



Quality Indicator Empirical Methods

Prepared for:

Agency for Healthcare Research and Quality
U.S. Department of Health and Human Services
540 Gaither Road
Rockville, MD 20850
<http://www.qualityindicators.ahrq.gov>

Contract No. HHS290201200001C

Prepared by:

Battelle
505 King Avenue
Columbus, OH 43201

Revised November 2013

Disclaimer

This document is based on research conducted by Battelle under contract to the Agency for Healthcare Research and Quality (AHRQ), Rockville, MD (Contract No. HHS290201200001C). The findings and conclusions in this document are those of the author(s), who are responsible for its content, and do not necessarily represent the views of AHRQ. No statement in this report should be construed as an official position of AHRQ or of the U.S. Department of Health and Human Services.

The information in this report is intended to help clinicians, employers, policymakers, and others make informed decisions about the provision of health care services. This document is intended as a reference and not as a substitute for clinical judgment.

This document is in the public domain and may be used and reprinted without permission except those copyrighted materials that are clearly noted in the document. Further reproduction of those copyrighted materials is prohibited without the specific permission of copyright holders.

Suggested Citation:

Geppert, J., Rhoda, D., Morara, M. Quality Indicator Empirical Methods (Revised by Battelle, under Contract No. HHS A290201200001C). Rockville, MD: Agency for Healthcare Research and Quality. September 2013.

None of the investigators has any affiliations or financial involvement that conflicts with the material presented in this document.

Contents

Overview.....	2
Chapter 1. The User’s Dataset	5
Chapter 2. Calculating Volume and Count Indicators	7
Chapter 3. Calculating Area-Level Indicators – Observed Rates	9
Chapter 4. Risk Adjustment for Area-Level Indicators	12
Chapter 5. Calculating Area-Level Indicators – Expected, Risk-Adjusted, & Smoothed Rates ..	13
Chapter 6. Overview of Provider-Level QI & Present on Admission (POA)	15
Chapter 7. Calculating Provider-Level Observed Rates – Ignoring POA	19
Chapter 8. Calculating Provider-Level Observed Rates – With Complete POA Data.....	21
Chapter 9. Calculating Provider-Level Observed Rates – With Missing POA Data.....	23
Chapter 10. Risk Adjustment for Provider-Level Indicators	26
Chapter 11. Estimating Composite Measures.....	34
Chapter 12. Software Maintenance – Updating the Reference Population	39
Chapter 13. Software Maintenance – Other Updates.....	44
References.....	45
Appendix A. Table of AHRQ QI Risk-adjustment / POA.....	47
Appendix B. Table of AHRQ QI Provider-Level Risk-adjustment Covariates.....	52
Appendix C. Provider-Level Risk Adjustment - Detailed Methods	55
Appendix D. Helpful Background Information	66

List of Tables

Table 1.1 Required Data Elements	5
Table 1.2 Data Elements and Data Values To Be Constructed by the User	6
Table 1.3 Analysis Data Inclusion Rule	6
Table 2.1 AHRQ QI Volume Indicators	7
Table 2.2 AHRQ QI Count Indicators	7
Table 3.1 AHRQ QI Area-Level Indicators.....	9
Table 6.1 Methods Used by QI Software to Distinguish Complications from Comorbidities	16
Table 6.2 Values for the Present-on-Admission Data Element	18
Table 10.1 Parameter Estimates CSV Files for Provider-Level Risk Adjustment	27

Overview

This document describes the empirical methods used to calculate the AHRQ Quality Indicators™ (AHRQ QI). The QI measure health care quality and can be used to highlight potential quality concerns, identify areas that need further study and investigation, and track changes over time. The QIs are calculated using software that is freely available at www.qualityindicators.ahrq.gov.

The current AHRQ QI modules represent various aspects of quality:

- Prevention Quality Indicators (PQI) identify hospital admissions in geographic areas that evidence suggests might have been avoided through access to high-quality outpatient care. (first released November 2000, last updated May 2013)
- Inpatient Quality Indicators (IQI) reflect quality of care inside hospitals, as well as across geographic areas, including inpatient mortality for medical conditions and surgical procedures. (first released May 2002, last updated May 2013)
- Patient Safety Indicators (PSI) reflect quality of care inside hospitals, as well as geographic areas, to focus on potentially avoidable complications and iatrogenic events. (first released March 2003, last updated May 2013)
- Pediatric Quality Indicators (PDI) use indicators from the other three modules with adaptations for use among children and neonates to reflect quality of care inside hospitals, as well as geographic areas, and identify potentially avoidable hospitalizations. (first released April 2006, last updated May 2013)

The input data for QI calculation consist of discharge-level administrative records from inpatient hospital stays; this document often refers to them as **discharge records**. Each indicator can be described as giving results at either the **provider-level** (i.e., Did the patient experience an adverse quality-related event while in the healthcare provider's facility?) or **area-level** (Was the inpatient admission for a condition that might have been avoided if the patient's area of the country had more or better preventive or outpatient care?). Some indicators report the number of times a hospital performed a medical **procedure of interest**. These **volume indicators** do not have denominators. Most of the AHRQ QI are ratios where the **numerator** is a count of hospitalizations with the condition or outcome of interest and the **denominator** is an estimate of the population (or hospitalizations) at risk for that outcome. The QI software calculates several rates:

1. **Observed rate** – Conceptually, provider-level rates are the number of discharge records where the patient experienced the QI adverse event divided by the number of discharge records at risk for the event; area-level rates are the number of hospitalizations for the condition of interest divided by the number of persons who live in that area who are at risk for the condition.
2. **Expected rate** – A comparative rate that incorporates information about a **reference population** that is not part of the user's input dataset – what rate would be observed if the

expected level of care observed in the reference population and estimated with risk adjustment regression models, were applied to the mix of patients with demographic and comorbidity distributions observed in the user’s dataset? The expected rate is calculated only for risk-adjusted indicators. [Chapter 4](#) describes the QI reference population.

3. **Risk-adjusted rate** – A comparative rate that also incorporates information about a **reference population** that is not part of the input dataset – what rate would be observed if the level of care observed in the user’s dataset were applied to a mix of patients with demographics and comorbidities distributed like the reference population? [Appendix A](#) lists which QIs are risk-adjusted.
4. **Smoothed rate** – A weighted average of the risk-adjusted rate from the user’s input dataset and the rate observed in the **reference population**; the smoothed rate is calculated with a shrinkage estimator to result in a rate near that from the user’s dataset if the provider’s (or area’s) rate is estimated in a stable fashion with minimal noise, or to result in a rate near that of the reference population if the rate from the input dataset is unstable and based on noisy data. In practice, the smoothed rate brings rates toward the mean, and does this more so for outliers (such as rural hospitals).

In data collected beginning October 1, 2007, each diagnosis code may be accompanied by a data element that indicates whether the diagnosed condition was **Present-on-Admission (POA)**, and is therefore a pre-existing **comorbidity**, or whether the condition developed during the hospitalization of interest and is therefore a **complication**. Some datasets include POA data, while others do not. Some datasets have POA data for many, but not all of the discharge records. POA is handled in different ways in the QI software depending on a) whether POA data are present in the discharge record and b) whether the user specifies that the software should use the POA data elements when calculating QI rates, or ignore the POA data elements.

This document begins with a brief description of the dataset that a user must assemble to run the QI software and then it describes the methods associated with various types of indicators. Simpler indicators are described first. Volume indicators are the simplest of the QI. Area-level indicators are described next, along with their several possible denominators, and the method used to risk adjust them. Building in complexity, the document describes the calculation of provider-level indicators, where the denominator is tailored to the indicator and the QI may be affected by the POA data element, and how the software accounts for missing POA data. Composite indicators are described next and then the document finishes with a description of the methods used to maintain the QI software – specifically the calculations performed to update the reference population and to update denominator data.

Other Helpful Documents

Readers may wish to access additional QI-related documentation. Helpful examples include:

QI Software Instructions

SAS: See <http://www.qualityindicators.ahrq.gov/software/SAS.aspx>

WinQI: See <http://www.qualityindicators.ahrq.gov/Software/WinQI.aspx>

QI Technical Specifications

- PQI: See http://www.qualityindicators.ahrq.gov/Modules/PQI_TechSpec.aspx
- IQI: See http://www.qualityindicators.ahrq.gov/Modules/IQI_TechSpec.aspx
- PSI: See http://www.qualityindicators.ahrq.gov/Modules/PSI_TechSpec.aspx
- PDI: See http://www.qualityindicators.ahrq.gov/Modules/PDI_TechSpec.aspx

QI Risk-adjustment Coefficient Tables

- PQI: See http://www.qualityindicators.ahrq.gov/modules/pqi_resources.aspx
- IQI: See http://www.qualityindicators.ahrq.gov/modules/iqi_resources.aspx
- PSI: See http://www.qualityindicators.ahrq.gov/modules/psi_resources.aspx
- PDI: See http://www.qualityindicators.ahrq.gov/modules/pdi_resources.aspx

QI Population Documentation File

- See <http://www.qualityindicators.ahrq.gov/software/SAS.aspx>

QI Prediction Module Testing Report

- See <http://www.qualityindicators.ahrq.gov/Modules/Default.aspx>

Healthcare Cost and Utilization Project (HCUP) State Inpatient Database (SID) Documentation (to better understand the source of the reference population)

- See <http://www.hcup-us.ahrq.gov/db/state/sidbdbdocumentation.jsp>

Chapter 1. The User's Dataset

An AHRQ QI software user should prepare the input dataset according to the software instructions.

Table 1.1 Required Data Elements

Data Element	Label	PQI	IQI	PSI	PDI
AGE	Age in years at admission	X	X	X	X
AGEDAY	Age in days (when age < 1 year)				X
ASCHED	Admission scheduled vs. unscheduled			X	X
ASOURCE	Admission source (uniform)	X	X	X	X
ATYPE	Admission type			X	X
DISPUNIFORM	Disposition of patient (uniform)		X	X	X
DQTR	Discharge quarter	X	X	X	X
DRG	DRG in effect on discharge date	X	X	X	X
DRGVER	DRG grouper version used on discharge date	X	X	X	X
DSHOSPID	Data source hospital identifier		X	X	X
DX1-DX30	Diagnosis	X	X	X	X
DXPOA1-DXPOA30	Diagnosis present on admission indicator		X	X	X
E_POA1-E_POA10	E code present on admission indicator		X	X	X
ECODE1-ECODE10	E code		X	X	X
HOSPST	Hospital state postal code		X	X	X
KEY	HCUP record identifier	X	X	X	X
LOS	Length of stay (cleaned)		X	X	X
MDC	MDC in effect on discharge date	X	X	X	X
PAY1	Primary expected payer (uniform)		X	X	X
PAY2	Secondary expected payer (uniform)		X	X	X
POINTOFORIGINUB04	Point of origin for admission or visit, UB-04 standard coding	X	X	X	X
PR1-PR30	Procedure	X	X	X	X
PRDAY1-PRDAY30	Number of days from admission			X	X
PSTCO	Patient state/county FIPS code	X	X	X	X
PSTCO2	Patient state/county FIPS code, possibly derived from ZIP Code	X	X	X	X
RACE	Race (uniform)	X	X	X	X
SEX	Sex	X	X	X	
YEAR	Calendar year	X	X	X	X

Note: The AHRQ QI software deletes discharge records with missing values for SEX.

In preparing a dataset for analysis, data elements and data values shown in the right side of Table 1.2 are constructed from the discharge data elements.

Table 1.2 Data Elements and Data Values To Be Constructed by the User

DISCHARGE DATA (e.g., SID)		AHRQ QI	
Data Element	Data Value	Data Element	Data Value
FEMALE	0 – Male 1 – Female	SEX	1 – Male 2 – Female
ATYPE, ASCHEDED and AGEDAY	IF ATYPE = Missing AND ASCHEDED = 1 (Scheduled admission) AND AGEDAY ~ = 0	ATYPE	3- Elective
ECODE1-ECODE10	As reported	DX31-DX40	As reported
E_POA1-E_POA10	As reported	DXPOA31-DXPOA40	As reported

Discharge records in the dataset are analyzed as either adult or pediatric data based on age and Major Diagnostic Category (MDC) (Table 1.3). Discharges in MDC 14 (Pregnancy, Childbirth & the Puerperium) are assigned to the adult analysis data regardless of age.

Table 1.3 Analysis Data Inclusion Rule

Analysis data	Inclusion Rule
Adult	AGE greater than or equal to 18 or MDC equal to 14
Pediatric	AGE less than 18 and MDC not equal to 14

Adult analysis data are used to calculate Prevention Quality Indicators (PQI), Inpatient Quality Indicators (IQI), and Patient Safety Indicators (PSI). Pediatric records are used to calculate Pediatric Quality Indicators (PDI), Neonatal Quality Indicators (NQI) and indicators from other modules defined on pediatric discharges (i.e., PQI #9 Low Birth Weight Rate, PSI #17 Birth Trauma Rate – Injury to Neonate).

Chapter 2. Calculating Volume and Count Indicators

Table 2.1 lists the seven **volume indicators** for inpatient procedures for which there is evidence that a higher volume of procedures conducted by a provider is associated with lower mortality. The volume indicators are measured as counts of hospitalizations in which particular procedures were performed.

Table 2.1 AHRQ QI Volume Indicators

Name
IQI #1 – Esophageal Resection Volume*
IQI #2 – Pancreatic Resection Volume*
IQI #4 – Abdominal Aortic Aneurysm (AAA) Repair Volume*
IQI #5 – Coronary Artery Bypass Graft (CABG) Volume
IQI #6 – Percutaneous Coronary Intervention (PCI) Volume
IQI #7 – Carotid Endarterectomy Volume
PDI #7 – RACHS-1 Pediatric Heart Surgery Volume

*IQI 1, IQI 2 and IQI 4 are intended to be reported with IQI 8 IQI 9 and IQI 11, respectively.

Table 2.2 lists the four **count indicators** for serious reportable events.

Table 2.2 AHRQ QI Count Indicators

Name
PSI #15 – Retained Surgical Item or Unretrieved Device Fragment Count
PSI #16 – Transfusion Reaction Count
PDI #3 – Retained Surgical Item or Unretrieved Device Fragment Count
PDI #13 – Transfusion Reaction Count

Discharge Level Indicator Data Element (T)

The phrases **numerator** and **denominator** appear throughout the QI documentation. There are no denominators for volume or count indicators. The quantity of interest at the provider level is the magnitude of the number of times the procedure or the event occurs, and that number is not normalized by or divided by any denominator. The technical specifications do, however, use the phrase “numerator” to define the procedure of interest. Discharge records are flagged for inclusion or exclusion from the numerator of each volume QI based on the data elements, data values, and logic described in the technical specifications for each indicator.

For each discharge record, a binary flag variable is calculated by the software for each volume or count QI. In this document, we denote the discharge level indicator data element with the letter T. Each discharge record has a T variable for each QI, so in the software the data elements have longer names to clarify which QI they describe. (e.g., The variable for IQI #1 is called TPIQ01.)

Numerator

Discharges are flagged for inclusion in the numerator of each volume QI according to the specification for the **procedure of interest** (for volume indicators) or **outcome of interest** (for count indicators). Discharges flagged for inclusion in the numerator are assigned a value of “1” for T.

Exclusions

The specifications often stipulate that records should be excluded from calculation of a volume indicator if the record is missing an important data element. Discharges are also excluded from the numerator of a volume QI if the procedure of interest has more than one component, and the discharge is not in the population at risk for one component but remains in the population at risk for another component. These discharges are assigned a value of “0” for T.

The Observed Value

The observed provider-level value of a volume or count indicator is simply the sum of T over all records for that provider in the dataset.

Chapter 3. Calculating Area-Level Indicators – Observed Rates

Area-level indicators identify hospital admissions that evidence suggests might have been avoided through access to high-quality outpatient or preventive care. The numerator is a count of admissions for the condition of interest. The denominator is an estimate of the number of persons at risk for such a hospitalization. The denominator is usually a population estimate from a U.S. Census Bureau dataset.

Table 3.1 lists the area level indicators.

Table 3.1 AHRQ QI Area-Level Indicators

Name
IQI #26 – Coronary Artery Bypass Graft (CABG) Rate
IQI #27 – Percutaneous Coronary Intervention (PCI) Rate
IQI #28 – Hysterectomy Rate
IQI #29 – Laminectomy or Spinal Fusion Rate
PDI #14 – Asthma Admission Rate
PDI #15 – Diabetes Short-Term Complications Admission Rate
PDI #16 – Gastroenteritis Admission Rate
PDI #17 – Perforated Appendix Admission Rate
PDI #18 – Urinary Tract Infection Admission Rate
PQI #1 – Diabetes Short-Term Complications Admission Rate
PQI #2 – Perforated Appendix Admission Rate
PQI #3 – Diabetes Long-Term Complications Admission Rate
PQI #5 – Chronic Obstructive Pulmonary Disease (COPD) or Asthma in Older Adults Admission Rate
PQI #7 – Hypertension Admission Rate
PQI #8 – Heart Failure Admission Rate
PQI #9 – Low Birth Weight Rate
PQI #10 – Dehydration Admission Rate
PQI #11 – Bacterial Pneumonia Admission Rate
PQI #12 – Urinary Tract Infection Admission Rate
PQI #13 – Angina Without Procedure Admission Rate
PQI #14 – Uncontrolled Diabetes Admission Rate
PQI #15 – Asthma in Younger Adults Admission Rate
PQI #16 – Lower-Extremity Amputation Among Patients With Diabetes Rate

The software provides the user with the option of producing output by metropolitan area or by county. The term **metropolitan area (MA)** was adopted by the U.S. Census in 1990 and referred collectively to metropolitan statistical areas (MSAs), consolidated metropolitan statistical areas (CMSAs), and primary metropolitan statistical areas (PMSAs). In addition, “area” could refer to

either 1) FIPS county, 2) modified FIPS county, 3) 1999 OMB Metropolitan Statistical Area, or 4) 2003 OMB Metropolitan Statistical Area. As an aside, Micropolitan Statistical Areas are not used in the QI software.

