unless there are conceptual reasons or empirical evidence indicating that adjustment is unnecessary or inappropriate…"

In the context of this NQF recommended policy, we believe that there is sufficient evidence regarding the association of SDS factors and readmission to justify the study of these factors in our Risk-Adjusted Coronary Artery Bypass Graft (CABG) Readmission Rate (NQF# #2514) measure. The following brief summary reviews the arguments and evidence.

Readmission and SES factors—Arguments pro and con[1-10]

Risk of mortality and other short-term clinical outcomes is mostly influenced by clinical factors present on admission, such as cardiogenic shock. By convention, given the plausible causal pathways leading to these outcomes, risk models used for mortality profiling have generally excluded non-clinical patient factors or local environmental factors, as their inclusion might theoretically adjust out important inequities in care.

Historically, the same general approaches have been used for readmission models. However, compared with the risk of early clinical events such as mortality, readmission risk is associated with a broader and more complex range of predisposing factors, which vary in the degree to which they are under the control of the index hospital. There is broad consensus in the literature that non-clinical patient factors (e.g., race, ethnicity, socioeconomic status) and local environmental factors (e.g., availability and quality of post-discharge healthcare services) are associated with readmissions and probably to a greater extent than they are with early clinical outcomes such as mortality (See Appendix—Literature Review). Although these factors may all confound the apparent association between quality of care and readmission, by convention, they have not been included in profiling risk models, although they are perfectly acceptable and even desirable for use by hospitals in identifying patients for targeted interventions to reduce readmissions.

Recently, because of the disproportionate impact of such non-clinical variables on the risk of readmission compared with mortality, and because certain hospitals care for much higher proportions of vulnerable populations, many have questioned whether this policy should be reconsidered for readmission models. Under the Hospital Readmissions Reduction Program, hospitals are penalized for readmission rates that are higher than expected, and these rates are currently adjusted only for patient clinical comorbidities. This has resulted in disproportionate penalties to hospitals serving disadvantaged populations. Joynt and Jha [7] note that the proportion of hospitals receiving penalties and the magnitude of penalties are directly related to the percentage of their patients receiving Supplemental Security Income. Lipstein and Dunagan [4] report that in the St. Louis area, the four hospitals with the highest poverty index also had the highest readmission rates and in some cases the highest penalties, potentially jeopardizing their financial survival.

Hospitals caring for the most vulnerable populations argue for SDS adjustment in order to avoid penalties for excess readmissions which they believe are inevitable given their patient populations. If readmissions are thought to be strongly associated with non-clinical factors in the external environment (e.g., a lack of community resources, poor living environment), then it is a societal and health delivery system problem of a larger scale than could be addressed by most hospitals. Hospitals serving predominately vulnerable patients, those at highest risk for readmission, may simply not have the necessary resources to broadly implement readmission-mitigation interventions in a non-research setting.

While summary Hospital Compare Chartbook data [11] suggest that some hospitals serving higher proportions of Medicaid or African American populations have readmission rates comparable to those serving wealthier non-minority populations (i.e., substantial overlap), the distributions of readmission rates for hospitals serving more vulnerable populations show higher rates at every quantile examined [11-13]. It seems unlikely that all such hospitals will be able to institute the interventions necessary to overcome major social and local environmental challenges. As pointed out by Lipstein and Dunagan [4], "Although some safety-net providers across the United States are able to keep readmission rates below national averages, policymakers should not assume that all safety-net providers are equally resourced at the local level so that the playing field is, indeed, level. It is not. Some of these hospitals receive substantial economic support from local taxing jurisdictions; others receive no local funding. The former may well have the necessary patient care infrastructure to manage discharged patients in an outpatient or home setting; the latter probably do not."

Reimbursement penalties for excess readmissions may thus "make the poor poorer", a potential unintended negative consequence. If some hospitals caring for the most disadvantaged populations are financially unable to positively impact the local outpatient environment, perhaps the most important determinant of readmission for many conditions, then penalizing them will further reduce their effectiveness, and disparity gaps will widen. Such hospitals may also be increasingly reluctant to care for the neediest patients because they are the most likely to require readmission, a form of risk aversion that will reduce access to care for these patients.

On the other hand, some experts are concerned that inclusion of SDS adjustment to readmission measures would make poor outcomes in disadvantaged patients "expected", in the same way we expect worse outcomes in patients who have multiple comorbidities, and that this would essentially adjust away disparities in care (importantly, as pointed out in the NQF policy report [1], "expected" in this sense does not refer to ethical or moral acceptability but rather to the statistical output of a risk algorithm). These experts argue that if such patients were appropriately identified by hospitals before discharge, targeted interventions (e.g., more intensive follow-up phone calls) might reduce the subsequent need for readmission. Those holding this view argue that knowledge of the external environment and home living situation of patients is within the purview of hospitals, which then have a responsibility to focus additional post-discharge resources on patients from such environments.

Strategies for dealing with the effect of SDS factors

The preceding considerations have stimulated debate regarding ways in which the legitimate goal of reducing readmissions may be incentivized, while at the same time limiting the potential for unintended negative consequences. Many alternative or adjunctive strategies have been recommended [1-10]. These include the investigation of readmission profiling models with and without SDS variables, and comparison with stratified results (as in the NQF recommendation); comparison of safety-net hospitals' readmission performance with that of other similar hospitals rather than those serving less vulnerable populations; assessing improvements in readmissions rates over time rather than absolute values only; slower phasing in of readmission penalties; incentives for reducing disparities in care; and the use of process measures that incentivize effective transitions and care coordination. Additional funding might also be considered for hospitals serving vulnerable populations to assist them in developing and implementing programs to reduce readmissions (the opposite of current plans to penalize such hospitals).

Summary

We believe the preponderance of evidence suggests an association between SDS factors and readmission rates, and this has profound implications for the health care system if not addressed.

Notwithstanding many excellent suggestions and strongly held beliefs, the best way to deal with this issue has yet to be determined. There is very little information regarding this topic in the CABG population. Therefore, with the permission of NQF, and contingent upon our ability to secure funding support, STS requests that our CABG readmission measure enter the NQF trial period.

We appreciate the opportunity to share our thoughts and recommendation with the NQF All-Cause Admissions and Readmissions Standing Committee. Thank you for your thoughtful consideration.

QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

Please refer to response in #2 above.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

Payor/insurance variables are available in the STS Adult Cardiac Surgery Database, and STS plans to use dual-eligible beneficiary status (i.e., those qualifying for both Medicare and Medicaid benefits) as its SDS risk factor. As described below, dual-eligible beneficiary status is a suitable surrogate for SDS.

STS considered geocoding patients' addresses as a proxy for SDS; however, the rate of missing data for this field was too high in the STS Adult Cardiac Surgery Database. STS will explore the possibility of obtaining patients' addresses from CMS data, which STS representatives will be prepared to discuss during the webinar on September 14.

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

STS believes that there is sufficient evidence to support the fact that dual-eligible beneficiary status well represents the underlying conceptual relationship between SDS factors and readmission.

Prior research indicates a relationship between dual-eligible beneficiary status and the outcome of readmission. Bennett and Probst[1] studied readmission rates of dual-eligible vs. Medicare-only beneficiaries. While dual-eligible beneficiaries represented 19% of Medicare and 14% of Medicaid enrollment in 2009, they generated 34% of expenditures in both programs. In the analysis reported by Bennett and Probst, of Medicare discharges among dually eligible beneficiaries, 21.5% resulted in a 30-day rehospitalization. Meanwhile, of Medicare discharges among Medicare-only beneficiaries, 12.8% resulted in a 30-day rehospitalization.

Similarly, a recent study by Inovalon [2] reported that dual-eligible beneficiaries were at higher risk for readmission in comparison with non-dual-eligible beneficiaries.

In addition to the prior research that indicates a relationship between dual-eligible beneficiary status as a surrogate for SDS and the outcome of readmission, it is clear that a logical relationship and theory exists about the relationship between SDS and the outcome. Dual-eligible beneficiary status is associated with patients who have fewer resources available to them to support their healthcare and prevent readmission.

1. Bennett KJ, Probst JC. Thirty-Day Readmission Rates Among Dual-Eligible Beneficiaries. J Rural Health 2015; doi: 10.1111/jrh.12140. [Epub ahead of print].
2. Inovalon. An Investigation of Medicare Advantage Dual Eligible Member Level Performance on CMS Five-Star Quality Measures. 2015. Available at: http://resources.inovalon.com/h/i/60106948-an-investigation-of-medicare-advantage-dual- eligible-member-level-performance-on-cms-five-star-quality-measures. Accessed August 2015.

QUESTION 5: Appendix (includes literature review, reference list, etc.)

Appendix: Readmission and SDS factors—Focused Literature Review

In a study of nearly 12,000 patients in Massachusetts hospitals, Weissman and colleagues [15] found that patients were more likely to be readmitted within 60 days if they were poor (adjusted OR = 1.25, $p < .05$), worked in unskilled or semiskilled occupations (adjusted OR = 1.25, $p < .05$), or rented their homes (adjusted OR = 1.23, $p < .01$). Philbin and colleagues [16] studied readmission risk among 41,776 New York heart failure patients in 1995. Patients living in lower income neighborhoods were more often women or African-Americans, they had more comorbid illnesses, more frequently used Medicaid insurance, and were more often admitted to rural hospitals. The crude frequency of readmission decreased from the lowest quartile of income (23.2%) to the highest (20.0%, $p <0.0001$). Even after adjustment for baseline differences and care processes, income was still a significant predictor, with an increased readmission risk for lower levels of income (adjusted odds ratio for comparing quartile 1 to quartile 4, 1.18; 95% CI 1.10- 1.26, $p <0.0001$).

Amarasingham and colleagues [17] developed a real-time predictive model to identify hospitalized heart failure patients at high risk for readmission or death, using data from a major urban medical center collected in 2007-2008. As in virtually all other studies, this readmission model had inferior predictive performance compared with mortality risk models. However, discrimination of their electronic readmission model (c-index 0.72) was superior to that of most other readmission algorithms, including the CMS model. Variables for social instability and lower socioeconomic status were largely responsible for the improved performance of the readmission model, as demonstrated by c-indices with and without these variables (0.72 vs. 0.61, $p < 0.05$). The authors conclude that the addition of complex social factors may significantly enhance performance of readmission models. This view is further supported by the work of Rathore and colleagues [18] who found that low SES heart failure patients had a higher risk of readmission (RR 1.08, 95% 1.03– 1.12).

Joynt and colleagues [19] studied Medicare fee-for-service patients who had readmissions for heart failure, MI, and pneumonia between 2006 and 2008. Black patients had higher readmission rates than white patients (24.8% vs 22.6%, OR 1.13; 95% CI, 1.11-1.14), and patients from minority-serving hospitals had higher readmission rates than those from non-minority-serving hospitals (25.5% vs 22.0%, OR 1.23; 95% CI, 1.20-1.27). Compared with white patients from non- minority serving hospitals, black MI patients from minority-serving hospitals had the highest readmission rate (26.4% vs. 20.9%; OR 1.35; 95% CI 1.28-1.42), while white patients from minority-serving hospitals had a 24.6% readmission rate (OR, 1.23; 95% CI, 1.18-1.29). Black patients from non-minority-serving hospitals had a 23.3% readmission rate (OR 1.20; 95% CI 1.16-1.23). Patterns were similar for CHF and pneumonia, and the results suggest that site of care may be at least as important a predictor of readmission risk as race. This may reflect the financial inability of hospitals serving predominately minority populations to plan and execute coordinated post-discharge care. Commenting on these findings, Hernandez and Curtis [20] conclude that hospitals serving large minority populations may be penalized to a proportionately greater extent by impending reimbursement changes tied to higher than average readmission rates.

Many of these factors are a failure of the health care and societal support systems rather than a particular hospital [21]. The authors argue that if inferior care is being provided to patients solely because of race, then this should not be included in risk models as it masks disparate care. On the other hand, if black race is a proxy for socioeconomic or other markers of vulnerable populations that are unrelated to in-hospital care and outside the control of hospitals, then failure to include this in risk models may result in widening of disparities. It may be unreasonable for hospitals serving low income areas to be held responsible for assuring effective care transitions and outpatient care if the local community environment does not have the necessary resources. The authors conclude that current plans to penalize hospitals based on readmission rates, at least as currently calculated, have the potential of harming the hospitals most in need of support, and that the result may be a progressive widening of disparities.

