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REPORT

FINAL REPORT

# Risk Adjustment of HCBS Composite Measures, Volume 1

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# EXECUTIVE SUMMARY

This is the first of two reports describing the development of risk-adjusted home- and community-based services (HCBS) composite measures. This report (Volume 1) describes the methods used to account for differences in health and case mix when comparing HCBS composites rates across states or populations ("risk adjustment"); this includes the statistical approach and challenges, and the guidance provided by a Technical Expert Panel (TEP) (Bohl et al. 2015). A subsequent report (Volume 2) will focus on how to best utilize the risk adjusted HCBS composite measures to identify opportunities to improve quality of care for Medicaid fee-for-service (FFS) beneficiaries using HCBS. We anticipate Volume 2 will be available by October 2015.

The Agency for Healthcare Research and Quality (AHRQ) began the development of the HCBS composite measures 10 years ago as directed by the Deficit Reduction Act of 2005. Through this process, AHRQ finalized a set of HCBS quality measures that included composite measures adapted from the Prevention Quality Indicators (PQIs) (Schultz et al. 2012), which report rates of potentially avoidable hospitalization for select chronic or acute ambulatory care sensitive conditions (ACSC's). The HCBS composites (one for chronic and one for acute conditions) are intended to assess the quality of care for HCBS recipients under a shared accountability framework: the measures profile the HCBS population and reflect the care delivered by all providers (not just HCBS providers). However, to fairly assess the quality of care for the HCBS population, the composites need further methodological refinements to account for differences in age and health status across HCBS populations—achieved through statistical risk adjustment. Mathematica is tasked with building risk-adjustment models for the HCBS composites.[1]

This report describes the final risk-adjustment models for the acute and chronic HCBS composites, which are used to profile the quality of care received by the 2010 HCBS Medicaid FFS user population. In Chapter II, we summarize the data, methods, and approach to developing the risk-adjustment models; this includes a list of risk factors available for risk adjustment, including age, gender, chronic health conditions, intellectual and developmental disabilities, mobility and sensory limitations, mental health conditions, and substance use disorders. In Chapter III, we outline the model development process, including the selection of statistical models and guidance from the HCBS Composite Measure TEP. Chapters IV and V provide descriptive statistics on the HCBS user population, the prevalence of risk factors, and the incidence of HCBS composite events. Chapter VI reports the risk-adjusted HCBS composite rates at the state level with supporting information on the validity of these results.[2] The report summarizes the input from the first meeting of the HCBS Composite Measures TEP held in

[1] Mathematica is also tasked with the development of a risk-adjusted measure to assess potentially avoidable hospitalizations due to pressure ulcers in the HCBS user population. The final measure specifications and risk-adjustment models will be published in two volumes, which will be publicly available by October 2015.

[2] The state-level results in this report are descriptive and should not be used to rank performance. Instead, these results should be used to guide states or other stakeholders to further examine quality issues. The HCBS composites need further development if they are to be used for state profiling, including reliability adjustment, establishing benchmarks, defining a statistical framework for comparison, and accounting for managed care HCBS users.

March 2015. The TEP members reviewed a draft of this report and recommended how to proceed with the work.

Drawing on the TEP's guidance, Volume 2 of the report will discuss how to utilize the final HCBS risk adjusted measures to: (1) account for the uncertainty of HCBS composite rates through establishment of minimum case sizes or reliability adjustment, (2) establish relevant HCBS composite benchmarks based on national, subgroup, or peer group distributions, (3) formalize a statistical framework for how to compare HCBS composites to benchmarks, and (4) report risk-adjusted HCBS composite rates for policy-relevant subgroups, such as persons who transition from institutional long-term care setting to HCBS. Detailed measure specifications and (SAS) programming code for the risk adjusted HCBS measures will also accompany Volume 2.

The goal of this work is to continue to develop quality measures that can be used to assess the care provided to Medicaid FFS beneficiaries receiving long-term services and supports in the community. This report, as well as other reports related to the effort to develop quality measures for the HCBS population, can be found at: http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Long-Term-Services-and-Supports/Balancing/Money-Follows-the-Person.html.

# I. INTRODUCTION

This report presents the preliminary risk-adjustment models for three home- and community-based services (HCBS) composite measures, with detail on the model development process and risk-adjusted results for several HCBS populations of interest to the Centers for Medicare & Medicaid Services (CMS). The development of the HCBS composite measures began 10 years ago when the Deficit Reduction Act of 2005 directed the Agency for Healthcare Research and Quality (AHRQ) to develop "program performance indicators, client function indicators, and measures of client satisfaction" for Medicaid beneficiaries receiving HCBS (U.S. Congress 2006). Subsequent work by AHRQ finalized a set of HCBS quality measures, including three composite measures adapted from the Prevention Quality Indicators (PQIs) (Schultz et al. 2012). The HCBS composite measures report the rate of potentially avoidable hospitalization as a result of either chronic or acute ambulatory care sensitive conditions (ACSCs), as shown in Table I.1. These measures monitor the occurrence of hospitalizations that should rarely occur when high quality outpatient care is provided, and as such, have been recognized by several expert panels as highly relevant to the HCBS community (Schultz et al. 2012; Davies et al. 2009).

**Table I.1. Final AHRQ recommended measures**

| HCBS composites | Component indicators |
|---|---|
| ACSC Chronic Conditions Composite (PQI 92) | 1. Diabetes, short-term complications (PQI 1)<br>2. Diabetes, long-term complications (PQI 3)<br>3. COPD (PQI 5)<br>4. Hypertension (PQI 7)<br>5. Heart Failure (PQI 8)<br>6. Angina without procedure (PQI 13)<br>7. Uncontrolled diabetes (PQI 14)<br>8. Adult asthma (PQI 15)<br>9. Lower extremity amputations among people with diabetes (PQI 16) |
| ACSC Acute Conditions Composite (PQI 91) | 1. Dehydration (PQI 10)<br>2. Bacterial pneumonia (PQI 11)<br>3. Urinary tract infection (PQI 12) |
| ACSC Overall Composite (PQI 90) | All components from both the ACSC Chronic Conditions and ACSC Acute Conditions composites |

Source: Adapted from Schultz, E., S. Davies, and K. McDonald. "Development of Quality Indicators for Home and Community-Based Services Population: Technical Report." June 2012.

Note: The individual PQIs are largely mutually exclusive, due to the utilization of the primary diagnosis field to identify qualifying numerator events. However, the PQI 16 numerator utilizes specific procedure codes in combination with a diabetes diagnosis in any diagnosis field. For this reason, the same discharge can qualify as both a PQI 16 event and a PQI 1, 3, or 14 event. The composites only flag discharges with at least one PQI component, meaning that such a discharge can contribute only once to the chronic or overall composite numerators.

ACSC = ambulatory care-sensitive condition; AHRQ = Agency for Healthcare Research and Quality; COPD = chronic obstructive pulmonary disease; PSI = Patient Safety Indicator; PQI = Prevention Quality Indicator.

These HCBS composites have the potential to inform states about the quality of care experienced by the HCBS user population. As state and federal governments set up performance-based payment programs, they are incorporating ACSCs as the basis of incentives to manage

population health. However, the HCBS composites need to be risk adjusted because the HCBS user population is diverse and varies by state, and some ACSC admissions are inevitable and necessary. AHRQ's original analyses gave empirical motivation for risk adjusting the HCBS composites by demonstrating large variations in ACSC rates by population characteristics (Schultz et al. 2012). In addition to risk adjustment, to support the ultimate goal of motivating quality improvement in Medicaid through performance measurement, the HCBS composites needed a methodology account for statistical uncertainty to support comparisons between states or programs targeting Medicaid beneficiaries.

To address this gap, CMS, AHRQ, and the Office of the Assistant Secretary for Planning and Evaluation (ASPE) directed Mathematica Policy Research to develop a risk-adjustment methodology for these measures. As a first step, Mathematica proposed a methodology to build risk-adjustment models (Bohl et al. 2015). This methodology was vetted by CMS, AHRQ, and ASPE, as well as a technical expert panel (TEP). The risk-adjustment process followed the proposed approach with refinements based on feedback from stakeholders.[3]

The purpose of this report is to describe the methods and processes used to develop and test the risk-adjusted models for the HCBS composites. It includes a description of the data available for modeling, a formal statistical specification of the risk-adjustment model, and statistical validation and summary of model results. The HCBS composites are intended to assess the quality of care for HCBS recipients under a shared accountability framework: the measures profile the experience of the HCBS population and reflect the care delivered by all providers (not just HCBS providers). The risk-adjusted HCBS composites will ultimately be used to guide quality-improvement efforts led by HCBS stakeholders such as CMS and state Medicaid offices. With this goal in mind, the remainder of the report addresses:

- Analytic populations, measure definitions, candidate risk factors
- Development framework and model development process
- Descriptive statistics on HCBS users, comorbidities, and HCBS composite rates
- Model development and validation
- Risk-adjusted HCBS composite results by state for the following populations:
  - Medicaid beneficiaries using HCBS in 2010
  - Medicaid beneficiaries using HCBS in 2009
- Discussion and next steps

This report focuses solely on risk adjustment. A subsequent report (Volume 2) will formalize the methods for reliability adjustment, benchmarking, and display and use, and be accompanied by detailed measure specifications and associated programming (SAS) code.