For information about how the denominators are calculated from Census data, see the QI Population Documentation File at <http://www.qualityindicators.ahrq.gov/software/SAS.aspx>.

For diabetes-related area measures, the QI software user has an option of calculating rates where the denominator is an estimate of the number of persons living in the state who have diabetes. For information on how those **condition-specific denominators** are estimated, see [Chapter 3](#). The diabetes indicators are PQI #1 Diabetes Short-Term Complications Admission Rate, PQI #3 Diabetes Long-Term Complications Admission Rate, PQI #14 Uncontrolled Diabetes Admission Rate, and PQI #16 Lower-Extremity Amputation among Patients with Diabetes Rate. [Chapter 13](#) describes how the diabetes denominators are estimated.

Future versions of the QI software may include other condition-specific denominator options.

Discharge Level Indicator Data Element (T)

Numerator

Discharges are flagged for inclusion in the numerator of each area-level QI according to the specification for the condition of interest. Discharges flagged for inclusion in the numerator are assigned a value of “1” for T.

Exclusions

Generally, discharges may be flagged for exclusion from the numerator of an area-level AHRQ QI for one (or more) of several reasons.

1. The outcome of interest is very difficult to prevent, and therefore not an indication of substandard care.
2. The patient was transferred from another health care facility.
3. Some exclusion criteria are included for the purpose of enhancing face validity with clinicians.
4. Some exclusion criteria are an inherent part of the QI definition.

Discharge records that meet one or more of the exclusion criteria in the QI technical specification are assigned a value of “missing (.)” for T.

The Observed Rate

The observed rate of an area-level indicator is simply the sum of T over all records for that area of the country divided by the Census population estimate for the area (adult population for adult measures and child population for pediatric measures). For condition-specific indicators, if the

user requests it, the denominator is the estimated count of persons living in that area of the country who are living with the condition of interest.

Area Rates Stratified by Quarter of the Year

The WinQI software has an option to stratify area-level rates by quarter of the year in which they occurred. When the user selects that option, the rate reported for each quarter is the number of admissions for the condition of interest that occurred during that quarter, divided by the Census population for the area divided by four. The four quarterly rates sum to the annual rate.

Chapter 4. Risk Adjustment for Area-Level Indicators

In order to make meaningful comparisons of the area-level rate for one area with that of another area, it is helpful to account statistically for differences in demographics between areas. To do so for most QIs, the software calculates a **risk-adjusted rate** which answers the question: What QI rate would we expect to observe in a particular area of the country if the persons living there shared the same demographic profile of a reference population? In statistical language, the risk-adjustment **controls for demographic differences** via logistic regression.

For area rates, the risk-adjustment models adjust for age-group proportions by gender, and optionally for poverty. That is to say that the models include age (in 5 year groups), gender, and if it is statistically significant, the model includes the interaction between age and gender.

When comparing outcomes from different areas, there may be several reasons for differences in risk-adjusted rates. Some of the most important reasons may be related to the availability of quality preventive and outpatient care, and other reasons may contribute as well, but after risk-adjustment, the differences should not be attributable to differences in the age and gender profiles in the areas.

The AHRQ QI Reference Population

To accomplish risk adjustment, in annual updates of the QI software a **reference population** is analyzed that consists of all HCUP SID data that are available for the year most recently released by AHRQ at the time the QI software is updated. For example when version 4.5 of the QI software was updated in January of 2013 for the May 2013 software release, SID data were available from 2010 from 44 states, so those records serve as the reference population for AHRQ QI software version 4.5.

For area-level indicators, the reference population plays two important roles:

1. The **reference population rate** for each QI is calculated and included in the software to serve as a comparative standard for areas of the country. One can analyze data to determine which areas have higher or lower rates than the overall reference population. The reference population rates are published on the AHRQ QI website in documents named Benchmark Tables (formerly known as Comparative Data Tables). See the [links](#) in the Overview chapter of this document.
2. The **risk adjustment models** are re-estimated on the new reference population dataset in an annual process that is described in [Chapter 12](#) of this document. The models are distributed within the QI software, and they facilitate the calculation of risk-adjusted rates. The risk adjustment model covariates and regression coefficients are published on the AHRQ website. See the [links](#) in the Overview chapter of this document.

Chapter 5. Calculating Area-Level Indicators – Expected, Risk-Adjusted, & Smoothed Rates

In addition to observed rates, three other sets of QI rates are calculated for risk-adjusted area-level indicators.

The Expected Rate

The **expected rate** for an area-level QI is the rate that would be observed if the amount and quality of outpatient and preventive care available across the reference population were available to persons living in this specific area. It is predicted for each area using risk-adjustment model coefficients and covariates that summarize the age and gender distribution of the area's population.

The Risk-Adjusted Rate

The AHRQ QI use indirect standardization to calculate the risk-adjusted rate. The risk-adjusted rate equals the reference population rate multiplied by the ratio of observed rate divided by expected rate.

$$\text{Risk Adjusted Rate} = \text{Reference Population Rate} \times (\text{Observed Rate} / \text{Expected Rate})$$

Note that for the reference population, the observed rate equals the expected rate equals the reference population rate equals the risk-adjusted rate.

The software estimates the standard error of the risk adjusted rate for each area using a method recommended by Iezzoni and described by Hosmer and Lemeshow (1995) that represents the amount of within provider or area variance due to sampling (i.e. as the number of patients per provider or persons per area increases this variance tends to zero). This standard error is used to calculate lower and upper bound 95% confidence intervals around the risk adjusted rate as [risk adjusted rate +/- 1.96 * risk adjusted rate SE] (stored in a data element with a "L" and "U" prefix). (See [Chapter 10](#) section entitled: Computing the Risk-Adjusted Rate Variance. See also http://qualityindicators.ahrq.gov/Downloads/Resources/Publications/2011/Calculating_Confidence_Intervals_for_the_AHRQ_QI.pdf)

The Smoothed Rate

Each area's **smoothed rate** is a weighted average of the risk-adjusted rate and the reference population rate; the smoothed rate is calculated with an empirical Bayes shrinkage estimator to result in a rate near that from the input dataset if the area's rate is estimated in a stable fashion with minimal noise, or to result in a rate near that of the reference population if the rate from the area is unstable and based on noisy data. Thus, the smoothed rate for a hospital with stable estimates will be similar to the hospital's risk adjusted rate, while the smoothed rate for a hospital with unstable estimates will be more similar to the reference population rate.

The formula for the smoothed rate is:

$$\text{Smoothed Rate} = (\text{Risk Adjusted Rate} \times \text{Shrinkage Weight}) + \text{Reference Population Rate} * (1 - \text{Shrinkage Weight})$$

where

$$\text{Shrinkage Weight} = \frac{\text{Signal Variance}}{\text{Signal Variance} + \text{Noise Variance}}$$

The noise variance is an estimate of variability in the QI outcome within the area of interest (county), and the signal variance is an estimate of variability across all areas.

$$\begin{aligned} \text{Noise Variance } \hat{\sigma}_a^2 &= \left(\frac{\bar{Y}}{n_a E_a} \right)^2 \sum_{i \in A_a} \hat{Y}_i (1 - \hat{Y}_i) \\ \text{Signal Variance } \hat{\tau}^2 &= \frac{1}{A} \sum_{a=1}^A \frac{1}{(\sigma_a^2)^2} \sum_{a=1}^A \frac{1}{(\hat{\tau}^2 + \sigma_a^2)^2} \{ (RAR_a - \overline{RAR})^2 - \hat{\sigma}_a^2 \} \end{aligned}$$

where A is the number of areas with persons at risk for the measure, \bar{Y} is the observed rate for the reference population; \hat{Y}_i is the person-level predicted probability for area i ; and for area a , A_a is the collection of persons in the population at risk, n_a is the number of persons, E_a is the expected rate, and RAR_a is the risk-adjusted rate. Note that $\hat{\tau}^2$ appears on both sides of the signal variance equation; it is estimated in an iterative fashion.

For purposes of confidence interval estimation, the *smoothed rate* is assumed to follow a Gamma distribution $G(\text{shape}, \text{scale})$ where

$$\begin{aligned} \text{shape} &= \frac{(\text{Smoothed Rate})^2}{\text{Posterior Variance}} \\ \text{scale} &= \frac{\text{Posterior Variance}}{\text{Smoothed Rate}} \end{aligned}$$

$$\text{Posterior Variance} = \text{Signal Variance} - (\text{Shrinkage Weight} * \text{Signal Variance})$$

When there is a fixed comparative rate of interest, it is possible to parameterize the smoothed rate posterior probability based on the Gamma distribution and calculate the probability that the smoothed area rate falls below or above the comparative rate that is of interest.

Chapter 6. Overview of Provider-Level QI & Present-on-Admission (POA)

Provider-level indicators address questions like: Did the patient experience an adverse quality-related event while in the care of a specific healthcare provider? Or did the patient have an inpatient procedure for which there are questions of overuse, underuse, or misuse?

Adverse-event indicators are for medical conditions and procedures that have been shown to have complication/adverse event rates that vary substantially across institutions and for which evidence suggests that high rates may be associated with deficiencies in the quality of care. They usually include only those cases where a secondary diagnosis code flags a potentially preventable complication. A few indicators are based on procedure codes that imply a potential preventable adverse event.

Mortality indicators are for medical conditions and surgical procedures that have been shown to have mortality rates that vary substantially across institutions and for which evidence suggests that high mortality may be associated with deficiencies in the quality of care.

Utilization indicators track procedures where there are questions of overuse, underuse, or misuse. The usage of the procedures being examined varies significantly across hospitals and areas, and high or low rates by themselves do not represent poor quality of care; rather the information is intended to inform consumers about local practice patterns.

Provider-level indicators are measured as rates—number of hospitalizations with the outcome (or procedure) of interest divided by the population at risk for the outcome (or procedure). Recall that area-level indicators each use the same denominator for each area – the Census-derived estimate of the count of persons who live in the area. Provider-level indicators are more complicated because they have **indicator-specific denominators**, to identify only the hospitalizations that were at risk for the outcome of interest.

Recall that area-level indicators all use similar risk-adjustment coefficients: age-groups by gender. But the risk-adjustment models for provider-level measures are more complicated. Each risk-adjusted provider-level indicator uses a customized list of regression covariates that are selected when the QI software is updated annually using methods described in [Chapter 12](#).

Present-on-Admission (POA) status is a third factor that makes provider-level indicators more complex than volume or area-level indicators. Current AHRQ QI that use POA are listed in [Appendix A](#). Some of the indicators look for adverse conditions that develop as **medical complications** during the hospitalization of interest. Evidence suggests that high rates may be associated with lower quality of care. Think, for instance, of pressure ulcers, which are measured with PSI #3. However, some of these complications may have been present on admission, which would not be related to the quality of inpatient care. The AHRQ QI software uses three methods to distinguish between **complications**, which develop during the hospitalization and should be counted in the QI numerator, and **comorbidities**, which are present on admission and should exclude the discharge record from the QI calculation, because the patient is not at risk for the

event. Table 6.1 summarizes those methods, and they are described in more detail in the following chapters, and in [Appendix C](#).

Table 6.1 Methods Used by QI Software to Distinguish Complications from Comorbidities

Method	Description	Can the QI User Turn This Off?
<p>1. The POA-Related Exclusion Method (See Chapter 7.)</p>	<p>Some QIs use data elements other than DX_POA to infer that the condition is more likely than not to be POA. Those records are excluded from the population at risk.</p>	<p>No. The WinQI software does not allow modifications to the exclusion criteria. However, the SAS software can be altered by the User, noting that the User should document any modifications to the program.</p>
<p>2. DX_POA Data Element (See Chapter 8.)</p>	<p>If the diagnosis is flagged as POA using the DX_POA data element, then the record is excluded from the population of interest.</p>	<p>Yes. The user can specify %LET USEPOA = 0; in the CONTROL.SAS program or un-check the WinQI box entitled “Use POA in rate calculation”, either of which will cause the software to ignore DX_POA data that are present in the dataset. Every potential complication will be flagged as an adverse event, and if it does not meet any of the exclusion criteria, it will contribute to the QI numerator. For the purposes of risk-adjustment, a set of coefficients will be employed that were estimated ignoring POA; all complications will be treated as comorbidities.</p>
<p>3. Model the effect of missing data when DX_POA is missing for a particular record, or for the entire dataset (See Chapter 9.)</p>	<p>Use a statistical model included with the QI software and updated annually using reference population data to estimate the probability that the outcome of interest is POA. Use that probability along with the other variables in the record to estimate the probability that the patient experienced the adverse event, conditional on the (possibly large or possibly small) probability that the</p>	<p>Yes. The user can specify %LET USEPOA = 0; in the CONTROL.SAS program or un-check the WinQI box entitled “Use POA in rate calculation”, either of which will cause the software to skip modeling missing POA data.</p> <p>Alternatively, the user can provide complete POA data, so there is no missing data to be modeled. Note that for</p>

	<p>event was <u>not</u> POA. See Chapter 9 and Appendix C.</p>	<p>indicators where POA is a factor in the model, the predicted values are always calculated using the Prediction Module. If the user models the missing POA, then the downstream software uses predictions from the Markov Chain Monte Carlo simulation described in Chapter 9 and Appendix C. If the user ignores POA, then the downstream software uses predictions that the Prediction Module calculates using simple scalar multiplication of regression coefficients times covariate values.</p>
--	--	--

POA Data Element - Background Information

Present-on -Admission was added as a data element to the uniform bill form (UB-04) effective October 1, 2007, and hospitals incurred a payment penalty for not including POA on Medicare records beginning October 1, 2008. Each of the several diagnoses in a discharge record can be flagged as “present at the time the order for inpatient admission occurs”¹ or not. This is accomplished with data element DX_POA_i which uses a one-character text code to characterize the POA status of the diagnosis in DX_i. Conditions that develop during an outpatient encounter, including treatment in an emergency department, are considered as present on admission. Most states have adopted POA in the discharge data submitted by hospitals to either the state department of health or the state hospital association.

Table 6.2 lists the possible character values of the POA data elements (Y,N,U,W,E, or missing) along with corresponding numeric values (0 or 1) used in the AHRQ QI software. Additional information about the coding guidelines for POA can be found at: www.cdc.gov/nchs/data/icd/icd9cm_guidelines_2011.pdf Again, current AHRQ QI that use POA are listed in [Appendix A](#).

¹ <http://www.cdc.gov/nchs/data/icd9/icdguide10.pdf>.

Table 6.2 Values for the Present-on-Admission Data Element

ICD-9-CM Guidelines	Description	AHRQ QI POA Data Element	Description
Y - Yes	Diagnosis is present at the time of inpatient admission	1	Diagnosis present at admission
N – No	Diagnosis is not present at the time of inpatient admission	0	Diagnosis not present at admission
U - Unknown	Documentation is insufficient to determine if condition is present on admission	0	Diagnosis not present at admission
W – Clinically undetermined	Provider is unable to clinically determine whether condition was present on admission or not	1	Diagnosis present at admission
E - Unreported/Not used; Also includes UB-04 values previously coded as "1"	Exempt from POA reporting	1	Diagnosis present at admission

Source: http://www.cms.hhs.gov/HospitalAcqCond/05_Coding.asp#TopOfPage;
http://www.hcup-us.ahrq.gov/db/vars/siddistnote.jsp?var=e_poan.

An individual discharge record might include 20 or more diagnoses. For purposes of the AHRQ QI, the principal diagnosis is always assumed to be present on admission by definition, regardless of the coding of the POA data element in the principal field. Secondary diagnosis codes are considered present on admission if the POA data element is coded with a Y, W, E or 1. Secondary diagnosis codes are considered not present on admission if the POA data element is coded with a N, U or 0.

Chapter 7. Calculating Provider-Level Observed Rates – Ignoring POA

Provider-level QI calculations are simplest when POA is ignored altogether, so those calculations are described first. Later chapters describe what happens when POA data are present and accounted for, and how the calculations are performed when POA data are missing but modeled. The AHRQ QI software user may ignore the influence of DX_POA data, either present or missing, by specifying “%LET USEPOA = 0;” in the CONTROL.SAS file or by or un-checking the WinQI box entitled “Use POA in rate calculation”.

When ignoring POA, the main difference between area-level indicators and provider-level indicators is the way the denominator is calculated.

Discharge Level Indicator Data Element (T)

Each provider-level observed QI rate consists of a conceptually simple fraction where the denominator is the count of discharge records at risk and the numerator is the count of the records with the outcome of interest. This fraction is calculated using a single discharge level indicator data element, T, described in earlier chapters for volume and area-level indicators. In those earlier chapters, the T variable took on the value “1” if the discharge record met the definition for the numerator that is spelled out in the technical specifications. For volume and area-level indicators it does not matter whether the T variable takes the value “0” or “missing (.)” for other records, because the numerator is simply the count of records where T=1.

Provider-Level Denominator

Discharges are flagged for inclusion in the denominator of each AHRQ QI according to the specification for the **population at risk**. Discharges flagged for inclusion in the denominator are assigned a value of “0” for T unless the discharge also experienced the outcome of interest in which case the value of “1” is assigned. Discharges that experienced the outcome of interest are in the population at risk by definition.