Kansagara and colleagues [22] conducted a comprehensive review of risk prediction models for hospital readmission. Thirty studies of 26 unique risk models met their search criteria. Fourteen models were derived from retrospective administrative data and were thought to be potentially useful for comparative hospital profiling. Nine of these were tested in large US studies and demonstrated predictive discrimination (c-index 0.55 - 0.65) that was poor compared with most mortality prediction models, including the three current CMS models [23] for AMI [24], heart failure [25], and pneumonia [26] which have c-indices of 0.61-0.63. Three studies used real-time administrative data collected during the hospitalization to identify patients at high risk of readmission for targeted interventions. Because they were not being used for hospital profiling, these models included a broad range of social factors such as number of address changes, census tract socioeconomic status, cocaine use, marital status, in addition to comorbidities and prior use of medical services. The discrimination of these models (0.69-0.72) was superior to that of profiling models with more limited range of variables, which suggests that social factors play an important role in the risk of readmission.

Arbaje and colleagues [14] found that among Medicare beneficiaries, after adjusting for demographics and clinical status, the odds of early readmission were increased by living alone (odds ratio or OR = 1.50, 95% confidence interval or CI = 1.01-2.24), having unmet functional need (OR = 1.48, 95% CI = 1.04-2.10), lacking self-management skills (OR

= 1.44, 95% CI = 1.03-2.02), and having limited education (OR = 1.42, 95% CI = 1.01-2.02). Using the Singh census block area deprivation index (ADI) and a 5% Medicare sample from 2004 to 2009, Kind and colleagues [28] found that within the most disadvantaged 15% of neighborhoods, rehospitalization rates increased from 22% to 27% with worsening ADI, even with full adjustment. The magnitude of this effect was comparable to that of chronic pulmonary disease and actually greater than that of uncomplicated diabetes. In a study of 30-day readmission rates for a variety of surgical procedures, using Medicare data from 2007 to 2010, Tsai and colleagues [27] found that "Black patients had higher readmission rates than white patients (14.8% vs 12.8%, odds ratio [OR] 1.19; 95% confidence interval [CI], 1.16– 1.22; P < 0.001). Patients undergoing major surgery at minority-serving hospitals also had higher readmission rates (14.3% vs 12.8%, OR 1.14, 95%CI 1.09–1.19; P < 0.001). In multivariate analyses, black patients at minority serving hospitals had the highest overall odds of readmissions (OR 1.34). White patients at minority-serving hospitals (OR 1.15) and black patients at non–minority-serving hospitals (OR 1.20) also had higher odds of readmission than the reference group of white patients at non–minority-serving hospitals. Racial disparities were mediated in part by poverty."

In a study of patients at Henry Ford Hospital, Hu and colleagues [8] found that patients living in high-poverty neighborhoods were 24 percent more likely than others to be readmitted, after adjustment for demographic characteristics and clinical conditions. Married patients were less likely to be readmitted, perhaps because they had more social support.

In their comprehensive review, Calvillo-King and colleagues [29] found that "Our systematic review identified 72 studies that had some information on the impact of social factors on risk of readmission or mortality in patients with CAP and HF… a broad spectrum of social factors were associated with worse outcomes in two common but different conditions: CAP, an acute infectious illness, and HF, a chronic disease with acute exacerbations. There were some themes across conditions and outcomes. Among Level 1 sociodemographic characteristics, older age was clearly the most consistent risk factor. Findings of disparities by race/ethnicity or gender were very mixed. Among Level 2 factors, various measures of low socioeconomic status (low income, education, Medicaid insurance) clearly increased risk. While few studies examined the same Level 3 variables, there was proof of concept evidence that social environment (housing stability, social support), behavioral (adherence, smoking, substance abuse), socio-cognitive (language proficiency), and neighborhood (rurality, distance to hospital) factors were independent predictors of poor posthospital outcomes."

Cardiac Surgery

There is little current information regarding the association of SES factors with readmission after cardiac surgery, and specifically CABG. However, in the excellent review of New York CABG readmissions by Hannan and colleagues [30], in multivariable analyses African American patients had an increased odds of 30-day readmission (1.16, 1.01-1.32, p = 0.03) and Medicaid patients had an increased odds ratio of 1.44 (1.22-1.70, p <0.0001).

Reference List

(1) NQF Risk adjustment for Socioeconomic Status or other Sociodemographic Factors, accessed at http://www.qualityforum.org/Publications/2014/08/Risk_Adjustment_for_Socioeconomic_Status_or_Other_Sociodemogr aphic_Factors.aspx Accessed on January 15, 2015.

(2) Bernheim SM. Measuring quality and enacting policy: readmission rates and socioeconomic factors. Circ Cardiovasc Qual Outcomes 2014; 7(3):350-352.

(3) Krumholz HM, Bernheim SM. Considering the role of socioeconomic status in hospital outcomes measures. Ann Intern Med 2014; 161(11):833-834.

(4) Lipstein SH, Dunagan WC. The risks of not adjusting performance measures for sociodemographic factors. Ann Intern Med 2014; 161(8):594-596.

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Measure: NQF #2513 Hospital 30-Day All-Cause Risk-Standardized Readmission Rate (RSRR) following Vascular Procedures

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

A variety of sociodemographic status (SDS) risk factors may influence readmission risk following a hospital visit for a vascular procedure. Although some recent literature evaluates the relationship between patient SDS and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways. Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission. The risk factors that have been examined in the SDS readmission literature can be categorized into three domains: (1) patient-level variables, (2) neighborhood/community-level variables, and (3) hospital-level variables. Patient-level variables describe characteristics of individual patients, and range from the race or ethnicity of the patient to the patient's income or education level [1, 2]. Neighborhood/community-level variables use information from sources such as the American Community Survey (ACS) as either a proxy for individual patient-level data or to measure environmental factors. Studies using these variables use one dimensional measures such as median household income or composite measures such as the Agency for Healthcare Research and Quality (AHRQ)-validated SES index score [3]. Hospital-level variables measure attributes of the hospital which may be related to patient risk. Examples of hospital-level variables used in studies are ZIP code characteristics aggregated to the hospital level or the proportion of Medicaid patient days [4, 5].