[3] The TEP did not recommend refinements to the statistical models or demographic or health conditions included in the risk-adjustment models; instead, the TEP focused on how to use and report the risk-adjusted HCBS composites to the target audiences: states and other HCBS stakeholders.

# II. DATA AND MEASURES

## A. Analytic populations

To develop risk-adjustment models, we used the data on Medicaid beneficiaries using HCBS in 2010, which is the most recent year for which the required Medicare and Medicaid data are available for nearly all states. The 2010 HCBS user population includes persons enrolled in HCBS 1915(c) waiver plans or using HCBS state plan or 1915(c) waiver services at any point during 2010.[4] This population includes HCBS users who are enrolled only in Medicaid, as well as those eligible for both Medicare and Medicaid (referred to as Medicare–Medicaid eligible, or MME). In addition to the 2010 HCBS population, we use data on the 2009 HCBS user population for model validation and comparison. The data are derived from Medicare and Medicaid administrative data, including the Medicaid Analytic eXtract (MAX) Person Summary (PS), Other Services/Therapies (OT), and Long-term Care (LT), and Inpatient (IP) files, Medicare Beneficiary Summary File (MBSF), and Medicare Part A (from the Medicare Provider Analysis and Review (MedPAR) files)[5], and B claims data available on the Chronic Conditions Data Warehouse (CCW).[6]

In alignment with AHRQ's recommended specifications, we imposed several important exclusions on these populations (Schultz et al. 2012). We excluded both Medicaid managed care and Medicare Advantage enrollees, because their claims are either unavailable or incomparable to those for beneficiaries enrolled in fee-for-service programs. The population is also limited to HCBS users who are age 18 or older as of January 1, 2010. Finally, we excluded people with a record of HCBS enrollment only (that is, no observed HCBS claims) and at least one month with an institutional claim for long-term care. This step removes individuals who are enrolled in HCBS 1915(c) waivers but are only receiving institutional long-term services and supports (LTSS) during the period of interest.

## B. Measure definitions

### 1. Denominator

The denominator for the HCBS composites uses units of person-time. The number of HCBS person-years is calculated by summing the total number of months during the period of interest when eligible Medicaid beneficiaries were either enrolled in or using HCBS 1915(c) waivers or state plan HCBS. Because not all individuals use HCBS throughout the entire observation period, it's important to account for this variation when calculating observed rates. However, in the calculation of the risk-adjusted rates, which use the ratio of observed to expected rates, the duration of HCBS enrollment is effectively removed from consideration. We perform a

[4] HCBS 1915(c) waivers include aged/disabled, aged only, disabled only, traumatic brain injury, HIV/AIDS, intellectually disabled/developmentally disabled, mental illness, technologically dependent, an unspecified waiver, or autism. HCBS 1915(c) or state plan services include personal care, at-home private duty nursing, adult day, home health of at least 90 days, residential care, at-home hospice, rehabilitation, case management, transportation, or durable medical equipment.

[5] For additional information on these data files see the Centers for Medicare & Medicaid Services (CMS) Research Data Assistance Center (ResDAC) at http://www.resdac.org/.

[6] For additional information see the Chronic Conditions Data Warehouse (CCW) at www.ccwdata.org/.

sensitivity analysis to assess whether observed rates vary depending on whether duration of HCBS enrollment is included in the models, as discussed in Section III of this report.

### 2. Numerator

For each composite measure, the numerator includes the total count of inpatient acute care hospital admissions with diagnosis or procedure codes meeting the criteria for any of the component measures (Table I.1). These specifications are taken from the AHRQ Prevention Quality Indicators software version 4.4. Admissions that meet the criteria for multiple component measures are counted only once in the composite numerator.[7] To better attribute events to the HCBS care experience, Mathematica imposed an additional restriction so that qualifying admissions are included in the numerator only if the admission date occurs during a month of HCBS use.

If an HCBS user experiences multiple qualifying hospital admissions during the period of interest, all of these admissions are counted in the numerator. Therefore, although an HCBS user can be counted only once in the denominator, a user with more than one distinct hospital admission can contribute multiple times to the numerator. In the event that an HCBS user is transferred between acute care settings, the second stay (the "transfer in") is excluded from the analysis, to align with AHRQ's specifications (Schultz et al. 2012).

### 3. Observed (unadjusted) rates

The observed (unadjusted) composite rate for the time period of interest is calculated as the number of qualifying inpatient admissions divided by the number of months of HCBS use, i.e.,

$$\frac{Number\ of\ qualifying\ inpatient\ admissions\ during\ HCBS\ months}{Total\ number\ of\ HCBS\ months} = Rate\ of\ all\ events\ during\ HCBS\ months.$$

This rate will include qualifying inpatient admissions from HCBS users who are admitted to the hospital once, as well as admissions from those who are admitted to the hospital multiple times during the period of interest. The rate defined in this way is the primary focus of the risk-adjustment work described in this report. For ease of discussion, we multiply rates by 12 to generate rates in person-years. In addition, we multiply rates by 100,000 to present the HCBS composites with units of ACSC events per 100,000 person-years.

## C. Candidate risk factors

When building risk-adjustment models for the HCBS composite measures, Mathematica had access to information on demographics, HCBS enrollment and use, chronic conditions, disability-related conditions, mental health conditions, substance use disorders, Medicare–

[7] The individual PQIs are largely mutually exclusive, due to the utilization of the primary diagnosis field to identify qualifying numerator events. However, the PQI 16 numerator utilizes specific procedure codes in combination with a diabetes diagnosis in any diagnosis field. For this reason, the same discharge can qualify as both a PQI 16 event and a PQI 1, 3, or 14 event. The composites only flag discharges with at least one PQI component, meaning that such a discharge can contribute only once to the chronic or overall composite numerators.

Medicaid enrollment, and waiver enrollment. We list the set of potential risk factors or stratification variables below, describing their rationale and data source.

**Age and gender.** These two characteristics are included in the basic risk-adjustment algorithm developed by AHRQ for the PQIs. In this work, these variables are derived from the MAX PS file.

**Chronic conditions, disability-related conditions, mental health conditions, and substance use disorders.** Information on these health conditions and disorders are determined using the algorithms developed for the CCW (Appendix C includes information on the data and methods used to define the CCW indicators). The CCW was developed as a result of the Medicare Modernization Act of 2003, which required CMS to develop a research database to facilitate research on chronic illness that could be used to improve quality of care and reduce program spending. Currently, the comorbidities defined in the CCW include 27 chronic conditions, 15 disability-related conditions, 9 mental health conditions, and 2 substance use disorders (Tables II.1-3).

Compared with other claims-based comorbidity classification schemes, the CCW comorbidities have the advantage of relative simplicity (53 conditions, compared with 189 conditions in the Hierarchical Condition Classification and 285 in the Clinical Classification Software), and the CCWs are readily available for both MME and Medicaid-only beneficiaries. The CCW algorithms search both Medicare and Medicaid inpatient and outpatient claims using a one-, two-, or three-year look-back period.

### Table II.1. CCW Chronic conditions

| | |
|---|---|
| Alzheimer's disease | Chronic obstructive pulmonary disease and bronchiectasis |
| Alzheimer's disease and related disorders or senile dementia | Depression |
| Acute myocardial infarction | Diabetes |
| Anemia | Glaucoma |
| Asthma | Hip/pelvis fracture |
| Atrial fibrillation | Hyperlipidemia |
| Breast cancer | Hypertension |
| Colorectal cancer | Benign prostatic hyperplasia |
| Endometrial cancer | Acquired hypothyroidism |
| Lung cancer | Ischemic heart disease |
| Prostate cancer | Osteoporosis |
| Cataract | Rheumatoid arthritis/osteoarthritis |
| Heart failure | Stroke/transient ischemic attack |
| Chronic kidney disease | |

Source: Chronic Conditions Data Warehouse: https://www.ccwdata.org/.

### Table II.2. CCW Disability-related conditions

| | |
|---|---|
| Autism spectrum disorders | Muscular dystrophy |
| Cerebral palsy | Other developmental delays |
| Cystic fibrosis and other metabolic developmental disorders | Sensory: deafness and hearing impairment |
| Epilepsy | Sensory: blindness and visual impairment |
| Intellectual disabilities and related conditions | Spina bifida and other congenital abnormalities of the nervous system |
| Learning disabilities | Spinal cord injury |
| Mobility impairments | Traumatic brain injury and nonpsychotic mental disorders due to brain damage |
| Multiple sclerosis and transverse myelitis | |

Source: Chronic Conditions Data Warehouse: https://www.ccwdata.org/.

### Table II.3. CCW Mental health conditions and substance use disorders

| | |
|---|---|
| Anxiety disorders | Schizophrenia |
| Bipolar disorder | Schizophrenia and other psychotic disorders |
| Conduct disorders and hyperkinetic syndrome | Tobacco use |
| Depressive disorders | Alcohol use |
| Personality disorders | Substance abuse |
| Post-traumatic stress disorders | |

Source: Chronic Conditions Data Warehouse: https://www.ccwdata.org/.

**Waiver enrollment and use.** Due to the variation in implementation among 1915(c) waivers across states, a group of experts convened in 2013 cautioned against using enrollment in or use of 1915(c) waivers in risk adjustment (Ross and Bohl 2013). However, it may be useful in select cases, such as profiling specific subpopulations (for example, individuals enrolled in 1915(c) waivers for intellectual disabilities/developmental disabilities or HIV/AIDS). These data are derived from the MAX PS and OT files.

