

**Measure Methodology Report: Clinician and Clinician Group  
Risk-standardized Hospital Admission Rates for Patients with Multiple  
Chronic Conditions**

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## Executive Summary

Under contract to the Centers for Medicare & Medicaid Services (CMS), Yale New Haven Health Services Corporation – Center for Outcomes Research and Evaluation (CORE) developed an outcome measure for the Merit-based Incentive Payment System (MIPS) for patients with multiple chronic conditions (MCCs). Specifically, we adapted for MIPS a measure of acute, unplanned hospital admissions for MCC patients that CMS currently reports for Medicare Accountable Care Organizations (ACOs). The measure fills the Meaningful Measures gap areas of tracking outcomes and care coordination for the high-priority patient group of patients with MCCs. This report presents the measure design, the rationale for measure design decisions, and measure testing results.

The measure will expand the choice of outcome measures providers have under MIPS. MIPS requires eligible clinicians to report at least one outcome measure (or alternative high-priority measure if none is available). This measure covers primary care providers (PCPs) and a subset of specialists who typically coordinate or “quarterback” care for MCC patients and in that role would be expected to be able to minimize their risk of unplanned admissions through the provision of high-quality care. The measure is designed to work for MIPS eligible clinicians who report under MIPS as individuals or as groups (as defined by the program) under a common Taxpayer Identification Number (TIN).

The measure, in brief, is a risk-adjusted outcome measure that uses the outcome of acute, unplanned admissions per 100 person-years at risk of admission to assess care quality. Using outcomes to assess ambulatory care quality requires specifying the outcome carefully and assigning patients to clinicians. Hence, in contrast to the MCC admission measure used for Medicare ACOs, this measure’s outcome is more narrowly drawn to ensure it reflects the quality of ambulatory care. Fewer types of admission are counted in the outcome reflecting ambulatory clinicians’ more limited ability to influence the outcome; for example, the outcome does not count post-surgical admissions.

The cohort includes Medicare Fee-for-Service (FFS) beneficiaries aged  $\geq 65$  years who have two or more of the following nine chronic conditions: 1) acute myocardial infarction, 2) Alzheimer’s disease and related disorders or senile dementia, 3) atrial fibrillation, 4) chronic kidney disease, 5) chronic obstructive pulmonary disease or asthma, 6) depression, 7) diabetes, 8) heart failure, and 9) stroke or transient ischemic attack.

Hierarchical negative binomial regression modeling is used to calculate a provider’s measure score, the risk-standardized acute admission rate (RSAAR). The statistical model accounts for differences in patient sample size across providers and adjusts for age, clinical variables (including comorbidities and measures of frailty and disability), and social risk factors (including area-level measures of neighborhood deprivation and access to care).

Because Medicare beneficiaries typically see multiple healthcare providers in the ambulatory setting, the measure includes a novel algorithm for attributing patients and their outcomes to providers for measurement. Patients are attributed to MIPS eligible clinicians using a visit-based algorithm that assigns patients to the PCP with the most visits, unless there is a dominant specialist likely coordinating care. We developed the algorithm in consultation with a national Technical Expert Panel (TEP) and CMS, informed by analyses of alternatives presented in an appendix to this report.

We tested the measure using 2015 as the measurement year in a MIPS-like Medicare FFS population (derived based on individual clinicians and clinician groups participating in the Value-Based Payment Modifier [VM] program, the predecessor program to MIPS). 6,148,751 patients met the



inclusion/exclusion criteria. The attribution algorithm assigned 79.5% of patients to PCPs and 7.6% to specialists scored by the measure. A total of 12.9% of patients were excluded from measure scoring; 2.2% were assigned to hematologists and oncologists not scored by the measure, and 10.7% were unassigned because they did not visit a PCP or relevant specialist at least twice in the measurement year or whose pattern of visits did not allow us to identify the clinician most responsible for the patients' care. Thus, the final MCC cohort used for model building and testing included 4,937,865 patients.

We calculated measure scores at the TIN level (n=64,025 TINs), which included individual clinicians and those who reported as groups under MIPS. As expected, the results showed wide variation in the number of patients per TIN, ranging from 1 to 10,328 MCC patients, with a median of 22 and an interquartile range (IQR) of 7 to 59. TIN risk-standardized acute admission rates (RSAARs) also showed wide variation, ranging from 16.9 to 112.8 per 100 person-years, with a median of 41.5 and an IQR of 39.1 to 44.7 per 100 person-years.

Different types of providers scored similarly on the measure, suggesting the measure fairly evaluates quality for a range of MIPS providers caring for patients with MCCs. Generally similar distributions in measure scores were found across TINs with different combinations of PCPs and/or specialists within the TIN (for example, TINs limited to one type of specialist such as cardiologists, TINs with a mix of PCPs and specialists, and TINs with just PCPs). In addition, solo clinician and multi-provider TINs had similar score distributions.

We determined the minimum sample size needed to achieve TIN-level measure score reliability of  $\geq 0.5$  (an acceptable cutoff for outcome measures) among TINs likely to participate in MIPS. We calculated that  $\geq 28$  patients per TIN are needed to achieve measure score reliability estimates of 0.5 or greater. If CMS established this volume cutoff for public reporting, about half the TINs (55.7%) would be excluded; however, the measure would include 92.9% of patients and 78.9% of clinicians if reported with this reliability.

This measure was developed consistently with CMS's quality measure development guidance.<sup>1</sup> The CORE project team, a multidisciplinary team of clinicians, health services researchers, and statisticians, was supported and informed by a national TEP consisting of clinicians, methodologists, researchers, and patients. CMS also held a 4-week public comment period, soliciting stakeholder input on the measure methodology, and prepared a report for posting on CMS's public comment website summarizing and responding to the comments and describing updates CMS made to the measure in response to the comments.<sup>2</sup>

In summary, this MIPS MCC admission measure as currently structured illuminates substantial differences in admission rates across TINs after adjusting for case mix and social risk factors. The measure therefore has the potential to inform patient choice, drive quality improvement, and enhance care coordination. The measure specifications reflect extensive input from the TEP and numerous stakeholders through public comment.

## 1. INTRODUCTION

### 1.1 Measure Development Overview and Call for Public Comment

In 2017, the Centers for Medicare & Medicaid Services (CMS) contracted with Yale New Haven Health Services Corporation - Center for Outcomes Research & Evaluation (CORE) to develop an outcome measure that reflects the quality of care for patients with multiple chronic conditions (MCCs). Specifically, CMS asked CORE to adapt its existing outcome measure developed for and currently used in CMS's Accountable Care Organization (ACO) quality measure set (ACO-38).<sup>3</sup> The ACO-38 measure of risk-standardized acute, unplanned admission rates was designed to assess ambulatory care delivered jointly by ACOs, groups of providers who share responsibility for patients' care and outcomes.

In response, CORE re-specified CMS's ACO-38 measure for use in assessing individual or groups of clinicians participating in the Merit-based Incentive Payment System (hereinafter, MIPS MCC admission measure). We re-specified the ACO-38 measure with input from a national Technical Expert Panel (TEP). We recognized that, in contrast to ACOs, ambulatory clinicians participating under MIPS may not have the same ability or resources to influence the range of factors that affect patients' admission risk. We therefore adapted the MIPS MCC admission measure from ACO-38 to reflect the differences in the care settings with the goal of measuring and incentivizing high-quality ambulatory care accurately and fairly in the MIPS context.

This MIPS MCC admission measure provides an assessment of the quality of care provided by ambulatory clinicians who manage the care of patients with MCCs. The measure uses the outcome of acute, unplanned admissions to assess care quality. It reflects the assumption, informed by the literature, that clinician or clinician groups with lower risk-adjusted rates of admissions included in the measure are providing better quality care.

The measure is intended for use under MIPS, a track of CMS's Quality Payment Program (QPP), to assess the performance of MIPS eligible clinicians. It is consistent with CMS's goal of providing eligible clinicians with actionable data, while at the same time providing patients with a meaningful outcome. CMS expects that sharing measure scores with eligible clinicians, in addition to tying reimbursement payment adjustments to these scores, will strongly encourage eligible clinicians to improve care quality and patient outcomes.

In this report, we provide:

- [Section 1](#): An introduction to the development of the MIPS MCC admission measure.
- [Section 2](#): Detailed information on the methods of development and measure specifications.
- [Section 3](#): Results of measure testing.
- [Section 4](#): A summary of measure development and testing.
- [Section 5](#): A glossary of terms used throughout the report.
- [Appendices](#) with supplementary information about measure development and specifications.

Additionally, this report is posted with an accompanying Excel file that contains the codes used for measure specification. We refer to this Excel file throughout the report.

## 1.2 Background on Quality Payment Program

There is a growing consensus that the traditional Medicare Fee-for-Service (FFS) payment model needs to shift to a model of value-based care to control healthcare costs and to improve patient outcomes nationwide. To that end, Congress passed the Medicare Access and CHIP Reauthorization Act of 2015 (MACRA). MACRA created a value-based reimbursement system, called the Quality Payment Program (QPP) by CMS, which requires participation by clinicians who care for Medicare FFS beneficiaries. Among other provisions, the QPP creates a financial incentive to provide higher-quality care and a financial disincentive to provide low-quality care.<sup>4</sup> Clinicians and clinician groups can participate in the QPP in one of two tracks:

1. The Merit-based Incentive Payment System (MIPS): Participating clinicians are subject to payment adjustments assessed across four performance categories: 1) quality, 2) promoting interoperability, 3) improvement activities, and 4) cost.
2. Advanced Alternative Payment Models (APMs): Participating clinicians can earn Medicare incentive payments.

The MIPS MCC admission measure has been developed to assess the quality of care provided by clinicians participating in the MIPS track.

### 1.2.1 Eligible Clinicians and Clinician Groups

Currently, the types of clinicians who qualify for participation under MIPS are physicians, physician assistants, nurse practitioners, clinical nurse specialists, certified registered nurse anesthetists, clinical psychologists, occupational therapists, qualified speech-language pathologists, qualified audiologists, and registered dietitians and nutrition professionals. This list may be expanded over time as directed by MACRA.<sup>5</sup>

These clinicians must participate under MIPS if they exceed the program's low-volume threshold, are enrolled in Medicare, or did not have APM Qualified Participant (QP) or Partial QP status during the MIPS performance year.<sup>5</sup>

MIPS eligible clinicians can participate in three arrangements,<sup>6</sup> as:

- An individual (NPI/TIN): Identified by unique combination of an individual's National Provider Identifier (NPI) and Taxpayer Identification Number (TIN). Hereinafter in this report, we refer to providers participating under MIPS as an individual clinician or as an NPI/TIN.
- A group (TIN): Identified as a TIN with  $\geq 2$  clinicians, at least one of whom is MIPS eligible, who bill under the TIN. Hereinafter in this report, we refer to providers participating under MIPS as a group as a TIN. Beginning with the MIPS 2019 performance period:
  - Solo providers or groups with  $< 10$  clinicians could form and participate as virtual groups under a TIN. For measure development, we used historical data from prior to the implementation of MIPS; we therefore did not have data or use this classification status during measure development. For rollout of the measure, CMS would be able to identify clinicians forming and participating as part of a virtual group.
- Both: In instances where MIPS eligible clinicians report as both an individual and group, the clinician is evaluated as both and receives performance scores for each; however, payment adjustments are applied to the participation type with the higher performance score. For measure development, we used historical data from prior to the implementation of MIPS; we

therefore did not have data or use this classification status during measure development. For rollout of the measure, CMS would be able to identify clinicians participating as both.

### **1.2.2 Quality Measurement Under the Merit-based Incentive Payment System**

There were over 250 MIPS quality measures from which clinicians could choose for the MIPS 2019 performance period. The full list of MIPS quality measures is available online at: <https://qpp.cms.gov/mips/quality-measures>. The menu of 250+ quality measures included measures previously used in other payment programs prior to MIPS (for example, Physician Quality Reporting System [PQRS] and Value-Based Payment Modifier [VM]), newly developed measures such as clinician registry-based measures, and measures that assessed processes of care as well as health outcomes. CMS requires clinicians to report on six quality measures, including one outcome measure (or alternatively, a high-priority measure if an outcome measure is not available), and anticipates clinicians will choose to report on measures applicable to their specialties.<sup>4</sup>

CMS remains committed to using at least one outcome measure to assess the quality of care provided by each type of MIPS eligible clinician (81 FR 77290 through 77291, 82 FR 30047, 83 FR 59756), in alignment with the statutory requirement to use outcome measures to measure quality under MIPS (Pub L 114–10, 129 Stat 87). Currently, however, there are few outcome measures available from which clinicians can select. CMS/CORE therefore developed this outcome measure for quality reporting under MIPS.

## 2. METHODS

### 2.1 Overview of Measure Development and Methods Section

This quality measure calculates risk-standardized acute admission rates (RSAARs) for individual clinicians and groups of clinicians under a common TIN. It includes Medicare Fee-for-Service (FFS) patients aged ≥65 years with multiple chronic conditions (MCCs). The RSAAR is calculated using a hierarchical negative binomial regression model that accounts for the clustering of patients within providers and adjusts for patient factors and social risk factors that vary across providers, are related to admission risk, and are unrelated to quality. To adapt the ACO-level measure for MIPS clinicians, we modified key measure components (the cohort, outcome, and risk-adjustment variables) to align with the care delivery context. This section presents the rationale for these adaptations. It also presents the approach to attribution and to evaluating model performance. The measure development work was informed by input from national TEP review of the conceptual issues and testing results. Additionally, CMS held a 4-week public comment period to solicit input on the measure's methodology and preliminary specifications. We revised the measure in response to public comment, and CMS will post a summary of the comments received as well as the updates made to the measure in response to comments on CMS's public comment website.<sup>2</sup> This report includes the measure's final specifications, inclusive of the revisions after consideration of the public comments.

### 2.2 Data Sources

For the development and validation of the measure, we primarily used Medicare FFS administrative claims and enrollment information from calendar years 2013 through 2015. We assessed provider performance in calendar year 2015 (referred to as the measurement year) and used the prior years to identify the patient cohort and patient risk factors. Outpatient Evaluation and Management (E&M) visits during the measurement year, identified using the 2015 Medicare FFS non-institutional carrier claims, were used to attribute patients to providers. We gathered information for the cohort and risk variables from 2013-2014 claims. For risk adjustment:

- We ascertained clinical comorbidities using Medicare FFS institutional inpatient and outpatient claims, as well as non-institutional carrier claims, from 2014.
- Frailty indicators were identified using 2014 durable medical equipment (DME) claims.
- The original reason for Medicare entitlement came from the Medicare Enrollment Database (EDB).
- The social risk factors for analysis and the data sources used to define them were as follows:
  - Medicare/Medicaid dual-eligibility status: 2014-2015 Medicare Master Beneficiary Summary File (MBSF).
  - Agency for Healthcare Research Quality (AHRQ) Socioeconomic Status (SES) Index: 2009-2013 American Community Survey (ACS).
  - Rural residence: 2014 United States Department of Agriculture Economic Research Service.
  - PCP and physician-specialist density variables: 2017-2018 Area Health Resources File (AHRF).

The status of enrollment in Medicare Parts A and B and Medicare's hospice benefit for 2014-2015 were obtained from the CMS Medicare EDB. The outcome of acute, unplanned hospital admissions was

identified using 2015 Medicare FFS institutional inpatient claims. Information on skilled nursing facility (SNF) and acute rehabilitation facility stays, which factor into the outcome definition, was obtained using CMS's Integrated Data Repository (IDR) and Medicare Provider Analysis and Review (MedPAR) files, respectively. The cohort of beneficiaries assigned to MIPS eligible clinicians was approximated by including only those patients attributed to Value Modifier-eligible providers or non-risk-bearing Shared Savings Program ACOs in 2015 – the providers most likely to be eligible to participate in the QPP under MIPS. The patient-provider assignments for 2015 were provided by CMS's Value Modifier program contractor.

In this section ([Section 2: Methods](#)) and the next section ([Section 3: Results](#)), we refer to the final analytic sample for measure development, which included patients assigned to likely MIPS eligible providers, as the 2015 Medicare MCC Full Sample. We developed the measure using data years that included both International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) and International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) codes so have defined the measure in both as provided in the accompanying Excel workbook.

## 2.3 Cohort Definition

The cohort, or group of patients included in the measure, is comprised of patients whose combinations of chronic conditions put them at high risk of admission and whose admission rates could be lowered through better care. This definition reflects NQF's "Multiple Chronic Conditions Measurement Framework," which defines patients with MCCs as people "having two or more concurrent chronic conditions that ... act together to significantly increase the complexity of management, and affect functional roles and health outcomes, compromise life expectancy, or hinder self-management."<sup>7</sup>

The specific inclusion and exclusion criteria are as follows.

### *Inclusion Criteria*

- Patient is alive at the start of the measurement period and has two or more of nine chronic disease groups in the year prior to the measurement period:
  1. Acute myocardial infarction (AMI),
  2. Alzheimer's disease and related disorders or senile dementia,
  3. Atrial fibrillation,
  4. Chronic kidney disease (CKD),
  5. Chronic obstructive pulmonary disease (COPD) or asthma,
  6. Depression,
  7. Diabetes,
  8. Heart failure, and
  9. Stroke or transient ischemic attack (TIA).

Rationale: As noted above, this definition of MCCs is consistent with NQF's "Multiple Chronic Conditions Measurement Framework." The specific list of chronic conditions, except for diabetes, is the same as that used in the MCC admission measure that CORE previously developed for CMS's ACO program and has been vetted nationally and published in the literature.<sup>8</sup> In brief, it reflects the chronic conditions that most increased risk of admission. In adapting the ACO

measure for the MIPS setting, we added diabetes as a cohort-qualifying condition based on input from our TEP and further guidance from CMS. In addition, the inclusion of diabetes acknowledges the complexity that diabetes introduces to caring for patients with MCCs.

Definition of chronic conditions: Chronic conditions, except for diabetes, are defined using CMS's Chronic Conditions Data Warehouse (CCW). For diabetes, we used the diabetes cohort definition from the ACO diabetes admission measure developed by CORE (v2018a ACO-36) as opposed to the definition used in CCW, which includes diagnoses for secondary and drug-induced diabetic conditions that are not the focus of the MIPS MCC admission measure. See Tab 2 in the accompanying Excel workbook for the specific codes used to define the nine cohort-qualifying conditions. The sample we used for measure development and testing used ICD-9-CM codes only. Since the measure would be implemented using data after October 1, 2015 and would use only ICD-10-CM codes, we have provided both ICD-9-CM and ICD-10-CM codes in the accompanying Excel workbook.

- Patient is aged  $\geq 65$  years at the start of the year prior to the measurement period.

Rationale: Younger Medicare patients represent a distinct population with dissimilar characteristics and outcomes. Additionally, these patients tend to cluster among certain providers. These factors make risk adjustment difficult.

- Patient is a Medicare FFS beneficiary with continuous enrollment in Medicare Parts A and B during the year prior to the measurement period.

Rationale: Enrollment is necessary to provide clinical information for cohort identification and risk adjustment.

#### *Exclusion Criteria*

- Patients without continuous enrollment in Medicare Part A or B during the measurement period.

Rationale: The measure excludes these patients to ensure full data availability for outcome assessment and attribution.

- Patient was in hospice at any time during the year prior to the measurement year or at start of the measurement year.

Rationale: The measure excludes these patients even though once a patient enters hospice care, a goal of care is to prevent the need for hospital care. However, ambulatory care providers may have relatively little influence on end-of-life care once a patient is enrolled in hospice and served by a hospice team.

- Patient had no E&M visit to a MIPS eligible clinician.

Rationale: The measure excludes these patients because they could not be attributed to a provider using the visit-based attribution algorithm (see [Section 2.5](#) for details).

The starting cohort for attribution, therefore, is patients with at least one E&M visit to an outpatient provider reporting under a MIPS-eligible specialty. In addition to these patient-level exclusions, the following exclusions are applied after attribution due to program restrictions and for outcome calculation.

- Patients assigned to clinicians who do not participate in the QPP on the MIPS track.

Rationale: These patients are excluded because the clinicians to whom they are assigned do not participate in MIPS. For measure development, since we used data from 2015 that predated the QPP, we approximated which patients would likely have been assigned to non-MIPS clinicians (i.e., clinicians in risk-bearing ACOs) and excluded them.

- Patients attributed to hematologists and oncologists.

Rationale: The outcomes for patients who are predominantly cared for by hematologists and oncologists, including patients actively being managed for cancer, do not likely reflect primary care provider (PCP) or other relevant specialists' quality. The aim of this measure is not to assess the quality of care given during such instances of active cancer treatment. Excluding patients assigned to hematologists and oncologists takes out of the measure patients who are being actively treated for cancer during the measurement period but retains in the measure patients with MCCs who have a history of cancer or are occasionally being seen by a cancer specialist for follow-up.

- Patients not at risk for hospitalization at any time in 2015.