The conceptual relationship, or potential causal pathways by which these possible SDS risk factors influence the risk of return to the hospital following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider. We briefly describe them here and comment on their implications for the hospital readmission measures.

1. Relationship of SDS to health at admission. Sociodemographic disadvantage often leads to worse general health status and therefore patients who have lower income/education/literacy or unstable

housing may present for their hospitalization or procedure with a greater severity of underlying illness. These SDS risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may also contribute to worse health status at admission due to patients failing to respond to early symptoms and presenting for treatment later in their disease progression. This causal pathway should be largely accounted for by current clinical risk- adjustment.

However, while studies have shown that variables such as race are associated with worse health status, race itself may not directly affect health status at hospital admission. Rather, the association of race with worse health is likely mediated through the association between race and other sociodemographic factors such as poverty or disparate access to high quality care.

2. Use of low-quality hospitals. SDS risk factors may be associated with access to quality healthcare providers because of the distribution of providers and prohibitive costs. In particular, SDS factors can influence the likelihood that patients access high quality care. Patients of lower income, lower education, or unstable housing may not have access to high quality facilities because such facilities are less likely to be found in lower SDS geographic areas. Poor and minority patients are more likely to be seen in lower quality hospitals, which can contribute to the likelihood of hospital readmission [6-8]. To the extent that the relationship between SDS and readmission is driven by clustering of low SDS patients within lower quality facilities, traditional patient-level risk adjustment for SDS would be inappropriate.

3. Differential care within a hospital. The third major pathway by which SDS factors may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, patients of low income or minority race may experience differential, lower quality, or discriminatory care within a given facility [9]. Alternatively, patients with SDS risk factors may require differentiated care – e.g. provision of lower literacy information – that they do not receive. That is to say, hospitals may provide the same care for all populations (e.g. the same discharge instructions) and this may represent substandard care for patients for whom the standard approach is not effective (e.g. due to low literacy). By failing to actively address the unique needs of patients with SDS risk factors, institutions may be providing lower quality care to these patients. Again, in such circumstances, patient-level risk adjustment for SDS is problematic as it would essentially adjust for a characteristic of the care provided rather than for a patient risk factor.

4. Influence of SDS on readmission risk outside of hospital quality and health status. Some SDS risk factors, such as income or wealth, may affect the likelihood of hospital readmission without directly

affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may be less likely to follow prescribed care (e.g. refill a prescription or keep a follow-up visit with a primary care provider) because limited resources create competing priorities for the patient or their community may have a limited supply of primary care providers. These kinds of pathways present more complex questions about appropriate risk-adjustment decisions.

References:

1. Hu J, Gonsahn MD, Nerenz DR. Socioeconomic status and readmissions: evidence from an urban teaching hospital. Health affairs (Project Hope). 2014;33(5):778-785.
2. Eapen ZJ, McCoy LA, Fonarow GC, Yancy CW, Miranda ML, Peterson ED, Califf RM, Hernandez AF. Utility of socioeconomic status in predicting 30-day outcomes after heart failure hospitalization. Circ Heart Fail. 2015 May;8(3):473-80.
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QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

Since these measures have been developed and implemented using national-level data, there is substantial variation in SDS risk factors across hospitals. Two variables we have presented in our NQF applications provide empirical evidence that this variation exists. For the Vascular Readmission measure, the percentage of patients who are black ranges from 0% to 93.0% across hospitals, with a median of 4.3% (interquartile range [IQR] 1.4%-10.7%). The percentage of patients who are Medicaid beneficiaries ranges from 0% to 73.9%, with a median of 17.4% (IQR 11.8%- 21.9%). This information was based on 2009 data used for development.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The variables that are available within or that can be linked directly to Medicare administrative claims data used for these measures include the following:

1. Race (black, white, other). Data source: Medicare claims, enrollment database
2. Medicaid dual-eligible status. Data source: Medicare claims, enrollment database.
3. Neighborhood SES factors as proxies for patient-level SES [1]. Data source: Enrollment database and Census data (American Community Survey).

References:

1. Creation of New Race-Ethnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries: Final Report. August 2012. Agency for Healthcare Research and Quality, Rockville, MD. http://archive.ahrq.gov/research/findings/final-reports/medicareindicators/index.html

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

SDS is a multifaceted phenomenon (more so than clinical factors) and therefore it is unlikely that a single SDS factor will fully and consistently capture the aspects of SDS which affect the risk of readmission through the causal pathways described above.

Dual-eligible status: For our readmission measures, which include Medicare fee-for-service (FFS) beneficiaries aged 65 years and older, dual-status is a good indicator of current assets and income and dual-eligibility criteria are consistent across most states (though cost of living varies) [1]. We think this is, therefore, a reasonable patient-level variable to assess the relationship between SDS and readmission in that it provides a reliably-obtained indication of patients with low income/assets. There are two important caveats: first, dual-eligible status is a dichotomous variable and thus provides less gradation of SDS; and second, for some patients dual-eligibility is the result of a “spending down” to obtain coverage for nursing care. For such patients, it is difficult to differentiate between those who may have faced a lifetime of low SDS and associated challenges versus those who have had more resources earlier in life and only recently became classified as low income.

Race: The particular case of race as a predictor of health outcomes illuminates the complexity of the role SDS variables play in assessing hospital performance. Racial identity itself confers no differential risk of mortality or readmission following hospitalization. The evidence suggests that a greater prevalence of risk factors in combination with the effects of bias and discrimination account for differential outcomes observed among certain racial groups. This is not to say that there are no meaningful biological variations among groups whose genetic ancestry can be traced to different geographic regions of the world. However, these variations are quite specific and narrowly defined and have not been shown confer broad health risks across groups absent specific genetic markers. Nevertheless, numerous studies have demonstrated greater disease burden, lack of access to health care services, and bias in application of medical intervention among racial minorities, particularly black patients seeking care for a variety of medical and surgical conditions.