## D. Development framework

To provide state and federal governments with actionable information on the experiences of Medicaid beneficiaries using HCBS, it is necessary to address (1) differences in population characteristics, (2) statistical uncertainty across entities of interest, and (3) a framework for understanding performance. The risk-adjustment models proposed in this report seek to address the first of these challenges. The HCBS Composite Measures TEP discussed the second and third items in May 2015, and we will incorporate the TEP's feedback in the final HCBS composite measure report.

**Statistical uncertainty**. We propose to reliability adjust (stabilize or shrink) the risk-adjusted HCBS composites using a two-stage approach used by AHRQ's Quality Indicators of hospital quality. Although the HCBS composites focus on states rather than hospitals, AHRQ's methodology is well established and should be familiar to stakeholders and other interested parties.

**Performance framework**. To provide an appropriate framework for understanding observed, risk-adjusted, and reliability-adjusted results, we will explore methods for assessing states' performance relative to that of their peers. Table II.4 summarizes each of these methods, listing their distinct features and interpretation. The two most common approaches are (1) ranking the entity's rate compared with that of its peers and (2) testing the significance of the difference between the entity's rate and a benchmark, where significance is measured using the confidence interval around the rate. We will also consider probabilistic methods (Shwartz 2014).

**Table II.4. Summary of common methods for evaluating performance**

| Method | Description | Interpretation of lower rate[a] |
|---|---|---|
| Ranking | Ordering states based on their rates without making statistical inference | State A has the lowest rate, but this ranking may be due to chance |
| Performance categorization | Distinguishing which states are statistically different from a benchmark without reference to the magnitude of the difference | There less than a 5 percent chance of observing such a low rate for State A if its true quality is no different from average |
| Exceedance probability | Articulating the degree to which rates differ from a benchmark | State A has a 95 perfect probability of being lower than the benchmark |

[a] This example is for interpreting results for a state with the lowest HCBS composite rate.

Volume 2 will summarize the work to develop reliability-adjustment methods and appropriate comparison frameworks.

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# III. MODEL DEVELOPMENT PROCESS

## A. Analytic approach

The model development process followed the steps defined in the Proposed Methods for Developing and Testing Risk- and Reliability-Adjustment Models for HCBS Composite Measures (Bohl et al. 2015) and featured the following primary components:

**Definition of statistical model.** This analysis assessed whether to model counts using a Poisson, negative binomial, zero-inflated Poisson, or zero-inflated negative binomial (ZINB) model. These models can all be used to fit count data, but they differ in their assumptions about the conditional means and variance of the counts.

**Selection of person-level risk factors**. As discussed previously, candidate risk factors included age, gender, comorbidity information from the CCW conditions, and waiver enrollment.

**Consideration of HCBS "exposure" or use**. Our analysis includes persons using HCBS for at least one and up to 12 months in calendar year 2010. We considered using an offset variable in the count model; however, the TEP advised against it (see HCBS Composite Measures TEP summary in Section III.B below).

**Inclusion of state effects**. The focus of this work is to identify state-level differences or "effects" in the HCBS composite measure rates, after accounting for differences in person-level risk factors, exposure time, and other influences that may affect rates but are not directly related to the quality of care. To accomplish this goal, we might include these state effects directly in the model as fixed effects, model them via random intercepts (random effects), or omit them from the model entirely.

**Model diagnostics and performance.** Each HCBS composite is modeled separately, which may result in models with different risk factors. The following diagnostics were used to select and evaluate model fit: (1) the dispersion parameter from the negative binomial model, (2) comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC), and (3) consideration of scaled deviance (Gelman and Hill 2007; Ash et al. 2012; Clark and Linzer 2014).

We further detail the model development process and rationale for each of these steps in our previous report, Proposed Methods for Developing and Testing Risk- and Reliability-Adjustment Models for HCBS Composite Measures (Bohl et al. 2015).

## B. HCBS Composite Measures Technical Expert Panel (TEP)

As part of the model development process, Mathematica recruited HCBS providers, individuals familiar with acute and managed long-term care health plans, representatives from state Medicaid programs, clinical experts, representatives from the disability community, LTSS researchers, statisticians, and measurement experts to provide input on our technical approach and candidate risk factors. This TEP convened twice during the course of this work. The first

meeting occurred on March 23, 2015, during which the TEP members provided the following recommendations to Mathematica:

**Combine the acute and chronic models to produce the overall model.** Instead of modeling the overall composite directly, model the acute and chronic composites separately, and then combine results to calculate the overall composite. This approach allows the relationship between risk factors to differ between the acute and chronic events, and ensures that this variation is not lost within the overall composite model.

**Allow risk factors to vary between the acute and chronic models.** TEP members completed a survey to indicate which of the 53 CCW comorbidities were clinically relevant to the outcomes captured in the acute, chronic, and overall composites. All the disability and mental health conditions were considered clinically related to all three measures, but only 9 of 27 chronic conditions were deemed clinically important to all three measures, and 2 chronic conditions (hypertension and ischemic heart disease) were considered relevant only to the chronic composite. These results indicate that the theoretical models and their risk factors differ between the acute and chronic measures.

**Do not adjust for waiver enrollment.** The eligibility criteria for HCBS waivers vary by state. Therefore, using waiver enrollment as a proxy for identifying individuals with comorbidities (for example, intellectual or development disabilities) may lead to risk factor misspecification. Instead, the TEP recommended reporting results for waiver groups (for example, persons with traumatic brain injuries) separately.

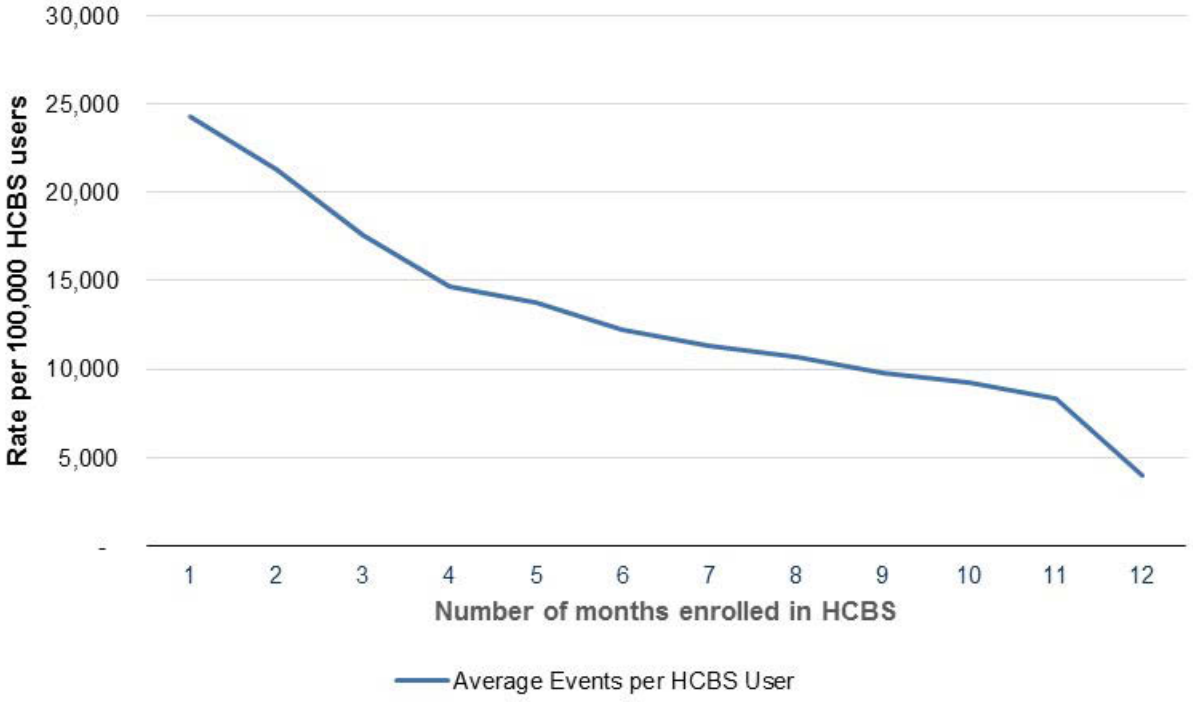
**Consider both clinical and statistical significance to select risk factors.** For clinically important risk factors, the TEP recommended that we relax the statistical significance threshold for inclusion. Mathematica settled on a p-value threshold of 0.3. All risk factors with unanimous support from the TEP survey were included, regardless of statistical significance.

**Stratify the models by MME (dual-eligibility) status.** The TEP recommended that we develop separate risk-adjustment models for HCBS users who are MME compared with those who are eligible only for Medicaid. Although there are other subgroups of interest, the MME split is the most important due to significant differences in case-mix, data availability, data standardization, and available policy levers.

**Do not account for prior-year outcomes.** TEP members agreed that because the end goal of these measures is state-to-benchmark comparisons, and not comparison within a state over time, prior-year outcomes (i.e., numerator events) should not be included in the adjusted models.

**Do not directly account for months of HCBS use.** Although the preliminary version of the risk-adjustment models included duration of HCBS enrollment, the TEP advised against including months of HCBS use due to concerns about endogeneity and specification. The duration of HCBS use is endogenous with the composite rates. Although we hypothesized that HCBS users with longer periods of enrollment may experience more events, the opposite relationship is observed (Figure III.1). This finding is most likely explained by the relationship between the ACSC events and the probability of future HCBS use: because of inpatient rehabilitation or mortality, HCBS use is less likely after an ACSC event.