Rationale: The outcomes for these patients cannot be assessed as they are not at risk. See [Section 2.4.3](#) for methods used to calculate person-time at risk.

## **2.4 Outcome Definition**

The measure outcome is the number of acute, unplanned hospital admissions per 100 person-years at risk for hospitalization during the measurement period. The numerator is the number of eligible admissions that occurred. The denominator is the patients' time at risk for hospitalization. Admissions are only counted while the patient is considered at risk.

### **2.4.1 Admissions as a Quality Indicator**

Improving the health and health care of patients with MCCs is a strategic priority of the U.S. Department of Health and Human Services.<sup>9</sup> Over two-thirds of Medicare beneficiaries have been diagnosed with or treated for two or more chronic conditions as of 2010.<sup>10</sup> Patients with MCCs are more likely to be admitted to the hospital than those without chronic conditions or those with a single chronic condition. Additionally, they are more likely to visit the emergency department, use post-acute care (such as skilled nursing facilities), and require home health assistance.<sup>11</sup>

This measure uses the outcome of acute, unplanned admissions to assess care quality. We target this adverse event for several reasons.

1. The quality of care for people with MCCs is generally best assessed by examining outcomes rather than care processes.<sup>7</sup> Patients with multiple conditions vary in the priorities they set for their care. Therefore, disease-specific process or intermediate measures addressed by traditional care measures may not be aligned with patient preferences. In addition, disease-specific treatments may often be contraindicated in the context of co-existing comorbidities.<sup>12</sup> Moreover, surrogate or intermediate markers of outcomes, such as cholesterol levels, may not have the same relationship to outcomes of importance to patients as they do in patients with the single condition.<sup>13</sup> In contrast, outcome measures can focus on endpoints of importance to patients that reflect how the combined care people receive affects their health. Hence, experts have recommended measuring several "universal" outcomes including health status, functional status, symptom burden, and death to evaluate care for patients with MCCs. Researchers have



used additional outcomes,<sup>14-16</sup> including admission rates, to assess the success of interventions to improve care.

2. Patients with MCCs are typically frailer and at higher risk for hospitalization due to, for example, potentially life threatening exacerbations of their conditions and complications of complex treatment regimens.<sup>7,13,17</sup> They may be persistently physiologically stressed due to challenges maintaining adequate circulation, renal function, and respiration. Moreover, depression, dementia, and/or fatigue may contribute to the challenges they face implementing potentially complex care plans designed to maintain their health status, and their disease burden and treatment regimens in turn can affect their mental well-being. As a result, patients with MCCs may experience an increased vulnerability to common causes of admission including pneumonia and other infections, admissions due to exacerbations of their chronic conditions, and admissions related to frailty (for example, due to falls).<sup>17</sup>
3. The outcome is actionable; improvements in care delivery have successfully lowered admission rates for patients with MCCs. Efforts to redesign care for patients with MCCs have used admission rates as one outcome to evaluate the success of interventions. Ambulatory care clinicians can potentially lower the risk of acute admissions in this high-risk population through better coordinated, more timely, and more effective health care.<sup>15,16,18-28</sup>

#### **2.4.2 Types of Admissions Excluded from the Outcome**

Not all types of admissions reflect the quality of care being provided to patients with MCCs. A key consideration in defining the outcome for MIPS was focusing on admissions where risk can be reduced by providing high-quality care. In narrowing the outcome, the goal was to include an easily explained, consensus-based, actionable subset of admissions that can be influenced by outpatient care. Thus, based on input from our TEP and stakeholders, the measure excludes seven types of admissions from the outcome that do not reflect the quality of ambulatory care:

1. Planned hospital admissions;
2. Admissions that occur directly from a SNF or acute rehabilitation facility;
3. Admissions that occur within a 10-day “buffer period” of time after discharge from a hospital, SNF, or acute rehabilitation facility;
4. Admissions that occur after the patient has entered hospice;
5. Admissions related to complications of procedures or surgeries;
6. Admissions related to accidents or injuries; and
7. Admissions that occur prior to the first visit with a clinician in the assigned TIN.

##### **1. *Planned hospital admissions***

Rationale: Consistent with the approach CMS has taken for other admission and readmission measures, the measure excludes planned hospital admissions because planned admissions are not a signal of poor-quality care. Planned admissions are those planned by providers and patients for anticipated medical treatment or procedures that must be provided in the inpatient setting. Most planned admissions are part of ongoing clinical care and do not represent acute events that could have been prevented by high-quality care. Moreover, for ambulatory patients with chronic diseases, admissions for certain planned procedures (for example, placement of a cardiac device designed to

prolong life) are consistent with the highest quality of care. For these reasons, planned admissions are not counted in the measure outcome.

To identify planned admissions, the measure adopted an algorithm CORE previously developed for CMS's hospital readmission measures, CMS's Planned Readmission Algorithm Version 4.0.<sup>29,30</sup> In brief, the algorithm uses the procedure codes and principal discharge diagnosis code on each hospital claim to identify admissions that are typically planned. A few specific, limited types of care are always considered planned (for example, major organ transplant, rehabilitation, and maintenance chemotherapy). Otherwise, a planned admission is defined as a non-acute admission for a scheduled procedure (for example, total hip replacement or cholecystectomy). Admissions for an acute illness are never considered planned. See [Appendix A](#) for details on the planned admission algorithm and Tab 7 in the accompanying Excel workbook for the codes used to identify planned admissions.

2. *Admissions that occur directly from a skilled nursing facility (SNF) or acute rehabilitation facility*

Rationale: The measure excludes from the outcome hospital admissions that occur when patients are in SNFs or acute rehabilitation facilities because, during that time, institutional providers have a more direct influence on patients' care and safety as opposed to their primary ambulatory care clinicians. In addition, excluding admissions for patients in SNF care aligns well with CMS policy for a related MIPS cost measure (81 FR 77169), which states that Evaluation & Management (E&M) charges with a SNF modifier are not included in the measure attribution calculation – reinforcing the notion that such care is outside ambulatory care clinicians' sphere of influence.

3. *Admissions that occur within a 10-day "buffer period" of time after discharge from a hospital, SNF, or acute rehabilitation facility*

Rationale: Within this buffer period of transition back to community-based care, other factors in addition to ambulatory care, including care received in the hospital and post-discharge planning, contribute to the risk of admission; therefore, the measure does not hold clinicians accountable for admissions in this timeframe. This buffer period allows time for patients to be seen within 7 days of discharge as recommended in CMS's Transitional Care Management (TCM) service guidelines<sup>31</sup> and for the ambulatory care provider's care plan to take effect. CMS's TCM service guidelines encourage providers to have a face-to-face visit within 7 days of discharge for Medicare patients with high medical decision complexity.

4. *Admissions that occur after the patient has entered hospice*

The measure excludes from the outcome admissions that occur when patients are enrolled in Medicare's hospice benefit (hereinafter, hospice care).

Rationale: Once a patient enters hospice care, a goal of care is to prevent the need for hospital care. However, ambulatory care providers may be attributed the patient and have relatively little influence on end-of-life care once a patient is enrolled in hospice and served by a hospice team.

5. *Admissions related to complications of procedures or surgeries*

Rationale: These admissions are unrelated to primary care and the management of patients' chronic conditions.

Using the AHRQ's CCS – which clusters diagnoses into clinically meaningful categories using ICD-9-CM or ICD-10-CM codes – the measure excludes from the outcome admissions related to the following CCS categories, based on our team's clinical review and input from the TEP and CMS:

*Complications of procedures or surgeries*

1. 145: Intestinal obstruction without hernia;
2. 237: Complication of device; implant or graft;
3. 238: Complications of surgical procedures or medical care; and
4. 257: Other aftercare.

6. *Admissions related to accidents or injuries*

Rationale: These admissions may represent random events that are not likely a reflection of care quality.

There are both pros and cons to removing random events. Rare events, such as motor vehicle accidents, may to some extent be due to poor ambulatory care (for example, polypharmacy), but they may also be completely unrelated. They are not likely to affect a provider's measure score; however, we exclude them as admissions we count as outcomes to improve the face validity of the measure.

Based on our team's clinical review and input from the TEP and CMS, the measure excludes the following CCS categories:

*Accidents or injuries*

1. 2601 E Codes: Cut/pierce;
2. 2602 E Codes: Drowning/submersion;
3. 2604 E Codes: Fire/burn;
4. 2605 E Codes: Firearm;
5. 2606 E Codes: Machinery;
6. 2607 E Codes: Motor vehicle traffic (MVT);
7. 2608 E Codes: Pedal cyclist, not MVT;
8. 2609 E Codes: Pedestrian, not MVT;
9. 2610 E Codes: Transport, not MVT;
10. 2611 E Codes: Natural/environment;
11. 2612 E Codes: Overexertion;
12. 2613 E Codes: Poisoning;
13. 2614 E Codes: Struck by, against;
14. 2615 E Codes: Suffocation;
15. 2616 E Codes: Adverse effects of medical care;
16. 2618 E Codes: Other specified and classifiable;
17. 2619 E Codes: Other specified, not elsewhere classifiable (NEC);
18. 2620 E Codes: Unspecified; and
19. 2621 E Codes: Place of occurrence.

As further background, we have provided the list of CCS categories and their corresponding ICD-9-CM codes (ICD-10-10 codes are omitted for redundancy) grouped by AHRQ CCS, or clinical category. See Tab 8 in the accompanying Excel workbook for a complete list of all complications of procedures/surgeries, accidents, and injuries excluded from the outcome.

7. *Admissions that occur prior to the first visit in the measurement year with a clinician in the assigned TIN who has not seen the patient in the prior year*

Rationale: As detailed in [Section 2.5](#), attribution of patients to providers is determined using a visit-based algorithm. During the measurement period, it is possible for a patient to have a hospital admission before the first visit with a clinician in the assigned TIN. In such cases, we do not want to unfairly count the admission against the TIN. This exclusion will not apply, however, if the clinician saw the patient in the previous year, suggesting an established relationship with the patient.

### 2.4.3 Calculation of Person-Years

The time at risk for hospitalization is calculated by first determining when a patient becomes attributable to a provider. For patients who had at least one outpatient visit in the prior year with their attributed provider (that is, evidence of an existing relationship), their time at risk begins at the start of the measurement year. However, for patients who had not previously seen their attributed provider (that is, evidence of a new relationship), their time at risk begins at the first visit in the measurement year. However, if the first visit to the attributed provider occurred after the patient has entered hospice, the patient would not have any time at risk and would thus be excluded. Time at risk is then calculated as the number of days a patient is alive from the start of the measurement year or first visit until enrollment in hospice, death, or the end of the measurement period. The following times are not considered at risk and thus removed from the person-time calculation during the measurement period:

- Days spent in a hospital, SNF, or acute rehabilitation facility; and
- 10 days following discharge from a hospital, SNF, or acute rehabilitation facility.

### 2.5 Attribution

In this section, we describe how patients are attributed to clinicians and clinician groups for measure score calculation.

#### 2.5.1 Clinicians Covered by the Measure

Because we use the outcome of acute, unplanned admissions to assess quality, we limit the clinicians covered by the measure – those to whom CMS will attribute patients for measure score calculation -- to two categories of providers for whom this outcome reflects care quality. This includes 1) primary care providers (PCPs) and 2) a subset of specialists who manage the care of MCC patients.

1. PCPs: CMS designates PCPs as physicians who practice:
  - Internal medicine,
  - Family practice,
  - General practice, or
  - Geriatric medicine;

As well as the following non-physician clinicians:

- Nurse practitioners,
  - Certified clinical nurse specialists, and
  - Physician assistants.<sup>32</sup>
2. **Relevant specialists:** Based on input from the TEP, specialists covered by the measure are limited to those who plausibly provide overall coordination of care for patients with MCCs and who manage the chronic diseases that put the MCC patients in the measure at risk of admission. These “relevant” specialists, defined using the Medicare Provider Specialty Codes (see Tab 6 in the accompanying Excel workbook), are:
- Cardiologists,
  - Pulmonologists,
  - Nephrologists,
  - Neurologists,
  - Endocrinologists, and
  - Hematologists and oncologists.

## 2.5.2 Criteria Guiding the Design of the Attribution Model for MCC Patients

CMS is interested in developing a measure that can be applied at both the individual clinician and the clinician group levels. Given the structure of the MIPS program, CMS needs to be able to assign and account for the fact clinician participation status, or how a clinician chooses to report under MIPS, may vary for MIPS performance periods. Clinicians can decide annually whether to report as individuals, as part of a group, or as both as described in [Section 1.2.1](#). The Taxpayer Identification Number (TIN) level includes both solo clinicians (clinicians opting not to report with other clinicians under MIPS) and groups of clinicians who have chosen to report their quality under a common TIN. Thus, we developed and tested an attribution approach at both levels.

Acknowledging that there are multiple reasonable approaches for attributing patients to providers, we began by developing a set of criteria for selecting among attribution approaches. Building on key principles for attribution models set forth by the National Quality Forum (NQF),<sup>33</sup> we sought to develop an attribution model that is fair to providers, aligned with the goals of the MIPS program, and transparent. Specifically, we judged attribution options based on the following principles and criteria, which were endorsed by our TEP:

- **Principle: Attribution models should be fair and accurate.** Corresponding attribution criteria are:
  - Attributes patients to providers with a reasonable degree of accuracy (acknowledging there is no gold standard for determining patients’ primary providers).
  - Assigns the vast majority of patients (that is, minimizes unassigned patients).
  - Does not systematically disadvantage patient subgroups.
- **Principle: Attribution models should align with the stated goals and purpose of the measure.** Corresponding attribution criteria are:
  - Attributes patients to providers able to influence the measured outcome.
  - Incentivizes high quality, coordinated ambulatory care for MCC patients.

- Minimizes unintended consequences.
- **Principle: Attribution models should be transparent.** Corresponding attribution criteria are:
  - Is straightforward and understandable by patients and providers.
  - Reflects input from stakeholders, informed by discussion and testing of alternatives.

### 2.5.3 Approach to Attribution

The attribution algorithm involves two steps. In the first step, the algorithm assigns patients to the clinician (NPI/TIN) most responsible for the patient’s care. In the second step, patients assigned to each NPI/TIN are aggregated at the TIN level. That is, patients “follow” their assigned clinician (NPI/TIN) to the TIN under which they choose to report. With this algorithm, MIPS patients unassigned in the first step continue to be unassigned in the second step.

#### 2.5.3.1 Step 1: Attribution to Individual Clinicians

We tested three options for the first step of. Based on the a priori criteria above, input from the TEP, and further guidance from CMS, we selected and refined one of the options. The final attribution approach is described below. For full details on the attribution options that we developed and tested, please see [Appendix B](#).

The attribution approach uses the plurality of E&M visits.<sup>1</sup> Focusing on visits over charges when assigning responsibility acknowledges the importance of provider interaction with the patient in establishing accountability for outcomes. In most instances, the provider with the most visits is a PCP.

The attribution approach prioritizes assignment to a PCP over a specialist given the PCP’s central role in coordinating patient services, including specialty care. However, we recognize that there may be situations in which a specialist may be more likely to be managing the patient, even when a PCP is involved. Thus, the approach assigns patients to a “dominant” specialist, if one is present, as defined below.

Key features of this visit-based attribution approach are (see the flowchart in [Figure 1](#)):

- If the patient does not see a PCP or any relevant specialist, the patient is unassigned.
- In most instances,  $\geq 2$  PCP visits triggers assignment to a PCP. In consultations with clinicians at CMS and CORE and on our TEP, we received feedback that PCPs who see their complex patients with MCCs even twice a year may feel as though they are serving in the “quarterback” role and coordinating patients’ care. If more than 1 PCP meets the minimum, assignment goes to the PCP with the greatest number of visits (with charges used to break ties). In rare instances when a patient had only 1 visit with a PCP and no other relevant visits, the patient is assigned to that PCP as the most responsible clinician.
- Recognizing that there may be situations in which a specialist may be more likely to be managing the patient, even when a PCP is involved, the algorithm determines whether the patient might be managed primarily by a “dominant” specialist, which we defined as having  $\geq 2$  more visits compared with the PCP and any other specialist. If a dominant specialist is found, the

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<sup>1</sup> See Tab 6 in the accompanying Excel workbook for E&M service codes used to identify the clinician most responsible for a patient’s care.

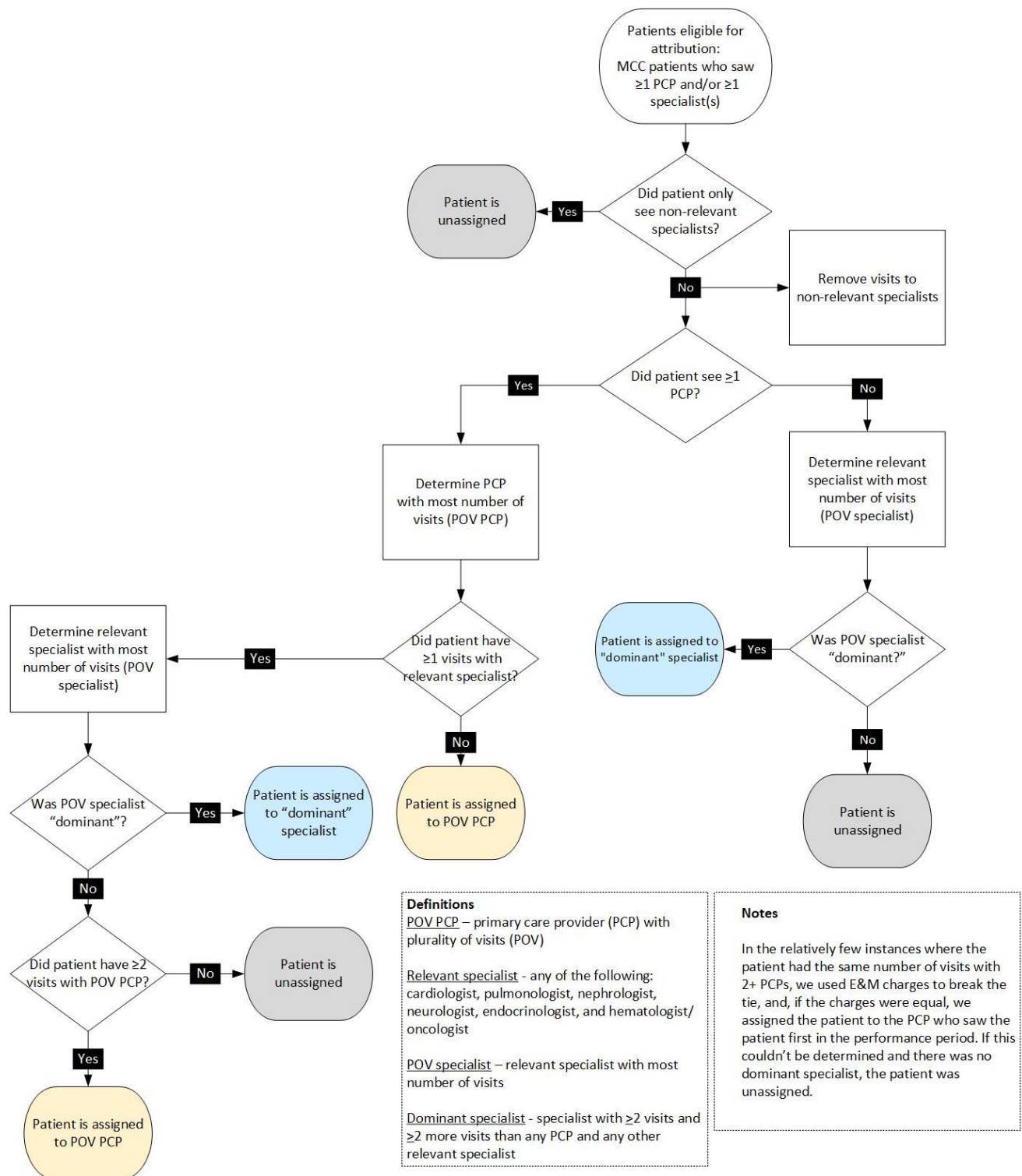
specialist is assigned the patient; otherwise, the patient stays with the PCP who had the plurality of visits above the  $\geq 2$  minimum threshold.

- If the patient is seen once by one or more PCPs, the patient:
  - Is assigned to the PCP with the most charges if the patient did not see a relevant specialist;
  - Is assigned to a specialist if minimum for “dominant” specialist (which we have defined as having  $\geq 2$  visits and  $\geq 2$  more visits than any PCP and any other relevant specialist) is satisfied; or
  - Is unassigned if care is diffused across the PCP(s) and specialist(s).
- If the patient has 0 PCP visits, assignment goes to specialist if minimum for “dominant” specialist is satisfied (that is, having  $\geq 2$  visits and  $\geq 2$  more visits than any other relevant specialist) or to unassigned if not.