Denominator Exclusions

Generally, discharges may be flagged for exclusion from the denominator of an AHRQ QI for one (or more) of several reasons.

1. The outcome of interest is more likely than not to be present on admission and conditions that are POA should not “count” as an adverse event.
2. The outcome of interest is very difficult to prevent, and therefore not an indication of substandard care.
3. The exclusion identifies populations who are at very low risk for the adverse event and who are excluded to keep from diluting the QI denominator.

4. Some exclusion criteria are included for the purpose of enhancing face validity with clinicians (e.g., exclude patients from being at risk of a pressure ulcer (PSI #3) if they have not been hospitalized for at least 5 days).
5. Some exclusion criteria are an inherent part of the QI definition (e.g., exclude persons from being at risk for a post-operative hip fracture if the hip repair is the only surgical procedure during the hospitalization).

Discharge records that meet one or more of the denominator exclusion criteria in the QI technical specification are assigned a value of “missing (.)” for T.

Three Values of T

To summarize:

- A “1” in the T variable means that the record was in the population at risk, experienced the outcome of interest, and was not excluded for any reason.
- A “0” in the T variable means the record was in the population at risk, did not experience the outcome of interest, and was not excluded for any reason.
- A “missing (.)” value for the T variable means that the record was not in the population of interest, either because it did not meet the denominator definition, or because it met one or more of the exclusion criteria.

The Observed Rate

For provider-level indicators, the observed rate is simply the arithmetic mean of the T variable over all of the provider’s discharge records.

Consequence of Ignoring POA Data

When POA data are ignored, the observed rate calculation will include records where the outcome of interest was indeed present on admission, and so will inflate the numerator, the denominator, and the observed rate, compared with an **unknown but true underlying rate** that excludes records from population at interest when the outcome was truly POA.

Chapter 8. Calculating Provider-Level Observed Rates – With Complete POA Data

Consideration of POA should improve the accuracy of QI rate calculation because pre-existing comorbidities can be distinguished from complications that develop during the hospital stay of interest. Records with outcomes that were POA will no longer appear erroneously in the numerator, denominator, or observed rate, and the risk adjustment models will no longer erroneously treat complications as comorbidities, thus yielding improvement in the comparative expected, risk-adjusted, and smoothed rates above and beyond that in the numerator, denominator, and observed rates.

The degree of improvement attained when accounting for POA will vary depending on the number of records where the outcomes were POA, and with the accuracy of POA coding. This document does not address the topic of POA accuracy. The QI software treats values in the DX_POA data elements as if they were completely accurate.

The QI calculation procedures are more complicated when some or all of the POA data are missing, so this chapter describes the calculations conducted when POA is present for every record. The following chapter addresses missing POA data.

Discharge Level POA Exclusion Data Element (Q)

When accounting for POA, the QI software codes the discharge level indicator data element, T, in the same manner described in [Chapter 7](#), using technical specifications to define which records are included in the denominator, numerator, and which should be excluded for one or more reasons. The meaning and possible values of T are described in [Chapter 7](#).

A second, POA-related binary flag is calculated, also. The **discharge level POA exclusion data element** is abbreviated with the letter Q.² Put simply, Q records whether the outcome of interest was present on admission or not. The outcome of interest is considered present on admission (Q is assigned “1”) if any of the diagnosis codes that define the outcome of interest are coded as present on admission. Otherwise a value of “0” is assigned to Q. For every record that includes POA data in the SID DX_POA data elements, Q will have a value of “0” or “1” and will not be “missing (.).”

The Observed Rate

Before calculating the observed rate, Q is used to correct the value of T if the condition of interest was POA. If the value of Q is “1” (outcome was POA) then the record is removed from the population at risk by setting T to “missing (.).” The observed rate is simply the arithmetic

² The letter P was not available, having been used already for the notion of population at risk. In this document the variables are denoted simply as T and Q, but each discharge record has a binary T variable and a binary Q variable for each QI, so the variables have longer names to clarify which QI they describe. (e.g., The variables for PSI #8 are called TPPS08 and QPPS08.)

mean of the T variable after this correction. Note that if POA had been ignored, as in [Chapter 7](#), every record removed from the population at risk by the Q variable would have appeared as a “1” in both the numerator and the denominator. So accounting for POA data yields lower observed rates than when the POA data are ignored. The magnitude of the difference between the rate estimated when POA are ignored and when POA are incorporated will depend on the proportion of records that are flagged as POA that do not meet any of the other indicator exclusion criterion. The accuracy of the difference between the rate estimated when POA are ignored and the rate estimated when POA are incorporated (via the Q flag) depends both on the magnitude of the difference, and the accuracy of the POA coding.

Chapter 9. Calculating Provider-Level Observed Rates – With Missing POA Data

When POA data are ignored ([Chapter 7](#)) or present in the discharge record ([Chapter 8](#)) then each record in the population at risk contributes a simple “0” or “1” to the QI denominator and if it is a “1” in the denominator, the record contributes a simple “0” or “1” to the numerator. When POA data are missing, the situation is not as simple. Records that do not meet the denominator criteria, regardless of POA, are still simple...they are not in the population at risk. Records where T=0 ignoring POA are simple because they did not experience the outcome of interest, so it could not have been POA. But for other records, the missing DX_POA flags would determine whether the record was in the population at risk, or not, and if so, whether the patient experienced the outcome of interest. Because we cannot confidently assign a simple 0 or 1 to the numerator and denominator, the QI software calculates expected values of both the numerator and denominator contribution – these expected values fall between 0 and 1, and the software uses them to calculate the observed rate.

The DX_POA flags can affect the patient record in three ways:

1. The outcome of interest is clearly POA and the record should be excluded from the population at risk.
2. The outcome of interest is clearly not POA and the record should be included in the population at risk.
3. DX_POA helps distinguish between comorbidities (present at the time of admission) and complications (developed after admission) which affects the assignment of APR-DRG and risk-adjustment.

If some or all of the discharge records in the user’s dataset are missing DX_POA data elements, the dataset can still be analyzed using methods that take POA into account. The missing POA data are modeled using information from the reference population records that had complete POA data to estimate the expected value of the probability that the outcome of interest was POA, and the expected value of the probability that the patient experienced the outcome of interest if it was not POA.

The expected value calculations use Markov Chain Monte Carlo (MCMC) methods and augmented datasets where the missing POA data are modeled based on relationships observed in the reference population. Specifically, the portion of the reference population dataset where POA was observed yields probabilistic insight into the relative frequency of APR-DRG assignment as well as comorbidities versus complications. In the user’s dataset, if POA data are missing from a discharge record, then the expected values of both the Q flag and the outcome of interest are estimated using an MCMC to approximate the weighted sums over all possible combinations of missing data. The weights in the sums are the probabilities of observing each combination of missing POA flags.

Prediction Module Nomenclature: $Y = T$ and $P = Q$ and POA improves Z to form X

There is a change of nomenclature between the QI software that calculates discharge level data elements and the Prediction Module (PM)³ software that models the effect of missing POA. In the PM, the outcome is called Y rather than T and the POA flag is called P rather than Q . In this document we observe this change, and refer to Y and P when talking about values that are calculated by the PM.

The set of relevant covariates as coded from the discharge record are collectively described as the vector Z . After a set of observed or imputed POA flags are applied to the Z vector, and the covariates are re-calculated, the improved covariates form a vector that we call X . Data elements that are not affected by POA (e.g., age and gender) take on the same values in the Z and X vectors. Data elements that might have changed if POA data had been included with the record (e.g., APR-DRG and comorbidities versus complications) may take different values in Z and X . Specifically, the APR-DRG might be changed altogether or shifted to a lower risk of mortality subclass if some of the secondary diagnoses are POA, and some conditions that meet the definition of comorbidity might be changed to complications or vice versa.

Run Prediction Module to Account for Missing POA

With regard to the observed rate, the Prediction Module does two important things:

1. It calculates the expected value of the probability that the outcome of interest was POA: $E[P=1 | Y, P, X, Z]$. Conceptually it does this by imputing POA flags many times and re-calculating whether the outcome of interest was POA. The specifics of the actual MCMC expected value calculation are described in [Appendix C](#). The expected value is a number between 0 and 1 and it is used to determine the record's contribution to the QI denominator. For records with complete POA data, the P flag takes the value 0 or 1, and the record contributes $1-P$ to the denominator. (It contributes 1 if the condition is not POA, and 0 if it is POA.) For records with missing POA data, the expected value of P falls between 0 and 1, and the contribution to the denominator is $1 - E[P=1 | Y, P, X, Z]$. That is to say that if there is a 50% chance that the outcome was POA, then the record contributes 0.5 to the denominator. If there is a 99% chance that it was POA, the record contributes 0.01 to the denominator.
2. It calculates the expected value of the contribution of the record to the numerator. If the contribution to the denominator is non-zero and $Y=1$, then this probability is equal to $(1 - \text{the denominator contribution})$. Otherwise it is zero. If $T=Y=0$ when POA is missing,

³ The word 'module' is a possible source of confusion. We refer to the four sets of QI as QI *modules*: the *PQI*, *IQI*, *PSI*, and *PDI*. In a different context, the word 'module' is also used to describe two C++ executable programs that a) estimate the risk-adjustment models during the QI software update process, (the so-called **Analysis Module**) and b) predict the expected value of the outcome in the user's data subject to uncertainty about missing POA (the so-called **Prediction Module**). The Prediction Module is an executable program that is called by SAS or WinQI when the user analyzes their dataset to calculate QI rates.

then Y would not be affected if POA data were present, and the record makes 0 contribution to the QI numerator.

Note that for observations where DX_POA is present in the user's dataset, the prediction module does not model an expected value. The expected value of Y and P is calculated with certainty as being equal to the observed values T and Q, respectively. These observations make contributions of 1-P (=1-Q) to the denominator, and Y * (1-P) (which = T * (1-Q)) to the numerator.

The Observed Rate

The formula for the observed rate is as follows:

$$\text{Observed Rate} = \frac{\text{Sum of expected value of discharges of the outcome of interest}}{\text{Sum of expected value of discharges in the population at risk}}$$

Chapter 10. Risk Adjustment for Provider-Level Indicators

This chapter describes risk-adjustment for provider-level QIs. Three special cases are described explicitly: ignoring POA data, accounting for POA in records with complete POA data, and accounting for POA in records with missing POA data.

Provider-level indicators are risk-adjusted in a manner similar to that described in Chapters [4](#) and [5](#) for area-level indicators. One important difference is that the list of covariates for provider-level indicators differs from indicator to indicator more than those for the area-level indicators. The next section describes the types of data elements that are considered as potential risk-adjusters.

Where possible, the logistic regression models use a generalized estimating equations (GEE) approach to account for correlation at the provider level. When GEE models do not converge during the annual AHRQ QI software update, then multivariable logistic regression models are employed that do not account for that correlation. See [Chapter 12](#) for more details.

Risk-adjustment Covariates

Each risk-adjusted QI (listed in [Appendix A](#)) has a set of covariates that have been identified as useful covariates in a logistic regression risk-adjustment model. [Chapter 12](#) describes the variable selection process.

For the PSIs, covariates indicate whether the discharge record meets the technical specification for gender, age, modified Diagnosis-Related Group (MDRG) and at least one of twenty-five (25) co-morbidities that are used as covariates in the risk-adjustment model.

For the IQIs, covariates indicate whether the discharge record meets the technical specification for gender, age, All Patient Refined Diagnosis Related Groups (APR-DRG) and risk-of-mortality subclass (minor, moderate, major, extreme) that are used as covariates in the risk-adjustment model.

For the PDIs, covariates indicate whether the discharge record meets the technical specification for birth weight, age in days, age in years, modified Diagnosis-Related Group (MDRG), at least one of forty-six (46) clinical classification software (CCS) co-morbidities and some indicator-specific risk categories that are used as covariates in the risk-adjustment model.

The Prediction Module

Regardless of whether POA data are ignored or accounted for, and whether the POA data are complete or missing, the provider-level risk adjustment is accomplished using the AHRQ QI Prediction Module software. In the case of accounting for missing POA, it uses an MCMC approach to calculate relevant expected values, as described below. If the user elects to ignore

POA data, or for records where the POA data are complete, then the Prediction Module simply performs scalar multiplication of covariates and coefficients, which is also described below.

Risk Adjustment Parameters CSV File

Each risk-adjusted provider-level indicator has its risk adjustment parameter estimates stored in a comma separated values (.csv) file that accompanies the QI software. Those files have 21 columns of numbers, and Table 10.1 describes their contents and how they are used in the QI software.

Table 10.1 Parameter Estimates CSV Files for Provider-Level Risk Adjustment

Column Number	Column Headings (if any)	Meaning
1-2	Variable Names	List of numbered Z and X covariate names
3-6	[X Z]	Probabilities used for imputation: $P(X=0 Z=0)$, $P(X=0 Z=1)$, $P(X=1 Z=0)$, $P(X=1 Z=1)$. Note that if these numbers are 1,0,0,1 respectively then the Markov Chain Monte Carlo (MCMC) imputation always imputes $X=Z$. If the numbers fall between 0 and 1, then sometimes $X = Z$ and sometimes $X \neq Z$.
7-9	[P X], mse, ese	Regression coefficients (col 7) for the model for $POA X$, and their standard errors

Column Number	Column Headings (if any)	Meaning
10-12	[Y Z], mse, ese	Regression coefficients (col 10) for the model for the QI outcome, $Y Z$, and their standard errors. This is the model of the outcome that ignores POA. These are the model coefficients that are employed if the user elects to ignore POA. They are multiplied by the Z vector using simple scalar multiplication; the MCMC is not involved in the estimation of this model's parameters or in the computation of the predicted value using this model.
13-15	[Y X], mse, ese	Regression coefficients (col 13) and their standard errors for the model that predicts Y given that POA was coded and therefore the vector X is observed. These coefficients are not used in any calculations that affect the user's output at this time.
16-18	[Y X, P=0], mse, ese	Regression coefficients (col 16) and standard errors for the model that predicts Y given that POA was coded and the outcome Y is known to not have been POA. These coefficients are not used in any calculations that affect the user's output at this time.

Column Number	Column Headings (if any)	Meaning
19-21	[Y X,P=0, MCMC], mse, ese	Regression coefficients (col 19) and standard errors for the model that uses imputed values of POA in the MCMC to predict the probability of the adverse event. These are the coefficients that are typically published in the risk adjustment tables on the AHRQ QI website, and the ones that are used when the user elects to model the effects of missing POA in the data.

CSV File for the Prediction Module

For each risk-adjusted QI, the software prepares a comma separated values (.csv) file that contains one row per discharge record in the population at risk. The csv file has the following columns:

- Y – For purposes of risk-adjustment, Y=T, the discharge level indicator data element; its value is 0 if the record does not meet the numerator definition, and 1 if it does. Records where T is missing are not at risk for the QI, and are excluded from the QI’s csv file.
- P – This is the discharge level POA exclusion data element, Q; its value is 0 if Y = 0; its value is 0 if Y=1 and the outcome of interest was not POA; its value is 1 if Y=1 and the outcome of interest was POA or met a POA exclusion criterion. If POA is missing, its value is missing.
- ZCV1 to ZCV n – A set of n observed risk-adjustment covariates, each of which is coded using 0/1 indicator data elements. The number of data elements in the vector (n), varies from QI to QI. The covariate labels for each QI are listed in the Risk-adjustment Coefficient Tables. (See [links](#) in the Overview.)
- XCV1 to XCV n – A vector of n **enhanced risk-adjustment covariates**. When POA data are present, the vector of XCV values is exactly equal to the vector of ZCV values. When POA data are missing, the XCV values are missing and are modeled in the MCMC.

Prediction Module Output

The Prediction Module returns a dataset with one row per discharge record, and the following estimated quantities that are used to estimate QI rates. Note that these quantities correspond to the regression models listed in Table 10.1.

- Y – This is the outcome, T . If POA was observed and the outcome was known to be POA, then T would have been set to missing and the record would have been eliminated from this dataset.
- $E[Y|Z]$ – This is the expected value of the outcome using the risk-adjustment model that ignores POA data. All comorbidities are treated as POA for the purpose of APR-DRG assignment and for comorbidity terms in the risk-adjustment models. This is the contribution to the numerator of the expected rate if POA is being ignored.
- $E[Y|P=0]$ – This is the contribution to the numerator of the observed rate if POA is being accounted for. If $Y = 1$ and P is missing, then this value is $1 - E[P|YPXZ]$. If P is observed, accounted for, and 0, then this is the numerator contribution for the record. If P is modeled and accounted for, then this is the numerator contribution for the record.
- $E[Y|X,P=0]$ -MCMC – This is the risk-adjusted expected value of the outcome, given X and $P=0$. If POA data are observed, this is simply the scalar product of the risk adjustment coefficients and the risk adjustment covariates. If P is missing, this quantity is an expected value calculated with the MCMC. This is the contribution to the expected rate numerator if POA is being accounted for. (Note that in the software a small correction is applied to this figure to ensure that the reference population’s observed rate equals its expected rate and equals its risk-adjusted rate.)
- $E[P|YPXZ]$ – is the MCMC modeled probability that the outcome was POA. When P is missing, the denominator contribution of the record is $1 - E[P|YPXZ]$ and the numerator contribution is between 0 and $1 - E[P|YPXZ]$.