**Figure III.1. Relationship between months of HCBS use and acute composite rate**




Sources: Mathematica analysis of 2009 HCBS users. Data source included the 2009 MAX PS, OT, and IP files, 2009 MedPAR file, and 2009 MBSF.

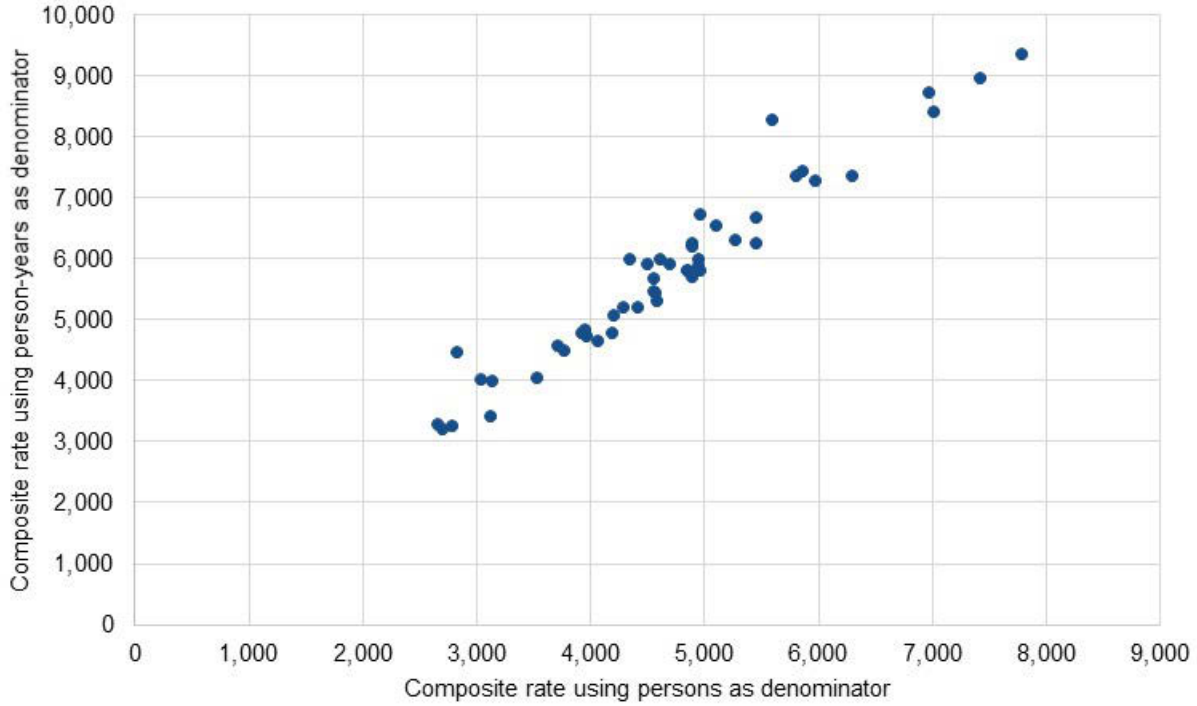
Notes: This figure shows the rate of acute composite events per 100,000 HCBS users. Rates are calculated for each cohort of individuals grouped by months of HCBS use.

Furthermore, because we primarily evaluate the duration of HCBS use during a single calendar year, we can only quantify HCBS use during that specific year, not longitudinally. For example, a person with one month of HCBS use in 2010 may have previous HCBS use in 2009, or may be a new or short-term HCBS user in 2010. Duration of HCBS use, however, remains an important consideration for the HCBS composite; therefore, the TEP recommended performing sensitivity analyses to determine how persons with short spells or breaks in enrollment impact results.

Without accounting for duration of HCBS time directly in risk-adjustment models, the resulting risk-adjusted rates will not account for varying time of enrollment. This is due to the use of indirectly standardized rates, which essentially divide the observed number of HCBS composite events by the predicted number of events in a given state, thereby canceling out HCBS duration. To understand the impact of removing HCBS duration from the risk-adjusted rates, we compared observed HCBS composite rates using two denominator definitions: (1) HCBS users and (2) HCBS person-years. In the first approach, the denominator is the number of Medicaid beneficiaries using HCBS during 2010, without consideration for the duration of that HCBS use (e.g., one month versus twelve months). In the second approach, the denominator is the total number of *months* where Medicaid beneficiaries use HCBS, such that a person using services for twelve months contributes twice as much observation time as a person using services for six months. These HCBS person-months are divided by twelve to yield HCBS person-years.

The close relationship we observed between these rates reduces the concern about incorporating duration of HCBS in the risk-adjustment models (Figure III.2). However, as recommended by the TEP, final results should report rates separately for the subgroup of short-term HCBS users.

**Figure III.2. Comparison of observed acute rates using HCBS users versus HCBS person-years**




Sources: Mathematica analysis of 2010 HCBS users. Data source included the 2010 MAX PS, OT, and IP files, 2010 MedPAR file, and 2010 MBSF.

Notes: This figure shows the rate of acute composite events per 100,000 HCBS users or person-years. Rates are calculated for each cohort of individuals grouped by months of HCBS use.

Based on the TEP's guidance (summarized in detail in Appendix A), we set forth on developing risk-adjustment models for the HCBS composite measures for acute and chronic conditions. During the process, we also emphasized model simplicity by trying to align risk factor definitions whenever possible. The following sections detail our results.

# IV. DESCRIPTIVE STATISTICS

## A. Demographic characteristics of the 2010 HCBS population

The risk-adjustment model development process utilized the 2010 HCBS user population, which included 1,834,198 Medicaid beneficiaries meeting the inclusion criteria outlined in Section II.A (Table IV.1). Data from 49 states were available at the time of this analysis, but Medicaid fee-for-service beneficiaries using HCBS in Arizona and Hawaii were excluded, because the high concentration of managed care in these states resulted in very small HCBS user populations available for modeling. California had the largest population, with 390,239 users, and all states other than Tennessee had more than 2,000 HCBS users in 2010. The age distribution varied substantially by state, with Tennessee's HCBS population primarily consisting of younger adults between the ages of 18 to 24, compared with an overall population mean of 60. Tennessee and New Mexico are also unique in our analysis because many of their HCBS users were excluded because of managed care enrollment, but we kept them in this report to demonstrate how HCBS user populations can vary substantially by state.

In addition, there was substantial state-level variation in Medicare eligibility and average duration of HCBS use (Table IV.1). In all states but Tennessee and Idaho, we observe that the majority of HCBS users are MME (in Idaho, no HCBS users are MME).[8] Furthermore, in New Jersey, New Mexico, and Michigan, more than 90 percent of the HCBS population is MME. HCBS users in most states are enrolled on average for at least nine months of a calendar year. North Dakota, which has a relatively high proportion of HCBS users older than 85, has the lowest average duration of HCBS use (7.6 months). The relationship between duration of HCBS use and age is multifaceted, but in general, states with older populations are more likely to see shorter periods of HCBS use because of mortality or the loss of independence, which may lead to institutional care.

**Table IV.1. Demographics of the 2010 HCBS user population, by state**

| State | HCBS users (n) | Female (%) | Age (mean) | Age 18–24 (%) | Age 85+ (%) | MME (%) | Months of HCBS (mean) |
|---|---|---|---|---|---|---|---|
| ALL | 1,834,198 | 62 | 60 | 6 | 12 | 74 | 10.0 |
| Alaska | 6,586 | 61 | 60 | 7 | 10 | 70 | 9.96 |
| Alabama | 16,133 | 64 | 57 | 6 | 9 | 64 | 9.96 |
| Arkansas | 19,666 | 67 | 62 | 5 | 16 | 76 | 9.58 |
| California | 390,239 | 62 | 64 | 5 | 12 | 71 | 10.29 |
| Colorado | 27,818 | 57 | 57 | 7 | 11 | 71 | 10.03 |
| Connecticut | 26,906 | 61 | 60 | 6 | 13 | 78 | 9.99 |
| District of Columbia | 8,264 | 59 | 59 | 3 | 9 | 59 | 9.23 |
| Delaware | 3,003 | 54 | 57 | 3 | 9 | 78 | 10.54 |
| Florida | 66,900 | 58 | 60 | 8 | 18 | 76 | 10.10 |

[8] Analyses by Mathematica indicate that the lack of 2010 HCBS users in Idaho who are MME is due to the state's transition to a new Medicaid Management Information System in 2010, not a lack of MME HCBS users (Mathematica Policy Research 2014).