#### **2.5.3.2 Step 2: Attribution to TIN**

TINs can be either solo clinicians reporting under their own unique NPI/TIN combination or groups of clinicians who have chosen to report their quality under a common TIN. When moving to the second step of attribution – assignment of patients to TINs for measure score calculation – we considered two approaches (see [Appendix C](#)). Under the final approach for the measure, patients “follow” the clinician they were assigned to in Step 1 to the TIN designated by the clinician. Patients unassigned at the individual clinician level continue to be unassigned in this step.

**Figure 1. Flowchart outlining attribution to individual clinicians among patients eligible for attribution**





## 2.6 Candidate Risk Variables and Approach to Selection of Final Variables

In this section, we describe the conceptual basis for risk adjustment, our rationale for candidate variables, including social risk factors, and our approach to selecting final variables from the candidate variables. We present the final variables in [Section 3.3](#).

### 2.6.1 Goal of Risk Adjustment

The overall goal of risk adjustment is to ensure that the measure fairly accounts for patient mix across MIPS providers. Hence, the measure risk adjusts to account for factors that are associated with the outcome (that is, unplanned hospital admissions), vary across MIPS providers, and are unrelated to quality of care so that measure scores reflect differences in care quality. Accounting for case-mix differences is important because it recognizes that some providers care for older, sicker patients, and avoids penalizing providers who do, since, through the risk-adjustment modeling, a higher expected outcome rate is set for providers who care for patients with these risk factors. Guided by the conceptual framework described below, we identified potential candidate risk factors through: (1) prior work on related quality measures (specifically, the MCC and diabetes admission measures previously developed for ACOs), (2) a focused literature review, and (3) TEP and CMS input.

### 2.6.2 Conceptual Framework for Risk Adjustment

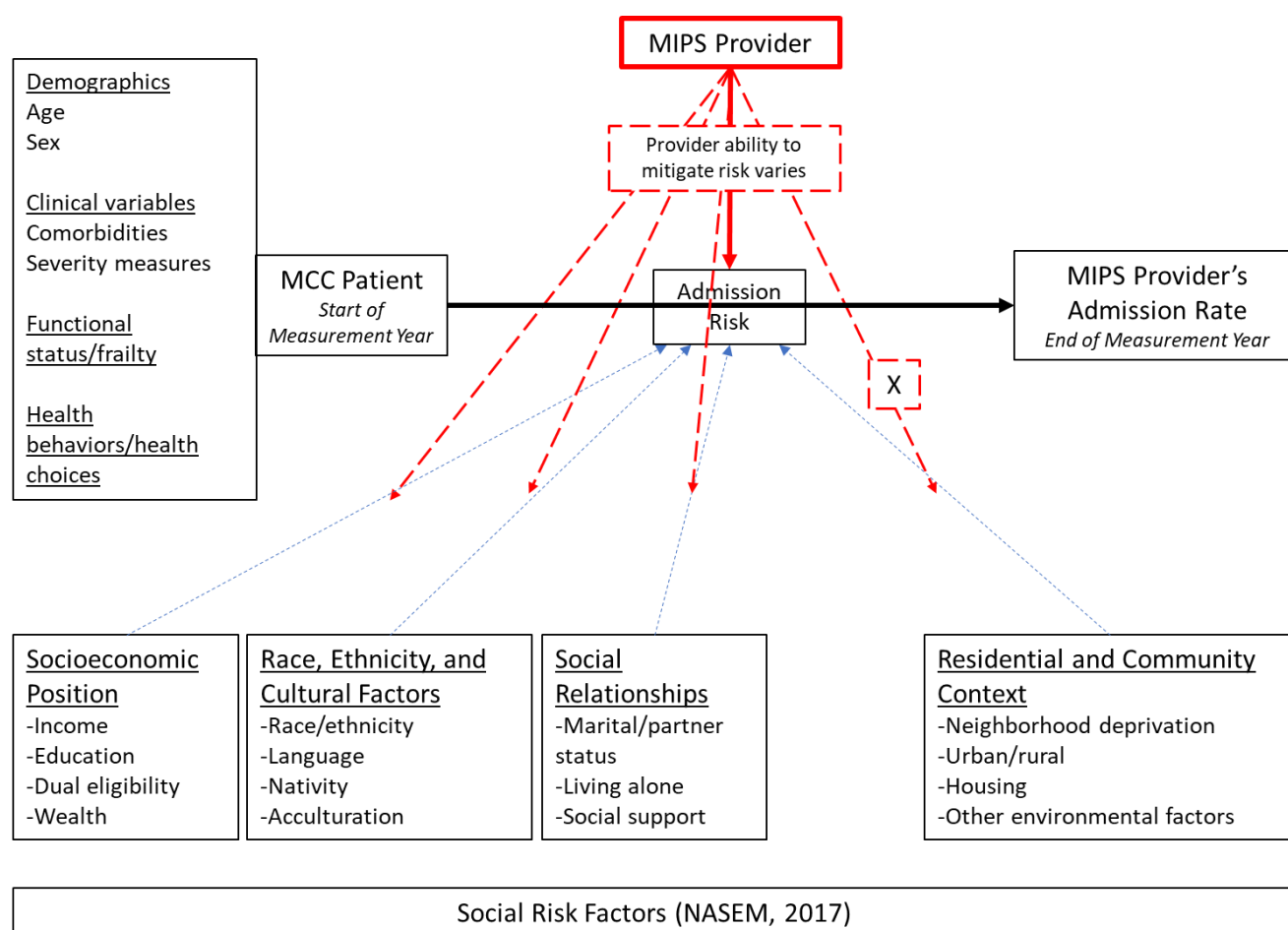
Building on the conceptual framework we developed with CMS for the ACO MCC admission measure,<sup>34</sup> we defined and illustrated the potential relationships between different categories of risk factors and the outcome of hospital admissions (see [Figure 2](#)). This MIPS conceptual framework guided the selection of candidate risk factors. We identified patient demographic factors and clinical variables, including comorbidities and measures of frailty and disability, that reflect the characteristics of the patients at the start of the measurement year and are independent of quality of care. As noted in [Figure 2](#) (box on the left), the potential clinical variables included not only clinical comorbidities but also measures of disease severity and frailty/functional status.

We also considered social risk factors that may influence patients' risk of acute, unplanned admissions. There are many ways to conceptualize or categorize social risk factors. We adopted the framework of the National Academies of Sciences, Engineering, and Medicine (NASEM) comprehensive, expert report of 2017, in which they categorized social risk factors into the four domains represented in the bottom row of [Figure 2](#).<sup>35</sup>

- Socioeconomic position;
- Race, ethnicity, and cultural factors;
- Social relationships; and
- Residential and community context.

(Note: There is a fifth domain in the NASEM report related to gender and sexual orientation; however, we have left it out because the authors noted that more research is needed to understand the relationship of these factors to outcomes and because of lack of available data.)

**Figure 2. Conceptual framework for risk adjustment**



Variables in all of these domains are or are hypothesized to be associated with increased risk of admission. The domains differ, however, in the extent to which we expect an individual MIPS clinician or group of clinicians to be able to mitigate the risk conferred by such variables. These differences inform their potential use as risk adjusters, since adjusting for factors that can more easily be mitigated by higher quality care is more likely to mask low quality care.

As represented by a boxed "X" in the conceptual framework figure, MIPS providers have the least ability to mitigate the risk of admission associated with broader residential and community factors, such as neighborhood deprivation and relative lack of access to primary and specialty medical care. In contrast, however, we expect that there is more although not unlimited ability for a MIPS provider to intervene to mitigate some or all of the risk conferred by the other, individual-level domains noted above. For example, a provider can take into account a patient's education level, health literacy level, and home living situation when planning and delivering care. In addition, high-quality care may be characterized as being more racially, linguistically, and culturally sensitive and informed. While such tailored care can likely mitigate risk of admission, our TEP emphasized that providing it also requires resources so MIPS providers may be limited in their capacity to deliver it. We discuss our approach to testing social risk factors for inclusion in the model in [Section 2.6.4](#).

### 2.6.3 Candidate Demographic and Clinical (Including Frailty and Disability) Variables

To represent demographic and clinical risk factors, the candidate variables were:

1. Age;
2. Indicator variables for each of the nine MCC cohort-qualifying conditions;
3. Clinical risk adjusters from the ACO MCC admission measure that we are adapting for the MIPS program;
4. Any additional clinical risk adjusters from the ACO diabetes admission measure, not already captured by the ACO MCC admission measure, since we added diabetes as a cohort-qualifying condition; and
5. Measures of frailty/disability based on:
  - a. Use of selected durable medical equipment (DME) and
  - b. Original reason for Medicare entitlement.

Each of these sets of variables is described below. See Tabs 2, 3, 4, and 5 of the accompanying Excel workbook for the complete list of 54 candidate demographic and clinical risk-adjustment variables and the specific Condition Category (CC), ICD-9-CM, ICD-10-CM, and Healthcare Common Procedure Coding System (HCPCS) codes used to define the clinical variables.

1. Age (1 variable with 5 levels).

In terms of demographic variables, we included age but not sex, consistent with the rationale and approach taken for other CORE outcomes measures. Studies suggest that sex-based differences in outcomes are generally driven by age and comorbidities (which we include in the risk adjustment), as well as disparities in care delivery (for example, women with diabetes and heart failure tend to receive less evidence-based treatment), and not by biological differences.<sup>36-39</sup> (Note: Race/ethnicity is addressed below in [Section 2.6.5](#) under social risk factors.)

2. Indicator variables for the MCC cohort-qualifying conditions (9 variables).

We included indicator variables for each of the nine cohort-qualifying conditions in order to adjust for differences in risk of admission across conditions.

3. Clinical risk adjusters from the ACO MCC admission measure (34 candidate variables).

Final risk adjusters for the ACO MCC admission measure that we are adapting for the MIPS program include 35 clinical comorbidities (specified using CC v22). In adapting the candidate list for the MIPS MCC admission measure, we eliminated “Diabetes with complications” as a clinical comorbidity since it is now part of the cohort definition.

4. Additional clinical risk adjusters from the ACO diabetes admission measure (3 candidate variables).

In order to capture potential risk-adjustment variables that might be specific to diabetes since we added diabetes to the MIPS MCC admission measure cohort, we compared the clinical risk adjusters for the ACO diabetes and the ACO MCC admission measures and added to the list of candidates any that were on the diabetes, but not MCC, list. Specifically, we added “Other organ transplants” (CC 187) to the list of candidate risk adjusters as it is a clinical comorbidity for the ACO diabetes, but not the ACO MCC, measure.

In addition, the diabetes measure adjusts for disease severity using the Diabetes Complications Severity Index (DCSI).<sup>39</sup> Based on our team’s clinical review, we noted that – with the exception of conditions related to diabetic retinopathy and precerebral arterial occlusion and transient cerebral ischemia without infarction – all of the conditions in the DCSI were already captured by the risk-adjustment variables noted above. Thus, we added these additional two clinical comorbidities to the list of candidate risk factors (see Tab 4 in the accompanying Excel workbook for the specific codes used to define the variables).

5. Measures of frailty/disability.

- a. Frailty based on DME (5 candidate variables): Frail elderly patients are at increased risk of hospitalization.<sup>40,41</sup> The list of candidate clinical comorbidities already includes CC-defined diagnosis variables related to frailty, including “Marked disability/frailty” (CCs 21, 70, 71, 73, 157-161, 189, 190) and “Hip or vertebral fracture” (CCs 169, 170). Based on recent studies<sup>40,41</sup> that have examined claims-based proxy measures of frailty using HCPCS codes for durable medical equipment (DME), we also considered five variables capturing past-year use of walking aids, wheelchairs, home hospital beds, lifts, and home oxygen. We defined these variables using the Policy Group Map currently maintained by Palmetto GBA under contract to CMS.<sup>42</sup> (See Tab 5 in the accompanying Excel workbook for the codes used to define the variables.)
- b. Original reason for Medicare entitlement (2 candidate variables): Individuals may enroll in Medicare before the age of 65 years if they qualify for disability insurance benefits (DIB) and/or have end-stage renal disease (ESRD). Those whose original reason for Medicare entitlement was one or both conditions (as opposed to aging in) represent a particularly vulnerable, at-risk group. Thus, we additionally considered original entitlement reason as potential risk adjusters.

## 2.6.4 Candidate Social Risk Factors

### 2.6.4.1 Approach to Social Risk Factors

#### Risk Adjusting for Social Risk Factors

In developing and evaluating social risk factors for potential inclusion in the model, we considered with CMS and stakeholders the program context and the pros and cons of the alternatives. CMS does not adjust the ACO MCC measure for social risk factors, because participation in ACOs is voluntary and ACOs have an explicit mission to optimize care for patients at risk through traditional and novel strategies. Moreover, testing showed that some ACOs with high proportions of patients with social risk factors such as dual eligibility performed well on the measures. In the MIPS setting, in contrast to the ACO setting, individual providers have more limited resources and a more limited ability to influence health system and community factors to mitigate any increased risk of admission for patients with social risk factors.

However, there are several potential downsides to adjusting for SRFs. Statistically, adjusting will set different expected rates of admission for different patient groups (that is, higher expected admission rates for patients with SRFs). This approach could contribute to greater acceptance of higher admission rates for people with SRFs. Adjusting could also mask quality differences associated with the risk factor. If people with MCCs and the risk factor systematically receive poorer quality care, and their admission rates are higher as a result of that worse care, adjusting for the SRF will make that worse care less visible in the measure score.

On the other hand, there are potential unintended consequences of not adjusting. In a mandatory program, such as MIPS, if these factors strongly influence the outcome, not adjusting for them could result in measure scores that translate into downward Medicare payment adjustments for providers serving patients with social risk factors. If the lower scores reflected case mix rather than quality, it would not advance MIPS policy goals. Further, not adjusting might reduce resources among the providers already facing the largest resource constraints. Moreover, if providers anticipate a poor score on the measure may further reduce their Medicare payments, the measure could create an incentive to reduce access to care for vulnerable patients.

To inform further consideration of these tradeoffs, we examined the marginal effects social risk factors have after adjusting for demographic and clinical variables. If, after adjusting for demographic, comorbidity, and frailty/disability factors, social risk factors still have an independent relationship to the outcome, the balance of these concerns may tip toward adjusting for social risk factors in the context of a quality program assessing individual providers, especially for those social risk factors that providers have less of an ability to address. We therefore developed candidate variables ([Section 2.6.4](#)), explored the marginal effect of these variables after adjusting for other factors ([Section 3.3.2](#)), and sought public comment on adjustment for dual eligibility).

For further context, we note that the MIPS program has a “complex patient” policy adjustment that may diminish the potential unintended consequences of not adjusting for social risk factors in this measure; the policy adjustment raises the score used to calculate provider payment increases/decreases by up to 5 points (out of a 100 maximum). It allocates points based on each provider’s proportion of patients who are dual eligible and their patients’ average risk score (82 FR 53771 through 53776).

#### Stratifying for Social Risk Factors

Finally, we note that as an alternative to adjusting the measure for social risk factors, the measure could be reported separately for patients with and without particular social risk factors, such as dual eligibility (that is, stratified). This approach has the advantage of not creating disincentives to caring for people with social risk factors and not masking disparities in care. CMS has not yet tested stratifying the measure by social risk factors but will consider doing so prior to implementation of the measure; given sample sizes, we expect stratification will only be feasible in the small subset of providers with a high case volume and higher proportion of patients with social risk factors.

#### **2.6.4.2 Development of Candidate Social Risk Factors**

As with the demographic and clinical variables above, we explored available data that could be used to operationalize candidate social risk factors guided by our conceptual framework ([Figure 2](#)). Based on our team’s prior work and a focused literature review, we began with an initial list of 33 potential social risk factors in [Table D1 in Appendix D](#), which we narrowed to the five. We used the following considerations to help guide candidate variable construction:

- If an individual-level variable was not available, we considered whether a corresponding area-level variable may be a reasonable alternative.
- If a construct (for example, housing) could be defined using a range of variables and there was no clear rationale for why any particular variable(s) would be associated with increased risk of hospitalization, we favored using a summary variable that captures multiple aspects of the construct to avoid a multiple-comparisons problem and spurious findings.

- We focused on variables that would be expected to have a more direct impact on the outcome of interest. For example, social capital has been shown to be associated with a broad range of individual- and community-level health outcomes.<sup>43</sup> However, there is no clear relationship with unplanned hospital admissions; any hypothesized or observed association would be mediated by intermediate factors.

As shown in [Figure 2](#), we categorized social risk factors into one of four domains highlighted in the recent expert NASEM report:<sup>35</sup>

1. Socioeconomic position;
2. Race, ethnicity, and cultural factors;
3. Social relationships; and
4. Residential and community context.

Evaluating potential data sources and variables for each of these domains yielded 5 candidate variables.

1. Socioeconomic position (1 candidate variable)

The focus of this domain is on individual-level measures of patients' SES. Direct measures of Medicare beneficiaries' income, wealth, and education are not available. Consistent with the NASEM model, we included the readily available and widely used dual-eligibility status variable as it is a marker of low income and assets. We defined Medicare beneficiaries as being dual eligible if they were enrolled in Medicaid with full benefits for at least 3 months during the measurement year or the 6 months prior.

Note: Area-level measures of income, education, and assets (for example, home ownership) are available through the US Census and are discussed below under the residential and community context domain.

2. Race, ethnicity, and cultural factors (0 candidate variables)

We did not include any candidate variables from this domain. Except for race, data are not available for variables such as language, immigrant status, and acculturation. Lack of data notwithstanding, we do not want to adjust for factors associated with care quality. As noted in our conceptual framework ([Figure 2](#)), we expect that there is an ability on the part of MIPS providers – at least to some extent – to intervene on the risk conferred by such variables. For example, high-quality care may be characterized as being more racially, linguistically, and culturally sensitive and informed. Moreover, consistent with guidance from our TEP and CMS, we did not consider race as a final candidate social risk factor to avoid setting different standards of care for different groups of patients.

3. Social relationships (0 candidate variables)

Similarly, we did not include any candidate variables from this domain. Individual-level measures of variables such as marital/partner status and social support are not available for Medicare beneficiaries. Although some area-level Census variables are available for related concepts (for example, percentage of residents never married or percentage living alone), they are not available at a more granular level (for example, 9-digit ZIP code level).

4. Residential and community context (4 candidate variables)

In contrast to the domains above, we conceptualized that there is less ability on the part of a MIPS provider to mitigate the risk of admission associated with broader residential and community factors. In total, we included 4 candidate variables that reflect aspects of

neighborhood deprivation (AHRQ SES Index), place of residence (rurality), and access to care (measures of PCP and physician-specialist density).

- The AHRQ SES Index is a widely used variable that summarizes area-level measures of employment, income, education, and housing. In our team’s previous work and the work of others, various aspects of income (for example, household income, poverty rate, income inequality) and housing (for example, value, ownership, crowding) have been examined in relation to quality measurement. Because there is no hypothesized reason specifically supporting the use of any particular neighborhood variable(s) for this measure of unplanned hospital visits, we favored the use of a composite variable that was more likely to capture relative SES across neighborhoods. Each of the index components is available at the census block level, which we then used to link to patient’s residence using 9-digit ZIP code.
- Consistent with the NASEM model, we also categorized beneficiaries’ place of residence in terms of rurality, given its implications for timely receipt of care and concerns that individuals in more rural areas may suffer delays due to longer travel distance and time and relative lack of providers.
- To more fully and directly characterize access to care, we additionally included as candidate variables two measures of provider density:
  1. PCP density and
  2. Physician-specialist density.

[Table 1](#) below summarizes the name, description, level of information, and data source for each of the 5 candidate social risk factors we evaluated statistically for their marginal effect and impact on the model, after adjusting for demographic and clinical factors.

**Table 1. Candidate social risk factors**

Variable	Description	Level of information	Data source	Year(s) of data
Medicare/Medicaid dual-eligibility status	Enrollment in Medicaid with full benefits for at least 3 months during the measurement year or the 6 months prior	Individual	Medicare Master Beneficiary Summary File (MBSF)	2014-2015
Agency for Healthcare Research and Quality (AHRQ) Socioeconomic Status (SES) Index	Summary measure of neighborhood deprivation based on 7 Census variables <sup>2</sup>	Match to Census block data based on patient’s 9-digit ZIP code	American Community Survey (ACS)	2009-2013

<sup>2</sup> AHRQ SES Index is a composite of the following 7 Census variables: 1) Percentage of persons in the labor force who are unemployed, 2) Percentage of persons living below poverty level, 3) Median household income, 4) Median value of owner-occupied dwellings, 5) Percentage of persons 25 years of age or older with less than a 12<sup>th</sup> grade education, 6) Percentage of persons ≥25 years of age completing ≥4 years of college, and 7) Percentage of households that average ≥1 persons per room



Variable	Description	Level of information	Data source	Year(s) of data
Rural residence <sup>44</sup>	Two-level variable categorized as: 1. Small and isolated small rural town, or 2. Urban or large rural city/town	5-digit ZIP code	United States Department of Agriculture Economic Research Service	2014
Density of primary care providers (PCPs)	$(\text{Number of PCPs} \div \text{population estimate}) \times 100,000$	Federal Information Processing Standard (FIPS) county code	Area Health Resources File (AHRF)	2017-2018
Density of physician specialists*	$(\text{Number of specialists} \div \text{population estimate}) \times 100,000$	FIPS county code	AHRF	2017-2018

\*Note: Includes all medical specialists, not just the six “relevant” specialists that patients in the measure can be attributed to, because the AHRF does not provide specialty-level data.