The Expected Rate

To recap, the predicted rate for each discharge comes from the Prediction Module and its method of calculation depends on whether POA is present and being accounted for:

- POA Ignored: $E[Y|Z]$
- POA Present and accounted for: $E[Y|X,P=0]$ – MCMC holds the scalar product of the risk adjustment coefficients to calculate $Y|X,P=0$ and the X vector.
- POA Absent but accounted for: $E[Y|X,P=0]$ – MCMC holds the expected value of Y , calculated by using an MCMC to approximate the weighted average over all possible combinations of missing data.

$$\text{Expected rate} = \frac{\text{Sum of the predicted rate for each discharge}}{\text{Count of discharges in the population at risk}}$$

The Risk-Adjusted Rate

The AHRQ QI use indirect standardization to calculate the risk-adjusted rate.

$$\text{Risk Adjusted Rate} = \text{Reference Population Rate} \times (\text{Observed Rate} / \text{Expected Rate})$$

Note that for the reference population, the observed rate equals the expected rate equals the reference population rate equals the risk-adjusted rate.

The software estimates the standard error of the risk adjusted rate for each provider or area using a method recommended by Iezzoni and described by Hosmer and Lemeshow that represents the amount of within provider or area variance due to sampling (i.e. as the number of patients per provider or persons per area increases this variance tends to zero). This standard error is used to calculate lower and upper bound 95% confidence intervals around the risk adjusted rate as [risk adjusted rate +/- 1.96 * risk adjusted rate SE] (stored in a data element with a “L” and “U” prefix). (See the note below entitled: Computing the Risk-Adjusted Rate Variance. See also http://qualityindicators.ahrq.gov/Downloads/Resources/Publications/2011/Calculating_Confidence_Intervals_for_the_AHRQ_QI.pdf)

The Smoothed Rate

The formula for the smoothed rate is:

$$\text{Smoothed Rate} = (\text{Risk Adjusted Rate} \times \text{Shrinkage Weight}) + \text{Reference Population Rate} * (1 - \text{Shrinkage Weight})$$

where

$$\text{Shrinkage Weight} = \frac{\text{Signal Variance}}{\text{Signal Variance} + \text{Noise Variance}}$$

The noise variance is calculated for each hospital based on the user’s data. The signal variance is a parameter calculated from the reference population. Beginning in Version 4.3, there are two signal variance estimates: one using POA and one ignoring POA data.

$$\begin{aligned} \text{Noise Variance } \hat{\sigma}_h^2 &= \left(\frac{\bar{Y}}{n_h E_h} \right)^2 \sum_{i \in A_h} \hat{Y}_i (1 - \hat{Y}_i) \\ \text{Signal Variance } \hat{\tau}^2 &= \frac{1}{H} \sum_{h=1}^H \frac{1}{(\hat{\tau}^2 + \sigma_h^2)^2} \sum_{h=1}^H \frac{1}{(\hat{\tau}^2 + \sigma_h^2)^2} \{ (RAR_h - \overline{RAR})^2 - \hat{\sigma}_h^2 \} \end{aligned}$$

where H is the number of hospitals with patents at risk for the QI, \bar{Y} is the observed rate for all discharges in the reference population; \hat{Y}_i is the patient-level predicted probability; and for hospital h , A_h is the collection of patients, n_h is the number of patients, E_h is the expected rate, and RAR_h is the risk-adjusted rate. Note that $\hat{\tau}^2$ appears on both sides of the signal variance equation; it is estimated in an iterative fashion.

For purposes of confidence interval estimation, the **smoothed rate** is assumed to follow a Gamma distribution $G(\text{shape}, \text{scale})$ where

$$shape = \frac{(Smoothed\ Rate)^2}{Posterior\ Variance}$$

$$scale = \frac{Posterior\ Variance}{Smoothed\ Rate}$$

$$Posterior\ Variance = Signal\ Variance - (Shrinkage\ Weight * Signal\ Variance)$$

When there is a fixed comparative rate of interest, it is possible to parameterize the smoothed rate posterior probability based on the Gamma distribution and calculate the probability that the smoothed area rate falls below or above the comparative rate that is of interest.

Computing the Risk-Adjusted Rate Variance

Let

- E_i be the expected (predicted) rate;
- n_h be the number of discharges at hospital h ; and
- α be the reference population rate (average outcome in the entire sample).

We define the observed rate at hospital h as

$$O_h = \frac{1}{n_h} \sum_{\substack{i \\ h_i=h}} Y_i$$

the expected rate at hospital h as

$$E_h = \frac{1}{n_h} \sum_{\substack{i \\ h_i=h}} \hat{\Pi}_i$$

and the Risk Adjusted Rate

$$RAR_h = \alpha \times \frac{O_h}{E_h}$$

Using a Taylor expansion for the formula for the variance of the ratio of two stochastic variables R, S

$$Var\left(\frac{R}{S}\right) \cong \frac{E[R]^2}{E[R]^2} \left(\frac{Var(R)}{E[R]^2} - 2 \frac{Cov(R, S)}{E[R]E[S]} + \frac{Var(S)}{E[S]^2} \right)$$

we compute the variance on the risk-adjusted rate

$$\text{Var}(RAR_h) \cong \alpha^2 \frac{E[O_h]^2}{E_h^2} \left(\frac{\text{Var}(O_h)}{E[O_h]^2} - 2 \frac{\text{Cov}(O_h, E_h)}{E[O_h]E_h} + \frac{\text{Var}(E_h)}{E_h^2} \right)$$

It is common practice in these calculations to neglect the variance of the predictor $\hat{\Pi}_i$ (Hosmer & Lemeshow, 1995) and to consider a normal distribution for the Risk Adjusted Rate (only true in the limit $n_h \rightarrow \infty$). In this case the above formula simplifies to

$$\text{Var}(RAR_h) \cong \alpha^2 \frac{\text{Var}(O_h)}{E_h^2}$$

and the 95% confidence intervals are calculated assuming normality. However, arguments to support using non-approximate equations (see Luft & Brown, 1993 for an example) for the **RAR** confidence intervals (in particular when n_h is small) may be considered in future releases of the AHRQ QI software.

Computing the Smoothed Rate Variance

The detailed formula for calculating the probability interval around the smoothed rate is described in [Chapter 11](#) on composite measures. Calculation of the smoothed rate is a step in the process of computing the composite measures. However, the basic formula is:

$$\text{Smoothed Rate} = (\text{Risk Adjusted Rate} \times \text{Shrinkage Weight}) + \text{Reference Population Rate} * (1 - \text{Shrinkage Weight})$$

$$\text{Shrinkage Weight} = \frac{\text{Signal Variance}}{\text{Signal Variance} + \text{Noise Variance}}$$

$$\text{Posterior Variance} = \text{Signal Variance} - (\text{Shrinkage Weight} * \text{Signal Variance})$$

The *smoothed rate* to follows a Gamma distribution $G(\text{shape}, \text{scale})$ where

$$\text{shape} = \frac{(\text{Smoothed Rate})^2}{\text{Posterior Variance}}$$

$$\text{scale} = \frac{\text{Posterior Variance}}{\text{Smoothed Rate}}$$

When there is a fixed comparative rate of interest, it is possible to parameterize the posterior probability based on the Gamma distribution and calculate the probability that the smoothed area rate falls below or above the comparative rate that is of interest.

Chapter 11. Estimating Composite Measures

The general methodology for the AHRQ QI **composite measures** might be described as constructing a “composite of composites.” The first “composite” is the reliability-adjusted ratio, which is a weighted average of the risk-adjusted ratio and the reference population ratio, where the weight is determined empirically as described below. The second “composite” is a weighted average of the component indicators, where the weights are selected based on the intended use of the composite measure. These weights might be determined empirically or based on non-empirical considerations.

Composite Value

The basic steps for computing the composite are as follows:

Step 1. Compute the risk-adjusted rate and confidence interval

The AHRQ QI risk-adjusted rate and confidence interval are computed as described above.

Step 2. Scale the risk-adjusted rate using the reference population

The levels of the rates vary from indicator to indicator. To combine the component indicators using a common scale, each indicator’s risk-adjusted rate is first divided by the reference population rate to yield a ratio. The components of the composite are therefore defined in terms of a ratio to the reference population rate for each indicator. The component indicators are scaled by the reference population rate so that each indicator reflects the degree of deviation from the overall average performance.

Step 3. Compute the reliability-adjusted ratio

The reliability-adjusted ratio is computed as the weighted average of the risk-adjusted ratio and the reference population ratio, where the weights vary from 0 to 1, depending on the degree of reliability for the indicator and provider (or other unit of analysis).

$$\begin{aligned} \text{Reliability Adjusted Ratio} = & (\text{risk - adjusted ratio} \times \text{weight}) \\ & + \text{reference population ratio} \times (1 - \text{weight}) \end{aligned}$$

For small providers, the weight is closer to 0. For large providers, the weight is closer to 1. For a given provider, if the denominator is 0, then the weight assigned is 0 (i.e., the reliability-adjusted ratio is the reference population ratio).

Step 4. Select the component weights

The composite measure is the weighted average of the scaled and reliability-adjusted ratios for the component indicators. The AHRQ QI software user has the ability to

modify these weights in the software, either in the SAS code, or in the WinQI user interface. Options for weights include:

Single indicator weight. In this case, the composite is simply the reliability-adjusted ratio for a single indicator. The reference population rate is the same among all providers.

Equal weight. In this case, each component indicator is assigned an identical weight based on the number of indicators. That is, the weight equals 1 divided by the number of indicators in the composite (e.g., $1/11 = 0.0909$).

Numerator weight. A numerator weight is based on the relative frequency of the numerator for each component indicator in the reference population. In general, a numerator weight reflects the amount of harm in the outcome of interest, in this case a potentially preventable adverse event. One might also use weights that reflect the amount of excess mortality or complications associated with the adverse event, or the amount of confidence one has in identifying events (i.e., the positive predictive value).

Denominator weight. A denominator weight is based on the relative frequency of the denominator for each component indicator in the reference population. In general, a denominator weight reflects the degree of risk of experiencing the outcome of interest in a given population. For example, the denominator weight might be based on the demographic composition of a health plan, the employees of a purchaser, a state, an individual hospital, or a single patient.

Factor weight. A factor weight is based on an analysis that assigns each component indicator a weight that reflects the contribution of that indicator to the common variation among the indicators. The component indicator that is most predictive of that common variation is assigned the highest weight. The weights for each composite are based on a principal components factor analysis of the reliability-adjusted ratios.

Note: The IQI composites (IQI #90 and #91) use denominator weights and the PSI and PDI composites (PSI #90 and PDI #19) use numerator weights.

Step 5. Construct the composite measure

The composite measure is the weighted average of the component indicators using the selected weights and the scaled and reliability-adjusted indicators.

$$\begin{aligned} \text{Composite} = & (\text{indicator}_1 \text{ RAR} \times \text{weight}_1) \\ & + (\text{indicator}_2 \text{ RAR} \times \text{weight}_2) + \dots + (\text{indicator}_N \text{ RAR} \times \text{weight}_N) \end{aligned}$$

Composite Variance

The probability interval of the composite measure is based on its standard error, which is the square root of the variance. The variance is computed based on the signal variance-covariance matrix and the reliability weights.

Let M be a $1 \times K$ vector of observed quality measures (for a given hospital, suppress hospital subscript for convenience), noisy measures of the true underlying $1 \times K$ quality vector μ , such that:

$$M = \mu + \varepsilon \quad (11.1)$$

where ε is a $1 \times K$ noise vector with zero mean and $K \times K$ variance-covariance matrix $Var(\varepsilon) = \Omega_\varepsilon$. Let the $K \times K$ signal variance-covariance be $Var(\mu) = \Omega_\mu$.

Let $\hat{\mu}$ a $1 \times K$ vector indicating the posterior (filtered) estimate of μ , such that:

$$\hat{\mu} = \mu + v \quad (11.2)$$

where v is a $1 \times K$ vector with zero mean and $K \times K$ variance-covariance matrix $Var(v)$ representing the prediction error of the posterior estimates.

The goal is to estimate the variance for any weighted average of the posterior estimates. For a given $1 \times K$ weighting vector w , this is given by:

$$Var(vw) = w'Var(v)w$$

where w' indicates the transpose of w .

Thus, we need an estimate of $Var(v)$. We simplify the calculation by assuming that the filtered estimates are formed in isolation for each measure (univariate) and the estimation error is assumed not correlated across measures (e.g., each measure is based on a different sample of patients or independent patient outcomes).

Forming each measure in isolation, using superscripts $k = 1, \dots, K$ to indicate the measure, we have:

$$\hat{\mu}^k = M^k \hat{\beta}^k = M^k (\Omega_\mu^{kk} + \Omega_\varepsilon^{kk})^{-1} \Omega_\mu^{kk} \quad (11.3)$$

$$Var(v^k) = \Omega_\mu^{kk} (1 - \hat{\beta}^k) = \Omega_\mu^{kk} - \Omega_\mu^{kk} (\Omega_\mu^{kk} + \Omega_\varepsilon^{kk})^{-1} \Omega_\mu^{kk} \quad (11.4)$$

where

$$\hat{\beta}^k = (\Omega_\mu^{kk} + \Omega_\varepsilon^{kk})^{-1} \Omega_\mu^{kk}$$

is the signal ratio of measure k , the reliability of the measure, and is the r-squared which measures how much of the variation in the true measure can be explained with the filtered measure. Note that in this simplified case the filtered estimate is a univariate shrinkage estimator.

For the non-diagonal elements of the covariance matrix (for $j \neq k$):

$$Cov(v^j, v^k) = E[(\mu^j - \hat{\mu}^j)(\mu^k - \hat{\mu}^k)] \quad (11.5)$$

assuming independent estimation error in the two measures, one gets the following simplified expression (see supplemental notes below for the derivation):

$$Cov(v^j, v^k) = \Omega_{\mu}^{jk} (1 - \hat{\beta}^j)(1 - \hat{\beta}^k) \quad (11.6)$$

Note that this is just the signal covariance times 1 minus the signal ratio for each of the measures. Thus, if the signal ratio is 0 for each measure, the covariance in the estimates is simply the signal covariance. As either measure gets a stronger signal ratio (becomes more precise), the covariance in the estimates shrinks to 0.

Also note that if one measure is missing, then the signal ratio is simply set to 0. The filtered estimate is shrunk all the way back to the (conditional) mean, and the variance and covariance are as defined above.

The standard error on the composite is the square root of the variance, which is then used to compute the 95% probability interval.

The *composite value* follows a Gamma distribution $G(shape, scale)$ where

$$shape = \frac{(Composite\ Value)^2}{Posterior\ Variance}$$

$$scale = \frac{Posterior\ Variance}{Composite\ Value}$$

A 95% probability interval can be calculated using the inverse CDF of the gamma distribution as

$$lower\ bound = inv_cdf_gamma(0.025, shape, scale)$$

$$upper\ bound = inv_cdf_gamma(0.975, shape, scale)$$

Supplemental Notes:

To derive formula (11.6), we substitute

$$\hat{\mu} = M\hat{\beta} = (\mu + \epsilon)\hat{\beta}$$

into (11.5) and obtain (for $j \neq k$)

$$\begin{aligned} Cov(v^j, v^k) &= E[(\mu^j - (\mu^j + \epsilon^j)\hat{\beta}^j)(\mu^k - (\mu^k + \epsilon^k)\hat{\beta}^k)] = \\ &= E[(\mu^j(1 - \hat{\beta}^j) - \epsilon^j\hat{\beta}^j)(\mu^k(1 - \hat{\beta}^k) - \epsilon^k\hat{\beta}^k)] = \\ &= E[\mu^j\mu^k(1 - \hat{\beta}^j)(1 - \hat{\beta}^k) + \mu^k\epsilon^j(1 - \hat{\beta}^k)\hat{\beta}^j + \mu^j\epsilon^k(1 - \hat{\beta}^j)\hat{\beta}^k + \epsilon^j\epsilon^k\hat{\beta}^j\hat{\beta}^k] = \\ &= E[\mu^j\mu^k](1 - \hat{\beta}^j)(1 - \hat{\beta}^k) + E[\mu^k\epsilon^j](1 - \hat{\beta}^k)\hat{\beta}^j + E[\mu^j\epsilon^k](1 - \hat{\beta}^j)\hat{\beta}^k + E[\epsilon^j\epsilon^k]\hat{\beta}^j\hat{\beta}^k \end{aligned}$$

Assuming $E[\mu^j\epsilon^k] = E[\epsilon^j\mu^k] = E[\epsilon^j\epsilon^k] = 0$ and $E[\mu] = 0$, we have

$$\begin{aligned} Cov(v^j, v^k) &= E[\mu^j\mu^k](1 - \hat{\beta}^j)(1 - \hat{\beta}^k) = \\ &= Cov(\mu^j, \mu^k)(1 - \hat{\beta}^j)(1 - \hat{\beta}^k) - E[\mu^j]E[\mu^k](1 - \hat{\beta}^j)(1 - \hat{\beta}^k) = \\ &= Cov(\mu^j, \mu^k)(1 - \hat{\beta}^j)(1 - \hat{\beta}^k). \end{aligned}$$

QED.

Chapter 12. Software Maintenance – Updating the Reference Population

In order to maintain the scientific acceptability of the AHRQ QI, the indicators are updated annually to reflect the Uniform Bill (UB-04) coding updates effective each year on July 1st, and the International Classification of Diseases- Ninth Revision- Clinical Modification (ICD-9-CM) and Medicare Severity Diagnosis-related Group (MS-DRG) coding updates effective each fiscal year on October 1st of the prior year. In addition, the annual updates include new Census data on the population of counties and new Healthcare Cost and Utilization Project (HCUP) data for the reference population and risk-adjustment covariate coefficients. This chapter describes the methods employed to update the QI reference population and the associated risk-adjustment covariate coefficients.