Table IV.1 (continued)

| State | HCBS users (n) | Female (%) | Age (mean) | Age 18–24 (%) | Age 85+ (%) | MME (%) | Months of HCBS (mean) |
|---|---|---|---|---|---|---|---|
| Georgia | 38,738 | 63 | 56 | 6 | 8 | 64 | 8.00 |
| Iowa | 27,756 | 60 | 58 | 9 | 12 | 80 | 10.00 |
| Idaho | 13,463 | 61 | 57 | 9 | 12 | 0* | 10.14 |
| Illinois | 105,593 | 62 | 60 | 5 | 9 | 73 | 10.55 |
| Indiana | 21,189 | 55 | 50 | 13 | 6 | 71 | 10.57 |
| Kentucky | 19,801 | 60 | 56 | 8 | 9 | 65 | 9.23 |
| Louisiana | 31,201 | 65 | 52 | 10 | 7 | 55 | 9.50 |
| Massachusetts | 45,122 | 61 | 60 | 4 | 11 | 74 | 9.76 |
| Maryland | 18,940 | 56 | 57 | 6 | 10 | 88 | 10.59 |
| Michigan | 51,553 | 66 | 61 | 3 | 9 | 92 | 10.06 |
| Minnesota | 40,927 | 52 | 45 | 13 | 2 | 63 | 10.06 |
| Missouri | 63,350 | 64 | 60 | 3 | 10 | 74 | 9.36 |
| Mississippi | 16,739 | 67 | 63 | 3 | 14 | 78 | 9.78 |
| Montana | 7,421 | 65 | 46 | 15 | 7 | 56 | 8.44 |
| North Carolina | 85,919 | 65 | 61 | 5 | 12 | 73 | 9.74 |
| North Dakota | 4,681 | 58 | 56 | 7 | 16 | 76 | 7.60 |
| Nebraska | 10,156 | 61 | 57 | 10 | 15 | 74 | 10.12 |
| New Hampshire | 7,637 | 57 | 52 | 13 | 9 | 72 | 10.27 |
| New Jersey | 44,741 | 66 | 69 | 2 | 19 | 90 | 9.98 |
| New Mexico | 2,092 | 43 | 43 | 7 | 0 | 91 | 11.66 |
| Nevada | 8,594 | 64 | 60 | 6 | 11 | 69 | 9.69 |
| New York | 162,775 | 59 | 60 | 7 | 14 | 78 | 10.57 |
| Ohio | 79,610 | 64 | 62 | 6 | 14 | 80 | 9.64 |
| Oklahoma | 29,524 | 65 | 60 | 4 | 9 | 76 | 9.93 |
| Oregon | 13,079 | 60 | 61 | 9 | 17 | 80 | 9.89 |
| Pennsylvania | 37,699 | 60 | 59 | 6 | 12 | 83 | 10.06 |
| Rhode Island | 5,823 | 64 | 61 | 2 | 12 | 78 | 9.89 |
| South Carolina | 22,340 | 58 | 57 | 6 | 11 | 74 | 10.41 |
| South Dakota | 4,718 | 56 | 53 | 12 | 11 | 76 | 10.43 |
| Tennessee | 234 | 38 | 20 | 96 | 0 | 12 | 8.86 |
| Texas | 111,879 | 62 | 62 | 6 | 12 | 79 | 10.04 |
| Utah | 4,432 | 54 | 50 | 16 | 12 | 63 | 9.74 |
| Virginia | 36,055 | 62 | 62 | 6 | 17 | 75 | 8.28 |
| Vermont | 6,491 | 60 | 57 | 11 | 14 | 72 | 10.11 |
| Washington | 58,650 | 62 | 60 | 7 | 12 | 73 | 10.13 |
| Wisconsin | 11,477 | 56 | 53 | 11 | 9 | 71 | 8.64 |
| West Virginia | 14,615 | 63 | 57 | 6 | 7 | 66 | 9.74 |
| Wyoming | 3,669 | 57 | 52 | 11 | 6 | 72 | 10.56 |

Source: Mathematica analysis of MAX 2010 PS and OT files, and MBSF

Notes: Analyses by Mathematica indicate that the lack of 2010 HCBS users in Idaho who are MME is due to the state's transition to a new Medicaid Management Information System in 2010, not a lack of MME HCBS users (Mathematica Policy Research 2014).

## B. Comorbidities in the 2010 HCBS population

An analysis of comorbid conditions in the 2010 HCBS user population further helps characterize this population and emphasizes the existence of substantive case-mix differences by state and MME status. The distribution of risk-factor prevalence across states (in other words, the proportion of HCBS users with a given risk factor) was highly skewed. For most comorbid conditions, the distribution of state-level comorbidity prevalence is clustered around a value, but one or two outlier states may have exceptionally high prevalence of a condition. As an example, the overall prevalence of development disabilities is one percent across all states; however, in two states, the prevalence is 8 and 35 percent. This skewness is not captured when looking solely at the mean prevalence and suggests that states with exceptionally high or low prevalence of risk factors may warrant special considerations in final comparisons of risk-adjusted composite rates.

Among the three types of comorbidities examined—chronic conditions, disabilities-related conditions, and mental health conditions—the frequency of chronic conditions was substantially higher than disabilities or mental health conditions. For example, all ten of the most common chronic conditions were more prevalent than the most frequently reported disability-related condition (intellectual disabilities, 8.1 percent) and most frequently reported mental health condition (depressive disorders, 12.3 percent) among 2010 HCBS users (Tables IV.2–IV.4). Tables IV.2–IV.4 list the mean, minimum, and maximum among states to provide a sense of the distribution of these conditions.

Chronic conditions varied markedly by state and MME status. For example, hypertension was the most common comorbidity in this population, observed in 37.8 percent of 2010 HCBS users. The prevalence of hypertension ranged from a high of 63.7 percent in Mississippi to a low of 7.3 percent in Tennessee (Table IV.2). Similarly, there was at least a 30 percentage point difference in the highest and lowest state percentages of diabetes, ischemic heart disease, and rheumatoid arthritis/osteoarthritis. We also observe that the same states tend to fall at the top or the bottom of the range for these comorbidities, with Mississippi and Oklahoma frequently having high prevalence of chronic conditions, while the HCBS users in Tennessee, New Mexico, and Utah have much lower prevalence. Chronic condition prevalence is also generally higher among HCBS users who are MME, compared with those eligible for only Medicaid. These results indicate that the MME population bears a larger burden of chronic disease than their younger, Medicaid-only counterparts.

**Table IV.2. Frequency of most common chronic comorbidities, 2010 HCBS users**

| Comorbidity | All states (%) | All MMEs (%) | All Medicaid-only (%) | State with highest percentage | Value of highest percentage | State with lowest percentage | Value of lowest percentage |
|---|---|---|---|---|---|---|---|
| Hypertension | 37.8 | 40.5 | 30.4 | Mississippi | 63.7 | Tennessee | 7.3 |
| Diabetes | 27.7 | 29.5 | 22.9 | Mississippi | 40.5 | Tennessee | 6.0 |
| Ischemic heart disease | 20.4 | 23.5 | 11.6 | Oklahoma | 33.7 | Tennessee | 1.3 |
| Rheumatoid arthritis/osteoarthritis | 19.2 | 20.8 | 14.8 | Oklahoma | 40.7 | Tennessee | 2.6 |
| Hyperlipidemia | 15.5 | 14.6 | 17.8 | Oklahoma | 23.2 | Utah | 5.1 |
| Anemia | 14.6 | 14.9 | 13.9 | North Carolina | 22.7 | New Mexico | 5.4 |
| Congestive heart failure | 14.4 | 16.3 | 9.2 | Mississippi | 28.1 | Tennessee | 1.3 |
| Depression | 13.3 | 13.3 | 13.4 | Minnesota | 28.6 | Tennessee | 5.1 |
| Chronic obstructive pulmonary disorder | 13.0 | 13.6 | 11.3 | Oklahoma | 28.5 | New Mexico | 5.1 |
| Chronic kidney disease | 12.6 | 14.0 | 8.7 | Virginia | 18.8 | Tennessee | 3.4 |

Source: Mathematica analysis of MAX 2010 PS and OT Files, and MBSF.

Note: The conditions in this table were identified by applying the Chronic Conditions Warehouse (CCW) algorithms to Medicare and Medicaid claims.

Among HCBS users, disability-related conditions were much less prevalent than chronic conditions; nonetheless, some states do have high concentrations of HCBS users with disability-related conditions. For example, while 8.1 percent of HCBS users were observed to have intellectual disabilities overall, in Tennessee, two-thirds of HCBS users were observed to have this condition (Table IV.3). This likely is due to the fact that Tennessee transitioned most HCBS users other than persons with intellectual disabilities to managed care plans. Disability rates also differ notably between MME and Medicaid-only users, with the Medicaid-only HCBS users exhibiting a higher proportion of these disability conditions than their MME counterparts. States with specialized HCBS fee-for-service users like Tennessee merit separate consideration when assessing performance.

### Table IV.3. Frequency of most common disability-related conditions, 2010 HCBS Users

| Comorbidity | All states (%) | All MMEs (%) | All Medicaid-only (%) | State with highest percentage | Value of highest percentage | State with lowest percentage | Value of lowest percentage |
|---|---|---|---|---|---|---|---|
| Intellectual disabilities | 8.1 | 7.0 | 11.1 | Tennessee | 66.7 | Washington | 2.0 |
| Epilepsy | 6.4 | 5.2 | 9.9 | Tennessee | 21.8 | North Dakota | 2.8 |
| Mobility impairments | 5.6 | 5.7 | 5.6 | Mississippi | 12.2 | New Mexico | 2.7 |
| Cerebral palsy | 2.8 | 1.9 | 5.3 | Tennessee | 24.4 | North Dakota | 0.9 |
| Sensory impairment: deafness | 2.4 | 2.4 | 2.3 | New York | 7.3 | Utah | 0.7 |

Source: Mathematica analysis of MAX 2010 PS and OT Files, and MBSF.