## 2.6.5 Final Risk-Adjustment Variable Selection

In this section, we describe the methods for selecting the final set of demographic and clinical risk adjusters as well as our approach to then evaluating and handling social risk factors.

### 2.6.5.1 Selection of Demographic and Clinical Variables

For development and testing of the patient-level model, we randomly split the 2015 Medicare MCC Full Sample into Development and Validation samples. The Development Sample included a random 50% sample, and the Validation Sample included the remaining 50% of MCC patients not selected into the Development Sample.

Prior to model selection, we first evaluated the prevalence and bivariate relationship between each candidate risk variable and the outcome using the 2015 Medicare MCC Full Sample. Candidate variables with a prevalence less than 0.5% or a rate ratio (RR) less than 1.3 were not considered for model selection. To select the final set of demographic and clinical variables to include in the risk-adjustment model, we performed backward variable selection on bootstrap samples. Briefly, 1,000 samples were selected with replacement from the Development Sample. For each of the 1,000 samples, a parsimonious negative binomial regression model (see [Section 2.6.6](#)) was selected by iteratively removing non-significant candidate variables from the model using backward selection approach. All variables significant at  $p < 0.05$  were retained in the final risk model. This approach yielded 1,000 models from which we then selected all variables that were retained in the model at least 90% of the time for inclusion in the measure’s final risk model. The 90% cut-off was selected as a more conservative inclusion criterion due to the large sample size of the measure’s cohort. This method selects variables that reliably and consistently enter the model across the 1,000 bootstrap samples.

### 2.6.5.2 Evaluation of Social Risk Factors

We examined the marginal effects of adding social risk factors to the model, after adjusting for the selected demographic and clinical factors, using the 2015 Medicare MCC Full Sample. Given our conceptual framework and the MIPS policy adjustment for dual eligibility, we took a phased approach. We first considered the added contribution of the residential and community context variables and then



sought to determine the incremental effect of dual-eligibility status above and beyond all other variables in the model. We began by analyzing the 4 residential and community context variables since MIPS providers are less able to mitigate the risk of admission associated with this domain of variables, and thus accounting for these variables would contribute to greater fairness in measure score comparisons across MIPS providers. We then examined the marginal impact of adding dual-eligibility status to the model after all other variables had been added.

For each of the continuous variables (AHRQ SES Index and the two provider density variables for PCPs and specialists), we first categorized the variable into deciles and examined the outcome rate by decile to determine whether its effect on admission rates was linear or non-linear and, if non-linear, where appropriate cutpoints would be. Based on this preliminary analysis, we dichotomized each variable as the lowest quartile (Q1) vs. above (Q2-Q4).

We then analyzed the four residential and community context variables and dual eligibility using negative binomial regression modeling (described below in [Section 3.3.2](#)):

Step 1. For each social risk factor, we calculated its univariate rate ratio (RR), which reflects how much more the admission rate is for individuals with a given social risk factor than those without the social risk factor.

Step 2. We then calculated the RR adjusted for the demographic and clinical variables.

Step 3. Statistically significant social risk factors with an adjusted  $RR \geq 1.05$  were included in a multivariable model that included these social risk factors and the demographic and clinical risk factors.

Step 4. If the social risk factor continued to be statistically significant even after adjusting for all other variables in the multivariable model, we considered its use in the final model given our conceptual model of providers' ability to mitigate social risk factors and the program context.

## **2.6.6 Model Form**

The measure calculates RSAARs for MIPS TINs, which includes both individual clinicians and groups of clinicians reporting under a common TIN, based on their MCC patients' unplanned hospital admissions during the measurement period. The RSAAR for each TIN is calculated as the ratio of the number of "predicted" to the number of "expected" admissions per 100 person-years, multiplied by the national rate of admissions among all attributed Medicare FFS patients with MCCs. The measure uses a hierarchical (two-level) negative binomial model with linear variance that adjusts for demographic, clinical, and social risk factors; accounts for the clustering of patients within MIPS providers; and accommodates the varying MCC patient population size across MIPS providers.

We selected the model form based on statistical considerations. Since the outcome of number of acute hospital admissions was overdispersed (variance of the outcome exceeded the mean), we considered five alternative models: 1) negative binomial with quadratic variance or NB-2, 2) negative binomial with linear variance or NB-1, 3) zero-inflated negative binomial, 4) generalized Poisson, and 5) Poisson inverse Gaussian models. For each model form, we examined fit through use of 1) an internal calibration plot that compared observed and predicted admission rates across deciles of admission risk and 2) goodness-of-fit statistics, including the Akaike information criterion (AIC), using the Development Sample. We also tested whether the inclusion of an interaction term between age and number of cohort-qualifying chronic conditions significantly improved each model form's fit, which it did not.

## 2.6.7 Model Performance

To assess the performance of the demographic and clinical risk-adjustment model, we computed two summary statistics: 1) goodness-of-fit statistic (deviance R-squared) and 2) overfitting indices. We then compared the model performance in the Development Sample with its performance in the Validation Sample. Because the outcome is a count of admissions – rather than a binary outcome, such as whether a patient has been admitted – several routinely used metrics of model performance cannot be applied (for example, we cannot use a c-statistic).

We calculated deviance R-squared using the model deviance residual defined by Cameron.<sup>45</sup> The deviance R-squared evaluates how successful the fit is in explaining the variation of the data and can take on any value between zero and one, with a value closer to one indicating that a greater proportion of deviance is accounted for by the model. For example, a deviance R-squared value of 0.12 means that the fit explains 12% of the total deviance.

Overfitting refers to the phenomenon in which a model accurately describes the relationship between the predictive variables and the outcome in the development dataset but fails to provide valid predictions in new patients. Overfitting indices ( $\gamma_0$ ,  $\gamma_1$ ) provide evidence of overfitting. Specifically, estimated values of  $\gamma_0$  far from 0 and estimated values of  $\gamma_1$  far from 1 provide evidence of overfitting.

In order to determine whether the model performs well across groups of patients at different risk of admission, the sample was divided into quartiles of predicted admission rate. We then assessed the predicted probability of the number of admissions derived from the model compared with the observed probability of the number of admissions. The predicted probability for a group of patients is the average probability of observing 0, 1, 2, ...n hospital admissions, given these patients' risk factors for admission. The observed probability of each count of admissions for a group of patients is the proportion of these patients admitted to the hospital 0, 1, 2, ...n times.

## 2.7 Measure Score Calculation and Testing

In this section, we present the methods for measure score calculation, and measure reliability and validity testing.

### 2.7.1 Statistical Approach to Measure Score Calculation

The measure uses a hierarchical (two-level) statistical model that accounts for the clustering of patients within MIPS providers and accommodates the varying patient sample sizes of different providers. For a full description of the modeling, please see [Appendix E](#). Briefly, the measure uses a NB-1 model since the measure's outcome is a count of the number of admissions. The first level of the model adjusts for patient factors. The relationship between patient risk factors and the outcome of admissions is determined based on all patients attributed to MIPS eligible clinicians. Therefore, the "expected" number of admissions (described below) for each provider is based on the performance of all eligible MIPS providers nationwide.

The second level of the model estimates a random-intercept term that reflects the provider's contribution to admission risk, based on their actual admission rate, the performance of other providers, their case mix, and their sample size.

The measure score is a RSAAR, calculated as the ratio of the number of predicted admissions to the number of expected admissions multiplied by the crude national rate. The predicted to expected ratio of

admissions is analogous to an observed over expected ratio, but the numerator accounts for clustering, sample-size variation, and provider-specific performance. The expected number of admissions is calculated based on the provider's case mix and average intercept among all MIPS providers. The predicted number of admissions is calculated based on the provider's case mix and the estimated provider-specific random intercept term. We multiply the predicted to expected ratio for each provider by a constant – the crude rate of acute, unplanned admissions among all MIPS providers – for ease of interpretation.

### **2.7.2 Variation in Measure Scores**

We examined variation in RSAAR measures scores at the TIN level. Specifically, we evaluated the distribution of scores across all TINs and separately for each of the following types of TINs based on their provider composition: solo PCP providers, solo specialist providers, TINs with all PCPs (physician and/or non-physician PCPs), TINs with combination of physician PCP and  $\geq 1$  specialist (can also include non-physician PCP), single specialty group with non-physician PCP (mid-level provider assumed to be practicing as a specialist), single specialty group (no PCP, physician or non-physician), and multispecialty group (no physician PCP but can include non-physician PCP). We repeated the analyses above for TINs that had  $\geq 28$  MCC patients, corresponding to a minimum measure score reliability of 0.5 (see [Section 2.7.3.2](#) below).

### **2.7.3 Reliability**

#### **2.7.3.1 Data Element Reliability**

The measure uses only those data elements from claims data that have both face validity and reliability. We avoid the use of fields that are thought to be coded inconsistently. Specifically, we use fields that are consequential for payment and which are audited. We identify such variables through empiric analyses and our understanding of the CMS auditing and billing policies, and we seek to avoid variables which do not meet this standard.

CMS has in place several auditing programs used to assess overall claims coding accuracy, to ensure appropriate billing, and for overpayment recoupment. CMS routinely conducts data analysis to identify potential problem areas and to detect fraud, and audits important data fields used in CMS measures, including diagnosis and procedure codes and other elements that are consequential for payment.

We further assessed the reliability of the patient-level model by comparing risk factor frequencies and rate ratios from NB-1 regression models in the Development and Validation samples.

#### **2.7.3.2 Measure Score Reliability**

We considered signal-to-noise analysis as a measure of reliability when evaluating the MIPS MCC admission measure. The variation between entities ('signal') comprises the total variation ('noise' and 'signal') in the outcome. This is because the reliability of any one individual clinician's or TIN's measure score will vary depending on the number of patients. Entities with higher volume will tend to have more reliable scores, while those with lower volume will tend to have less reliable scores. We used the formula for signal-to-noise reliability presented by Adams et al. and the formula for intraclass correlation coefficient (ICC) presented by Nakagawa et al. to calculate individual clinician-level and TIN-level reliability scores.<sup>46,47</sup> To estimate the overall signal and noise, we first calculated the ICC for the provider entity (TIN)  $j$  using the estimates of between-entity variance  $\sigma^2$ , dispersion parameter  $\omega$ , and

mean of outcome  $\lambda$ , from a hierarchical generalized linear model (HGLM). The formula appropriate for the NB-1 model is  $ICC_j = \sigma^2 / (\sigma^2 + \ln(1 + \omega/\lambda))$ . We then used the equation:

$$R_j = n_j ICC_j / (1 + (n_j - 1) ICC_j)$$

where  $n_j$  is the number of observations for each entity, to calculate the reliability of each entity measurement.  $R_j$  can range from 0 (less than chance agreement) to 1.0 (perfect agreement).

In addition, we determined the minimum number of patients required to achieve reliability values of 0.4, 0.5, 0.6, and 0.7, which fall into the moderate to substantial range based on conventional interpretation,<sup>48</sup> using the equation:

$$n_j = R_j * (1 - ICC_j) / (ICC_j * (1 - R_j))$$

where  $R_j = 0.4, 0.5, 0.6$ , or  $0.7$ . We reported the distribution of  $R_j$  over all entities and for those meeting the different volume requirement  $n_j$ .

## **2.7.4 Measure Validity**

### **2.7.4.1 Validity of the Attribution Algorithm**

CMS/CORE held meetings with a national TEP throughout the measure development process to review draft measure specifications. Prior to developing the attribution algorithm, we reviewed the methodology used in the CMS Value Modifier (VM) program as well as the expert report issued by the NQF's Attribution Project Committee.<sup>33</sup>

### **2.7.4.2 Face Validity of Measure Scores**

Following presentation and review of the final measure specifications and testing results, we systematically assessed the face validity of the measure score as an indicator of quality by confidentially soliciting the TEP members' agreement with the following statements (via an online survey):

- The risk-standardized acute admission rates obtained from the MCC measure as specified:
  - Can be used to distinguish good from poor quality of care provided to MCC patients by TINs reporting under MIPS?
  - Will provide TINs reporting under MIPS with information that can be used to improve their quality of care for MCC patients?

TEP members were asked to report their level of agreement with each statement on a 6-point Likert scale, ranging from "strongly agree" to "strongly disagree;" and to provide rationale for their rating.

## **2.7.5 Statistical Software**

Statistical analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC) and Stata version 15 (StataCorp, College Station, TX).

### 3. RESULTS

#### 3.1 Cohort and Outcome

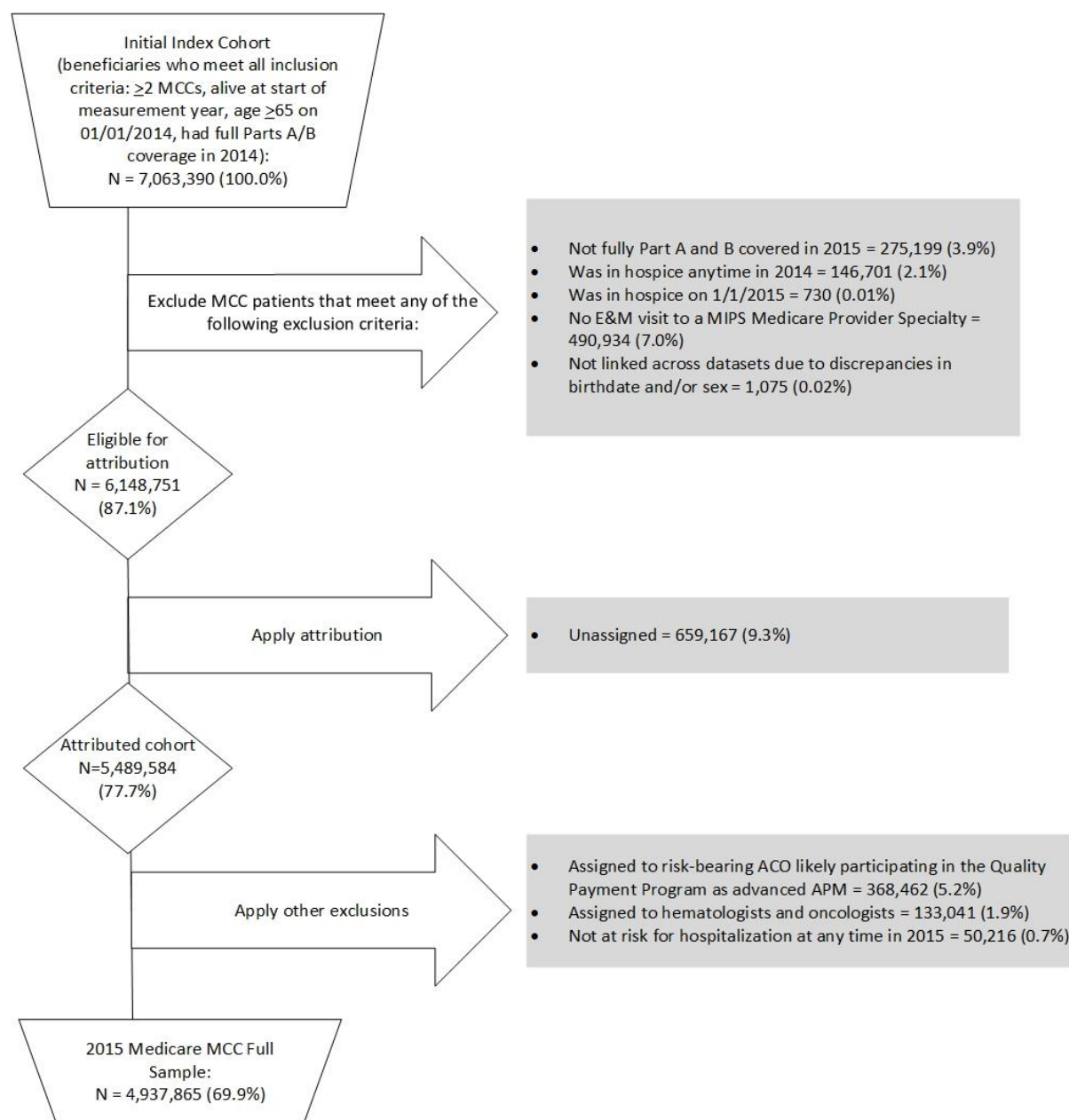
We identified 7,063,390 Medicare beneficiaries aged  $\geq 65$  years with MCCs who met the cohort inclusion criteria (see [Section 2.3](#) for the cohort definition). As shown in [Figure 3](#), 7.0% of initially eligible patients were excluded from the sample because they did not have an E&M visit with a MIPS eligible clinician in 2015 (the measurement year), and therefore could not be attributed to a provider, leaving 6,148,751 patients eligible for attribution.

The excluded group was older (median age of 80.3 vs. 78.4 years), was three times more likely to have died or entered hospice in 2015 (31.2% vs. 10.1%), and had a substantially higher prevalence of Alzheimer's and related disorders (41.1% vs. 26.7%). As the excluded group was closer to the end of life, they contributed less at-risk time and had a lower crude hospital admission rate compared with those who were eligible for attribution (35.2 vs. 44.4 admissions per 100 person-years) (data not shown).

Of the patients eligible for attribution, a total of 659,167 (9.3%) were unassigned to a provider based on the measure's attribution algorithm (see [Section 3.2](#)). After further excluding patients assigned to risk-bearing ACOs who would participate in the QPP as an advanced APM ( $n=368,462$ ), those not at risk for admission at any time in 2015 ( $n=56,063$ ), and those assigned to hematologists and oncologists ( $n=127,194$ ), the index MIPS MCC cohort included 4,937,865 patients (referred to as the 2015 Medicare MCC Full Sample); we used this 2015 Medicare MCC Full Sample for measure development and testing.

In the 2015 Medicare MCC Full Sample, the majority of patients were female (57.9%), and the average patient age was 79.0 years ( $\pm 7.9$  years). More than half (52.0%) of the people in the cohort had exactly two of the nine qualifying chronic conditions; 26.2% had three; 13.2% had four, and the remaining persons (8.6%) had five or more chronic diseases. Over the period of the measurement year, there were 1,818,298 acute, unplanned hospital admissions. The crude U.S. national Medicare FFS rate of acute, unplanned admissions was 42.0 per 100 person-years.