If the user wishes to account for missing POA, or calculate comparative expected, risk-adjusted, or smoothed rates, then the software makes use of a data frequencies, QI rates, and model coefficients that were estimated using a reference population. In the AHRQ QI software, the reference population consists of all the AHRQ HCUP SID data that are available at the time of the QI update for the year most recently processed. The v4.5 software, released in May 2013, uses 2010 SID data from 44 states for its reference population.

There are several important steps in the annual update process upstream from risk-adjustment and rate estimation. Changes may be made to QI technical specifications for one reason or another. Those must be implemented in the software. ICD-9 (and soon ICD-10) code sets may be modified. Those need to be updated in the software as well. The software is designed to be backward compatible, applying the appropriate sets of codes to older datasets. This work is accomplished before risk-adjustment models are calculated. Those steps are described briefly in [Appendix D](#).

Estimating risk-adjustment models and calculating QI rates in the reference population involves running the QI software on the reference population dataset.

Assemble the Reference Population Dataset

The user should prepare the input dataset according to the software instructions.

- SID data from all available states are appended together and processed in the manner described in [Chapter 1](#).
- The APR-DRG grouper is run on the adult dataset for the purpose of calculating IQIs. The grouper is run once considering all secondary diagnoses to be POA, and run a second time with POA diagnoses removed. The resulting APR-DRG from the former run is part of the Z vector of IQI covariates and the APR-DRG from the latter run is part of the X vector. This difference captures the fact that when POA is ignored, complications are treated like comorbidities for risk adjustment, and the risk of mortality is probably overstated compared to the risk if the patient were classified using only the conditions that were truly present on admission.

- Missing values of SEX are set to “0” (Male) so they will not be dropped by the QI software. (An alternative would be to impute SEX based on other data elements, like diagnosis codes.)
- Beginning in Version 4.3, discharges from non-community hospitals are deleted from the adult and pediatric analysis data. Community hospitals, as defined by American Hospital Association (AHA), include "all nonfederal, short-term, general and other specialty hospitals, excluding hospital units of institutions." Included among community hospitals are academic medical centers and specialty hospitals such as obstetrics, gynecology, ear nose throat, short-term rehabilitation, orthopedic, and pediatric hospitals. Non-community hospitals include federal hospitals (Veterans Administration, Department of Defense, and Indian Health Service hospitals), long-term hospitals, psychiatric hospitals, alcohol/chemical dependency treatment facilities and hospitals units within institutions such as prisons. (See http://hcup-us.ahrq.gov/db/state/siddist/siddist_hospital.jsp#2008).
- No other edits are applied to the State Inpatient Databases (SID).

Calculate Discharge Level Flags

The discharge level T and Q flags are calculated as described in Chapters 3-8.

Estimate Risk-adjustment Models

There are several steps involved in estimating the QI risk-adjustment models.

1. Construct candidate covariates
2. Select model covariates
3. Estimate the models
4. Evaluate the models

Construct Candidate Covariates for Risk-adjustment

For the PSIs, potential risk-adjustment covariates indicate whether the discharge record meets the technical specification for gender, age, modified Diagnosis-Related Group (MDRG) and at least one of twenty-five (25) co-morbidities that are used as covariates in the risk-adjustment model.

For the IQIs, potential risk-adjustment covariates indicate whether the discharge record meets the technical specification for gender, age, All Patient Refined Diagnosis Related Groups (APR-DRG) and risk-of-mortality subclass (minor, moderate, major, extreme) that are used as covariates in the risk-adjustment model.

For the PDIs, potential risk-adjustment covariates indicate whether the discharge record meets the technical specification for birth weight, age in days, age in years, modified Diagnosis-Related Group (MDRG), at least one of forty-six (46) clinical classification software (CCS) co-morbidities and some indicator-specific risk categories that are used as covariates in the risk-adjustment model.

For the PQIs, potential risk-adjustment indicate whether the discharge record meets the technical specification for gender, age in 5-year groups and poverty category that are used as covariates in the risk-adjustment model.

Covariates are coded for each discharge record based on the data elements, data values, and logic described in the technical specifications and the appendices of the risk-adjustment coefficient tables. For a given covariate, if the discharge meets the technical specification for that covariate a value of “1” is assigned to the discharge level covariate data element. Otherwise a value of “0” is assigned to the discharge level covariate data element. For discharge records with POA data, the software creates a second set of data elements (i.e., the **Z** data elements used in the modeling described in [Appendix C](#)) that do not consider secondary diagnosis codes that are not present on admission when assigning comorbidity or risk-of-mortality flags.

Select Model Covariates

For the provider level indicators, each module has a standard set of covariates grouped into four categories: demographics, severity of illness, comorbidities and other (See [Appendix B](#)). The standard set is tailored to each indicator to create a parsimonious set of covariates for each indicator. Based on cross tabulations between each covariate and the outcome of interest, only those covariates with at least 30 cases with the outcome of interest are retained. For categories that are mutually exclusive, covariates with fewer than 30 cases are pooled into the next covariate along the risk gradient. For example, age 70 to 74 is combined with age 65 to 69, or risk of mortality subclass 3 is combined with subclass 2. For categories with no risk gradient, covariates are pooled into broader covariates. For example, MS-DRGs are pooled into MDCs.

The omitted covariate within mutually exclusive categories is the reference group for those categories. Reference categories are usually 1) the most common and/or 2) the least risk. The choice of omitted reference category does affect how one might use the model coefficients or odds ratios in an English language sentence, but it does not affect predicted probabilities or model performance.

Once the preliminary multivariable model is specified, it is estimated on the adult or pediatric analytic data, as appropriate. Only those covariates that are statistically significant ($p < .05$) are retained. For covariates that are not statistically significant in categories that are mutually exclusive, the pooling process described above is repeated until a complete, parsimonious model is specified.

For the area level indicators, the models use the complete set of covariates for gender, age in 5-year age groups, an interaction with gender * age. There is also an optional set of covariates for poverty category based on the county of patient residence.

The final multivariable model parameters are published on the AHRQ website in Risk Adjustment Coefficient Tables. (See [links](#) in the Overview chapter.)

Estimate the Models

For models where POA is ignored, the AHRQ QI Analysis Module fits a logistic regression model that can be used to calculate the expected value of Y given Z. When possible, the Analysis Module estimates a Generalized Estimating Equations (GEE) model to properly account for within-hospital correlation. If the GEE model does not converge then the Analysis Module fits a more naïve logistic regression model that ignores that extra correlation. Whether the model is a GEE or not may be inferred by the .CSV filename for the QI. For example, PSI #4 uses a file named `gee_pps04_RegressionAnalysisGee.csv`. The ‘Gee’ near the end of the filename indicates that the Analysis Module used a GEE model. On the other hand, PSI #3 uses `gee_pps03_RegressionAnalysis.csv`. The missing ‘Gee’ in the filename tells the user that the model is not a GEE.

When POA data is accounted for, the Analysis Module uses Markov Chain Monte Carlo (MCMC) methods to fit several models.

1. It estimates coefficients to predict the expected value of Y given X, $P=0$ for records where POA is observed.
2. It estimates coefficients for a model for the expected value of the discharge level POA exclusion data element (P) when POA is missing.
3. And it estimates coefficients for the Prediction Module to calculate the expected value of the outcome, Y given $P=0$ and the observed data, for missing POA.

Computational details are described in [Appendix C](#). The Analysis Module generates a comma-separated values (.csv) file for each risk-adjusted QI that the Prediction Module uses when applying the models to a user’s dataset. These files are part of the AHRQ QI software package that is made available on the AHRQ website. See Table 10.1 for a description of the contents of those .csv files.

Calculate Rates

After the new risk-adjustment models are fit, the Prediction Module is run on the data to calculate expected values for P and Y so that observed rates may be calculated for the reference population. Reference population rates and signal variances are calculated both ignoring POA altogether and accounting for missing POA. These rates are stored in .TXT files that are part of the SAS AHRQ QI software package. The rates and variances are entered directly into WinQI program code, and do not appear as separate files in the WinQI package. Updating the risk-adjustment .CSV files and the population rate and signal variance .TXT files are a substantial milestone in the annual update process.

Update Software

In addition to the aforementioned .CSV and .TXT files, the AHRQ QI software must be updated to generate and combine the correct set of covariate variables for each risk adjusted QI. These covariates are generated in the so-called ~SAS3.SAS programs, and whenever the list of covariates in a risk-adjustment model changes, that code must be changed accordingly. Note that

it possible to fit new risk-adjustment model coefficients without updating the list of covariates. In that case, the ~SAS3.SAS program may need very little revision, if any.

Evaluate Models

Two desirable qualities of risk-adjustment models are that they discriminate well between discharge records that experience the outcome of interest and those that do not, and that they be well calibrated, predicting that the outcome will occur in approximately the right proportions, over a wide range of predicted probability.

Discrimination

One common scalar measure of logistic regression discrimination is the c-statistic. This may be calculated by computing the area under the Receiver Operating Characteristic (ROC) curve. Alternatively, it may be calculated by forming every possible pair in a dataset where one member of the pair is a discharge with the outcome of interest and the other member is a discharge without the outcome of interest. The c-statistic is the proportion of such pairs where the predicted probability for the member with the outcome of interest is higher than the predicted probability for the other record. Pairs with tied probabilities each contribute one-half to the numerator and denominator of the proportion. A c-statistic of 0.5 is the same discrimination performance as flipping a coin. A c-statistic of 1.0 indicates perfect discrimination. Hosmer and Lemeshow (2000, p.162) have coined three widely adopted labels for discrimination performance based on the c-statistic:

- $0.70 \leq c\text{-statistic} < 0.80$ indicates **acceptable discrimination**
- $0.80 \leq c\text{-statistic} < 0.90$ indicates **excellent discrimination**
- $0.90 \leq c\text{-statistic}$ indicates **outstanding discrimination**

The c-statistics for the AHRQ QI risk-adjustment models are published in on the AHRQ QI website in the Risk Adjustment Coefficient Tables. (See [links](#) in the Overview chapter.)

Calibration

Calibration is often described by sorting the dataset based on predicted probability and dividing it into deciles of risk. It is meaningful to compare the proportion of records in each decile that were observed to have the outcome of interest with the proportion of records that are expected to have that outcome. Hosmer and Lemeshow's logistic regression goodness-of-fit statistic (1980) is based on a chi-square test statistic calculated using the observed and expected counts across the ten deciles. Unfortunately that statistic always rejects the null hypothesis good calibration when the number of observations is large, as is the case with the AHRQ QI reference population. Although the test statistic and its p-value are not informative for these models, the models are sometimes characterized by publishing or plotting the observed and expected counts in the ten deciles of risk.

Chapter 13. Software Maintenance – Other Updates

The AHRQ QI software uses several other files or datasets that are updated periodically. This chapter lists those, and either describes the methods used to generate them, or references other stand-alone documents that do so.

Population Reference File

The file that contains stratified population counts by county and metropolitan statistical area is crucial for calculating the denominators of the area-level measures. That file and the method to construct it are described in a file entitled *AHRQ QI Population File Documentation* on the AHRQ website: (<http://www.qualityindicators.ahrq.gov/software/SAS.aspx>)

Condition-Specific Population File

The AHRQ QI program is conducting current methods research into options for estimating condition-specific denominators. At this time, the only condition-specific denominators are related to diabetes. There is a file name QICTYC13.TXT that is included with the v4.5 AHRQ QI module. That file was calculated using the following steps:

1. Use the population reference file to estimate 2013 population for each combination of state and age category. In the QI software, age categories are coded as:

```

VALUE AGECCAT
0 = '00 to 17'
1 = '18 to 44'
2 = '45 to 64'
3 = '65 to 74'
4 = '75+'
    
```

2. Obtain the latest diabetes prevalence figures broken out by state and age category from the Centers for Disease Control at <http://www.statehealthfacts.org/comparebar.jsp?ind=73&cat=2>.
3. Apply the diabetes proportions to the populations, to estimate the number of adults in each state in each of the four age categories who would have diabetes in 2013. (Population data from 2013 and proportion data from 2010.)

References

- Dempster AP; Laird NM; Rubin DB (1977). Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society, Series B (Methodological)* 39 (1): 1–38.
- Dimick JB, Staiger DO, Birkmeyer JD. (2006) Are Mortality Rates for Different Operations Related? Implications for measuring the quality of noncardiac surgery. *Med Care* Aug;44(8):774-8
- Fitzmaurice GM, Laird NM and Ware JH. *Applied Longitudinal Analysis*. John Wiley & Sons, Inc., Thirteenth edition, 2004.
- Hammersley JM & Handscomb DC, (1964) *Monte Carlo Methods*. Methuen & Co Ltd, London.
- Hosmer DW & Lemeshow S. (2000) *Applied Logistic Regression*, 2nd ed., Wiley, Inc., New York.
- Hosmer DW & Lemeshow S. (1980) A goodness-of-fit test for the multiple logistic regression model. *Communications in Statistics*, A10, 1043-1069.
- Hosmer DW & Lemeshow S. (1995). Confidence interval estimates of an index of quality performance based on logistic regression. *Statistics in Medicine*, Vol 14, Issue 19, 2161-2172
- Iezzoni, Lisa, ed. (2013) *Risk Adjustment for Measuring Health Care Outcomes*, 4th ed. Health Administration Press, Chicago.
- Liang KY & Zeger SL. Longitudinal Data Analysis Using Generalized Linear Models. *Biometrika*, 73(1):13-22, April 1986
- Little RJA & Rubin DB (2002). *Statistical Analysis with Missing Data*. Wiley, Hoboken, NJ.
- Luft, HS & Brown, BW Jr. (1993). Calculating the Probability of Rare Events: Why Settle for an Approximation? *Health Services Research* 28:4, 419-439
- McClellan M & Staiger D. (1999) The quality of health care providers. Cambridge, MA: National Bureau of Economic Research. NBER Working Paper #7327. Available at: <http://www.nber.org/papers/w7327>.
- Morris, CN (1983) Parametric Empirical Bayes Inference: Theory and Applications, *Journal of the American Statistical Association*, Vol. 78, No. 381 (Mar., 1983), pp. 47-55.
- Press WH., Teukolsky SA, Vetterling WT, Flannery BP, (1992) *Numerical recipes in C (2nd ed.): the art of scientific computing*. Cambridge University Press New York, NY, USA.
- Robert CP & Casella G. (2004). *Monte Carlo Statistical Methods*, 2nd Ed. Springer, New York, NY.
- Ripley BD, (1987) *Stochastic Simulation*. New York: Wiley & Sons, NY
- Rubinstein BY, (1981) *Simulation and the Monte Carlo Method*. Wiley & Sons., NY

Zeger SL & Liang KY. Longitudinal Data Analysis for Discrete and Continuous Outcomes.
Biometrics, 42(1):121-130, March 1986.

Appendix A. Table of AHRQ QI Risk-adjustment / POA

Appendix Table A.1 denotes which AHRQ QI are risk-adjusted and which use POA data and for what purpose (i.e., for technical specifications or risk-adjustment).

An entry of ‘AM/PM’ in the column entitled ‘Calculate Risk Adjusted Rate’ means that the indicator is a provider-level indicator and its risk adjustment model is estimated using the Analysis Module (AM) described in [Appendix C](#). The risk adjustment calculations are carried out using the Prediction Module (PM), also described in [Appendix C](#). An entry of ‘SAS’ in the column entitled ‘Calculate Risk Adjusted Rate’ means that the indicator is an area-level indicator and its risk adjustment model is estimated using PROC LOGISTIC in SAS.

An X in the column marked ‘Technical Specifications’ means that the indicator has an exclusion that explicitly references the POA data element. A QI software user may tell the software to ignore the DX_POA data element for purposes of risk-adjustment, but the software will never ignore DX_POA if it is referenced in the technical specifications for the purpose of defining exclusions, and if the data element is present in the discharge record. When a discharge record is missing the DX_POA data element, the Q flag will be set to “missing (.)” and the software will either ignore it (if USEPOA=0) or impute it (if USEPOA=1).

An X in the column marked ‘Risk Adjustment’ means that the risk adjustment logistic regression model includes covariates for conditions that are comorbidities if they are POA and are complications if they are not POA. When the discharge record is missing the DX_POA data element, the risk adjustment model will:

- Treat the covariates as comorbidities if the user elects to ignore POA data
- Model the missing POA data via the Markov Chain Monte Carlo (MCMC) if the user elects to account for POA data.

See [Chapter 10](#) for additional details on risk adjustment.