Note: The conditions in this table were identified by applying the CCW algorithms to Medicare and Medicaid claims.

Although the burden of mental health conditions and substance use and abuse is also low relative to chronic conditions, state-level variation is again evident. For example, the most commonly reported mental health condition among all 2010 HCBS users was depression and related disorders (12.3 percent), with a high of 25.3 percent in Minnesota (Table IV.4). The prevalence of mental health conditions is similar between MME and Medicaid-only HCBS populations. Although Minnesota's HCBS population is not as strikingly different as Tennessee's HCBS population, accounting for mental health and substance use conditions will still likely be important in our modeling approach.

### Table IV.4. Frequency of most common mental health conditions and substance uses, 2010 HCBS users

| Comorbidity | All states (%) | All MMEs (%) | All Medicaid-only (%) | State with highest percentage | Value of highest percentage | State with lowest percentage | Value of lowest percentage |
|---|---|---|---|---|---|---|---|
| Depressive disorders | 12.3 | 13.3 | 11.9 | Minnesota | 25.3 | Tennessee | 5.6 |
| Anxiety | 7.5 | 7.1 | 8.8 | Minnesota | 16.5 | California | 4.2 |
| Schizophrenia and related disorders | 6.8 | 6.1 | 8.8 | Minnesota | 16.1 | Vermont | 2.5 |
| Tobacco use | 6.3 | 5.8 | 7.6 | Oklahoma | 14.8 | New Mexico | 2.0 |
| Schizophrenia | 5.0 | 4.3 | 6.9 | Minnesota | 12.9 | Vermont | 1.3 |

Source: Mathematica analysis of MAX 2010 PS and OT Files, and MBSF.

Note: The conditions in this table were identified by applying the CCW algorithms to Medicare and Medicaid claims.

## C. Implications of demographics on modeling

The variation observed in the 2010 HCBS user population across all these characteristics—whether age, MME status, chronic conditions, disability-related condition, or mental health conditions—demonstrates the need to risk adjust quality measures for this population. However, not all of these differences can be addressed by risk adjustment, and they may require different strategies as follows:

**Stratification by MME status**. Importantly, the different case-mix profiles of the MME and Medicaid-only populations confirm the TEP's belief that these two groups are markedly different and should be treated separately in the risk-adjustment process. Accordingly, we will build separate risk-adjustment models for the MME and Medicaid-only populations.

**Treatment of unique states**. These descriptive statistics suggest that certain states have very specialized HCBS populations. For example, more than 60 percent of Tennessee's HCBS users have intellectual disabilities, which is much higher than all other states. Although risk adjustment can reconcile some of these differences, the uniqueness of such states may preclude them from comparisons to more "typical HCBS users" from other states; alternatively, comparisons with a peer-group benchmark might be warranted. Furthermore, for small states with unique populations, reliability-adjustment should consider shrinking toward either a peer-group or population-specific prior.

# V. OBSERVED (UNADJUSTED) HCBS COMPOSITE RESULTS

## A. Development population: 2010 HCBS users

Among the 2010 HCBS user population, there were more ACSC hospitalizations for chronic conditions than there were for acute conditions (Table IV.5). There were nearly 198,000 acute and chronic events in the 2010 HCBS user population, and 60 percent are for chronic conditions.[9] Together, four types of conditions or events account for 77 percent of all ACSC hospitalizations: heart failure (23 percent), chronic obstructive pulmonary disease (COPD) (22 percent), bacterial pneumonia (17 percent), and urinary tract infections (UTIs) (15 percent). The overall composite rate, which combines the acute and chronic composites, among 2010 HCBS users is 12,897 events per 100,000 person years. We present state-level acute and chronic HCBS composite observed rates later in the report.

### Table V.1. HCBS composite results for 2010 HCBS population

| PQI number | PQI description | Count | Proportion | Rate per 100,000 person-years |
|---|---|---|---|---|
| 1 | Diabetes short-term complications | 3,619 | 0.02 | 236.9 |
| 3 | Diabetes long-term complications | 16,752 | 0.08 | 1,096.4 |
| 5 | COPD or asthma in older adults | 44,324 | 0.22 | 2,900.8 |
| 7 | Hypertension | 4,615 | 0.02 | 302.0 |
| 8 | Heart failure | 44,753 | 0.23 | 2,928.9 |
| 10 | Dehydration | 13,109 | 0.07 | 857.9 |
| 11 | Bacterial pneumonia | 34,355 | 0.17 | 2,248.4 |
| 12 | Urinary tract infection | 29,965 | 0.15 | 1,961.1 |
| 13 | Angina without procedure | 1,416 | 0.01 | 92.7 |
| 14 | Uncontrolled diabetes | 2,461 | 0.01 | 161.1 |
| 15 | Asthma in younger adults | 772 | <0.01 | 50.5 |
| 16 | Lower-extremity amputation among patients with diabetes | 1,948 | 0.01 | 127.5 |
| 90 | Overall HCBS composite | 197,070 | 1.0 | 12,897.5 |
| 91 | Acute HCBS composite | 77,428 | 0.39 | 5,067.4 |
| 92 | Chronic HCBS composite | 119,661 | 0.60 | 7,831.4 |

Source: Mathematica analysis of MAX 2010 Person Summary and Other Files, and MBSF.

Note: The HCBS composite and component rates were calculated using the AHRQ specifications (Schultz et al. 2012) updated to version 4.4 of the PQI software. Certain hospitalizations can flag more than one acute or chronic ACSC event (specifically, PQI 16 can be flagged on the same discharge as PQI 1, 3 or 14), however each hospitalization can contribute only once to the composite counts. As a result, the sum of the components exceeds the composite counts, and the proportions do not sum exactly to 1.0.

## B. Validation population: 2009 HCBS users

The 2009 HCBS population serves to provide information about the stability of the HCBS composite rates over time, as well as to assess the validity of our models. Similar to the 2010 HCBS population, we observe that the majority of ACSC hospitalizations are for chronic conditions (Table V.2). There are approximately 197,000 acute and chronic events in the 2009

[9] It is possible for a hospitalization to be flagged as a PQI 16 event (lower-extremity amputation) as well as a PQI 1, 3or 14 event.

HCBS user population, and again, 60 percent are for chronic conditions.[10] Together, the same four types of conditions or events account for 78 percent of all ACSC hospitalizations: heart failure (23 percent), COPD (22 percent), bacterial pneumonia (18 percent), and UTIs (14 percent). The overall composite rate among 2009 HCBS users is 13,377 events per 100,000 person years. These results suggest that at a national level, the composites and their component indicators are relatively stable from year to year.

### Table V.2. HCBS composite results for 2009 HCBS population

| PQI number | PQI description | Count | Proportion | Rate per 100,000 person-years |
|---|---|---|---|---|
| 1 | Diabetes short-term complications | 3,418 | 0.02 | 226.5 |
| 3 | Diabetes long-term complications | 16,918 | 0.08 | 1,120.9 |
| 5 | COPD or asthma in older adults | 45,656 | 0.23 | 3,024.9 |
| 7 | Hypertension | 4,486 | 0.02 | 297.2 |
| 8 | Heart failure | 46,382 | 0.23 | 3,073.0 |
| 10 | Dehydration | 14,216 | 0.07 | 941.9 |
| 11 | Bacterial pneumonia | 36,077 | 0.18 | 2,390.2 |
| 12 | Urinary tract infection | 28,848 | 0.14 | 1,911.3 |
| 13 | Angina without procedure | 1,653 | 0.01 | 109.5 |
| 14 | Uncontrolled diabetes | 2,485 | 0.01 | 164.6 |
| 15 | Asthma in younger adults | 857 | < 0.01 | 56.8 |
| 16 | Lower-extremity amputation among patients with diabetes | 1,962 | 0.01 | 130.0 |
| 90 | Overall HCBS composite | 201,900 | 1.0 | 13,377.1 |
| 91 | Acute HCBS composite | 79,141 | 0.39 | 5,243.4 |
| 92 | Chronic HCBS composite | 122,766 | 0.60 | 8,133.7 |

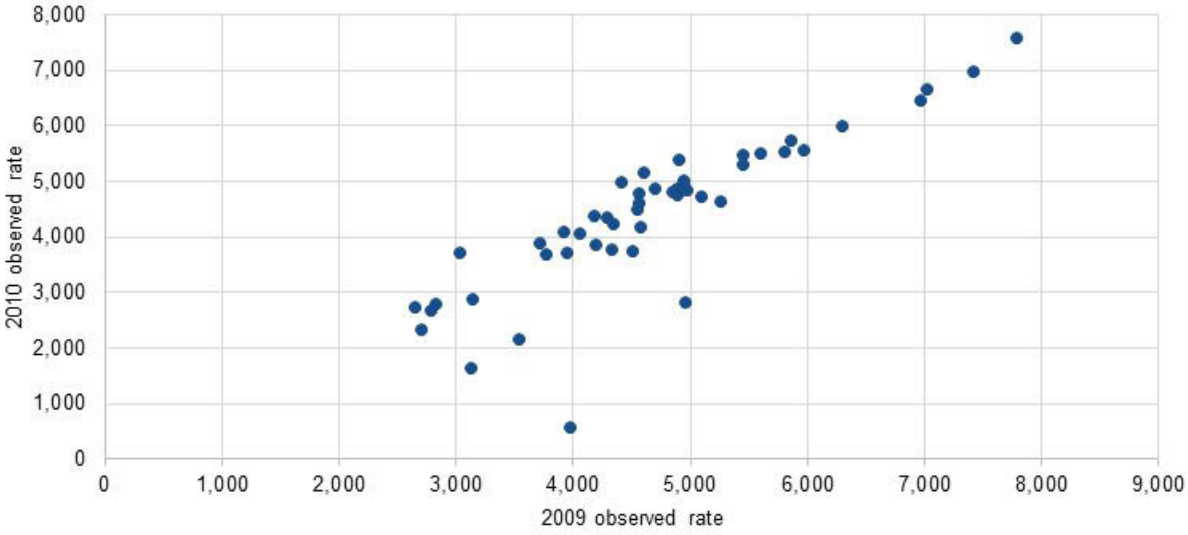
Source: Mathematica analysis of MAX 2009 PS, OT, and IP Files, MedPAR, and Medicare MBSF.