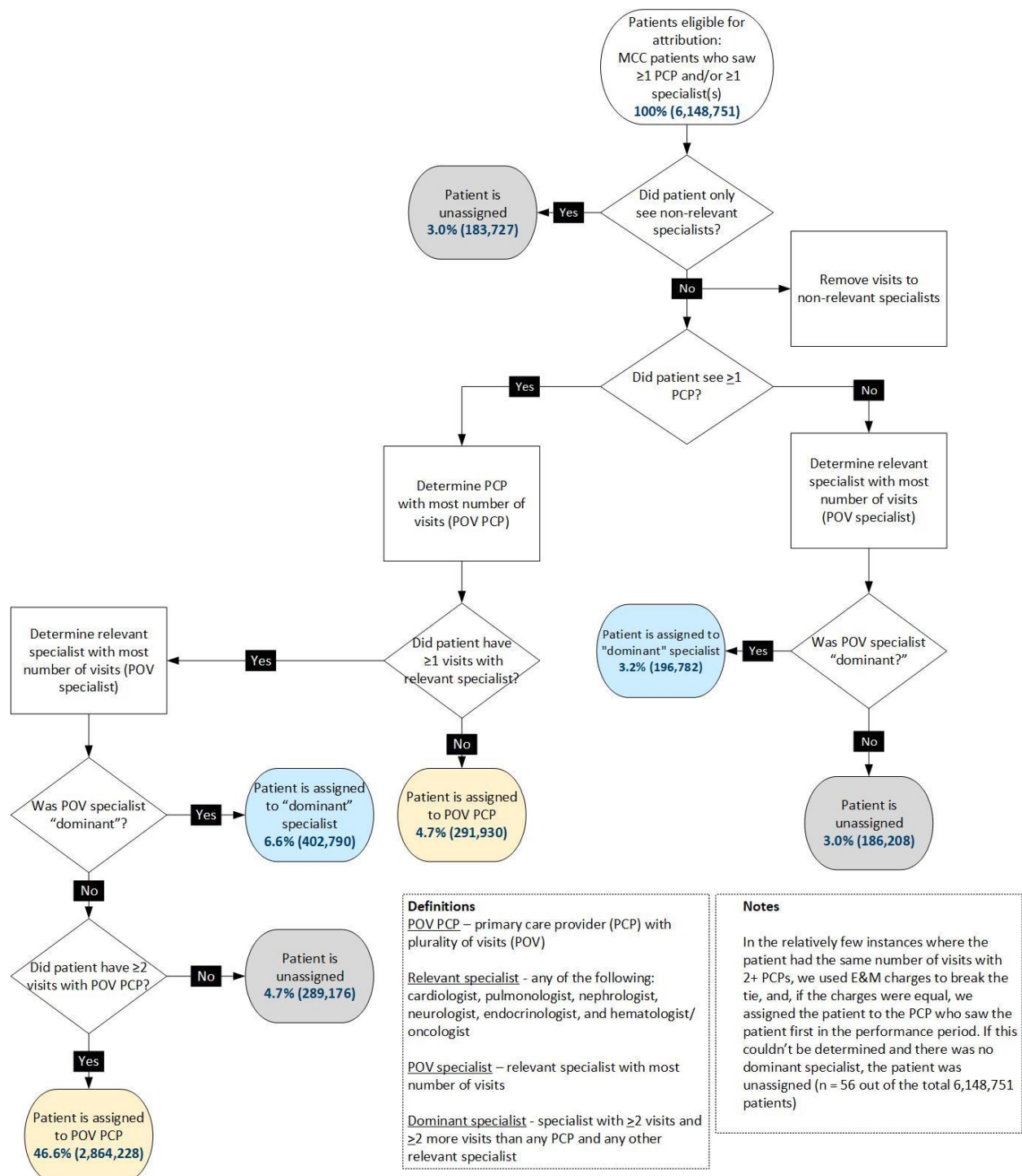
**Figure 3. Cohort flowchart among patients initially identified for inclusion in the MIPS MCC admission measure**



### 3.2 Distributions of Patients and Admissions and Unadjusted Admission Rates across Individual Clinician Provider Types

Overall, among the 6,148,751 patients eligible for provider attribution, 79.5% of patients were assigned to PCPs and 7.6% to specialists scored by the measure. A total of 12.9% of patients were excluded from measure scoring; 2.2% were assigned to hematologists and oncologists not scored by the measure, and 10.7% were unassigned because they did not visit a PCP or relevant specialist at least twice in the measurement year or whose pattern of visits did not allow us to identify the clinician most responsible for the patients' care ([Figure 4](#), [Table 2](#)).

**Figure 4. Flowchart outlining attribution to the individual clinicians among patients eligible for attribution, with results**



The characteristics of unassigned patients (those for which the attribution algorithm did not identify a clinician most responsible for the patients' care) were generally similar to those of assigned patients, except for the former having a higher proportion of patients who died or entered hospice in 2015 (18.1% vs. 10.1%) and a lower crude admission rate (39.7 vs. 44.4 per 100 person-years) (data not shown).



Among PCPs, the highest proportions of patients were assigned to internists (36.9%), family physicians (28.4%), and nurse practitioners (8.3%). Cardiologists were attributed more patients (4.6%) than any other PCP or specialist type.

Across individual clinicians, the distribution of admissions was similar to the distribution of patients ([Table 2](#)), suggesting that admissions were not disproportionately concentrated in any provider type. However, as shown in [Table 2](#), differences in unadjusted admission rates were observed. Among PCPs, patients assigned to nurse practitioners and geriatricians had the highest admission rates (48.7 per 100 person-years for nurse practitioners and 48.8 per 100 person-years for geriatricians). Of all the specialists, patients assigned to endocrinologists (19.9 per 100 person-years) and pulmonologists (55.9 per 100 person-years) had the lowest and highest admission rates, respectively.

**Table 2. Distributions of patients and admissions and unadjusted admission rates across individual clinician provider types among patients eligible for attribution**

Assigned clinician (NPI/TIN)	Number of patients (N=6,148,751)	Percent of patients	Number of admissions (N=2,254,931)	Percent of admissions	Unadjusted admission rate per 100 person-years
Primary care provider (PCP)	4,890,012	79.5%	1,762,583	78.2%	41.9
General practice	91,591	1.5%	32,691	1.4%	41.9
Family practice	1,743,193	28.4%	617,510	27.4%	40.3
Internal medicine	2,271,611	36.9%	834,580	37.0%	41.7
Geriatric medicine	73,446	1.2%	28,327	1.3%	48.8
Nurse practitioner	511,456	8.3%	185,722	8.2%	48.7
Certified clinical nurse specialist	13,682	0.2%	4,446	0.2%	44.0
Physician assistant	185,033	3.0%	59,307	2.6%	40.7
Specialist	466,531	7.6%	183,711	8.1%	43.1
Cardiologist	282,550	4.6%	118,024	5.2%	45.5
Pulmonologist	56,146	0.9%	27,975	1.2%	55.9
Nephrologist	53,593	0.9%	20,678	0.9%	42.5
Endocrinologist	38,700	0.6%	7,338	0.3%	19.9
Neurologist	35,542	0.6%	9,696	0.4%	31.1
Not scored by the measure	792,208	12.9%	308,637	13.7%	46.0
Unassigned	659,167	10.7%	220,757	9.8%	39.6
Assigned to hematologists and oncologists	133,041	2.2%	87,880	3.9%	78.1

At the TIN level ([Table 3](#)), 66.9% of patients were assigned to a multi-provider TIN. Nearly half (45.0%) were assigned to a TIN that included at least one physician PCP and one specialist. Approximately one-fifth (20.2%) of patients were assigned to a solo provider, and 12.9% were unassigned (patients unassigned in Step 1 of the attribution algorithm continue to be unassigned in Step 2 since patients follow their clinician to her/his designated TIN). Unassigned patients had the highest unadjusted admission rate (46.0 per 100 person-years).



**Table 3. Distributions of patients and admissions and unadjusted admission rates across TIN types among patients eligible for attribution**

Assigned TIN type	Number of patients (N=6,148,751)	Percent of patients	Number of admissions (N=2,254,931)	Percent of admissions	Unadjusted admission rate per 100 person-years
Solo providers	1,242,049	20.2%	447,326	19.8%	41.3
Primary care provider (PCP)	1,128,312	18.4%	406,283	18.0%	41.5
Specialist	113,737	1.8%	41,043	1.8%	39.5
Multi-provider TINs	4,114,494	66.9%	1,498,968	66.5%	42.2
All PCPs (physician and/or non-physician)	1,087,010	17.7%	395,918	17.6%	42.9
Combination of physician PCP and $\geq 1$ specialty (can also include non-physician PCP)	2,767,045	45.0%	1,015,366	45.0%	42.0
Multispecialty group (no physician PCP but can include non-physician PCP)	56,331	0.9%	19,070	0.8%	41.1
Single specialty group (includes non-physician PCP)	135,775	2.2%	42,124	1.9%	40.6
Single specialty group (no PCP, physician or non-physician)	68,333	1.1%	26,490	1.2%	42.3
Not scored by the measure	792,208	12.9%	308,637	13.7%	46.0

In the 2015 Medicare MCC Full Sample, 23,444 individual clinicians were attributed at least one patient with MCCs. The number of MCC patients per clinician ranged from 1 to 556, with a median of 9 patients and an interquartile range (IQR) of 3 to 28 ([Table 4](#)). After assigning patients to TINs, there were 64,086 TINs that were attributed at least one patient with MCCs. The number of MCC patients per TIN ranged from 1 to 10,328, with a median of 22 patients and an IQR of 7 to 59 ([Table 5](#)).

**Table 4. Distribution of patients per individual clinician (dataset: 2015 Medicare MCC Full Sample)**

Individual clinician specialty	Number of individual clinicians	Percent of individual clinicians	Percentile										
			Min.	1 <sup>st</sup>	5 <sup>th</sup>	10 <sup>th</sup>	25 <sup>th</sup>	Median	75 <sup>th</sup>	90 <sup>th</sup>	95 <sup>th</sup>	99 <sup>th</sup>	Max.
All	233,444	100%	1	1	1	1	3	9	28	58	81	138	556
Primary care providers	192,995	83%	1	1	1	1	3	11	32	63	86	144	556
Cardiologist	18,659	8%	1	1	1	1	3	7	17	35	52	97	504
Pulmonologist	5,882	3%	1	1	1	1	2	4	10	21	33	75	256
Nephrologist	5,645	2%	1	1	1	1	2	4	10	19	30	67	272
Endocrinologist	3,645	2%	1	1	1	1	2	5	12	24	34	70	188
Neurologist	6,618	3%	1	1	1	1	1	3	6	11	16	33	133

**Table 5. Distribution of patients per TIN (dataset: 2015 Medicare MCC Full Sample)**

TIN composition	Number of TINs	Percent of TINs	Percentile										
			Min.	1 <sup>st</sup>	5 <sup>th</sup>	10 <sup>th</sup>	25 <sup>th</sup>	Median	75 <sup>th</sup>	90 <sup>th</sup>	95 <sup>th</sup>	99 <sup>th</sup>	Max.
All TINs	64,086		1	1	1	2	7	22	59	130	233	1,124	10,328
Solo providers													
Primary care	30,010	47%	1	1	1	2	8	22	47	82	110	174	531
Specialist	6,693	10%	1	1	1	1	3	9	20	40	56	108	324
Multi-provider TINs													
All PCPs (physician and/or non-physician)	10,507	16%	1	1	2	5	20	57	120	215	309	597	3,603
Combination of physician PCP and ≥1 specialty (can also include non-physician PCP)	8,115	13%	1	1	2	3	12	55	244	858	1,514	3,852	10,328
Multispecialty group (no physician PCP but can include non-physician PCP)	1,765	3%	1	1	1	1	3	9	26	73	135	366	981
Single specialty group (includes non-physician PCP)	5,330	8%	1	1	1	1	2	6	18	49	86	303	1,996
Single specialty group (no PCP, physician or non-physician)	1,666	3%	1	1	2	3	9	21	47	94	130	284	701

### 3.3 Selection of Final Risk-adjustment Variables

#### 3.3.1 Demographic and Clinical Risk Factors

As noted in [Section 2.6.3](#), we identified 54 candidate demographic and clinical risk factors (see Tab 3 in the accompanying Excel workbook). In total, we excluded seven variables because their prevalence was <0.5% (pancreatic disease), their unadjusted RR was <1.3 (other malignancy, precerebral arterial occlusion and transient cerebral ischemia, and diabetic retinopathy), or they did not meet the 90% threshold for inclusion based bootstrapping results (pleural effusion/pneumothorax, bone/joint/muscle infections/necrosis, and other organ transplants). Thus, the final risk-adjustment model included 47 demographic and clinical risk variables, including age, clinical comorbidities, and measures of frailty/disability based on use of selected durable medical equipment (DME) and original reason for Medicare entitlement. Frequencies and adjusted rate ratios (RRs) and 95% confidence intervals (CIs) for the final set of 47 demographic and clinical variables were similar in the Development and Validation Samples, as shown in [Table 6](#).

**Table 6. Frequencies and adjusted rate ratios for the final set of demographic and clinical risk factors in the Development and Validation Samples**

Variable	Prevalence of risk factor, number (%)		Adjusted rate ratio (95% confidence interval)	
	Development Sample (N=2,468,933)	Validation Sample (N=2,468,932)	Development Sample	Validation Sample
<b>Demographic</b>				
Age <70 years	380,147 (15.4%)	380,037 (15.4%)	Reference	
Age 70 to <75 years	512,550 (20.8%)	512,378 (20.8%)	1.10 (1.09, 1.11)	1.10 (1.09, 1.11)
Age 75 to <80 years	501,601 (20.3%)	503,403 (20.4%)	1.24 (1.23, 1.25)	1.24 (1.23, 1.25)
Age 80 to <85 years	460,980 (18.7%)	460,133 (18.6%)	1.44 (1.43, 1.46)	1.45 (1.44, 1.46)
Age ≥85 years	613,655 (24.9%)	612,981 (24.8%)	1.77 (1.76, 1.79)	1.77 (1.75, 1.78)
<b>Nine chronic disease groups</b>				
Defined using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes				
Acute myocardial infarction	52,210 (2.1%)	52,211 (2.1%)	1.08 (1.07, 1.10)	1.08 (1.06, 1.09)
Alzheimer's disease and related disorders or senile dementia	657,467 (26.6%)	656,348 (26.6%)	1.26 (1.25, 1.27)	1.26 (1.25, 1.26)
Atrial fibrillation	652,252 (26.4%)	653,185 (26.5%)	1.14 (1.14, 1.15)	1.15 (1.14, 1.15)
Chronic kidney disease	1,151,246 (46.6%)	1,151,282 (46.6%)	1.21 (1.21, 1.22)	1.22 (1.21, 1.22)
Chronic obstructive pulmonary disease or asthma	857,115 (34.7%)	858,160 (34.8%)	1.24 (1.24, 1.25)	1.25 (1.24, 1.26)
Depression	835,667 (33.8%)	834,813 (33.8%)	1.08 (1.07, 1.09)	1.08 (1.07, 1.08)

Variable	Prevalence of risk factor, number (%)		Adjusted rate ratio (95% confidence interval)	
	Development Sample (N=2,468,933)	Validation Sample (N=2,468,932)	Development Sample	Validation Sample
<b>Diabetes</b>	1,450,709 (58.8%)	1,451,835 (58.8%)	1.09 (1.08, 1.09)	1.09 (1.08, 1.09)
<b>Heart failure</b>	1,021,929 (41.4%)	1,022,429 (41.4%)	1.37 (1.36, 1.37)	1.37 (1.36, 1.38)
<b>Stroke or transient ischemic attack</b>	273,450 (11.1%)	274,199 (11.1%)	1.07 (1.06, 1.08)	1.07 (1.06, 1.08)
<b>Clinical comorbidities</b> Defined using Condition Categories (CCs) or International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes				
<b>Dialysis status</b> (CC 134)	43,634 (1.8%)	44,108 (1.8%)	1.49 (1.47, 1.51)	1.48 (1.46, 1.50)
<b>Respiratory failure</b> (CC 82, 83, 84)	208,668 (8.5%)	208,879 (8.5%)	1.10 (1.10, 1.11)	1.10 (1.09, 1.11)
<b>Liver disease</b> (CC 27 [remove ICD-9-CM 572.4], 28, 29, 30)	49,928 (2.0%)	50,002 (2.0%)	1.24 (1.22, 1.26)	1.23 (1.21, 1.24)
<b>Pneumonia</b> (CC 114, 115, 116)	402,848 (16.3%)	402,518 (16.3%)	1.21 (1.20, 1.22)	1.21 (1.20, 1.22)
<b>Septicemia/shock</b> (CC 2)	141,507 (5.7%)	140,311 (5.7%)	1.03 (1.02, 1.04)	1.04 (1.03, 1.05)
<b>Marked disability/frailty</b> (CC 21, 70, 71, 73, 157, 158, 159, 160, 161, 189, 190)	298,989 (12.1%)	299,957 (12.1%)	1.18 (1.17, 1.19)	1.18 (1.18, 1.19)
<b>Hematologic/al diseases</b> (CC 46 [remove ICD-9-CM 283.11], 48)	254,913 (10.3%)	254,731 (10.3%)	1.04 (1.03, 1.05)	1.04 (1.03, 1.05)
<b>Advanced cancer</b> (CC 8, 9, 10, 13)	138,148 (5.6%)	138,084 (5.6%)	1.21 (1.20, 1.22)	1.21 (1.20, 1.22)
<b>Infectious and immune disorders</b> (CC 1, 3, 4, 5 [remove ICD-9-CM 016.00, 016.01, 016.02, 016.03, 016.04, 016.05, 016.06], 6, 47, 90)	123,336 (5.0%)	123,349 (5.0%)	1.06 (1.05, 1.07)	1.07 (1.06, 1.08)
<b>Severe cognitive impairment</b> (CC 50, 64, 65, 80)	194,886 (7.9%)	194,593 (7.9%)	1.07 (1.06, 1.08)	1.06 (1.05, 1.07)
<b>Major organ transplant status</b> (CC 132, 186)	17,114 (0.7%)	17,361 (0.7%)	1.09 (1.06, 1.11)	1.08 (1.05, 1.11)
<b>Pulmonary heart disease</b> (ICD-9-CM 415.0, 416.0, 416.1, 416.8, 416.9, 417.0, 417.1, 417.8, 417.9)	186,742 (7.6%)	186,981 (7.6%)	1.10 (1.09, 1.11)	1.12 (1.11, 1.12)
<b>Cardiomyopathy</b> (ICD-9-CM 425.2, 425.4, 425.5, 425.7, 425.8, 425.9, 429.0, 429.1, 425.11, 425.18)	230,338 (9.3%)	230,505 (9.3%)	1.09 (1.08, 1.10)	1.09 (1.08, 1.10)
<b>Gastrointestinal disease</b> (CC 31, 32, 33, 35, 36)	501,642 (20.3%)	503,248 (20.4%)	1.07 (1.06, 1.08)	1.06 (1.06, 1.07)

Variable	Prevalence of risk factor, number (%)		Adjusted rate ratio (95% confidence interval)	
	Development Sample (N=2,468,933)	Validation Sample (N=2,468,932)	Development Sample	Validation Sample
<b>Iron deficiency anemia</b> (CC 49)	1,105,812 (44.8%)	1,106,379 (44.8%)	1.12 (1.11, 1.12)	1.12 (1.12, 1.13)
<b>Ischemic heart disease except AMI</b> (CC 87, 88, 89, 98; ICD-9-CM 429.5, 429.6)	1,304,321 (52.8%)	1,306,171 (52.9%)	1.15 (1.14, 1.16)	1.15 (1.14, 1.15)
<b>Other lung disorders</b> (CC 112 [remove ICD-9-CM 494.0, 494.1], 118 [remove ICD-9-CM 490])	898,425 (36.4%)	900,194 (36.5%)	1.03 (1.02, 1.03)	1.03 (1.03, 1.04)
<b>Vascular or circulatory disease</b> (CC 106, 107, 108, 109 [remove ICD-9-CM codes 440.1, 442.1])	1,178,521 (47.7%)	1,178,427 (47.7%)	1.12 (1.11, 1.12)	1.12 (1.11, 1.12)
<b>Other significant endocrine disorders</b> (CC 23 [remove ICD-9-CM codes 271.4, 588.1, 588.81])	128,865 (5.2%)	129,266 (5.2%)	1.04 (1.03, 1.05)	1.03 (1.02, 1.04)
<b>Other disabilities and paralysis</b> (CC 72, 74, 103, 104, 119)	140,613 (5.7%)	141,119 (5.7%)	1.08 (1.07, 1.09)	1.09 (1.08, 1.10)
<b>Substance abuse</b> (CC 54, 55, 56)	269,506 (10.9%)	268,837 (10.9%)	1.21 (1.21, 1.22)	1.21 (1.21, 1.22)
<b>Other neurologic disorders</b> (75, 77, 78, 79, 81, 105)	796,067 (32.2%)	796,376 (32.3%)	1.11 (1.10, 1.11)	1.10 (1.10, 1.11)
<b>Specified arrhythmias and other heart rhythm disorders</b> (CC 96 [remove ICD-9-CM 427.31] and 97)	768,916 (31.1%)	769,109 (31.2%)	1.06 (1.05, 1.07)	1.05 (1.05, 1.06)
<b>Hypertension</b> (CC 95)	2,227,789 (90.2%)	2,228,966 (90.3%)	1.04 (1.03, 1.05)	1.05 (1.04, 1.06)
<b>Hip or vertebral fracture</b> (CC 169, 170)	146,367 (5.9%)	146,553 (5.9%)	1.07 (1.06, 1.08)	1.06 (1.05, 1.07)
<b>Lower-risk cardiovascular disease</b> (CC 91, 92, 93)	661,525 (26.8%)	663,393 (26.9%)	1.02 (1.01, 1.02)	1.02 (1.01, 1.03)
<b>Cerebrovascular disease</b> (CC 102)	175,501 (7.1%)	175,983 (7.1%)	1.07 (1.06, 1.08)	1.08 (1.07, 1.09)
<b>Morbid obesity</b> (ICD-9-CM V853.5, V853.6, V853.7, V853.8, 278.01, V853.9, V854.4, V854.5, V854.3)	180,908 (7.3%)	181,839 (7.4%)	1.06 (1.05, 1.07)	1.06 (1.06, 1.07)

Variable	Prevalence of risk factor, number (%)		Adjusted rate ratio (95% confidence interval)	
	Development Sample (N=2,468,933)	Validation Sample (N=2,468,932)	Development Sample	Validation Sample
<b>Urinary disorders</b> (CC 142 [remove ICD-9-CM codes 591, 753.21, 753.20, 753.29, 753.22, 753.23] and 145 [remove ICD-9-CM 587, 588.9, 588.89, 753.12, 753.13, 753.15, 753.16, 753.17, 753.19])	723,178 (29.3%)	722,694 (29.3%)	1.05 (1.04, 1.05)	1.04 (1.04, 1.05)
<b>Psychiatric disorders other than depression</b> (CC 57, 59 [remove ICD-9-CM 298.0], 60, 62, 63)	653,323 (26.5%)	653,403 (26.5%)	1.10 (1.09, 1.10)	1.10 (1.09, 1.11)
<b>Measures of frailty/disability</b> Defined using Policy Group Maps maintained by Palmetto GBA under contract to CMS for Durable Medical Equipment or original reason for Medicare entitlement				
<b>Walking aids</b> (140 and 590)	140,411 (5.7%)	140,029 (5.7%)	0.97 (0.96, 0.98)	0.98 (0.97, 0.99)
<b>Wheelchairs</b> (602, 603, 604, 606)	117,519 (4.8%)	118,095 (4.8%)	1.13 (1.12, 1.14)	1.13 (1.12, 1.14)
<b>Hospital bed</b> (250)	51,209 (2.1%)	51,388 (2.1%)	1.13 (1.11, 1.14)	1.11 (1.10, 1.13)
<b>Lifts</b> (430 and 460)	12,719 (0.5%)	12,590 (0.5%)	1.11 (1.08, 1.14)	1.10 (1.07, 1.13)
<b>Oxygen</b> (400)	243,602 (9.9%)	243,548 (9.9%)	1.42 (1.41, 1.43)	1.40 (1.39, 1.41)
<b>Original reason for entitlement: disability insurance beneficiary</b>	341,715 (13.8%)	342,527 (13.9%)	1.27 (1.26, 1.28)	1.28 (1.27, 1.29)
<b>Original reason for entitlement: end stage renal disease</b>	11,825 (0.5%)	12,084 (0.5%)	1.31 (1.28, 1.35)	1.32 (1.28, 1.36)

### 3.3.2 Social Risk Factors

As noted in [Section 2.6.4](#), we evaluated four residential and community context variables for possible inclusion in the risk-adjustment model: 1) the AHRQ SES Index, 2) rural residence, 3) PCP density, and 4) physician-specialist density. Of the four, only AHRQ SES Index and specialist density met our thresholds of having a demographic and clinical variables-adjusted RR of  $\geq 1.05$  and remaining statistically significant at the 0.05 level in the multivariable model that included all of the risk adjusters ([Table 7](#)). When the demographic and clinical variables, AHRQ SES Index, and physician-specialist density were included in the model (column 4), the adjusted RRs for AHRQ SES Index and physician-specialist density were 1.07 and 1.04, respectively; when dual eligibility was also added to the model (column 5), the RR for AHRQ SES Index was 1.06, and the RR for physician-specialty density was 1.05.