In risk-adjusted statistical models of readmission following hospitalization, race is a marker for other SDS factors, such as poverty or social support; however, we often find that the association between race and readmission is greater and more robust or consistent than that of economic factors. The absence of any biologically defined causal pathway suggests that this stronger association may result from exposure to broad societal racial bias. We can determine the specific health outcome-related effects of exposure to societal racial bias through quality measurement, as the health outcome is relatively consistent across exposed individuals. Poverty may have more nuanced effects dependent on unmeasured factors such as the surrounding community, familial support, and others.

Whether we should we include a risk variable to adjust for the presence of this bias depends on whether or not the risk conferred through bias is attributable to factors within or beyond the hospitals’ control. The evidence that blacks receive differential care across a variety of medical and surgical conditions suggests that, even as this bias exists broadly throughout the institutions of society, hospitals and providers also contribute to it [2]. If so, this contribution of the hospital – the effect of treatment bias – should not be included in risk adjusted models of hospital performance as to do so would, in effect, be giving hospitals credit for more disparate or discriminatory care.

ZIP Code-level SDS indicators: The American Community Survey (ACS) provides a number of SDS indicators that are available at the ZIP code level. We are in the process of developing an approach to linking these data to at the 9-digit ZIP code level, which will allow for a more granular perspective on local SDS. We propose to analyze an Agency for Healthcare Research and Quality (AHRQ)-validated composite index of SES which has been used and tested among Medicare beneficiaries [3]. This index is a composite of seven different variables found in the Census data which may capture SDS better than any single variable. The variables are: (1) median household income, (2) percentage of persons living below the federal poverty level, (3) percentage of persons who are aged >16 years and in the labor force but not employed, (4) median value of owner-occupied homes, (5) percentage of persons aged >25 years who completed at least a 12th grade education, (6) percentage of persons aged >25 years who completed at least four years of college, and (7) percentage of households that average one or more persons per room. This is a neighborhood-level variable, which we would use as a proxy for patient-level SDS factors.

References:

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Measure: NQF #2515 Hospital 30-day, all-cause, unplanned, risk-standardized readmission rate (RSRR) following coronary artery bypass graft (CABG) surgery

QUESTION 1: Describe the conceptual relationship between your outcome measure and possible SDS risk factors. Specifically, provide support from the literature or other empirical data on whether a conceptual relationship exists between at least one (1) specific SDS risk factor and the outcome being measured. Describe the possible risk factor(s) that exhibits the strongest relationship to admissions/readmissions. Possible SDS risk factors for examination may include income, level of education, homelessness status, English language proficiency, health insurance status, occupation, employment status, literacy, health literacy, or neighborhood-level data that can be used as a proxy for individual data such as median neighborhood income, education, or local funding availability for safety net providers.

A variety of sociodemographic status (SDS) risk factors may influence readmission risk following a hospital visit for coronary artery bypass graft surgery (CABG). Although some recent literature evaluates the relationship between patient SDS and the readmission outcome, few studies directly address causal pathways or examine the role of the hospital in these pathways. Moreover, the current literature examines a wide range of conditions and risk variables with no clear consensus on which risk factors demonstrate the strongest relationship with readmission. The risk factors that have been examined in the SDS readmission literature can be categorized into three domains: (1) patient-level variables, (2) neighborhood/community-level variables, and (3) hospital-level variables. Patient-level variables describe characteristics of individual patients, and range from the race or ethnicity of the patient to the patient's income or education level [1, 2]. Neighborhood/community-level variables use information from sources such as the American Community Survey (ACS) as either a proxy for individual patient-level data or to measure environmental factors. Studies using these variables use one dimensional measures such as median household income or composite measures such as the Agency for Healthcare Research and Quality (AHRQ)-validated SES index score [3]. Hospital-level variables measure attributes of the hospital which may be related to patient risk. Examples of hospital-level variables used in studies are ZIP code characteristics aggregated to the hospital level or the proportion of Medicaid patient days [4, 5].

The conceptual relationship, or potential causal pathways by which these possible SDS risk factors influence the risk of return to the hospital following an acute illness or major surgery, like the factors themselves, are varied and complex. There are at least four potential pathways that are important to consider. We briefly describe them here and comment on their implications for the hospital readmission measures.

1. Relationship of SDS to health at admission. Sociodemographic disadvantage often leads to worse general health status and therefore patients who have lower income/education/literacy or unstable housing may present for their hospitalization or procedure with a greater severity of underlying illness. These SDS risk factors, which are characterized by patient-level or neighborhood/community-level (as proxy for patient-level) variables, may also contribute to worse health status at admission due to patients failing to respond to early symptoms and presenting for treatment later in their disease progression. This causal pathway should be largely accounted for by current clinical risk- adjustment.

However, while studies have shown that variables such as race are associated with worse health status, race itself may not directly affect health status at hospital admission. Rather, the association of race with worse health is likely mediated through the association between race and other sociodemographic factors such as poverty or disparate access to high quality care.

2. Use of low-quality hospitals. SDS risk factors may be associated with access to quality healthcare providers because of the distribution of providers and prohibitive costs. In particular, SDS factors can influence the likelihood that patients access high quality care. Patients of lower income, lower education, or unstable housing may not have access to high quality facilities because such facilities are less likely to be found in lower SDS geographic areas. Poor and minority patients are more likely to be seen in lower quality hospitals, which can contribute to the likelihood of hospital readmission [6-8]. To the extent that the relationship between SDS and readmission is driven by clustering of low SDS patients within lower quality facilities, traditional patient-level risk adjustment for SDS would be inappropriate.

3. Differential care within a hospital. The third major pathway by which SDS factors may contribute to readmission risk is that patients may not receive equivalent care within a facility. For example, patients of low income or minority race may experience differential, lower quality, or discriminatory care within a given facility [9]. Alternatively, patients with SDS risk factors may require differentiated care – e.g. provision of lower literacy information – that they do not receive. That is to say, hospitals may provide the same care for all populations (e.g. the same discharge instructions) and this may represent substandard care for patients for whom the standard approach is not effective (e.g. due to low literacy). By failing to actively address the unique needs of patients with SDS risk factors, institutions may be providing lower quality care to these patients. Again, in such circumstances, patient-level risk adjustment for SDS is problematic as it would essentially adjust for a characteristic of the care provided rather than for a patient risk factor.