Note: The HCBS composite and component rates were calculated using the AHRQ specifications (Schultz et al. 2012) updated to version 4.4 of the PQI software. Some hospitalizations flag more than one acute or chronic ACSC event, however each hospitalization can only contribute once to the composite counts. As a result, the sum of the components exceeds the composite counts, and the proportions do not sum exactly to 1.0.

In turn, when we compare the 2009 and 2010 composite rates by state, we find that each state's observed acute and chronic rates are correlated over time (Figures V.1 and V.2). There are roughly 2.2 million unique HCBS users in 2009 and 2010, and 1.44 million (65 percent) are HCBS users in both 2009 and 2010. The fact that most users are the same in both years supports the finding that state HCBS composite rankings are correlated over time. Graphically, we can see this consistency: state rates are close in both years, which is confirmed by Spearman rank coefficients above 0.7 for each composite. The states farthest from the diagonal cluster generally have smaller HCBS populations (such as Wyoming) or unique or changing populations (such as Tennessee).

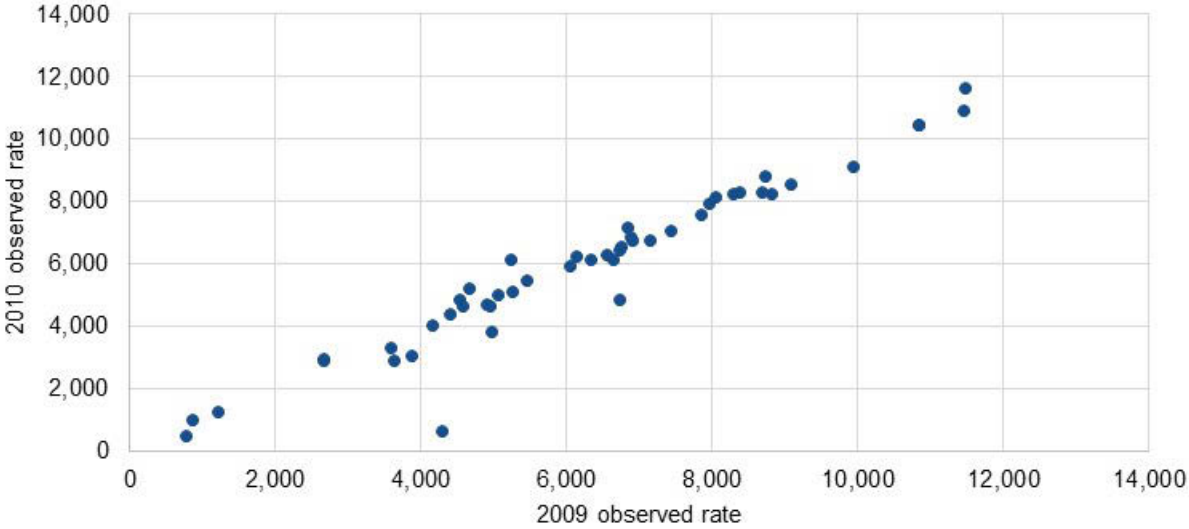
[10] It is possible for a hospitalization to be flagged as a PQI 16 (lower-extremity amputation) as well as PQI 1, 3, or 14. This discharge contributes only once to the chronic composite numerator.

## Figure V.1. State acute composite rates for 2009 and 2010 HCBS populations (per 100,000 HCBS users)




Sources: Mathematica analysis of 2009 and 2010 HCBS users. Data sources included the 2009 and 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

## Figure V.2. State chronic composite rates for 2009 and 2010 HCBS populations (per 100,000 HCBS users)




Source: Mathematica analysis of 2009 and 2010 HCBS users. Data sources included the 2009 and 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

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# VI. MODEL RESULTS

Model selection used a combination of 2009 and 2010 data, but the final coefficients and model are based on the 2010 HCBS population. Early in the process, we established the model structure. In this section we provide equations and specifications for the final model using 2010 data, as well as validation results produced through sensitivity analysis and by refitting the model on subsets of the data.

## A. Model structure

A zero-inflated negative binomial (ZINB) model was determined to have the best fit among the four models we evaluated (Poisson, negative binomial, zero-inflated Poisson, and ZINB). These models are all suitable for modeling count data, but the dispersion parameter indicated that the negative binomial model had a better fit than the Poisson model. A dispersion parameter close to one indicates that the mean and variance of the outcome distribution are similar, which would support the use of the Poisson distribution; however, our models show a dispersion parameter ranging from 2 and 5, providing support for negative binomial.

After selecting the negative binomial model, we then determined that a ZINB model also had better fit than the negative binomial model alone. Figure VI.1 shows that the AIC and BIC for the ZINB model is lower, indicating a better fit. The final models are therefore specified as ZINB.

**Table VI.1. Negative binomial and zero-inflated negative binomial model fit**

| | Acute composite | | Chronic composite | |
|---|---|---|---|---|
| Criterion | Negative binomial | Zero-inflated negative binomial | Negative binomial | Zero-inflated negative binomial |
| AIC (smaller is better) | 579,100 | 575,617 | 714,495 | 699,229 |
| BIC (smaller is better) | 579,409 | 576,224 | 714,804 | 699,835 |

Note: Results are based on models with 2009 data, adjusting for age, gender, and chronic conditions.

## B. Selecting risk factors

Risk-adjustment modeling began with a set of risk factors deemed relevant or clinically important for acute or chronic ACSC events. As recommended by the TEP, we allowed the important risk factors to vary between the acute and chronic models. Clinically important risk factors were defined as those conditions with unanimous support for inclusion from the TEP. In addition to retaining all statistically significant risk factors, we also included all clinically important risk factors regardless of their statistical significance. Two-part models such as the ZINB model allow for different risk factors in part one (the zero model) and part two (the count model), but we had no rationale to vary the risk factors, and therefore they were kept consistent.

Based on the TEP's recommendation, we fit separate models based on MME status. With two outcomes (acute and chronic ACSC events) and two subgroups (MME and Medicaid-only HCBS users), we fit a total of four models. The set of risk factors used in each model were allowed to vary by MME status and outcome (acute or chronic).

The models also incorporated age and gender flags regardless of statistical significance. Age and gender are used by AHRQ to risk adjust the original PQI measures at the population level. We used wide age groups (18–24, 25–44, 45–64,75–84, and 85+, with 65–74 as the referent), because more narrow definitions did not significantly improve model fit.

## C. Model specification

The ZINB distribution could handle a random event containing excess zero-count data. . It employs two components that correspond to two zero generating processes: (1) a logistic regression for a binary distribution that generates zeros, and (2) a negative binomial count model to predict the number of ACSC events, some of which may be zeros. When predictions from these models are combined, it produces an expected number of ACSC events per person.

**Specification of the ZINB**

Assume that $Y_{ACSC} = Y_{ACSC,1} \times Y_{ACSC,2}$, where the binary component $Y_{ACSC,1}$ and negative binomial component $Y_{ACSC,2}$ are independent and follow the following distribution.

Binary component $Y_{ACSC,1}$: $\text{Logit}(P(Y_{ACSC,1}=1 \mid X_{aj}, Z_j)) = \beta_{a1,0} + \sum_{j=1}^{n} \beta_{a1,j} X_{aj} + \sum_{j=1}^{6} \gamma_{a1,j} Z_j$ and $P(Y_{ACSC,1}=0 \mid X_{aj}, Z_j) = 1 - P(Y_{ACSC,1}=1 \mid X_{aj}, Z_j)$

Negative binomial component $Y_{ACSC,2}$: Negative binomial distribution. In particular,

$$P(Y_{ACSC,2}=k) = \binom{k+r_a-1}{k} p_a{}^k (1-p_a)^r \text{ for k=0, 1, 2, …,}$$

where $E(Y_{ACSC,2}) = \frac{p_a r_a}{1-p_a} = \beta_{a2,0} + \sum_{j=1}^{n} \beta_{a2,j} X_{aj} + \sum_{j=1}^{6} \gamma_{a2,j} Z_j$, $r_a$ is the shape parameter and $p_a / (1-p_a)$ is scale parameter for the negative binomial distribution that $Y_{ACSC,2}$ follows. Definitions of terms are as follows:

- $Y_{ACSC}$ is the count of HCBS composite events per person
- ACSC denotes the type of composite (chronic or acute)
- The subindex $\alpha$ denotes the coefficients ($\beta$ or $\gamma$) or set of risk factors (*X* or *Z*) used in acute or chronic models
- The subindex *j* denotes the index for the coefficients or set of risk factors used in acute or chronic models
- *k* denotes the positive integer values taken on by the ACSC composite

## D. Final risk factors

The final set of risk factors with coefficients and p-values are found in Appendix B. The final models include between 37 and 44 risk factors. After beginning with the original set of risk factors, we refit models twice by removing insignificant or unimportant risk factors according to our criteria. By reducing the number of risk factors in the model based on statistical significance, the final model had worse fit statistics, but the differences were not substantially large, and the resulting models are easier to work with (Table VI.2). Removing risk factors likely had little impact on fit, because most statistically insignificant factors had relatively small coefficients.