Appendix Table A.1. AHRQ QI Risk-adjustment and Uses of POA

	Calculate Risk Adjusted Rate	Use POA?	
		Technical Specifications	Risk Adjustment
IQI #1 - Esophageal Resection Volume			
IQI #2 - Pancreatic Resection Volume			
IQI #4 - Abdominal Aortic Aneurysm (AAA) Repair Volume			

	Calculate Risk Adjusted Rate	Use POA?	
		Technical Specifications	Risk Adjustment
IQI #5 - Coronary Artery Bypass Graft (CABG) Volume			
IQI #6 - Percutaneous Coronary Intervention (PCI) Volume			
IQI #7 - Carotid Endarterectomy Volume			
IQI #8 - Esophageal Resection Mortality Rate	AM/PM		X
IQI #9 - Pancreatic Resection Mortality Rate	AM/PM		X
IQI #11 - AAA Repair Mortality Rate	AM/PM		X
IQI #12 - CABG Mortality Rate	AM/PM		X
IQI #13 - Craniotomy Mortality Rate	AM/PM		X
IQI #14 - Hip Replacement Mortality Rate	AM/PM		X
IQI #15 - Acute Myocardial Infarction (AMI) Mortality Rate	AM/PM		X
IQI #16 - Heart Failure Mortality Rate	AM/PM		X
IQI #17 - Acute Stroke Mortality Rate	AM/PM		X
IQI #18 - Gastrointestinal Hemorrhage Mortality Rate	AM/PM		X
IQI #19 - Hip Fracture Mortality Rate	AM/PM		X
IQI #20 - Pneumonia Mortality Rate	AM/PM		X
IQI #21 - Cesarean Delivery Rate, Uncomplicated			
IQI #22 - Vaginal Birth After Cesarean (VBAC) Delivery Rate, Uncomplicated			
IQI #23 - Laparoscopic Cholecystectomy Rate			
IQI #24 - Incidental Appendectomy in the Elderly Rate			
IQI #25 - Bi-lateral Cardiac Catheterization Rate			
IQI #26 - Coronary Artery Bypass Graft (CABG) Rate	SAS		
IQI #27 - Percutaneous Coronary Intervention (PCI) Rate	SAS		
IQI #28 – Hysterectomy Rate	SAS		
IQI #29 - Laminectomy or Spinal Fusion Rate	SAS		
IQI #30 - Percutaneous Coronary Intervention (PCI) Mortality Rate	AM/PM		X
IQI #31 - Carotid Endarterectomy Mortality Rate	AM/PM		X

	Calculate Risk Adjusted Rate	Use POA?	
		Technical Specifications	Risk Adjustment
IQI #32 - Acute Myocardial Infarction (AMI) Mortality Rate, Without Transfer Cases	AM/PM		X
IQI #33 - Primary Cesarean Delivery Rate, Uncomplicated			
IQI #34 - Vaginal Birth After Cesarean (VBAC) Rate, All			
PSI #2 - Death Rate in Low-Mortality Diagnosis Related Groups (DRGs)	AM/PM		X
PSI #3 - Pressure Ulcer Rate	AM/PM	X	X
PSI #4 - Death Rate among Surgical Inpatients with Serious Treatable Complications	AM/PM		X
PSI #5 - Retained Surgical Item or Unretrieved Device Fragment Count		X	
PSI #6 - Iatrogenic Pneumothorax Rate	AM/PM	X	X
PSI #7 - Central Venous Catheter-Related Blood Stream Infection Rate	AM/PM	X	X
PSI #8 - Postoperative Hip Fracture Rate	AM/PM	X	X
PSI #9 - Perioperative Hemorrhage or Hematoma Rate	AM/PM	X	X
PSI #10 - Postoperative Physiologic and Metabolic Derangement Rate	AM/PM	X	X
PSI #11 - Postoperative Respiratory Failure Rate	AM/PM	X	X
PSI #12 - Perioperative Pulmonary Embolism or Deep Vein Thrombosis Rate	AM/PM	X	X
PSI #13 - Postoperative Sepsis Rate	AM/PM	X	X
PSI #14 - Postoperative Wound Dehiscence Rate	AM/PM		X
PSI #15 - Accidental Puncture or Laceration Rate	AM/PM	X	X
PSI #16 - Transfusion Reaction Count		X	
PSI #17 - Birth Trauma Rate – Injury to Neonate			
PSI #18 - Obstetric Trauma Rate – Vaginal Delivery With Instrument			
PSI #19 - Obstetric Trauma Rate – Vaginal Delivery Without Instrument			
PDI #1 - Accidental Puncture or Laceration Rate	AM/PM	X	X
PDI #2 - Pressure Ulcer Rate	AM/PM	X	X
PDI #3 - Retained Surgical Item or Unretrieved Device Fragment Count		X	
PDI #5 - Iatrogenic Pneumothorax Rate	AM/PM	X	X

	Calculate Risk Adjusted Rate	Use POA?	
		Technical Specifications	Risk Adjustment
PDI #6 - RACHS-1 Pediatric Heart Surgery Mortality Rate	AM/PM		X
PDI #7 - RACHS-1 Pediatric Heart Surgery Volume			
PDI #8 - Perioperative Hemorrhage or Hematoma Rate	AM/PM	X	X
PDI #9 - Postoperative Respiratory Failure Rate	AM/PM	X	X
PDI #10 - Postoperative Sepsis Rate	AM/PM	X	X
PDI #11 - Postoperative Wound Dehiscence Rate			X
PDI #12 - Central Venous Catheter-Related Blood Stream Infection Rate	AM/PM	X	X
PDI #13 - Transfusion Reaction Count		X	
PDI #14 – Asthma Admission Rate	SAS		
PDI #15 – Diabetes Short-Term Complications Admission Rate	SAS		
PDI #16 – Gastroenteritis Admission Rate	SAS		
PDI #17 – Perforated Appendix Admission Rate	SAS		
PDI #18 – Urinary Tract Infection Admission Rate	SAS		
NQI #01 - Neonatal Iatrogenic Pneumothorax Rate		X	X
NQI #02 - Neonatal Mortality Rate	AM/PM		X
NQI #03 - Neonatal Blood Stream Infection Rate	AM/PM	X	X
PQI #1 - Diabetes Short-Term Complications Admission Rate	SAS		
PQI #2 - Perforated Appendix Admission Rate	SAS		
PQI #3 - Diabetes Long-Term Complications Admission Rate	SAS		
PQI #5 - Chronic Obstructive Pulmonary Disease (COPD) or Asthma in Older Adults Admission Rate	SAS		
PQI #7 - Hypertension Admission Rate	SAS		
PQI #8 - Heart Failure Admission Rate	SAS		
PQI #9 - Low Birth Weight Rate	SAS		
PQI #10 - Dehydration Admission Rate	SAS		
PQI #11 - Bacterial Pneumonia Admission Rate	SAS		

	Calculate Risk Adjusted Rate	Use POA?	
		Technical Specifications	Risk Adjustment
PQI #12 - Urinary Tract Infection Admission Rate	SAS		
PQI #13 - Angina Without Procedure Admission Rate	SAS		
PQI #14 - Uncontrolled Diabetes Admission Rate	SAS		
PQI #15 - Asthma in Younger Adults Admission Rate	SAS		
PQI #16 - Lower-Extremity Amputation Among Patients With Diabetes Rate	SAS		

IQI = Inpatient Quality Indicator; PSI = Patient Safety Indicator; PDI = Pediatric Quality Indicator; NQI = Neonatal Quality Indicator

Appendix B. Table of AHRQ QI Provider-Level Risk-adjustment Covariates

The categories highlighted in blue are mutually exclusive and exhaustive, meaning that every discharge is assigned a value of “1” for one and only one covariate and there must be an omitted covariate (usually the most common or the least risk). If covariates within a highlighted category are excluded because $N < 30$ or $p < 0.05$ then the covariate is combined with another along the risk gradient. For example, combine birth weight 500-999g with 1000-1499g, age 18-24 with age 25-29 or combine ROM subclass “4” with ROM subclass “3”.

Appendix Table B.1 Table of AHRQ QI Risk-adjustment Covariates for Provider Level Indicators

Category	Mutually Exclusive	IQI	PSI	PDI	NQI
Demographics		Sex	Sex	Sex	Sex
		Age (5-year age groups)	Age (5-year age groups)	Birth weight (500g groups) Age in days (90 days to 1 year) Age in years (1 year and above)	Birth weight (500g groups)
Severity of Illness	DRGs pool into MDCs	APR-DRG Major Diagnosis Categories (MDC)	Modified MS-DRG* Major Diagnosis Categories (MDC)	Modified MS-DRG* Major Diagnosis Categories (MDC)	Modified MS-DRG* Major Diagnosis Categories (MDC)
Comorbidities		APR-DRG Risk of mortality subclass (1 – minor; 2 - moderate; 3 – major; 4 – extreme)	AHRQ Comorbidities	AHRQ Clinical Classification Software	Congenital anomalies
Other		Transfer-in status	Transfer-in status	Transfer-in status	Transfer-in status
		Point of Origin status	Point of Origin status Days to Procedure status	Point of Origin status Days to Procedure status Indicator-specific risk stratifiers	Point of Origin status Days to Procedure status

* Prior to October 1, 2007 use CMS-DRGs; highlighted categories are mutually exclusive with an omitted covariate.

Appendix C. Provider-Level Risk Adjustment - Detailed Methods

This appendix gives some statistical detail about how the provider-level risk adjustment models are fit and how they account for missing POA data. The Analysis Module is described first. It is used annually to fit models that are incorporated into updated AHRQ QI software. The Prediction Module is described second. It is called by the SASP3.SAS program for the IQI, PSI, and PDI indicators.

The Analysis Module

The purpose of the Analysis Module (AM) is to fit a set of regression coefficients using the data of the reference population. The input dataset is expected to have variables corresponding to the outcome of interest at discharge Y , one or more indicators of an outcome of interest present on admission (POA indicators P), and covariate vectors \mathbf{X} and \mathbf{Z} containing demographic, condition, co-morbidity, and potentially any other information, used as explanatory variables. The covariate \mathbf{X} is considered an improved measurement of the quantities measured by the covariate \mathbf{Z} .

Conceptually, there could be many ways in which \mathbf{X} might improve \mathbf{Z} . At this time, those improvements are the following:

1. In the \mathbf{Z} vector, the discharge level POA exclusion data element is sometimes observed and sometimes missing. In the \mathbf{X} vector, the missing values are modeled, when missing.
2. The \mathbf{Z} vector uses all secondary diagnoses to assign APR-DRG for the IQI, but the \mathbf{X} vector uses the DX_POA data element (observed or modeled) to take into account only the diagnoses that were present on admission.
3. The \mathbf{Z} vector considers all comorbidities to be complications for the purpose of calculating the observed rate and all to be comorbidities for the purpose of risk-adjustment. The \mathbf{X} vector uses the DX_POA data element (observed or modeled) to distinguish between complications and comorbidities.

The outcome Y and covariate \mathbf{Z} variables are never missing, but elements of the covariate \mathbf{X} and values of the present-on-admission indicators P can be missing. The dataset also contains a hospital identification number and a record identification number (a key identifying unique discharge records.)

Missing Data

Missing data are handled by integrating the likelihood over all the possible values of the missing variables. This technique for dealing with missing data is well-established in the statistical literature. Little and Rubin (2002) devote several chapters to analyzing missing data by integrating over the distribution, or likelihood, of the missing data. When the integral (or sum) of

the likelihood cannot be feasibly calculated, an alternative method known as the Expectation-Maximization (EM) algorithm can be used. The EM algorithm was developed in the 1970s by Dempster, Laird and Rubin (1977) to solve MLE equations in the presence of missing data. More recently, related methods based on Markov chain Monte Carlo (MCMC) algorithms have become popular for dealing with missing and censored data. MCMC algorithms include methods such as Metropolis-Hastings or Gibbs sampling which are widely used in Bayesian statistical analysis (Robert and Casella, 2004). MCMC methods are general and robust, and can be applied to a large variety of models. These methods are based on simulation, and they produce results that are approximations of the value being estimated. The approximation error can be controlled by the number of MCMC steps used in the simulation. In particular, as the number of MCMC steps goes to infinity, the approximation error goes to zero. We will give detail about the MCMC used in the Analysis and Prediction Modules in the following sections.

Data Notation

Here is the general statistical notation used to describe the model:

- h_i is the hospital associated with the i^{th} record (patient);
- Y_i is a binary variable indicating the outcome of interest at hospital discharge associated with the i^{th} record. $Y_i = 1$ if the patient experiences the outcome of interest, $Y_i = 0$ otherwise;
- P_i is a binary variable indicating whether an outcome of interest is present on admission. Notice that if $Y_i = 0$, then it is assumed that $P_i = 0$. If more than one POA indicators are present, the maximum value is considered;
- \mathbf{Z}_i is a vector of binary explanatory variables associated with the i^{th} record;
- \mathbf{X}_i is a vector of improved binary explanatory variables associated with the i^{th} record.

In the following formulae i indicates the record index while k indicates the component index of the covariate vectors. For example, indicating with K the number of components of the covariate vectors, then $\mathbf{X}_i \in R^K$ indicates the vector of covariates associated with the i^{th} record, X_{ik} indicates the value of the k^{th} covariate associated with the i^{th} record, while X_k without the record index is used to indicate the k^{th} covariate of a generic covariate vector.

The description of the Analysis Module proceeds with a brief outline of the MCMC calculations to account for missing POA data. The outline is a conceptual simplified description using formulae without explicit posterior parameters. The sections after the outline give additional detail

Outline of the MCMC algorithm to fit $[Y|X, P = 0]$ on data sets with missing data.

Before MCMC begins:

- Fit 2 by 2 binary tables $[X_k|Z_k]$ using observations where both X_k and Z_k are measured;
- Fit logistic regression model for $[P|X]$ using observations with complete data.

MCMC loop:

1. Build joint distribution $[Y, X, P, Z] = [Y|X, P][P|X][X|Z]$;
2. Use full conditional distribution $[X|Y, P, Z] = [Y, X, P, Z]/[Y, P, Z]$ to draw missing X s (Gibbs Sampling); write the drawn missing X values to the chain. This values can be referred to as *imputed data*;
3. Use full conditional distribution $[P|Y, X, Z] = [Y, X, P, Z]/[Y, X, Z]$ to draw missing P s (Gibbs Sampling); write the drawn missing P values to the chain. This values can be referred to as *imputed data*;
4. Fit logistic model $[Y|X, P = 0]$ using the available data, where measured, and the last imputed data, where X and P are missing (see 2. and 3.) Use either MLE or GEE (depending on the user's choice) to fit the model and obtain the estimated $\hat{\beta}$ and the estimated $\text{var}(\hat{\beta})$;
5. Draw a new set of regression coefficients β from a multivariate normal distribution with mean $\hat{\beta}$ and variance $\text{var}(\hat{\beta})$; write the drawn β values to the chain.
6. Go to 1 until total iterations equals that specified in the input XML file.

Note: the probability distribution density $[Y|X, P]$ is equal to the model probability distribution density $[Y|X, P = 0]$ when $P = 0$; and it is equal to the marginal probability $[Y = 1]$ when $P = 1$.

During the MCMC loop:

- Drop burn-in entries, as specified in input XML file.
- Thin the chain, as specified in input XML file.

After the loop:

- Estimate the regression coefficients $\hat{\beta}_{MCMC}$ and their standard error by calculating the expected values (mean) and the standard deviation of the components of the MCMC chain representing the regression coefficients β associated with the model $[Y|X, P = 0]$.

More Detailed Statistical Model

The main goal of the model is the estimation of Y given \mathbf{X} and $P = 0$. We assume the “conditional” binomial model

$$[Y|\mathbf{X}, P; \beta_Y] = \prod_i (\pi_{Y,i}^{1-P_i})^{Y_i} (1 - \pi_{Y,i}^{1-P_i})^{1-Y_i} \quad (\text{C.1})$$

with logistic link

$$\text{logit}(\pi_{Y,i}) = X_i \beta_Y$$

Another component of the model is the estimation of P given \mathbf{X} , which is used to predict P when that value is missing. We assume the binomial model

$$[P|\mathbf{X}; \boldsymbol{\beta}_P] = \prod_i \pi_{P,i}^{Y_i} (1 - \pi_{P,i})^{1-Y_i} \quad (\text{C.2})$$

with logistic link

$$\text{logit}(\pi_{P,i}) = X_i \boldsymbol{\beta}_P$$

Furthermore, we estimate \mathbf{X} when elements of that vector are missing by using the information contained in \mathbf{Z} . Since both \mathbf{X} and \mathbf{Z} contain binary variables, we model $[\mathbf{X}|\mathbf{Z}]$ using the two vectors of probabilities

$$\pi_{X,k}(0) = \Pr[X_k = 1 | Z_k = 0]$$

$$\pi_{X,k}(1) = \Pr[X_k = 1 | Z_k = 1]$$

and the likelihood

$$[\mathbf{X}|\mathbf{Z}; \boldsymbol{\pi}_X] = \prod_{ik} \pi_{X,ik}^{X_{ik}} (1 - \pi_{X,ik})^{1-X_{ik}} \quad (\text{C.3})$$

where

$$\pi_{X,ik} = \pi_{X,k}(Z_{ik})$$

Combining equations (C.1), (C.2) and (C.3), we obtain the likelihood

$$\begin{aligned} L(Y, \mathbf{X}, P, \mathbf{Z}; \boldsymbol{\beta}_Y, \boldsymbol{\beta}_P, \boldsymbol{\pi}_X) &= [Y, \mathbf{X}, P | \mathbf{Z}; \boldsymbol{\beta}_Y, \boldsymbol{\beta}_P, \boldsymbol{\pi}_X] = \\ &= [Y | \mathbf{X}, P; \boldsymbol{\beta}_Y] \times [P | \mathbf{X}; \boldsymbol{\beta}_P] \times [\mathbf{X} | \mathbf{Z}; \boldsymbol{\pi}_X] = \\ &= \prod_i (\pi_{Y,i}^{1-P_i})^{Y_i} (1 - \pi_{Y,i}^{1-P_i})^{1-Y_i} \pi_{P,i}^{P_i} (1 - \pi_{P,i})^{1-P_i} \pi_{X,ik}^{X_{ik}} (1 - \pi_{X,ik})^{1-X_{ik}} \end{aligned} \quad (\text{C.4})$$

Likelihood (C.4) is written as a distribution of Y, \mathbf{X}, P given \mathbf{Z} . In order to write the model for missing \mathbf{X} and P , we introduce the “true” variables \mathbf{X}', P' (to which we refer as “imputed”) and add the data model

$$[X'_{ik} | X_{ik}] = \begin{cases} X_{ik} & X_{ik} \text{ is measured} \\ 1/2 & \text{otherwise} \end{cases} \quad (\text{C.5})$$

$$[P'_i | P_i] = \begin{cases} P_i & P_i \text{ is measured} \\ 1/2 & \text{otherwise} \end{cases} \quad (\text{C.6})$$

The data model acts as a family of indicator variables, fixing the “imputed” variable to the measured value if the data are not missing. The likelihood integrated (summed) over the missing data can now be written as

$$\tilde{L}(Y, \mathbf{X}, P, \mathbf{Z}; \boldsymbol{\beta}_Y, \boldsymbol{\beta}_P, \boldsymbol{\pi}_X) = \sum_{P', \mathbf{X}'} L(Y, \mathbf{X}', P', \mathbf{Z}; \boldsymbol{\beta}_Y, \boldsymbol{\beta}_P, \boldsymbol{\pi}_X) \times [\mathbf{X}' | \mathbf{X}] \times [P' | P] =$$

$$= \sum_{P', X'} [Y | X', P'; \boldsymbol{\beta}_Y] \times [P' | X'; \boldsymbol{\beta}_P] \times [X' | Z; \boldsymbol{\pi}_X] \times [X' | X] \times [P' | P] \quad (\text{C.7})$$

Since the distribution inside the sum is the product of distributions for each record i , (see equation C.4), using the distributive property we can write

$$\begin{aligned} \tilde{L}(Y, \mathbf{X}, P, \mathbf{Z}; \boldsymbol{\beta}_Y, \boldsymbol{\beta}_P, \boldsymbol{\pi}_X) &= \\ &= \prod_i \left\{ \sum_{P'_i, X'_i} [Y_i | X'_i, P'_i; \boldsymbol{\beta}_Y] \times [P'_i | X'_i; \boldsymbol{\beta}_P] \times [X'_i | Z_i; \boldsymbol{\pi}_X] \times [X'_i | X_i] \times [P'_i | P_i] \right\} \end{aligned}$$

As the number of components of the covariate vector \mathbf{X} increases, to compute the above sum deterministically becomes unfeasible. For example, if X_i has 30 components, then the number of sums for every record i with missing X_i data is $2^{30} > 10^9$, and if the number of components is 100, then the number of sums becomes $2^{100} > 10^{30}$. The AM and PM employ alternative methods for integrating (summing) the likelihood over the missing data.