4. Influence of SDS on readmission risk outside of hospital quality and health status. Some SDS risk factors, such as income or wealth, may affect the likelihood of hospital readmission without directly

affecting health status at admission or the quality of care received during the hospital stay. For instance, while a hospital may make appropriate care decisions and provide tailored care and education, a lower-income patient may be less likely to follow prescribed care (e.g. refill a prescription or keep a follow-up visit with a primary care provider) because limited resources create competing priorities for the patient or their community may have a limited supply of primary care providers. These kinds of pathways present more complex questions about appropriate risk-adjustment decisions.

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1. Hu J, Gonsahn MD, Nerenz DR. Socioeconomic status and readmissions: evidence from an urban teaching hospital. Health affairs (Project Hope). 2014;33(5):778-785.
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QUESTION 2: Describe the relationship between the SDS risk factor(s) and the measured unit (hospital, SNF, etc.) to indicate the variation in the risk factor across the measured unit. Information from the literature is sufficient to indicate potential variation; however, empirical data for the measure as specified (e.g., via bivariate frequency distributions) would be needed to demonstrate that variation does not exist and therefore adjustment is not appropriate.

Since these measures have been developed and implemented using national-level data, there is substantial variation in SDS risk factors across hospitals. Two variables we have presented in our NQF applications provide empirical evidence that this variation exists. For the CABG Readmission measure, the percentage of patients who are black ranges from 0% to 93.5% across hospitals, with a median of 4.8% (interquartile range [IQR] 1.7%-11.0%). The percentage of patients who are Medicaid beneficiaries ranges from 0% to 58.5% across hospitals, with a median of 18.3% (IQR 13.0%-22.6%) This information was based on the most current data for reporting.

QUESTION 3: What are the patient-level sociodemographic variables that are available in the datasets used to develop the measure?

The variables that are available within or that can be linked directly to Medicare administrative claims data used for these measures include the following:

1. Race (black, white, other). Data source: Medicare claims, enrollment database
2. Medicaid dual-eligible status. Data source: Medicare claims, enrollment database.
3. Neighborhood SES factors as proxies for patient-level SES [1]. Data source: Enrollment database and Census data (American Community Survey).

References:

1. Creation of New Race-Ethnicity Codes and Socioeconomic Status (SES) Indicators for Medicare Beneficiaries: Final Report. August 2012. Agency for Healthcare Research and Quality, Rockville, MD. http://archive.ahrq.gov/research/findings/final-reports/medicareindicators/index.html

QUESTION 4: How well do the patient-level SDS variables that are available represent the underlying conceptual relationship identified?

SDS is a multifaceted phenomenon (more so than clinical factors) and therefore it is unlikely that a single SDS factor will fully and consistently capture the aspects of SDS which affect the risk of readmission through the causal pathways described above.

Dual-eligible status: For our readmission measures, which include Medicare fee-for-service (FFS) beneficiaries aged 65 years and older, dual-status is a good indicator of current assets and income and dual-eligibility criteria are consistent across most states (though cost of living varies) [1]. We think this is, therefore, a reasonable patient-level variable to assess the relationship between SDS and readmission in that it provides a reliably-obtained indication of patients with low income/assets. There are two important caveats: first, dual-eligible status is a dichotomous variable and thus provides less gradation of SDS; and second, for some patients dual-eligibility is the result of a “spending down” to obtain coverage for nursing care. For such patients, it is difficult to differentiate between those who may have faced a lifetime of low SDS and associated challenges versus those who have had more resources earlier in life and only recently became classified as low income.

Race: The particular case of race as a predictor of health outcomes illuminates the complexity of the role SDS variables play in assessing hospital performance. Racial identity itself confers no differential risk of mortality or readmission following hospitalization. The evidence suggests that a greater prevalence of risk factors in combination with the effects of bias and discrimination account for differential outcomes observed among certain racial groups. This is not to say that there are no meaningful biological variations among groups whose genetic ancestry can be traced to different geographic regions of the world. However, these variations are quite specific and narrowly defined and have not been shown confer broad health risks across groups absent specific genetic markers. Nevertheless, numerous studies have demonstrated greater disease burden, lack of access to health care services, and bias in application of medical intervention among racial minorities, particularly black patients seeking care for a variety of medical and surgical conditions.

In risk-adjusted statistical models of readmission following hospitalization, race is a marker for other SDS factors, such as poverty or social support; however, we often find that the association between race and readmission is greater and more robust or consistent than that of economic factors. The absence of any biologically defined causal pathway suggests that this stronger association may result from exposure to broad societal racial bias. We can determine the specific health outcome-related effects of exposure to societal racial bias through quality measurement, as the health outcome is relatively consistent across exposed individuals. Poverty may have more nuanced effects dependent on unmeasured factors such as the surrounding community, familial support, and others.

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ZIP Code-level SDS indicators: The American Community Survey (ACS) provides a number of SDS indicators that are available at the ZIP code level. We are in the process of developing an approach to linking these data to at the 9-digit ZIP code level, which will allow for a more granular perspective on local SDS. We propose to analyze an Agency for Healthcare Research and Quality (AHRQ)-validated composite index of SES which has been used and tested among Medicare beneficiaries [3]. This index is a composite of seven different variables found in the Census data which may capture SDS better than any single variable. The variables are: (1) median household income, (2) percentage of persons living below the federal poverty level, (3) percentage of persons who are aged >16 years and in the labor force but not employed, (4) median value of owner-occupied homes, (5) percentage of persons aged >25 years who completed at least a 12th grade education, (6) percentage of persons aged >25 years who completed at least four years of college, and (7) percentage of households that average one or more persons per room. This is a neighborhood-level variable, which we would use as a proxy for patient-level SDS factors.

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NATIONAL QUALITY FORUM

Meeting Summary

Admissions and Readmission Measure Endorsement Project
Standing Committee Call: SDS Trial Period Web Meeting #1
September 14, 2015 | 12:00-2:00PM ET

The Admissions and Readmissions Standing Committee met on September 14, 2015 to review the SDS factors/variables that measure developers in the NQF sociodemographic status (SDS) trial period plan to test in their empirical analysis of their risk adjustment model. This summary of the Admissions and Readmissions Standing Committee's deliberations highlights the data sources/variables presented by the measure developers, the Standing Committee feedback, and input on the draft empirical analysis plan, if provided by the measure developer for all 16 All-Cause Admissions and Readmissions measures trial period.