We tested five social risk factor variables that reflected factors identified in the conceptual framework and could be operationalized in data for potential adjustment. Three social risk factors met our criteria

for potential use in the final model. As shown in [Table 7](#), dual eligibility was strongly predictive of admissions (RR=1.42) in the univariate model (column 2). However, the effect of dual-eligibility status was greatly attenuated by adjustment for the demographic and clinical characteristics (RR=1.12, column 3), and relatively unchanged when the other two social risk factors were also in the model (RR=1.11, column 5).

**Table 7. Association between social risk factors and rate of hospital admissions, rate ratios, and 95% confidence intervals (dataset: 2015 Medicare MCC Full Sample)**

Social risk factor (definition)	Univariate model	Model adjusted for demographic and clinical variables	Multivariable model that includes social risk factors with adjusted rate ratio (RR)≥1.05 and demographic and clinical variables	Multivariable model with the addition of dual- eligibility status
<b>Low AHRQ SES index</b> (≤25 <sup>th</sup> percentile)	1.12 (1.11, 1.12)	1.08 (1.07, 1.08)	1.07 (1.07, 1.08)	1.06 (1.06, 1.06)
<b>Rural residence</b>	1.03 (1.02, 1.04)	1.04 (1.03, 1.04)		
<b>Low PCP density</b> (≤25 <sup>th</sup> percentile)	1.01 (1.00, 1.02)	1.03 (1.02, 1.04)		
<b>Low physician- specialist density</b> (≤25 <sup>th</sup> percentile)	1.05 (1.04, 1.06)	1.06 (1.05, 1.07)	1.04 (1.04, 1.05)	1.05 (1.04, 1.06)
<b>Medicare-Medicaid dual-eligibility status</b>	1.42 (1.42, 1.43)	1.12 (1.12, 1.13)		1.11 (1.10, 1.11)

Based on the conceptual model, program context, TEP input, and testing results, CMS adjusted the measure for two social risk factors – 1) the AHRQ SES Index and 2) physician-specialty density. These two community context variables primarily reflect factors that individual clinicians and clinician groups are unlikely to be able to mitigate; adjusting for them is therefore less likely to adjust away quality differences across TINs. To ensure community context is taken into account, CMS includes them in the model. These factors are deeply rooted in societal disparities, and MIPS clinicians have little influence on their effect.

While dual-eligible beneficiaries are likely to have fewer available health/healthcare supports, and may also have other unmeasured social risk factors (e.g., low health literacy), CMS is not adjusting the measure for dual eligibility because:

- Dual-eligibility enrollment criteria vary on a state-to-state basis and may not fairly capture vulnerable patients across states.
- Adjusting for dual eligibility can mask disparities in care for dual-eligible beneficiaries as acknowledged by one provider association in public comment.
- Clinicians may have more ability to mitigate social risk associated with dual eligibility, especially if a dual-eligible beneficiary is living in a non-socially deprived community.

- Not adjusting for dual eligibility is aligned with the conceptual model for the measure; the model developed with the TEP emphasizes adjusting for community not individual risk factors because patients living within very under-resourced areas pose challenges that are particularly hard for clinicians to address (e.g., lack of community services, transportation, poor housing, and/or low education).
- TEP members supported including only the AHRQ SES Index and specialist density social risk factors in the model given these factors and the program context.
- The marginal impact of including dual eligibility is attenuated after accounting for demographic, clinical, and frailty risk factors, as well as the AHRQ SES Index and specialist density social risk factors.

### 3.3.3 Final Risk-adjustment Model

The final model includes 49 risk adjusters (47 demographic and clinical variables and two social risk factors, as noted above). Their prevalence in the 2015 Medicare MCC Full Sample along with the adjusted RRs from the full multivariable model are included in [Table 8](#).

**Table 8. Final multivariable risk-adjustment model: demographic, clinical, and social risk factors (dataset: 2015 Medicare MCC Full Sample)**

Variable	Prevalence - n (%) (N=4,916,172*)	Adjusted rate ratio (95% CI)
<b>Demographic</b>		
Age <70 y/o	756,493 (15.4%)	REF
Age 70 to <75 y/o	1,020,066 (20.7%)	1.10 (1.09, 1.11)
Age 75 to <80 y/o	1,000,483 (20.4%)	1.24 (1.23, 1.25)
Age 80 to <85 y/o	917,172 (18.7%)	1.45 (1.44, 1.46)
Age ≥85 y/o	1,221,958 (24.9%)	1.78 (1.76, 1.79)
<b>Nine chronic disease groups</b>		
Defined using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes		
<b>Acute myocardial infarction</b>	103,973 (2.1%)	1.08 (1.07, 1.09)
<b>Alzheimer's disease and related disorders or senile dementia</b>	1,306,780 (26.6%)	1.26 (1.25, 1.26)
<b>Atrial fibrillation</b>	1,300,572 (26.5%)	1.15 (1.14, 1.15)
<b>Chronic kidney disease</b>	2,292,655 (46.6%)	1.22 (1.21, 1.22)
<b>Chronic obstructive pulmonary disease or asthma</b>	1,708,145 (34.7%)	1.24 (1.24, 1.25)
<b>Depression</b>	1,663,617 (33.8%)	1.08 (1.08, 1.08)
<b>Diabetes</b>	2,889,162 (58.8%)	1.08 (1.08, 1.09)
<b>Heart failure</b>	2,035,244 (41.4%)	1.36 (1.36, 1.37)
<b>Stroke or transient ischemic attack</b>	545,093 (11.1%)	1.07 (1.06, 1.08)
<b>Clinical comorbidities</b>		
Defined using Condition Categories (CCs) or ICD-9-CM codes		
<b>Dialysis status (CC 134)</b>	87,289 (1.8%)	1.47 (1.46, 1.49)
<b>Respiratory failure (CC 82, 83, 84)</b>	415,779 (8.5%)	1.10 (1.10, 1.11)
<b>Liver disease (CC 27 [remove ICD-9-CM 572.4], 28, 29, 30)</b>	99,475 (2.0%)	1.23 (1.22, 1.24)
<b>Pneumonia (CC 114, 115, 116)</b>	801,498 (16.3%)	1.21 (1.20, 1.21)
<b>Septicemia/shock (CC 2)</b>	280,490 (5.7%)	1.04 (1.03, 1.04)
<b>Marked disability/frailty (CC 21, 70, 71, 73, 157, 158, 159, 160, 161, 189, 190)</b>	596,051 (12.1%)	1.18 (1.18, 1.19)



Variable	Prevalence - n (%) (N=4,916,172*)	Adjusted rate ratio (95% CI)
<b>Hematologic/al diseases</b> (CC 46 [remove ICD-9-CM 283.11], 48)	507,655 (10.3%)	1.04 (1.03, 1.05)
<b>Advanced cancer</b> (CC 8, 9, 10, 13)	275,217 (5.6%)	1.21 (1.20, 1.22)
<b>Infectious and immune disorders</b> (CC 1, 3, 4, 5 [remove ICD-9-CM 016.00, 016.01, 016.02, 016.03, 016.04, 016.05, 016.06], 6, 47, 9)	245,668 (5.0%)	1.06 (1.05, 1.07)
<b>Severe cognitive impairment</b> (CC 50, 64, 65, 80)	387,687 (7.9%)	1.07 (1.06, 1.07)
<b>Major organ transplant status</b> (CC 132, 186)	34,345 (0.7%)	1.09 (1.07, 1.11)
<b>Pulmonary heart disease</b> (ICD-9-CM 415.0, 416.0, 416.1, 416.8, 416.9, 417.0, 417.1, 417.8, 417.9)	372,372 (7.6%)	1.11 (1.10, 1.11)
<b>Cardiomyopathy</b> (ICD-9-CM 425.2, 425.4, 425.5, 425.7, 425.8, 425.9, 429.0, 429.1, 425.11, 425.18)	458,899 (9.3%)	1.09 (1.09, 1.10)
<b>Gastrointestinal disease</b> (CC 31, 32, 33, 35, 36)	1,000,689 (20.4%)	1.07 (1.06, 1.07)
<b>Iron deficiency anemia</b> (CC 49)	2,202,631 (44.8%)	1.12 (1.11, 1.12)
<b>Ischemic heart disease except AMI</b> (CC 87, 88, 89, 98; ICD-9-CM 429.5, 429.6)	2,599,720 (52.9%)	1.15 (1.14, 1.15)
<b>Other lung disorders</b> (CC 112 [remove ICD-9-CM 494.0, 494.1], 118 [remove ICD-9-CM 490])	1,791,219 (36.4%)	1.03 (1.03, 1.03)
<b>Vascular or circulatory disease</b> (CC 106, 107, 108, 109 [remove ICD-9-CM codes 440.1, 442.1])	2,347,040 (47.7%)	1.12 (1.11, 1.12)
<b>Other significant endocrine disorders</b> (CC 23 [remove ICD-9-CM codes 271.4, 588.1, 588.81])	257,068 (5.2%)	1.04 (1.03, 1.04)
<b>Other disabilities and paralysis</b> (CC 72, 74, 103, 104, 119)	280,296 (5.7%)	1.08 (1.08, 1.09)
<b>Substance abuse</b> (CC 54, 55, 56)	535,945 (10.9%)	1.21 (1.21, 1.22)
<b>Other neurologic disorders</b> (75, 77, 78, 79, 81, 105)	1,585,519 (32.3%)	1.10 (1.10, 1.11)
<b>Specified arrhythmias and other heart rhythm disorders</b> (CC 96 [remove ICD-9-CM 427.31] and 97)	1,532,084 (31.2%)	1.06 (1.05, 1.06)
<b>Hypertension</b> (CC 95)	4,437,187 (90.3%)	1.04 (1.04, 1.05)
<b>Hip or vertebral fracture</b> (CC 169, 170)	291,734 (5.9%)	1.06 (1.06, 1.07)
<b>Lower-risk cardiovascular disease</b> (CC 91, 92, 93)	1,319,936 (26.8%)	1.02 (1.02, 1.02)
<b>Cerebrovascular disease</b> (CC 102)	349,959 (7.1%)	1.07 (1.07, 1.08)
<b>Morbid obesity</b> (ICD-9-CM V853.5, V853.6, V853.7, V853.8, 278.01, V853.9, V854.4, V854.5, V854.3)	361,362 (7.4%)	1.06 (1.06, 1.07)
<b>Urinary disorders</b> (CC 142 [remove ICD-9-CM codes 591, 753.21, 753.20, 753.29, 753.22, 753.23] and 145 [remove ICD-9-CM 587, 588.9, 588.89, 753.12, 753.13, 753.15, 753.16, 753.17, 753.19])	1,439,748 (29.3%)	1.05 (1.04, 1.05)
<b>Psychiatric disorders other than depression</b> (CC 57, 59 [remove ICD-9-CM 298.0], 60, 62, 63)	1,300,678 (26.5%)	1.10 (1.09, 1.10)
<b>Measures of frailty/disability</b> Defined using Policy Group Maps maintained by Palmetto GBA under contract to CMS for Durable Medical Equipment or original reason for Medicare entitlement		
<b>Walking aids</b> (140 and 590)	279,304 (5.7%)	0.97 (0.97, 0.98)
<b>Wheelchairs</b> (602, 603, 604, 606)	234,492 (4.8%)	1.12 (1.12, 1.13)
<b>Hospital bed</b> (250)	102,042 (2.1%)	1.12 (1.11, 1.13)

Variable	Prevalence - n (%) (N=4,916,172*)	Adjusted rate ratio (95% CI)
Lifts (430 and 460)	25,180 (0.5%)	1.10 (1.08, 1.12)
Oxygen (400)	485,155 (9.9%)	1.41 (1.40, 1.41)
Original reason for entitlement: disability insurance beneficiary	680,404 (13.8%)	1.27 (1.26, 1.27)
Original reason for entitlement: end stage renal disease	23,783 (0.5%)	1.31 (1.28, 1.34)
<b>Social risk factors</b>		
Low AHRQ SES index ( $\leq 25^{\text{th}}$ percentile)	960,598 (19.5%)	1.07 (1.07, 1.08)
Low physician-specialist density ( $\leq 25^{\text{th}}$ percentile)	162,755 (3.3%)	1.04 (1.04, 1.05)

\*Of the final 4,937,865 MCC sample size, 21,693 (0.44%) patients had missing data for one or both social risk factors included in the final model. Thus, the sample size for this analysis was 4,916,172.

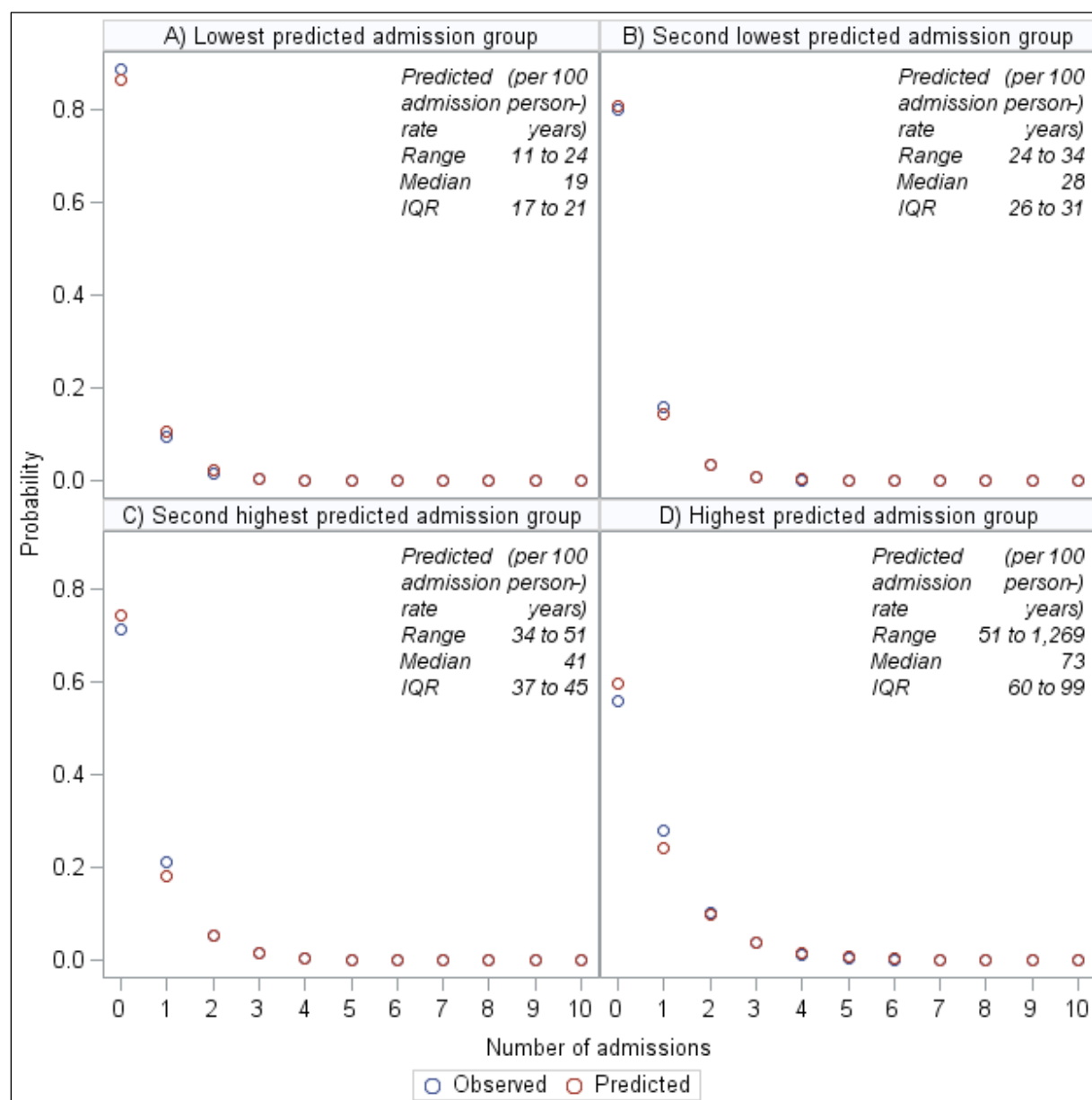
### 3.4 Model Performance

The deviance R-squared for the model with demographic and clinical risk factors was 0.105 in the Development and Validation sub-samples and in the 2015 Medicare MCC Full Sample, indicating that the model explains 10.5% of the variation in admission rates. The 2015 Medicare MCC Full Sample deviance R-squared was relatively unchanged after adding the AHRQ SES Index and physician-specialist density variables to the model (0.106) and after additionally including dual-eligibility status in the model (0.106).

In the Validation Sample, the over-fitting index of  $\gamma_0$  was close to 0 (-0.0002) and  $\gamma_1$  was close to 1 (0.9997), indicating good calibration of the demographic and clinical risk model.

Additionally, the plots of observed and predicted probabilities for each number of hospital admissions (0, 1, 2, ..., 10) across quartiles of risk showed that the model performs well across a broad range of risk (see [Figure 5](#)). In the highest-risk group, we found that the observed and predicted probabilities for zero and one admission differed slightly. However, these differences were small and somewhat expected among the highest-risk group of patients.

**Figure 5. Comparison of observed versus predicted probability for the number of hospital admissions among patients with multiple chronic conditions by risk quartile in the 2015 Development Sample**



### 3.5 Distribution of Measure Scores Across Provider Types

As the results in [Table 9](#) show, across the 64,025 TINs who had at least one MCC patient, RSAAR measure scores, including adjustment for the social risk factors of AHRQ SES Index and physician-specialist density, ranged from 16.9 to 112.8 per 100 person-years, with a median of 41.5 and an IQR of 39.1 to 44.7. Generally similar distributions in measure scores were found across TINs with different provider composition.