Model Fitting Approach using MCMC

To fit the $\boldsymbol{\beta}_Y$ coefficients using the *marginal* likelihood (C.7) (that is, the likelihood integrated over the missing data), we use Gibbs sampling, which is a standard MCMC technique (see Robert and Casella, 2004).

After reading the data, the AM fits the coefficients $\hat{\boldsymbol{\beta}}_P$ and $\hat{\boldsymbol{\pi}}_X$ using only the records in the dataset that have no missing data. Then, given $\hat{\boldsymbol{\beta}}_P$ and $\hat{\boldsymbol{\pi}}_X$, a sample of values of $\boldsymbol{\beta}_Y$, \mathbf{X}' , and P' is drawn from the posterior distribution:

$$[\mathbf{X}', P', \boldsymbol{\beta}_Y]_{post} \propto [Y | \mathbf{X}', P'; \boldsymbol{\beta}_Y] \times [P' | \mathbf{X}'; \hat{\boldsymbol{\beta}}_P] \times [X' | Z; \hat{\boldsymbol{\pi}}_X] \times [X' | X] \times [P' | P] \quad (\text{C.8})$$

The posterior distribution factors as

$$[\mathbf{X}', P', \boldsymbol{\beta}_Y]_{post} = \prod_i [X'_i, P'_i, \boldsymbol{\beta}_Y]_{post}$$

Univariate and multivariate Gibbs sampling is used to sample \mathbf{X}' , P' , and $\boldsymbol{\beta}_Y$. The sampling equations are the following:

- Sampling of P'_i (univariate Gibbs sampling)

$$P'_{i,new} \sim [P'_i | X'_i, \boldsymbol{\beta}_Y]_{post} = \frac{[X'_i, P'_i, \boldsymbol{\beta}_Y]_{post}}{[X'_i, \boldsymbol{\beta}_Y]_{post}} = \frac{[X'_i, P'_i, \boldsymbol{\beta}_Y]_{post}}{[X'_i, P'_i = 0, \boldsymbol{\beta}_Y]_{post} + [X'_i, P'_i = 1, \boldsymbol{\beta}_Y]_{post}}$$

Notice that posterior conditional distribution $[P'_i | \mathbf{X}'_i, \boldsymbol{\beta}_Y]_{post}$ is defined from the joint posterior on the left-hand-side of (C.8), and it is different from the conditional distribution $[P' | \mathbf{X}'; \hat{\boldsymbol{\beta}}_P]$, which appears on the right-hand-side of (C.8). Due to the constraint $Y_i = 0 \Rightarrow P_i = 0$, we have $P'_{i,new} = 0$ if $Y_i = 0$. When $Y_i = 1$, using equation (C.8) and simplifying the common factors in the numerator and the denominator, we can write

$$\begin{aligned} [P'_i = 1 | \mathbf{X}'_i, \boldsymbol{\beta}_Y; Y_i = 1]_{post} &= \\ &= \frac{[Y_i = 1 | \mathbf{X}'_i, P'_i = 1; \boldsymbol{\beta}_Y] \times \hat{\pi}_{P,i}}{[Y_i = 1 | \mathbf{X}'_i, P'_i = 0; \boldsymbol{\beta}_Y] \times (1 - \hat{\pi}_{P,i}) + [Y_i = 1 | \mathbf{X}'_i, P'_i = 1; \boldsymbol{\beta}_Y] \times \hat{\pi}_{P,i}} \end{aligned}$$

where $\hat{\pi}_{P,i}$ is the estimated probability⁴ $[P'_i = 1 | \mathbf{X}'_i; \hat{\boldsymbol{\beta}}_P]$. Noticing that $[Y_i = 1 | \mathbf{X}'_i, P'_i = 1; \boldsymbol{\beta}_Y] = 1$ and $[Y_i = 1 | \mathbf{X}'_i, P'_i = 0; \boldsymbol{\beta}_Y] = \pi_{Y,i}$, we obtain

$$[P'_i = 1 | \mathbf{X}'_i, \boldsymbol{\beta}_Y; Y_i = 1]_{post} = \frac{\hat{\pi}_{P,i}}{\pi_{Y,i}(1 - \hat{\pi}_{P,i}) + \hat{\pi}_{P,i}}$$

Hence, the sampling equations for $P'_{i,new}$ become

$$\begin{aligned} P'_{i,new} &= 0, & \text{if } Y_i &= 0 \\ P'_{i,new} &\sim \text{Bernoulli} \left(\frac{\hat{\pi}_{P,i}}{\pi_{Y,i}(1 - \hat{\pi}_{P,i}) + \hat{\pi}_{P,i}} \right), & \text{if } Y_i &= 1 \end{aligned}$$

- Sampling of X'_{ik} (univariate Gibbs sampling)

$$\begin{aligned} X'_{ik,new} \sim [X'_{ik} | \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post} &= \frac{[X'_{ik}, \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post}}{[X'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post}} = \\ &= \frac{[X'_{ik}, \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post}}{[X'_{ik} = 0, \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post} + [X'_{ik} = 1, \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post}} \end{aligned}$$

where \mathbf{X}'_{ik-} indicates all the components of the vector \mathbf{X}'_i except the k -th one, and $[X'_{ik}, \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post} \equiv [X'_i, P'_i, \boldsymbol{\beta}_Y]_{post}$. Using equation (C.8) and simplifying the common factors in the numerator and the denominator, we can write

$$[X'_{ik} = 1 | \mathbf{X}'_{ik-}, P'_i, \boldsymbol{\beta}_Y]_{post} = \frac{f(X'_{ik} = 1) \times \hat{\pi}_{X,ik}}{f(X'_{ik} = 0) \times (1 - \hat{\pi}_{X,ik}) + f(X'_{ik} = 1) \times \hat{\pi}_{X,ik}}$$

⁴ As mentioned at the beginning of the paragraph, the Analysis Module estimates $\hat{\boldsymbol{\beta}}_P$ and $\hat{\boldsymbol{\pi}}_X$ using only the records with no-missing data before the MCMC analysis.

where

$$f(X'_{ik}) = [Y_i | X'_{ik}, \mathbf{X}'_{ik-}, P'_i; \boldsymbol{\beta}_Y] \times [P'_i | X'_{ik}, \mathbf{X}'_{ik-}; \hat{\boldsymbol{\beta}}_P]$$

and $\hat{\pi}_{X,ik}$ is the estimated probability⁴ $[X_{ik} = 1 | Z_{ik}]$. Hence, the sampling equation for $X'_{ik,new}$ become

$$X'_{ik,new} \sim \text{Bernoulli} \left(\frac{f(X'_{ik} = 1) \times \hat{\pi}_{X,ik}}{f(X'_{ik} = 0) \times (1 - \hat{\pi}_{X,ik}) + f(X'_{ik} = 1) \times \hat{\pi}_{X,ik}} \right)$$

- Sampling of $\boldsymbol{\beta}_Y$ (multivariate Gibbs sampling)

$$\boldsymbol{\beta}_{Y,new} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \times N(\mathbf{0}, \sigma^2 \mathbf{I})$$

where $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is the multivariate normal approximation of the function

$$\boldsymbol{\beta}_Y \rightarrow [Y | \mathbf{X}', P'; \boldsymbol{\beta}_Y] = \prod_i \left(\pi_{Y,i}^{1-P'_i} \right)^{Y_i} \left(1 - \pi_{Y,i}^{1-P'_i} \right)^{1-Y_i}$$

using a second order Taylor expansion of the log-likelihood, as standard practice in Generalized Linear Models.

The AM includes an option to use Generalized Estimating Equations (Zeger & Liang, 1986, Liang & Zeger, 1986, Fitzmaurice, Laird & Ware, 2004) with an exchangeable correlation model to account for within hospital h_i correlation. The normal distribution $N(\mathbf{0}, \sigma^2 \mathbf{I})$ represents a non-informative prior distribution (for small values of the precision $\tau = 1/\sigma^2$) added to regularize cases with separable data.

Analysis Module Output

In addition to the quantities $\hat{\boldsymbol{\beta}}_Y, \hat{\boldsymbol{\beta}}_P, \hat{\pi}_X$ discussed above, the Analysis Module also calculates, for comparison purposes, the regression coefficients of the binomial model $[Y | \mathbf{Z}]$ fitted using all the data, the binomial model $[Y | \mathbf{X}]$ fitted using all the non-missing data, and the binomial model $[Y | \mathbf{X}, P = 0]$ fitted using all the non-missing data with $P = 0$.

The Prediction Module

The purpose of the Prediction Module (PM) is to predict, for each discharge record, the expected value of the adverse health outcome. These predictions are based on: i) the user's input dataset containing the same information, and having the same format as the analysis input dataset; and ii) a set of regression coefficients previously fitted by the Analysis Module using the data from a reference population. Since the adverse health outcome is binary (either it is present or it is not), the expected value for each discharge can be viewed as the probability that the adverse health outcome would have occurred for that discharge. These calculations are straightforward when there are no missing data, but they require high dimensional sums when data are missing.

Overview

If POA data are being ignored, then the relevant output from the PM is the expected value of $Y|Z$. This is calculated with a simple scalar product of regression coefficients and covariates. The calculation is performed in the PM, but it results in the same number that would be obtained using SAS PROC SCORE. There is no MCMC involved in its calculation.

IF POA data are being accounted for in the calculations, then the relevant output from the PM is the expected value of $Y|X, P=0$.

- a) For discharge records where POA is observed, this, too, is calculated with a simple scalar product of regression coefficients and covariates. The MCMC is not involved.
- b) For discharge records where POA is missing, the expected value is calculated using a Gibbs Sampler MCMC as described below.

Outline of the MCMC algorithm to predict $[Y|X, P = 0]$ using records with missing data

Before the MCMC begins:

- Read the 2 by 2 binary tables $[X_k|Z_k]$ and the estimated regression coefficients of the model $[P|X]$ fitted before the MCMC analysis discussed in the previous section;
- Read the estimated regression coefficients $\hat{\beta}$ of the model $[Y, X, P = 0]$ fitted by the MCMC analysis discusses in the previous section.

MCMC loop:

1. Build joint distribution $[X, P, Z] = [P|X][X|Z]$;
2. Use full conditional distribution $[X|P, Z] = [X, P, Z]/[P, Z]$ to draw missing X s (Gibbs Sampling); write the drawn missing X values to the chain. These values can be referred to as *imputed data*.
3. Use full conditional distribution $[P|X, Z] = [X, P, Z]/[X, Z]$ to draw missing P s (Gibbs Sampling); write the drawn missing P values to the chain. These values can be referred to as *imputed data*.

4. Calculate predicted probability of an adverse outcome using the fitted regression coefficient $\hat{\beta}_{MCMC}$, the available X and P data, where measured, and the last imputed data, where X and P are missing (see 2. and 3.) The predicted probability, when $P = 0$, is calculated according to a logistic regression as the inverse logit of the scalar product $\hat{\beta}_{MCMC} \cdot X$.
5. Write the predicted probabilities of an adverse outcome when $P = 0$ to the MCMC chain.
6. Go to 1 until total iterations equals that specified in the input XML file.

Note: points 1 through 3 of this section are similar to points 1 through 3 of the Analysis Module MCMC, only here we do not have Y data, which is what we are predicting.

During the MCMC loop:

- Drop burn-in entries
- Thin the chain, if appropriate (e.g., if the MCMC missing X s, missing P s, and the regression coefficients β are correlated in the chain)

After the MCMC loop:

- Calculate the expected values (average) of the components of the MCMC chain representing the predicted adverse outcome when $P = 0$;

Note 1. The MCMC expected values are an unbiased estimated of the predicted adverse outcome assuming that no value is missing;

Note 2. The random numerical relative error introduced by the finiteness of the MCMC chain is inversely proportional to the square root of number of MCMC steps, and it becomes negligible compared to the statistical error of the predictions as the number of MCMC increases. See the 2011 report on Prediction Model accuracy posted on the AHRQ website.

(<http://www.qualityindicators.ahrq.gov/Modules/Default.aspx>)

More Detailed Statistical Model

Let $\hat{\beta}_Y, \hat{\beta}_P, \hat{\pi}_X$ be the regression coefficients fit by the AM as described in the previous section, and set

$$p(\mathbf{X}', P') = [\mathbf{X}', P' | Y, \mathbf{X}', P', \mathbf{Z}; \hat{\beta}_Y, \hat{\beta}_P, \hat{\pi}_X] \propto \\ \propto [Y | \mathbf{X}', P'; \hat{\beta}_Y] \times [P' | \mathbf{X}'; \hat{\beta}_P] \times [\mathbf{X}' | \mathbf{Z}; \hat{\pi}_X] \times [\mathbf{X}' | \mathbf{X}] \times [P' | P]$$

The main goal of the Prediction Module is to calculate

$$\Pr[Y_i = 1 | \mathbf{X}_i, P_i = 0]$$

where we explicitly use the index i to indicate that the prediction is performed at the discharge record. For a record where both P_i and \mathbf{X}_i are measured and $P_i = 0$, the predicted probability is simply given by

$$\Pr[Y_i = 1 | \mathbf{X}_i, P_i = 0] = \hat{\pi}_Y(\mathbf{X}_i) \equiv \text{logit}^{-1}(\mathbf{X}_i \hat{\boldsymbol{\beta}}_Y)$$

If P_i is missing, then we calculate the expected value of $\hat{\pi}_Y(\mathbf{X}_i)(1 - P_i')$ over the distribution of the missing data $p(\mathbf{X}'_i, P'_i)$, namely

$$E_i[\hat{\pi}_Y] = \sum_{P'_i \in \{0,1\}} \hat{\pi}_Y(\mathbf{X}_i)(1 - P'_i) p(\mathbf{X}'_i, P'_i) = \hat{\pi}_Y(\mathbf{X}_i) p(\mathbf{X}_i, 0) = \text{logit}^{-1}(\mathbf{X}_i \hat{\boldsymbol{\beta}}_Y) p(\mathbf{X}_i, 0)$$

which is quick to compute. The general case however, where P_i and/or any combination of components of the vector \mathbf{X}_i is missing, requires the sum over all the possible combinations of missing values:

$$\begin{aligned} E_i[\hat{\pi}_Y] &= \sum_{P'_i, \mathbf{X}'_i} \hat{\pi}_Y(\mathbf{X}'_i)(1 - P'_i) p(\mathbf{X}'_i, P'_i) = \\ &= \sum_{P'_i, \mathbf{X}'_i} \text{logit}^{-1}(\mathbf{X}'_i \hat{\boldsymbol{\beta}}_Y)(1 - P'_i) p(\mathbf{X}'_i, P'_i) \end{aligned} \quad (\text{C.9})$$

Following the same argument used in the previous section, as the number of components of the vector of covariate \mathbf{X} increases, the deterministic sum quickly becomes unfeasible and an alternative approach is necessary. In this case, we evaluated the multidimensional sum using a Gibbs sampling implementation of the Importance Sampling Monte Carlo integration method (see chapter 7, paragraphs 7.6, 7.7 of the celebrated Numerical Recipes book (Press et al., 1992) for a primer introduction on Monte Carlo integration, references (Hammersley & Handscomb, 1964; Ripley, 1987; Rubinstein, 1981) for a deeper discussion, or many of the papers on the subject that can be freely found online.)