The Committee discussed the conceptual model as well as the variables provided by the developers. Overall, the Standing Committee recommended the following sociodemographic variables should be strongly considered in each measure:

- Age
- Gender

The Committee also provided feedback for the draft empirical analysis plan on several measures, where provided by the measure developer. The Standing Committee recognizes that every developer may not be able to react to each variable suggested, given data availability, resources, and time. The measure developer is ultimately responsible for making a final decision on the variables that will be included in the risk adjustment model and defend the validity of the final model and measure to the Standing Committee. The table below summarizes the Committee's discussion for each of the measures.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
0505	Hospital 30-day all-cause risk-standardized readmission rate (RSRR) following acute myocardial infarction (AMI) hospitalization	Medicare claims, enrollment database: • Age and Gender • Race (black, white, other) • Medicaid dual-eligible status Enrollment database and Census data (American Community Survey): • Neighborhood SES factors as proxies for patient-level SES	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. The variables represent the underlying conceptual construct well.	The draft plan was not provided for the Committee's review.
0695	Hospital 30-Day Risk-Standardized Readmission Rates following Percutaneous Coronary Intervention (PCI)	CathPCI Registry dataset and Medicare Provider and Analysis Review (MEDPAR) file: • Gender • Race • Hispanic ethnicity • Age • Zip code • Insurance status (from CathPCI)	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These represent the underlying conceptual construct well. Going forward, they are discouraged from using the five digit zip code as SDS variable as it is a heterogeneous construct that may not necessarily represent specific patient-level attributes.	The draft plan was not provided for the Committee's review.
2375	PointRight® Pro 30™ (Skilled Nursing Facility Rehospitalization)	Person characteristics from MDS (Minimum Data Set): • Race • Age (already included in RA model) • Gender (already included in RA model) • Marital status (possibly crossed with age and Gender) • Language • Gender • Dual eligibility/state buy-in	Given the long list of variables the developers have indicated they would be looking at, the SC suggested narrowing down the list to the most impactful variables, especially regarding facility and regional characteristics (disparities). The Committee was in agreement that looking at county-level data can provide a picture of the relationship between the community and healthcare facilities or	The draft plan was not provided for the Committee's review.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
		Facility characteristics: • Percent of patients by race • Percent of patients by age category • Percent of patients by Gender • Percent of patients by gender • Percent of patients by marital status • Percent of patients by language • Percent of patients by state buy-in indicator • Percent of the facility's census that is receiving post-acute care (i.e., admitted from a hospital in the prior 30 days) • Percent of the facility's census that is covered by Medicare FFS • Percent of facility's residents with Medicaid benefits interacted with three levels of liberality of Medicaid eligibility, and three levels of liberality of per diem Medicaid SNF reimbursement • The number of beds in the facility • The ownership of the facility (nonprofit, for profit individual, for profit chain, public) Regional characteristics (County or CBSA of SNF): • Median household income • Percent of households >= 133% of Federal poverty level • Percent of adults eligible for Medicaid (according to state standards) • Percent of persons >= 65 with private insurance	providers and how this affects patient's health status, especially for this setting.	

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
		• Percent of persons >= 65 with Medicaid • Percent of persons >= 65 with Medicare FFS • Percent of persons >= 65 with Medicare Advantage • Percent of persons in the labor force >= 25 who are unemployed • Percent of persons >= 18 who are homeless • Percent of persons aged >= 30 with a graduate degree; percent of persons aged >= 25 with a college degree • Percent of persons >= 30 who live in rented dwellings • Percent of people in the geographical region and the same demographic category who are poor		
2380/2505	**2380:** Rehospitalization during the First 30 days of Home Health **2505:** Emergency Department (ED) Use without Hospital Readmission during the First 30 Days of Home Health	Medicare Claims Data: • Prior Care Setting • Age and gender interactions • Health Status (from Medicare claims) • Medicare Enrollment Status • Additional interactions between Hierarchical Condition Categories (HCCs) and Medicare Enrollment Status (income and employment) Identified additional SDS factors to be tested from Medicare Enrollment Database (EDB) and Survey data: • Race/Ethnicity (EDB)	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well. In addition to looking at neighborhood characteristics, the Committee highlights the importance of looking at rural location, as stated in the developer's future analysis plan.	The draft plan was not provided for the Committee's review.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
		• Medicaid Status (EDB) • Rural location (EDB) • Neighborhood characteristics (survey)		
2393/2414	**2393:** Pediatric All-Condition Readmission Measure **2414:** Pediatric Lower Respiratory Infection Readmission Measure	Administrative claims, Patient Reported Data/Survey Case-mix adjustment model variables: • Age group • Gender • Presence of chronic conditions 2009 AHRQ HCUP State Inpatient Databases with Revisit Data for New York and Nebraska: • Race/Ethnicity • Insurance status Future dataset to be used New York State 2013 Medicaid and all payer datasets • Neighborhood-level income • Education	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well. They recommend additional variables for the developers to test: • Health and functional status such as mental illness or disability, if available	The draft plan was not provided for the Committee's review.
2496	Standardized Readmission Ratio (SRR) for dialysis facilities	National ESRD patient database and Medicare Claims Standard Analysis Files: • Unemployment status six months prior to onset of ESRD • Dual eligibility status at index discharge (low-income) • Medicare as secondary insurance coverage at index discharge (higher income)	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well. With the measures focus on dialysis setting, the Committee recommended testing several additional variables: • Regional characteristics (county-	The draft plan was not provided for the Committee's review.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
		• Race • Age	level variables) • Partial versus full dual or disability status (in addition to status at index discharge)	
2502	All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Inpatient Rehabilitation Facilities (IRFs)	Medicare claims data: • Age • Gender • Race • Dual Eligibility Indicator Long-Term Care Hospital (LTCH) Continuity Assessment Record & Evaluation (CARE) Data Set: • Marital status at time of admission • Preferred language County-level variables, (possible sources) U.S. Census data, the Health Professional Shortage Area designation database: • Median household income • Employment rate • Degree of urbanization • Median education level • Availability of primary care providers	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well.	SC supported the draft empirical analysis plan and encouraged the measure developer to continue with the testing. Committee members commented that if the intention is to develop a "new" index for county factors, it should be carefully studied to validate its use for the readmission measures.
2503 and 2504	**2503**: Hospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries (Population-level)	Medicare Part A Claims and Denominator File • Gender • Race/ethnicity (not viewed as reliable enough) • Age Group	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer, and suggested that developers look at all 3 variables. These variables represent the underlying	The draft plan was not provided for the Committee's review.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
	2504: 30-day Rehospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries (Population-level)		conceptual construct well. The Standing Committee recommended testing additional variables: • Neighborhood characteristics (area deprivation index – build on similar testing developer stated as having conducted in the past) • Housing status • Dual eligibility status • Facility characteristics	
2510	Skilled Nursing Facility 30-Day All-Cause Readmission Measure (SNFRM)	Medicare claims data: • Age • Gender • Race • Dual Eligibility Indicator Long-Term Care Hospital (LTCH) Continuity Assessment Record & Evaluation (CARE) Data Set: • Marital status at time of admission • Preferred language County-level variables: (possible sources) U.S. Census data, the Health Professional Shortage Area designation database: • Median household income • Employment rate • Degree of urbanization • Median education level • Availability of primary care providers	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These represent the underlying conceptual construct well. Here are additional variables that they would recommend: • County-level variables (zip code), with particular focus on frequency of updates depending on data source (annual survey or census data every 10 years) based on census data	SC supported the draft empirical analysis plan and encouraged the measure developer to continue with testing. Committee members commented that if the intention is to develop a “new” index for county factors, it should be carefully studied to validate its use for the readmission measures.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
2512	All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Long-Term Care Hospitals (LTCHs)	Medicare claims data: • Age • Gender • Race • Dual eligibility indicator Long-Term Care Hospital (LTCH) Continuity Assessment Record & Evaluation (CARE) Data Set: • Marital status at time of admission • Preferred language County-level variables: (possible sources) U.S. Census data, the Health Professional Shortage Area designation database: • Median household income • Employment rate • Degree of urbanization • Median education level • Availability of primary care providers	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well.	SC supported the draft empirical analysis plan and encouraged the measure developer to continue with the testing. Committee members commented that if the intention is to develop a "new" index for county factors, it should be carefully studied to validate its use for the readmission measures.
2513	Hospital 30-Day All-Cause Risk-Standardized Readmission Rate (RSRR) following Vascular Procedures	Medicare claims, enrollment database: • Age • Gender • Race (black, white, other) • Medicaid dual-eligible status Enrollment database and Census data (American Community Survey): • Neighborhood SES factors as proxies for patient-level SES	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. However; they agreed that there are only a few variables included and there are additional variables that developers can investigate. The SC recommended testing race, but expressed caution that this underlying construct for how race influences the outcome should be justified.	The draft plan was not provided for the Committee's review.