**Table 9. Distribution of risk-standardized admission rates (RSAARs) by TIN type (dataset: 2015 Medicare MCC Full Sample)**

TIN type	Number	Percent	Percentile										
			Min.	1 <sup>st</sup>	5 <sup>th</sup>	10 <sup>th</sup>	25 <sup>th</sup>	Median	75 <sup>th</sup>	90 <sup>th</sup>	95 <sup>th</sup>	99 <sup>th</sup>	Max.
All TINs	64,025*		16.9	30.2	34.1	36.1	39.1	41.5	44.7	49.4	53.2	61.9	112.8
<b>Solo providers</b>													
Primary care provider	29,983	46.8%	18.7	30.2	34.0	35.9	39.0	41.5	44.7	49.2	52.8	61.3	112.8
Specialist	6,681	10.4%	20.1	31.4	34.9	36.9	39.3	41.3	43.6	46.7	49.2	56.2	84.3
<b>Multi-provider TINs</b>													
All PCPs (physician and/or non-physician)	10,505	16.4%	16.9	29.5	33.5	35.3	38.7	41.9	46.2	51.5	55.4	65.3	93.4
Combination of physician PCP and ≥1 specialty (can also include non-physician PCP)	8,109	12.7%	18.8	29.7	34.0	36.2	39.5	42.2	46.5	52.1	55.8	64.8	100.3
Multispecialty group (no physician PCP but can include non-physician PCP)	1,762	2.8%	25.1	30.5	34.9	36.8	39.5	41.4	43.5	46.5	49.0	56.5	68.3
Single specialty group (includes non-physician PCP)	5,320	8.3%	24.1	31.7	35.4	37.3	39.8	41.4	43.0	45.5	48.3	56.9	85.9
Single specialty group (no PCP, physician or non-physician)	1,665	2.6%	23.0	30.3	33.8	36.1	38.7	41.5	44.7	48.4	51.6	58.4	66.3

\*This sample size excludes 61 TINs with missing social risk factor values.

Based on achieving a minimum measure score reliability of 0.5 (see [Section 3.6.2](#)), we repeated the analyses above for TINs with ≥28 attributed MCC patients ([Table 10](#)). At the TIN level, there was a wider distribution of measure scores with the 28-patient minimum threshold (5<sup>th</sup>-95<sup>th</sup> percentile: 32.2-56.5 per 100 person-years, [Table 10](#)) than without (5<sup>th</sup>-95<sup>th</sup> percentile: 34.1-53.2 per 100 person-years, [Table 9](#)).

**Table 10. Distribution of risk-standardized admission rates (RSAARs) by TIN type, restricted to TINs with  $\geq 28$  patients (dataset: 2015 Medicare MCC Full Sample)**

TIN type	Number	Percent	Percentile										
			Min.	1 <sup>st</sup>	5 <sup>th</sup>	10 <sup>th</sup>	25 <sup>th</sup>	Median	75 <sup>th</sup>	90 <sup>th</sup>	95 <sup>th</sup>	99 <sup>th</sup>	Max.
All TINs	28,357		16.9	28.4	32.2	34.1	37.5	41.8	47.0	52.7	56.5	65.9	112.8
<b>Solo providers</b>													
Primary care provider	12,877	45.4%	18.7	28.4	32.0	33.9	37.2	41.5	46.4	52.0	55.9	65.0	112.8
Specialist	1,178	4.2%	20.1	26.1	31.1	32.6	35.9	39.8	44.7	50.2	53.7	62.3	84.3
<b>Multi-provider TINs</b>													
All PCPs (physician and/or non-physician)	7,213	25.4%	16.9	28.9	32.5	34.5	37.8	42.3	47.5	53.3	57.0	67.1	93.4
Combination of physician PCP and $\geq 1$ specialty (can also include non-physician PCP)	5,048	17.8%	18.8	28.7	32.8	34.7	38.6	43.1	48.4	54.3	57.9	67.4	100.3
Multi-specialty group (no physician PCP but can include non-physician PCP)	414	1.5%	25.1	27.4	30.6	32.7	36.3	40.5	45.1	50.4	54.9	61.3	68.3
Single specialty group (includes non-physician PCP)	937	3.3%	24.1	27.4	31.4	33.3	36.0	40.0	45.2	51.4	55.9	65.9	85.9
Single specialty group (no PCP, physician or non-physician)	690	2.4%	23.0	28.0	32.0	33.8	37.3	41.3	46.1	50.6	53.8	62.2	66.3

## 3.6 Reliability

### 3.6.1 Data Element Reliability

Because this measure is calculated from claims submitted by hospitals and providers, adjudicated by CMS, and stored electronically, the reliability of the data is extremely high. When the measure is computed on the same set of admissions, for the same providers, using the same time period, precisely the same results are obtained.

We assessed the reliability of the data elements by comparing the risk factor frequencies and RRs ([Table 6](#)) in the Development and Validation Samples. These values were nearly identical in the two samples.

### 3.6.2 Measure Score Reliability

The median signal-to-noise reliability score was 0.45 (IQR: 0.21-0.68) for all clinician groups. We determined the minimum MCC patient sample size for TINs needed to achieve reliability scores of 0.4-0.7, to be between 19 and 64. [Table 11](#) shows the distribution of the reliability scores for TINs that met the minimum sample sizes. A minimum acceptable reliability of 0.5 was achieved for TINs with at least 28 MCC patients. At this threshold, reliability scores ranged from 0.51 to nearly 1.00, with a median value of 0.71 and an IQR of 0.61-0.82. With this 28-patient volume minimum, the measure included only 44.3% of TINs; however, it would report on 92.9% of the patients, 93.5% of the admissions, and 78.9% of clinicians who reported under these TINs. The median signal-to-noise reliability for all clinician groups was 0.45 (IQR: 0.205-0.681) indicating that there are many small volume TINs for which the measure cannot be reliably reported.

**Table 11. Distributions of measure score reliability across TINs for different minimum reliability (R) values (dataset: 2015 Medicare MCC Full Sample)**

Statistic	All TINs	TINs with volume $\geq 19$ (R=0.4)	TINs with volume $\geq 28$ (R=0.5)	TINs with volume $\geq 41$ (R=0.6)	TINs with volume $\geq 64$ (R=0.7)
Number (%) of TINs	64,025*	34,761 (54.3%)	28,357 (44.3%)	21,894 (34.2%)	14,765 (23.1%)
Number (%) of patients	4,916,172	4,713,085 (95.9%)	4,567,223 (92.9%)	4,350,053 (88.5%)	3,987,728 (81.1%)
Number (%) of admissions	1,810,459	1,744,441 (96.4%)	1,693,475 (93.5%)	1,615,805 (89.2%)	1,482,417 (81.9%)
Number (%) of individual clinicians reporting under the same TIN	233,194	194,573 (83.4%)	183,921 (78.9%)	172,760 (74.1%)	158,644 (68.0%)
<b>Distribution of reliability scores</b>					
Maximum	0.997	0.997	0.997	0.997	0.997
99 <sup>th</sup> percentile	0.976	0.984	0.986	0.988	0.991
95 <sup>th</sup> percentile	0.895	0.939	0.950	0.962	0.974
90 <sup>th</sup> percentile	0.827	0.888	0.906	0.925	0.948
75 <sup>th</sup> percentile	0.681	0.788	0.816	0.843	0.883
Median	0.448	0.662	0.709	0.756	0.811
25 <sup>th</sup> percentile	0.205	0.541	0.608	0.678	0.754
10 <sup>th</sup> percentile	0.069	0.459	0.549	0.629	0.721
5 <sup>th</sup> percentile	0.036	0.436	0.525	0.613	0.712
1 <sup>st</sup> percentile	0.036	0.412	0.508	0.602	0.702
Minimum	0.036	0.412	0.508	0.602	0.702

\*This sample size excludes 61 TINs with missing social risk factor values.

### 3.7 Measure Validity

#### 3.7.1 Face Validity of the Attribution Algorithm

The TEP strongly preferred a visit-based approach for attribution and supported the final algorithm.

#### 3.7.2 Face Validity of Measure Scores

TEP members were asked to complete a survey regarding validity and usability of the measure. Of 17 TEP members who were active through the end of the project, 11 responded. Their responses are reported in [Table 12](#).

**Table 12. Results of Technical Expert Panel survey of validity and usability**

The RSAARs obtained from the MCC measure as specified:	Agree			Disagree		
	Strongly	Moderately	Somewhat	Somewhat	Moderately	Strongly
Can be used to distinguish good from poor quality of care provided to MCC patients by TINs reporting under MIPS	0	5	4	0	1	1
Will provide TINs reporting under MIPS with information that can be used to improve their quality of care for MCC patients	1	5	2	2	1	0

As shown in [Table 12](#), the majority of the respondents, 9/11 or 82%, agreed that the MIPS MCC admission measure can be used to distinguish good from poor quality of care. The majority of the respondents, 8/11 or 73%, agreed that the MIPS MCC admission measure scores (RSAARs) will provide MIPS TINs with information that could be used to improve the quality of care for MCC patients.

Three of the 11 respondents somewhat, moderately, or strongly disagreed with one or both statements. Of these:

- One TEP member noted the measure would not be actionable unless CMS provided patient-level data alongside the overall measure score (RSAAR) to TINs.
- The second TEP member was concerned that the measure does not include any element of patient responsibility given challenges patients may encounter in managing their heart failure.
- The third TEP member questioned whether lower admission rates are a signal of higher-quality care. Further, the member noted the impacts of risk adjustment and of potential omission of risk variables are unclear. Regarding risk adjustment, the TEP member posited the reliance on diagnosis coding for clinical risk adjustment may favor better-resourced practices that could be more sophisticated in their approaches to coding. The TEP member concluded the risks or harms of deploying the measure may outweigh the benefits.

Overall, the survey indicates support of the validity and usability of the measure.

#### 4. SUMMARY

In this report, we described the development and testing of an outcome measure for MIPS providers based on their MCC patients' rate of acute, unplanned hospital admissions. CMS specified the final measure to align with the measure concept, informed by extensive testing of alternative approaches and with input from a nationally convened TEP and public comment.

The final risk model includes 49 variables, including two social risk factors (the AHRQ SES Index and physician-specialist density). When we calculated RSAARs for TINs (n=64,025), RSAAR measure scores ranged from 16.9 to 112.8 per 100 person-years, with a median of 41.5 (IQR: 39.1 to 44.7). Generally similar distributions in measure scores were found across TINs with different provider composition, including solo clinicians and multi-provider TINs.

We determined that to achieve a minimum measure score reliability of 0.5 (which corresponds to moderate agreement), at least 28 patients are needed at the TIN level. If CMS established this volume cutoffs for public reporting, the majority of TINs (55.7%) would be excluded; however, the measure would include 92.9% patients at the TIN level.

In summary, we have demonstrated the feasibility of measuring individual clinicians and groups of clinicians on the outcome of hospital admissions and have found variation in risk-adjusted admission rates. The MIPS MCC admission measure will illuminate differences in care quality among providers, inform patient choice, drive quality improvement, and enhance care coordination.



## 5. GLOSSARY

**Case mix:** The particular demographic, clinical, and social risk factors of patients attributed to MIPS providers.

**Clinical Classification Software (CCS):** Software maintained by the AHRQ that groups thousands of individual procedure and diagnosis codes into clinically coherent, mutually exclusive procedure and diagnosis categories. AHRQ CCS procedure and diagnosis categories are used to determine if an admission is planned. AHRQ CCS procedure categories are used to define planned and potentially planned procedures. AHRQ CCS diagnosis categories are used to define acute diagnoses and complications of care that are considered unplanned, as well as a few specific types of care that are always considered planned (for example, maintenance chemotherapy). Mappings which show the assignment of ICD-9/10 codes to the AHRQ CCS diagnosis and procedure categories are available on the [AHRQ website](#).

**Cohort:** The index MCC patient population used to calculate the measure after inclusion and exclusion criteria have been applied.

**Comorbidities:** Medical conditions that the patient had in the year prior to the measurement year.

**Condition Categories (CCs):** Groupings of ICD-9-CM/ICD-10-CM diagnosis codes in clinically relevant categories, from the HCCs system.<sup>49,50</sup> CMS uses the grouping but not the hierarchical logic of the system to create risk factor variables. Mappings which show the assignment of ICD-9-CM and ICD-10-CM codes to the CCs are available on tab 3 in the accompanying Excel workbook.

**Confidence interval (CI):** A CI is a range of values that describes the uncertainty surrounding an estimate. It is indicated by its endpoints; for example, a 95% CI for the rate ratio (RR) associated with acute myocardial infarction noted as “1.07 – 1.09” would indicate that there is 95% confidence that the RR lies between 1.07 and 1.09.

**Dominant specialist:** Specialist who saw a patient  $\geq 2$  times more than any primary care provider (PCP) or any other relevant specialist.

**Evaluation and management (E&M) services:** Category of codes used to document visit complexity for billing purposes.

**Expected admissions:** The number of admissions expected based on average provider performance with a given provider’s patient case mix.

**Hierarchical regression model:** A widely accepted statistical method that enables fair evaluation of relative provider performance by accounting for patient risk factors. This statistical model accounts for the hierarchical structure of the data (patients clustered within providers are assumed to be correlated) and accommodates modeling of the association between outcomes and patient characteristics. Based on the hierarchical model, we can evaluate (1) how much variation in provider admission rates overall is accounted for by patients’ individual risk factors (such as age and clinical comorbidities), and (2) how much variation is accounted for by provider contribution to admission risk.

**Medicare Fee-for-Service (FFS):** Original Medicare plan in which providers receive a fee or payment for each individual service provided directly from Medicare. Only beneficiaries in Medicare FFS, not in managed care (Medicare Advantage), are included in the measure.

**National observed admission rate:** All admissions counted in the outcome divided by the total person-years at risk for all attributed patients.

**Rate ratio (RR):** The RRs express the relative admission rate for each of the predictor variables. For example, the RR for acute myocardial infarction represents the admission rate for patients with that risk variable present relative to those without the risk variable present. The model coefficient for each risk variable is the log (rate ratio) for that variable.

**Outcome:** Acute, unplanned hospital admissions used to assess the quality of care provided by MIPS clinicians and groups of clinicians.

**Person-years:** The accumulated time patients are at risk for admission during the measurement period.

**Planned admissions:** An admission that is a scheduled part of the patient's plan of care. Planned admissions are not counted in the outcome of this measure.

**Predicted admissions:** The number of admissions predicted based on the provider's performance with its observed case mix.

**Predictive ability:** An indicator of the model's discriminant ability or ability to distinguish high-risk subjects from low-risk subjects. A wide range between the lowest decile and highest decile suggests better discrimination.

**Relevant specialist:** A specialist covered by the measure who plausibly provides overall coordination of care for patients with MCCs and who manages the chronic diseases that put the MCC patients in the measure at risk of admission. Relevant specialists include cardiologists, pulmonologists, nephrologists, neurologists, endocrinologists, and hematologists/oncologists.

**Risk-adjustment variables:** Patient demographics, clinical (including frailty) variables, and social risk factors used to standardize rates for differences in case mix across providers.

**Unplanned admissions:** Acute clinical events a patient experiences that require urgent hospitalization. Unplanned admissions are the outcomes of the measure.

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## APPENDICES

### Appendix A. CMS Planned Readmission Algorithm, Adapted to Identify Planned Admissions for Patients with Multiple Chronic Conditions

#### Appendix A.1. Planned Admission Algorithm Overview

The planned admission algorithm used in the development of this admission measure is adapted from the Centers for Medicare & Medicaid Services (CMS) Planned Readmission Algorithm. The algorithm is a set of criteria for classifying admissions as planned or unplanned using Medicare claims. CMS seeks to count only unplanned admissions in the measure outcome, because variation in planned admissions does not reflect quality differences.

We have adapted the planned admission algorithm for patients with multiple chronic conditions (MCCs). The adapted algorithm classifies admissions as planned or unplanned using a flow chart ([Figure A1](#), below) and four tables of procedures and conditions (Tab 7, Tables PA1-Table PA4 in the accompanying Excel workbook). On Tab 7 in the accompanying Excel workbook:

- Table PA1 identifies procedures that, if present in an admission, classify the admission as planned.
- Table PA2 identifies principal discharge diagnoses that classify admissions as planned.
- Table PA3 identifies procedures that, if present, classify an admission as planned as long as that admission does not have an acute (unplanned) principal discharge diagnosis.
- Table PA4 lists the acute principal discharge diagnoses that disqualify admissions with a potentially planned procedure in Table PA3 as planned.

The algorithm uses the Agency for Healthcare Research and Quality's (AHRQ's) Clinical Classification Software (CCS) codes to group thousands of individual procedure and diagnosis ICD-9-CM codes into clinically coherent, mutually exclusive procedure CCS categories and mutually exclusive diagnosis CCS categories, respectively.

In applying the algorithm to the MCC population, our team reviewed the General Population version of the planned readmission algorithm in the context of these specific groups of patients. Where clinically indicated, we adapted the content of the tables to better reflect the likely clinical experience of patients with MCCs.

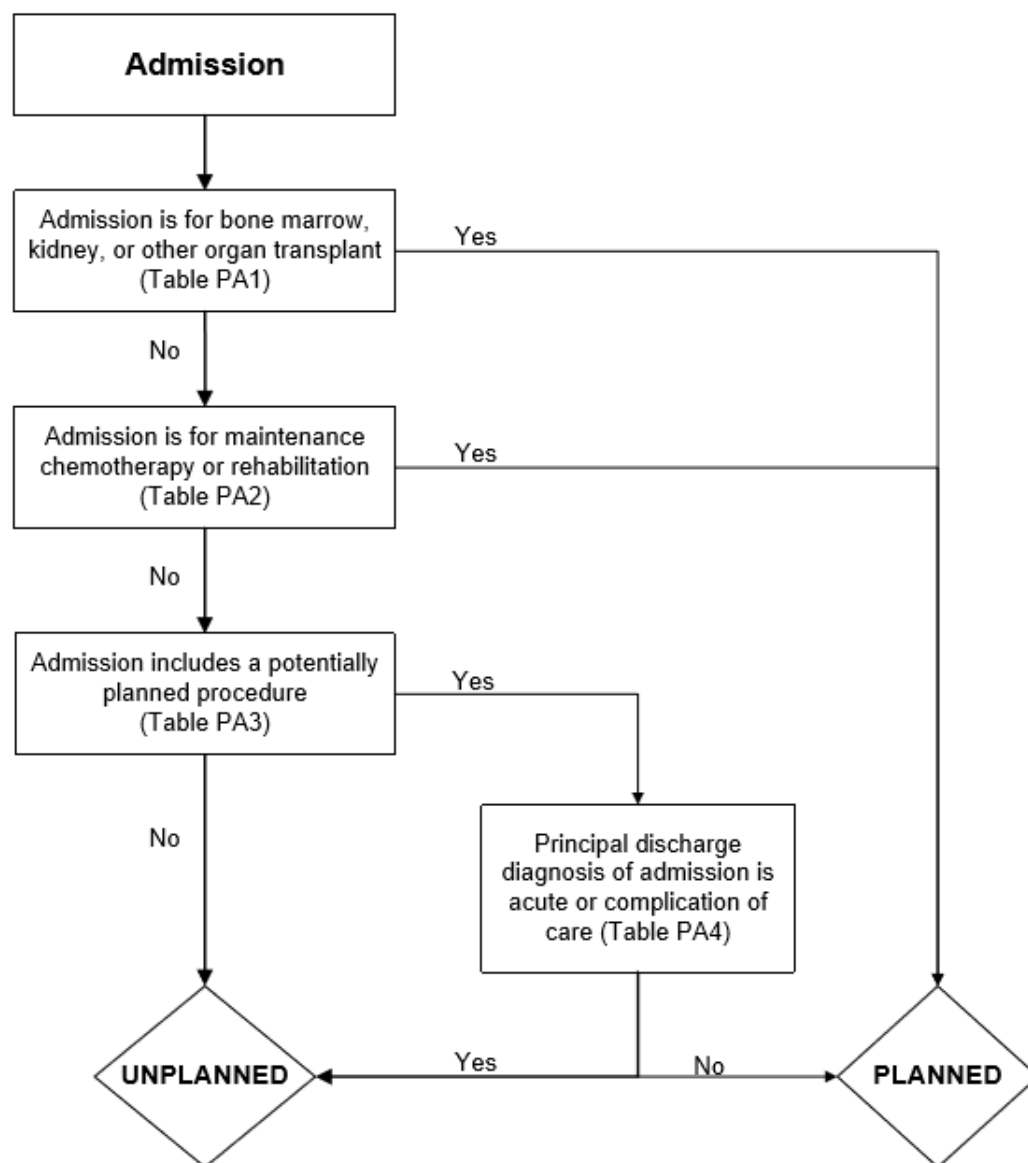
#### Appendix A.2. Detailed Description of Planned Admission Algorithm – Multiple Chronic Conditions Population

The adapted admission algorithm uses the flowchart ([Figure A1](#)) and Table 1-Table 4 in the accompanying Excel workbook, to identify specific procedure categories and discharge diagnosis categories to classify admissions as planned or unplanned. As illustrated in the flowchart, admissions that include certain procedures (see Tab 7, Table PA1 in the accompanying Excel workbook) or are for certain diagnoses (see Tab 7, Table PA2 in the accompanying Excel workbook) are always considered planned. If the admission does not include a procedure or diagnosis in Table PA1 or Table PA2 that is always considered planned, the algorithm checks whether the admission has at least one procedure that is considered potentially planned (see Tab 7, Table PA3 in the accompanying Excel workbook). If the admission has no procedures from Table PA3, the admission is considered unplanned. Table PA3 includes 64 AHRQ procedure CCS categories from among 231 AHRQ procedure CCS. Examples of

potentially planned procedures are total and partial hip replacement (Procedure CCS 153) and coronary artery bypass graft (CABG) (Procedure CCS 44).