The methods works as follows: we draw a sample of imputed \mathbf{X}'_i, P'_i values from the distribution $p(\mathbf{X}'_i, P'_i)$, namely

$$(\mathbf{X}'_{i,s}, P'_{i,s}) \sim p(\mathbf{X}'_i, P'_i) \quad s = 1, \dots, N$$

using Gibbs Sampling to sample \mathbf{X}'_i and P'_i discussed in the Analysis Module section, then we approximate the sum (C.9) with the sample sum

$$I_N = \frac{1}{N} \sum_{s=1}^N \hat{\pi}_Y(\mathbf{X}'_{i,s})(1 - P'_{i,s})$$

Because Gibbs sampling generates a Markov chain, this method can be considered a MCMC method.

The numerical approximation of the Monte Carlo integration is known to be controlled by the sample variance

$$V_N = \frac{1}{N-1} \sum_{s=1}^N \left(\hat{\pi}_Y(\mathbf{X}'_{i,s})(1 - P'_{i,s}) \right)^2 - \frac{N}{N-1} \left(\frac{1}{N} \sum_{s=1}^N \hat{\pi}_Y(\mathbf{X}'_{i,s})(1 - P'_{i,s}) \right)^2$$

Since the distribution p has compact support and the function $\hat{\pi}_Y(\mathbf{X}_i)$ is bounded, then the variance V_N is also bounded. Therefore, under the assumption that the sample $(\mathbf{X}'_{i,s}, P'_{i,s})$ is ergodic (i.e. random), it follows from the central limit theorem that

$$I_N \rightarrow E_i[\hat{\pi}_Y]$$

in a probabilistic sense with a standard error equal to

$$\sigma_N = \sqrt{V_N/N}$$

The value V_N can be calculated together with I_N to provide an estimate of the Monte Carlo approximation error. However, regardless of V_N , the error of the MCMC integration scales as $1/\sqrt{N}$.

The PM also calculates, for comparative purposes, the expected values of the predictor $\hat{\pi}_Y$ for the different sets of coefficients $\hat{\beta}_Y$ estimated in the Analysis Module, the expected values of the predictor $\hat{\pi}_P$, and the marginal posterior probability of $P'_i = 1$ given by

$$\sum_{\mathbf{X}'_i} p(\mathbf{X}'_i, 1)$$

Appendix D. Helpful Background Information

This appendix includes some helpful information on both annual coding updates and software that is related to, or used by the AHRQ QI software. This information is not specifically statistical in nature, but does inform and affect the methods described in the main body of the document.

A. Fiscal year coding updates

Each fiscal year there are new ICD-9-CM and MS-DRG codes and revisions to existing codes. These changes are effective on October 1st. For example, Version 29 (fiscal year 2012) codes were effective October 1, 2011 and were incorporated in the version 4.4 release of the QI software. Diagnosis and procedure codes are used in the numerator and denominator specifications for the Patient Safety Indicators (PSIs), Prevention Quality Indicators (PQIs), Pediatric Quality Indicators (PDIs), and Inpatient Quality Indicators (IQIs). ICD-9-CM procedure codes affect the Centers for Medicare and Medicaid Services (CMS) classification of “major operating room procedure” for postoperative PSIs and PDIs. Another use of ICD-9-CM is in risk stratification used in the AHRQ Comorbidity Software, AHRQ’s Clinical Classification System, and 3M’s All Patient Refined Diagnosis Related Groups (APR-DRGs). Diagnosis codes are maintained by the Centers for Disease Control and Prevention’s (CDC) National Center for Health Statistics (NCHS). Procedure and MS-DRG codes are maintained by the CMS. The activities of both agencies are conducted jointly through the ICD-9-CM Coordination and Maintenance Committee (the Committee). The Committee meets in September and March to consider proposals for new codes and revisions to existing codes.

The Committee has implemented a partial freeze of the ICD-9-CM and ICD-10-CM/PCS codes in preparation for the implementation of ICD-10 codes on October 1, 2013. As a result, the last regular, annual updates to both ICD-9-CM and ICD-10-CM/PCS codes were made on October 1, 2011 (fiscal year 2012). It is anticipated that October 1, 2012 will witness only limited coding updates (from the September 14-15, 2011 and March 5, 2012 meetings of the Committee) to both the ICD-9-CM and ICD-10-CM/PCS codes to capture new technologies and diseases. The Committee meeting agendas and ICD-9-CM timeline is located at the [CMS site](#).

Information on ICD-10-CM coding updates is located on both the NCHS (<http://www.cdc.gov/nchs/icd/icd10cm.htm>) and CMS (http://www.cms.gov/ICD10/11b14_2012_ICD10CM_and_GEMs.asp and http://www.cms.gov/ICD10/11b15_2012_ICD10PCS.asp#TopOfPage) web sites.

APR-DRG codes are maintained by 3M.

A.1 ICD-9-CM coding updates and coding guidelines

Information on ICD-9-CM coding updates is located on both the NCHS and CMS web sites: (<http://www.cdc.gov/nchs/icd/icd9cm.htm>)

(www.cdc.gov/nchs/data/icd/icd9cm_guidelines_2011.pdf)
(http://www.cms.gov/ICD9ProviderDiagnosticCodes/01_overview.asp)

The anticipated coding updates for the subsequent version of the AHRQ QIs will consist of:

- New codes, if released.
- Limited ICD-9-CM coding revisions or deletions.
- NQF related updates, which may affect one or more indicators (This activity is performed in collaboration with task C.08. A set of NQF requested refinements have been submitted by AHRQ).

Activities during the base year will focus on these coding updates for the subsequent version of the AHRQ QIs. In general, updates to diagnosis and procedure codes are available on the NCHS or CMS web site. Preliminary updates are posted in March and final updates are posted in July. Diagnosis code updates are reported in Volume 1 (a tabular listing containing a numerical list of the disease code numbers) and Volume 2 (an alphabetical index to the disease entries). Procedure code updates are reported in Volume 3 (an alphabetic index and tabular list for surgical, diagnostic, and therapeutic procedures in hospitals and inpatient settings).

The meeting calendar of the Committee will be monitored on an ongoing basis for meeting status and updates to the meeting minutes, and the published coding changes (Volumes 1 and 2 for the diagnosis codes and Volume 3 for the procedure codes) and errata, both preliminary and final, will be reviewed.

The processes for evaluating the updates are described within each subsection below.

Diagnosis Codes

An update consists of three documents.

- ICD-9-CM Index to Diseases Addenda – lists changes to the indexing of codes to diseases.
- ICD-9-CM Diagnosis Tabular Addenda – lists changes to the codes and code categories (defined as the first three digits).
- Conversion Table of New ICD-9-CM Codes – maps current codes to previous codes.

The update process consists of reviewing these documents to identify any coding changes that impact the numerator, denominator or exclusion logic of the AHRQ QI. There are two types of changes:

- A current code is split into two or more sub-codes and the current code is retired. Cases previously assigned to the current code are now assigned to the sub-codes.
- A new code or code category is created. Some cases previously assigned to a current code are now assigned to the new code.

Each change is evaluated to determine whether cases assigned to the codes belong in the numerator, denominator or exclusion logic of one or more AHRQ QI.

Procedure Codes

An update consists of two documents.

- ICD-9-CM Procedure Tabular Addenda – lists changes to the codes and code categories
- Conversion Table of New ICD-9-CM Codes – maps current codes to previous codes.

The update process consists of reviewing these documents to identify any coding changes that impact the numerator, denominator or exclusion logic of the AHRQ QI. There are two types of changes.

- A current code is split into two or more sub-codes and the current code is retired. Cases previously assigned to the current code are now assigned to the sub-codes.
- A new code or code category is created. Some cases previously assigned to a current code are now assigned to the new code.

Each change is evaluated to determine whether cases assigned to the codes belong in the numerator, denominator or exclusion logic of one or more AHRQ QI.

A.2 DRG coding updates

There are two editions of the DRGs. The first edition uses CMS-DRGs and the second edition uses MS-DRGs. The first edition is Version 24 and earlier; the second edition is Version 25 and later.

Updates to CMS-DRG are no longer supported by CMS.

Updates to MS-DRG codes are available on the CMS web site and in the Federal Register. Preliminary updates are posted in May and final updates or corrections are posted by August. (See <http://www.cms.gov/AcuteInpatientPPS>).

The update process consists of reviewing Table 5, which is a list of MS-DRGs, Relative Weighting Factors and Geometric and Arithmetic Mean Length of Stay and is one of the data tables from the fiscal year Inpatient Prospective Payment System from CMS. Ambiguity around the content of any update may usually be resolved through a review of the Federal Register notice. Prior to the implementation of the MS-DRGs, CMS would add and revise many DRGs annually. However, with the implementation of the MS-DRGs, changes are less frequent.

Activities during the base year will focus on reviewing the MS-DRG updates and determining what measure(s) are impacted with regards to the AHRQ QIs.

3M APR-DRG coding updates

There is no public posting of updates to the APR-DRG. The commercial product is released in October with an update in April. A research license for the commercial product is available from AHRQ. The limited license grouper used in the AHRQ QI software is available on an ad hoc

basis under a voluntary arrangement with 3M. Contact information for the APR-DRG is as follows:

Anne M. Boucher
Implementation Manager
Clinical and Economic Research
3M Health Information Systems
100 Barnes Road
Wallingford, CT 06492
Telephone: (203) 949 6497
Email: amboucher@mmm.com

Along with the limited license grouper, 3M provides documentation on changes to the APR-DRG logic. APR-DRG uses the same version numbering system used by NCHS and CMS. Prior to Version 23 (fiscal year 2006), 3M released a new version of the APR-DRG only once every five fiscal years with an ICD-9-CM mapping to maintain compatibility. Currently 3M releases a new version each fiscal year.

Updating the APR-DRG consists of the following steps:

1. Running the commercial product on the most recent year of Healthcare Cost and Utilization Project (HCUP) data available.
2. AHRQ has “pre-grouped” the HCUP data for selected states and made APR-DRG and risk-of-mortality subclass data elements available on the HCUP intramural databases. Step number 1 does not need to be done for these states.
3. Tabulating the frequency of APR-DRGs in the denominator of each IQI that uses the APR-DRG for risk-adjustment.
4. Retaining those APR-DRGs with at least 30 cases in the numerator.
5. Ensuring that those retained APR-DRGs are included in the covariate tables.

B. Related software maintained by HCUP at AHRQ

The AHRQ QI software uses other AHRQ software as components of the indicator specifications or risk-adjustment covariate specifications. These software components are also updated annually to reflect coding changes. The AHRQ QI support team does not independently review these changes; rather the coding changes are implemented without further review.

B.1 Comorbidity software

There are two editions of the comorbidity software. The first edition uses CMS-DRGs and the second edition uses MS-DRGs. The comorbidity software has its own version numbering system. The first edition is version 3.4 and earlier; the second edition is version 3.5 and later. (See <http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp>).

The comorbidity software consists of two SAS programs. The first program, Creation of Format Library for Comorbidity Groups (Comformat.txt), creates a SAS format library that maps diagnosis codes into comorbidity indicators. Additional formats are also created to exclude conditions that may be complications or that may be related to the principal diagnosis. The second SAS program, Creation of Comorbidity Variables (Comoanaly.txt), applies the formats created above to a data set containing administrative data and then creates the comorbidity variables used to define the risk-adjustment covariates.

Updating the comorbidity software as used in the AHRQ QI software consists of the following steps:

- Comparing the current format program with the previous format program to identify any changes.
- Comparing the current analysis program with the analysis format program to identify any changes.
- Determine whether any of the changes present a problem for backwards compatibility and, if there is such a problem, design a solution.
- Implement any changes and solutions in the AHRQ QI software.

B.2 Clinical Classification Software (CCS)

The CCS for ICD-9-CM is a diagnosis and procedure categorization scheme that collapses individual codes into a smaller number of clinically meaningful categories. The AHRQ QI uses the single-level edition of the CCS for diagnoses and procedures. The software consists of a SAS formats program.

(See <http://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp>).

Updating the clinical classification software as used in the AHRQ QI software consists of the following steps:

- Comparing the current format program with the previous format program to identify any changes.
- Determine whether any of the changes present a problem for backwards compatibility and, if there is such a problem, design a solution.
- Implement any changes and solutions in the AHRQ QI software.

B.3 Procedure classes

The procedure classes assign ICD-9-CM procedure codes to one of four categories:

- Minor Diagnostic - Non-operating room procedures that are diagnostic.
- Minor Therapeutic - Non-operating room procedures that are therapeutic.
- Major Diagnostic - All procedures considered valid operating room procedures by the DRG grouper and that are performed for diagnostic reasons.
- Major Therapeutic - All procedures considered valid operating room procedures by the DRG grouper and that are performed for therapeutic reasons.

(See <http://www.hcup-us.ahrq.gov/toolssoftware/procedure/procedure.jsp>).

There is one file per fiscal year (PC.csv) that includes three elements: ICD-9-CM procedure codes, ICD-9-CM code labels, and procedure class assignments. In general, most of the changes relate to new procedure codes. However, sometimes the procedure class changes for an existing code. In these circumstances, the most recent assignment is used.

Updating the procedure classes as used in the AHRQ QI software consists of the following steps:

- Comparing the current procedure class assignments with the previous procedure class assignments to identify any changes.
- Special attention is given to operating room procedures in classes 3 and 4 (used to identify surgical discharges).
- Implement any changes in the AHRQ QI software.

C. Related classifications maintained by the AHRQ QI support team

The AHRQ QI software also uses other classifications as a component of the indicator specification or risk-adjustment covariate specification. These classification components are updated annually to reflect coding changes. The classifications include the Modified DRGs (MDRGs), birth weight (BWHTCAT), Congenital Anomalies (CONGCAT), and indicator-specification stratifications for the PDIs (HPPD01, GPPD02, GPPD10, HPPD10 and GPPD12).

C.1 Modified DRGs (MDRGs)

The purpose of the MDRG is to maintain a consistent mapping between CMS DRGs and MS-DRGs, and to pool MS-DRGs with and without CCs and MCCs. A new MS-DRG code either divides an existing MS-DRG into sub-MS-DRGs or re-assigns cases from multiple existing MS-DRGs. The MDRG is a four digit code. The first two digits are the Major Diagnosis Category (MDC), and the second two digits are a sequence number (e.g., 01-04) within the MDC.

Updating the modified DRGs consists of the following steps:

- Identify the relevant AHRQ QIs for which the fiscal year MS-DRG changes apply. The MS-DRG changes are identified in the CMS Table 5 (a list of MS-DRGs, Relative Weighting Factors and Geometric and Arithmetic Mean Length of Stay) from the fiscal year Inpatient Prospective Payment System.
- Use the CMS crosswalk to pool CMS-DRGs and MS-DRGs into a single MDRG and compare with the MDRG categories table in the relevant risk adjustment tables document.
- Implement any changes in the AHRQ QI software.

C.2 Birth weight (BWHTCAT)

BWHTCAT in 250g increments are defined by ICD-9-CM codes. Occasionally new codes are derived from existing codes.

Updating the birth weight categories consists of the following steps:

- Identify the relevant ICD-9-CM coding updates that pertain to the definition of the birth weight categories.
- Update the specifications, appendix and change log for the PDIs.
- Implement any changes in the AHRQ QI software.

C.3 Congenital anomalies (CONGCAT)

CONGCAT for gastrointestinal, genitourinary, central nervous system, pulmonary, cardiovascular, skeletal, chromosomal syndromes and selected other congenital anomalies are defined by ICD-9-CM codes (Original source Phibbs, et. al.⁵). Occasionally new codes are derived from existing codes.

Updating the CONGCATs consists of the following steps:

- Identify the relevant ICD-9-CM coding updates that pertain to the definition of the congenital anomalies.
- Update the specifications and change log for the relevant AHRQ QIs.
- Implement any changes in the AHRQ QI software.

C.4 Indicator-specific

Some PDIs have classifications used in stratification and as covariates in risk-adjustment. These classifications are procedure type risk category (HPPD01), pressure ulcer risk category (GPPD02), wound class procedure type (GPPD10), immune-compromised risk category (HPPD10) and bloodstream infection risk category (GPPD12). Occasionally new codes are derived from existing codes.

Updating the indicator-specific classifications consists of the following steps:

- Identify the relevant ICD-9-CM coding updates that pertain to the definition of the classifications.
- Update the specifications, appendix and change log for the relevant AHRQ QIs.
- Implement any changes in the AHRQ QI software.

D. Risk-adjustment for Congenital Heart Surgery (RACHS-1) software

RACHS-1 is a type of specification (the numerator and denominator inclusion and exclusion rules). The Pediatric Heart Surgery Mortality (PDI #6) measure uses the RACHS-1 software to assign pediatric heart surgery cases to risk strata depending on the type of surgery (HPPD06). The stratification occurs upon running the RACHS-1 syntax which is embedded in the

⁵ Phibbs CS, Baker LC, Caughey AB, Danielsen B, Schmitt SK, Phibbs RH. Level and volume of neonatal intensive care and mortality in very-low-birth-weight infants. *New England Journal of Medicine*. 2007;356(21):2165-2175 & Supplement.

software. The RACHS-1 software is maintained on an ad hoc basis by Children's Hospital in Boston.

(See <http://www.ncbi.nlm.nih.gov/pubmed/15283367>).

Updating the RACHS-1 software consists of confirming the coding updates that apply to RACHS-1 from the Children's Hospital in Boston. The RACHS-1 stratifications should be added to the risk adjustment documentation under C.12.4.6 in the C.12 work plan.