Measure #	Measure Title	Data Sources and Variables	Committee Feedback	Draft Empirical Analysis Plan
2514	Risk-Adjusted Coronary Artery Bypass Graft (CABG) Readmission Rate	STS Adult Cardiac Surgery Database: • Age • Gender • Dual-eligible indicator	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. These variables represent the underlying conceptual construct well. The Standing Committee recommended testing an additional variable: • Insurance status	The draft plan was not provided for the Committee's review.
2515	Hospital 30-day, all-cause, unplanned, risk- standardized readmission rate (RSRR) following coronary artery bypass graft (CABG) surgery	Medicare claims, enrollment database: • Age • Gender • Race (black, white, other) • Medicaid dual-eligible status Enrollment database and Census data (American Community Survey): • Neighborhood SES factors as proxies for patient-level SES	Standing Committee (SC) reviewed and was generally in agreement with the variables provided by the developer. The SC recommended testing race, but expressed caution that this underlying construct for how race influences the outcome should be justified.	The draft plan was not provided for the Committee's review.

Next Steps

There will be two additional webinars for the SDS trial period. During the second and third webinar, the Committee will:

- Review and discuss the empirical analysis of the risk adjustment approach in context of the validity criterion;
- Review and discuss the developer's decision to include or not include SDS adjustment in the measure based on the empirical analysis provided; and
- Make an endorsement recommendation:
  - Recommend [continued] endorsement of the measure
  - Recommend to remove endorsement of the measure

The measures have been divided into two groups, in Table 1 below, according to feedback received by the developers on when they would be able to complete the empirical analysis of the relationship between SDS factors and their measured outcome.

TABLE 1. MEASURE GROUPING

Group 1 (March 8, 2016)	Group 2 (May 13, 2016)
• Measure # 0505 Hospital 30-day all-cause risk-standardized readmission rate (RSRR) following acute myocardial infarction (AMI) hospitalization • Measure # 0695 Hospital 30-Day Risk-Standardized Readmission Rates following Percutaneous Coronary Intervention (PCI) • Measure # 2393 Pediatric All-Condition Readmission Measure • Measure # 2414 Pediatric Lower Respiratory Infection Readmission Measure • Measure # 2513 Hospital 30-Day All-Cause Risk-Standardized Readmission Rate (RSRR) following Vascular Procedures • Measure # 2514 Risk-Adjusted Coronary Artery Bypass Graft (CABG) Readmission Rate • Measure # 2515 Hospital 30-day, all-cause, unplanned, risk-standardized readmission rate (RSRR) following coronary artery bypass graft (CABG) surgery.	• Measure # 2375 PointRight ® Pro 30™ • Measure # 2380 Rehospitalization During the First 30 Days of Home Health. • Measure # 2502 All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Inpatient Rehabilitation Facilities (IRFs) • Measure # 2503 Hospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries. • Measure # 2504 30-day Rehospitalizations per 1000 Medicare fee-for-service (FFS) Beneficiaries • Measure # 2505 Emergency Department Use without Hospital Readmission During the First 30 Days of Home Health • Measure # 2510 Skilled Nursing Facility 30-Day All-Cause Readmission Measure (SNFRM) • Measure # 2512 All-Cause Unplanned Readmission Measure for 30 Days Post Discharge from Long-Term Care Hospitals (LTCHs) • Measure # 2496 Standardized Readmission Ratio (SRR) for dialysis facilities