If an admission has at least one potentially planned procedure from Table PA3, the algorithm checks for a principal discharge diagnosis that is considered acute (Tab 7, Table PA4 in the accompanying Excel workbook). If the admission has an acute principal discharge diagnosis from Table PA4, the admission is considered unplanned. Otherwise, it is considered planned. The list of acute principal discharge diagnoses includes 101 diagnosis groups from among 285 AHRQ condition categories and six groupings of individual ICD-9-CM diagnosis codes that represent cardiac diagnoses that would not be associated with a planned admission. Examples of acute principal discharge diagnoses that would flag admissions with potentially planned procedures as unplanned are pneumonia (Diagnosis CCS 122) and cardiac arrest (Diagnosis CCS 107).

**Figure A1. Planned admission algorithm flowchart**





## Appendix B. Individual Clinician-Level Attribution Options Considered

### Appendix B.1. Criteria for Evaluating Attribution Options

CMS is interested in developing a measure that can be applied at both the individual clinical (NPI/TIN) level and the Taxpayer Identification Number (TIN) level, which includes both solo clinicians and groups of clinicians who have chosen to report their quality under a common TIN. We first developed an attribution algorithm at the individual clinician level (Step 1). Acknowledging there are multiple reasonable approaches for attributing patients to providers, we began by developing a set of criteria to consider when selecting among attribution approaches. Building on key principles for attribution models set forth by the National Quality Forum<sup>33</sup>, we sought to develop an attribution model that is fair to providers, aligned with the goals of the MIPS program, and transparent. Specifically, we judged attribution options based on the following principles and criteria, which were endorsed by the measure's national Technical Expert Panel (TEP) ([Table B1](#)).

**Table B1. Attribution principles and corresponding criteria**

Principle	Corresponding attribution criteria
Attribution models should be fair and accurate.	<ul style="list-style-type: none"><li>• Attributes patients to providers with a reasonable degree of accuracy (acknowledging there is no gold standard for determining patients' primary providers).</li><li>• Assigns the vast majority of patients.</li><li>• Does not systematically disadvantage patient subgroups.</li></ul>
Attribution models should align with the stated goals and purpose of the measure.	<ul style="list-style-type: none"><li>• Attributes patients to providers able to influence the measured outcome.</li><li>• Incentivizes high quality, coordinated ambulatory care for MCC patients.</li><li>• Minimizes unintended consequences.</li></ul>
Attribution models should be transparent.	<ul style="list-style-type: none"><li>• Is straightforward and understandable by patients and providers.</li><li>• Reflects input from stakeholders, informed by discussion and testing of alternatives.</li></ul>

We initially developed and tested three options. Based on the a priori criteria above, input from the TEP, and further guidance from CMS, we selected and refined one of the options. In this appendix, we detail the original options and the process by which we arrived at the final attribution approach for the measure, which is presented in [Section 2.5](#).

A common feature of all the approaches that we considered is that they prioritize assignment to a primary care provider (PCP) over a specialist given the PCP's central role in coordinating patient services, including specialty care. The first option, which is an adaptation of the two-step approach CMS uses for claims-based quality measures in MIPS, used the plurality of charges to assign patients to clinicians. In contrast, the other two initial options that we developed and tested used the plurality of visits to assign

patients to clinicians. These latter two options relied heavily on the number of visits to identify the most responsible provider, and only incorporated charges in the attribution algorithm to break ties between clinicians with equal numbers of visits. The two options differed in the minimum number of visits (2 or 3) at which PCPs are assumed to be coordinating patient care and, if not met, at which specialists are assumed to be managing the patient rather than PCPs. In consultations with clinicians at CMS and CORE and on our TEP, we received feedback that PCPs who see their complex patients with MCCs even twice a year may feel as though they are serving in the “quarterback” role and coordinating patients’ care. Based on our empirical finding that it left the highest proportion (16.5%) of patients unassigned and input from the TEP, we excluded the three-visit minimum option. As noted in [Section 2.5](#), the 2-visit minimum option was subsequently refined and adopted as the individual clinician-level attribution approach.

Below, we briefly describe: 1) the options we considered and 2) how they compared against the selection criteria we established based on key principles for attribution models set forth by the National Quality Forum.<sup>51</sup>

### **Option A: Adaptation of CMS’s Two-Step Attribution Algorithm for MIPS Claims-Based Outcome Measures**

As a reference point, we began with a modification of the Value Modifier and MIPS “two-step” approach used for claims-based quality measures. In MIPS, the approach is used to assign patients at the TIN level, whereas we have adapted it to assign patients at the individual clinician level. This approach attributes patients to providers based on the plurality of providers’ Evaluation & Management (E&M) charges. See Tab 7 in the accompanying Excel workbook for specific service codes using the two-step process that prioritizes assignment to PCPs.

- Step 1. The patient is assigned to a PCP based on the plurality of E&M charges billed during a calendar year.
- Step 2. If no PCP submitted E&M claims for the patient, the patient is assigned to the specialist (for example, cardiologist or pulmonologist) with the plurality amount of E&M charges (81 FR 77135).

#### Rationale

- This approach reflects the primary role of a PCP in managing/coordinating care for MCC patients.
- This approach aligns responsibility for cost and quality (more Medicare revenue equals more responsibility).

#### Key Features

- This approach is based solely on E&M charges.
- A patient is assigned to the individual PCP with the plurality of charges, even if those charges stem from a single visit, regardless of the number of visits to other PCPs or to specialists.
- Alternatively, if there are no PCP charges, the patient is assigned to a relevant specialist, if any, with the plurality of charges (regardless of the number of visits).

### **Option B: Visit-Based Attribution Algorithm with 2-Visit Minimum Threshold**

In this option, assignment goes to the PCP with the greatest number of visits over the  $\geq 2$  minimum threshold. However, if there is no PCP with  $\geq 2$  visits, the algorithm looks for a “dominant” specialist who met the 2-visit minimum and had  $\geq 2$  more visits than any other clinician.

#### Rationale

- A 2-visit minimum may be sufficient to identify the clinician most responsible for patient care and leaves fewer patients unassigned than 3-visit minimum threshold.
- Focus on visits over charges emphasizes interaction with patient when assigning responsibility.

#### Key Features

- This approach is driven by numbers of visits, with charges used to break ties.
- If the patient did not see a PCP or any relevant specialist, the patient is unassigned.
- $\geq 2$  PCP visits automatically triggers assignment to a PCP, regardless of number of specialist visits. If more than 1 PCP meets the minimum, assignment goes to the PCP with the greatest number of visits (with charges used to break ties).
- If 1 PCP visit, assignment:
  - Stays with PCP if no specialist visits;
  - Goes to specialist if minimum for “dominant” specialist (which we have defined as having  $\geq 2$  visits and  $\geq 2$  more visits than any PCP and any other relevant specialist) is satisfied; or
  - Is unassigned if care is diffused across PCP and specialist(s).
- If 0 PCP visits, assignment goes to specialist if minimum for “dominant” specialist is satisfied or to unassigned if not.

### **Option C: Revised Visit-Based Attribution Algorithm with 2-Visit Minimum Threshold**

With additional stakeholder input, we modified the  $\geq 2$  visit option to better attribute patients to specialists who are likely managing the patient even when a PCP is involved. This approach considers assignment to a “dominant” specialist among patients who would have been automatically assigned to a PCP based on meeting the 2-visit minimum threshold.

#### Rationale

- This approach continues to focus on visits over charges, emphasizing interaction with patient when assigning responsibility.
- It allows for greater opportunity to identify specialists who are actively involved in managing MCC patients’ care.

## Key Features

- Rather than automatically assigning a patient to the PCP with the plurality of visits and meeting the 2-visit minimum threshold – regardless of the number of specialist visits – this approach determines whether the patient might have seen a “dominant” specialist, which, as noted above, we define as having  $\geq 2$  more visits compared with the PCP and any other specialist.
- If a dominant specialist is found, the specialist is assigned the patient; otherwise, the patient stays with the PCP.

## Appendix B.2. Evaluation of Attribution Options Against Selection Criteria

In [Table B2](#), we summarize the relative pros and cons of the attribution options based on the a priori criteria; the results are based on preliminary measure specifications earlier in the measure development process. Based on TEP and CMS input and an evaluation of the selection criteria, we selected Option C for attributing patients with MCCs to individual clinicians. See the flowchart in [Figure 1](#) for a detailed description of the attribution algorithm.

**Table B2. Evaluation of attribution options against selection criteria**

Criterion	Option A: MIPS two-step, plurality of charges	Option B: $\geq 2$ visit minimum, plurality of visits*	Option C: Revised $\geq 2$ visits minimum, plurality of visits*
<b>Fair and accurate</b>			
Attributes patients to providers with a reasonable degree of accuracy	Concern that use of charges may result in assignment to less responsible provider	A majority of TEP members support a visit-based approach to attribution given its face validity; focus on visits over charges emphasizes interaction with patient when assigning responsibility	Likely better attributes patients to specialists who are actively managing MCC patients' care; compared with Option B, Option C results in a higher proportion of patients assigned to specialists (9.8% vs. 5.3%) and a lower proportion assigned to PCPs (79.5% vs. 84.0%)
Assigns the vast majority of patients	4.5% unassigned	10.7% unassigned	10.7% unassigned
<b>Aligns with measure and MIPS program goals</b>			
Attributes patients to providers able to influence the measured outcome	Yes, emphasis on PCP, but may miss “quarterback” specialists	Yes, but still may miss “quarterback” specialists	Yes, and more likely to attribute patients to “quarterback” specialists
Incentivizes high quality, coordinated ambulatory care for MCC patients	Since in nearly all cases assignment will go to PCP, may incentive PCP to coordinate with other providers to lower patient risk	Patients with more diffuse care may be unassigned, so may provide less incentive	Patients with more diffuse care may be unassigned, so may provide less incentive

Criterion	Option A: MIPS two-step, plurality of charges	Option B: ≥2 visit minimum, plurality of visits*	Option C: Revised ≥2 visits minimum, plurality of visits*
Potential unintended consequences	Denial of care to high-risk patients to avoid patient assignment	Limit to single visit to avoid patient assignment	Limit to single visit to avoid patient assignment
Aligns with attribution methods used for evaluation of costs for ambulatory MCC patients under MIPS	Yes, for total per capita cost measure; chronic condition episode-based cost measures are still pending, and attribution algorithms have not yet been defined	Not aligned with algorithms used to date; however, a tailored approach specific to the measure is important to ensure that patients and their outcomes are correctly attributed to providers for whom the specific measured outcome is a quality signal	Not aligned with algorithms used to date; however, a tailored approach specific to the measure is important to ensure that patients and their outcomes are correctly attributed to providers for whom the specific measured outcome is a quality signal
<b>Transparent</b>			
Is straightforward and understandable by patients and providers	Yes, simple algorithm based on preference for PCP assignment and plurality of charges	Yes, focus on visits defines responsibility in terms of patient interaction, but dominant specialist concept and fallback to PCP with 1 visit may be more difficult to explain/understand	Yes, focus on visits defines responsibility in terms of patient interaction, but dominant specialist concept and fallback to PCP with 1 visit may be more difficult to explain/understand

\*In rare instances when a patient had only 1 visit with a PCP and no other relevant visits, the patient is assigned to that PCP as the most responsible clinician.

## **Appendix C. TIN-Level Attribution Options Considered**

CMS is interested in developing a measure that could be applied at both the individual clinician level and the TIN level. The TIN level includes both solo clinicians and groups of clinicians who have chosen to report their quality under a common TIN. When moving to attribution at the TIN level (Step 2), we considered two approaches:

1. Patients who are assigned to an individual clinician follow that clinician to her/his TIN.
2. Patient assignment is run at the TIN level, independent of individual clinician assignment (TIN “roll-up” option).

### **Appendix C.1. TIN-Level Option 1**

The rationale for TIN-level Option 1 wherein patients who are assigned to an individual clinician follow that clinician to her/his TIN is:

- An individual clinician should have accountability for each individual patient.
- This is aligned with most insurance policies that require patients to choose a PCP.

Key features of this approach are:

- Patients who are assigned to an individual clinician follow that clinician to her/his TIN.
- Clinicians who elect to report their quality as part of a group bring their patients with them.
  - There may be instances, for example, where solo provider PCP1 is assigned a patient based on having 4 visits; however, PCP2, PCP3, and PCP4 with 2 visits each who are in a TIN together collectively have more visits.
- Patients unassigned at the individual clinician level continue to be unassigned at the TIN level.

### **Appendix C.2. TIN-Level Option 2**

The rationale for TIN-level Option 2 wherein patient assignment is run at the TIN level, independent of individual clinician assignment (TIN “roll-up” option), is:

- In a group/medical home model, clinicians assume joint responsibility for patients’ care and outcome.
- Care is optimized by a team-based approach that holds clinicians jointly accountable.

Key features of this approach are:

- The patient assignment algorithm is applied to total visits among PCPs and specialists within each TIN. For example, the algorithm first identifies the TIN that billed the greatest number of PCP visits, with a minimum of 2 visits, independent of whether the patient saw a single PCP or multiple PCPs within the TIN.
- Patients unassigned at the individual clinician level may be assigned to a multi-provider TIN based on visit totals across providers in the TIN.
- This is consistent with current charge-based approach to TIN attribution under the MIPS program.

### Appendix C.3. Evaluation of TIN-level Attribution Options

We evaluated the options using the criteria specified in [Table C1](#). Based on TEP and CMS input and an evaluation of the selection criteria above, we selected Option 1 for attributing patients with MCCs to TINs. The approach first assigns patients to the clinician most responsible for their care (using the algorithm for individual clinician-level attribution described in [Section 2.5](#)) and then has the patient follow her/his clinician to the TIN designated by the clinician.

**Table C1. Evaluation of TIN-level attribution options against selection criteria**

Criterion	Option 1 (patient follows clinician)	Option 2 (TIN roll-up)
<b>Transparency/ease of understanding</b>	<b>More</b> When patients follow clinicians to their TINs, it is clear to clinicians and TINs where patients will be assigned at the TIN level More consistent with program structure providing clinician choice of reporting at NPI/TIN or TIN level	<b>Less</b> Multi-provider TINs will be less able to anticipate which patients will be attributed to them based on the provider composition of the TIN
<b>Ease of implementation</b>	<b>More</b> Need to run only 1 algorithm for clinician-level and TIN-level attribution	<b>Less</b> Need to run 2 separate algorithms for clinician-level and TIN-level attribution
<b>Aligned with the current charge-based approach to TIN attribution under the MIPS program</b>	<b>No</b> However, a tailored approach specific to the measure is important to ensure that patients and their outcomes are correctly attributed to providers for whom the specific measured outcome is a quality signal	<b>Yes</b>
<b>Aligned with approach taken for inpatient MIPS outcome measures</b>	<b>To be determined</b> , CMS is re-specifying these measures for MIPS	

## Appendix D. Social Risk Factors

**Table D1. Candidate social risk factors**

Category	Social risk factor
Deprivation	Neighborhood deprivation
Driving	Driving alone
	Long commute
Eligibility for benefits	Benefits from Medicare shared savings program
	DE status
	Disability eligibility
	Number of Medicare beneficiaries per capita
	Part D low income subsidy
Health services	Fewer primary care providers per capita
	Lower ratio of primary care providers to specialists
	Number of hospital beds per capita
	Number of specialists per capita
Housing	Higher housing density
	Median home value
	More housing problems
	Occupancy rates
	Percentage of severe housing problems
Income	Household income
	Income inequality
	Poverty level
	Poverty rates
	Unemployment
Other	Average daily particulate matter (air quality)
	Education rate
	Employment rate
	Fewer public associations (community involvement)
	Proportion not married
	Proportion of residents living alone
	Race
	Sex
	Smoking rate
	Urbanicity



## Appendix E. Risk-Standardized Measure Score Calculation

In order to measure provider performance, we computed the ratio of the ‘predicted’ admissions to ‘expected’ admissions. To do this, we fitted a hierarchical generalized linear model (HGLM) to account for the natural clustering of patients within providers and estimated providers’ ‘predicted’ performance based on the effects of the patient-specific risk factors. We calculated the number of ‘expected’ admissions for each provider based on the performance of an average provider with the same case-mix of patients. Since the effects that risk factors exert on the number of admissions are estimated based on data from all MIPS eligible clinicians and attributed patients in the cohort, the ‘expected’ outcome reflects “nationwide” expectation.

### Appendix E.1. Detailed Description of Hierarchical Model

The MIPS MCC admission measure HGLM assumes the outcome has a known exponential family distribution and relates linearly to the covariates via a known link function,  $h$ . For the model, we assumed a negative binomial distribution with linear variance (NB-1) and a log link function (Note the NB-1 model was chosen to account for overdispersion in the data). Further, we accounted for the clustering within providers by estimating a provider-specific effect,  $\alpha_i$ , which we assume follows a normal distribution with mean  $\mu$  and variance  $\tau^2$ , the between-provider variance component. The following equations define the HGLM:

$$h(E(Y_{ij}|\mathbf{Z}_{ij}, \omega_i)) = \log(E(Y_{ij}|\mathbf{Z}_{ij}, \omega_i)) = \alpha_i + \beta\mathbf{Z}_{ij} \quad (1)$$

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

$$i = 1 \dots I; j = 1 \dots n_i$$

Where  $Y_{ij}$  denotes the outcome (number of unplanned admissions per the person-years of risk exposure) for the  $j$ -th patient attributed to the  $i$ -th provider;  $\mathbf{Z}_{ij} = (Z_{1ij}, Z_{2ij}, \dots, Z_{Pij})$  is a set of  $p$  patient-specific covariates derived from the data;  $I$  denotes the total number of providers and  $n_i$  the number of patients attributed to provider  $i$ . The provider-specific intercept of the  $i$ -th provider,  $\alpha_i$ , defined above, comprises  $\mu$ , the adjusted average intercept over all providers in the sample, and  $\omega_i$ , the provider-specific intercept deviation from  $\mu$ . A point estimate of  $\omega_i$ , greater or less than 0, determines whether the provider’s performance is worse or better compared to the adjusted average outcome.

Further,  $Y_{ij}$  can be expressed as  $Y_{ij} = N_{ij} / M_{ij}$  where  $N_{ij}$  denotes the total number of admissions during the measurement period and follows the negative binomial distribution with mean,  $\mu_{ij}|\mathbf{Z}_{ij}, \omega_i$ , and variance with dispersion parameter  $\theta$ ,  $\mu_{ij}|\mathbf{Z}_{ij}, \omega_i (1 + \theta)$ .  $M_{ij}$  denotes the person-years of risk exposure for the  $j$ -th patient attributed to the  $i$ -th provider. Given this, we re-write Equation (1) as:

$$\log(E(N_{ij}|\mathbf{Z}_{ij}, \omega_i)) = \alpha_i + \beta\mathbf{Z}_{ij} + \log(M_{ij}) \quad (2)$$

where  $\log(M_{ij})$  becomes the offset used to correct for the time at risk.

We estimate the HGLM using Stata version 15 (StataCorp, College Station, TX) (MENBREG function).

## Appendix E.2. Score Calculation

Using the HGLM defined by Equation (2), we obtain the parameters  $\hat{\mu}$ ,  $\{\hat{\alpha}_1, \hat{\alpha}_2, \dots, \hat{\alpha}_I\}$ ,  $\hat{\beta}$  and  $\hat{\tau}^2$ . We calculate a risk-standardized rate,  $s_i$ , for each provider by computing the ratio of the predicted to expected mean outcomes multiplied by the unadjusted national rate of admissions per 100 person-years,  $\bar{y}$ . Specifically, we calculate:

$$(1) \text{ Predicted Value: } \hat{Y}_{ij} = h^{-1}(\hat{\alpha}_i + \hat{\beta}Z_{ij}) = \exp(\hat{\alpha}_i + \hat{\beta}Z_{ij})$$

$$(2) \text{ Expected Value: } \hat{e}_{ij} = h^{-1}(\hat{\mu} + \hat{\beta}Z_{ij}) = \exp(\hat{\mu} + \hat{\beta}Z_{ij})$$

$$(3) \hat{s}_i = \frac{\sum_{j=1}^{n_i} \hat{Y}_{ij}}{\sum_{j=1}^{n_i} \hat{e}_{ij}} \times \bar{y}$$

If the “predicted” outcome is higher (lower) than the “expected” outcome, then that provider’s  $\hat{s}_i$  will be higher (lower) than the unadjusted average.