**Table VI.2. Original and final risk-adjustment model fit statistics**

| | | Medicaid-only | | MME | |
|---|---|---|---|---|---|
| Outcome | Statistic | Original | Final | Original | Final |
| Acute composite | Scaled Deviance | 93,459 | 93,731 | 493,015 | 493,348 |
| | AIC (smaller is better) | 93,641 | 93,881 | 493,197 | 493,514 |
| | BIC (smaller is better) | 94,650 | 94,713 | 494,300 | 494,520 |
| Chronic composite | Scaled Deviance | 123,737 | 123,759 | 571,562 | 571,562 |
| | AIC (smaller is better) | 123,915 | 123,917 | 571,740 | 571,740 |
| | BIC (smaller is better) | 124,901 | 124,793 | 572,819 | 572,819 |

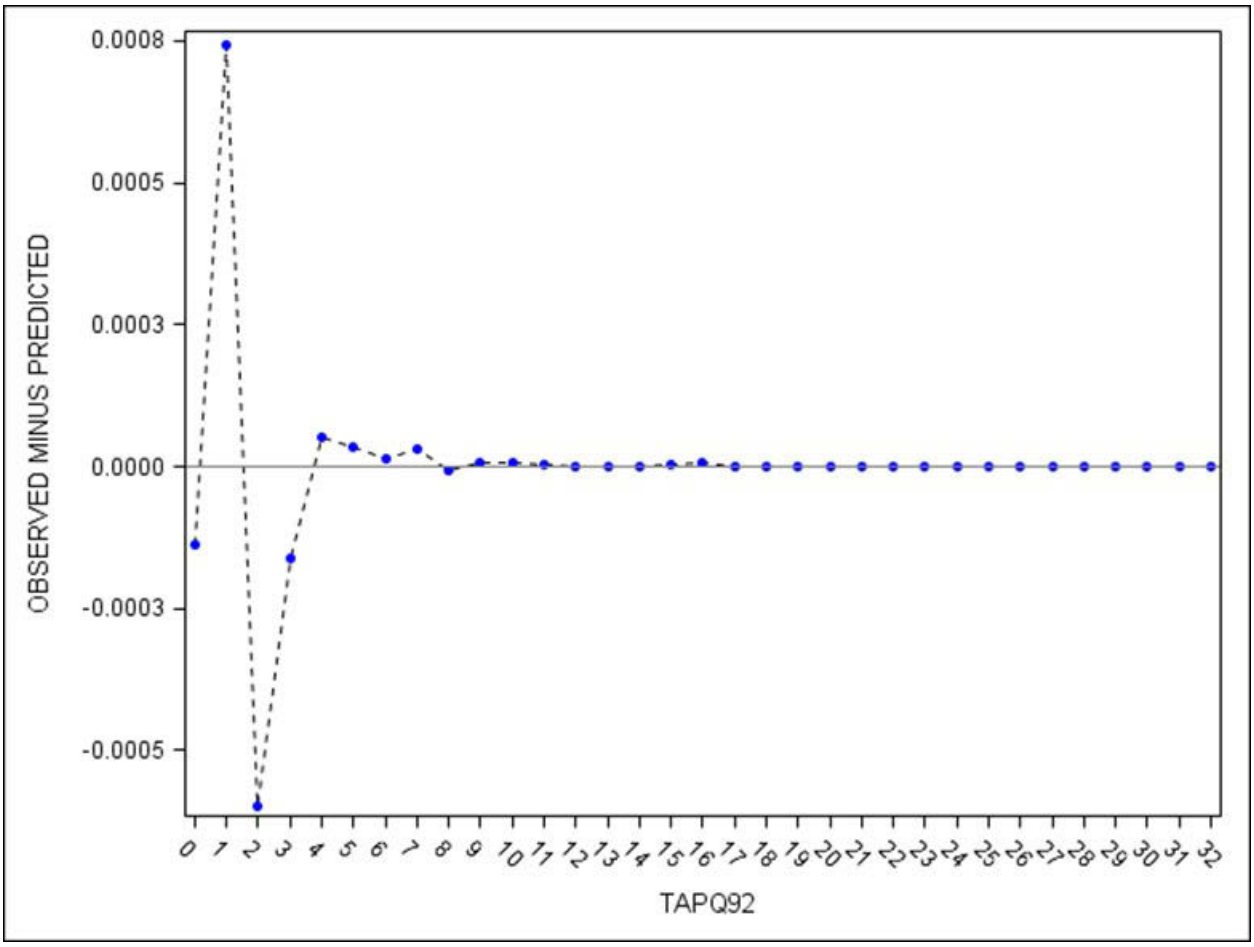
Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

Note: All results from ZINB models. Original model used all candidate risk factors, and final model used only those risk factors meeting selection criteria.

AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; MME = Medicare–Medicaid eligible

One important characteristic of the final model is that it predicts nearly the same number of observed events in the sample. This is an improvement over the models built in Phase I of this work, in which the models over-predicted events (Ross and Bohl 2013). To show how closely the model predicts the number of observed, we show the observed-to-predicted number of chronic ACSC events (Figure VI.1). The horizontal dot indicates perfect prediction, and although the dotted line does bounce above and below the horizontal line, the differences on the y-axis are very small. For all models, the observed-to-expected number of events are within 0.001.

**Figure VI.1. Observed-to-predicted chronic ACSC events among MME users**




Source: Mathematica analysis of 2010 HCBS users. Data source included the 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

Note: TAPQ92 = Chronic ACSC composite count

Two-part models such as the ZINB provide two sets of coefficents, making it difficult to understand how different risk factors are associated overall with HCBS composite risk. To ease interpretation, we calculated the joint relative risk for each risk factor by predicting the expected number of HCBS composite events for the reference population (a 65-year old male with no comorbidities) relative to a person with the risk factor (Appendix B). This joint relative risk statistic provided the following insights into the model:

- **Risk of acute and chronic ACSC events is greatest for older HCBS users.** Higher age is associated with greater risk of acute and chronic ACSC events for MME and Medicaid-only beneficiaries. However, because most Medicaid-only beneficiaries are under 65, acute and chronic ACSC risk is greatest among the 45 to 64-year old Medicaid-only beneficiaries.
- **Disability-related conditions have a strong association with higher acute ACSC risk.** Mobility impairment, spinal cord injuries, and multiple sclerosis are associated with higher risk of acute ACSC events in both the Medicaid-only and MME models.

- **Chronic conditions used in the ACSC specifications are associated with higher risk of chronic ACSC events.** Congestive heart failure, asthma, and COPD are strong predictors of the chronic composite in both the MME and Medicaid-only models. Potentially avoidable hospitalizations due to these conditions are also captured in the set of component indicators used to construct the chronic HCBS composite measure.
- **Depression and other mental health conditions had moderate or lower relative risk for acute and chronic ACSC events.** Depression was associated with moderately higher risk of acute and chronic ACSC events. In addition, when included in the model, substance abuse, alcohol abuse, and tobacco abuse were associated with moderately higher risk of acute or chronic ACSC events. On the other hand, bipolar disorders, learning disabilities, and schizophrenia were associated with lower risk for acute and chronic ACSC events.

## E. Model validation and sensitivity

When developing our model, we selected risk factors based on significance and performance on the full sample. To ensure the final set of risk factors performs well on other HCBS populations, we validated our model using multiple approaches.

### 1. Split-sample validation

We split the 2010 sample evenly and refit the ZINB model using the same risk factors to assess fit (Table VI.3). When fit on these independent samples, the likelihood-based indicators of fit showed similar performance for nearly all models. This finding gives us confidence that the final model is robust and not entirely specific to the larger sample.

**Table VI.3. Split-sample validation fit statistics**

| Outcome | Statistic | Medicaid-only | | MME | |
|---|---|---|---|---|---|
| | | Sample 1 | Sample 2 | Sample 1 | Sample 2 |
| Acute composite | Scaled deviance | 93,459 | 93,731 | 493,015 | 493,348 |
| | AIC (smaller is better) | 93,641 | 93,881 | 493,197 | 493,514 |
| | BIC (smaller is better) | 94,650 | 94,713 | 494,300 | 494,520 |
| Chronic composite | Scaled deviance | 123,737 | 123,759 | 571,562 | 571,562 |
| | AIC (smaller is better) | 123,915 | 123,917 | 571,740 | 571,740 |
| | BIC (smaller is better) | 124,901 | 124,793 | 572,819 | 572,819 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

Note: All results from ZINB models. Original model used all candidate risk factors, and final model used only those risk factors meeting selection criteria. AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; MME = Medicare–Medicaid eligible; Sample 1 and 2 = random split samples of the 2010 HCBS user population.

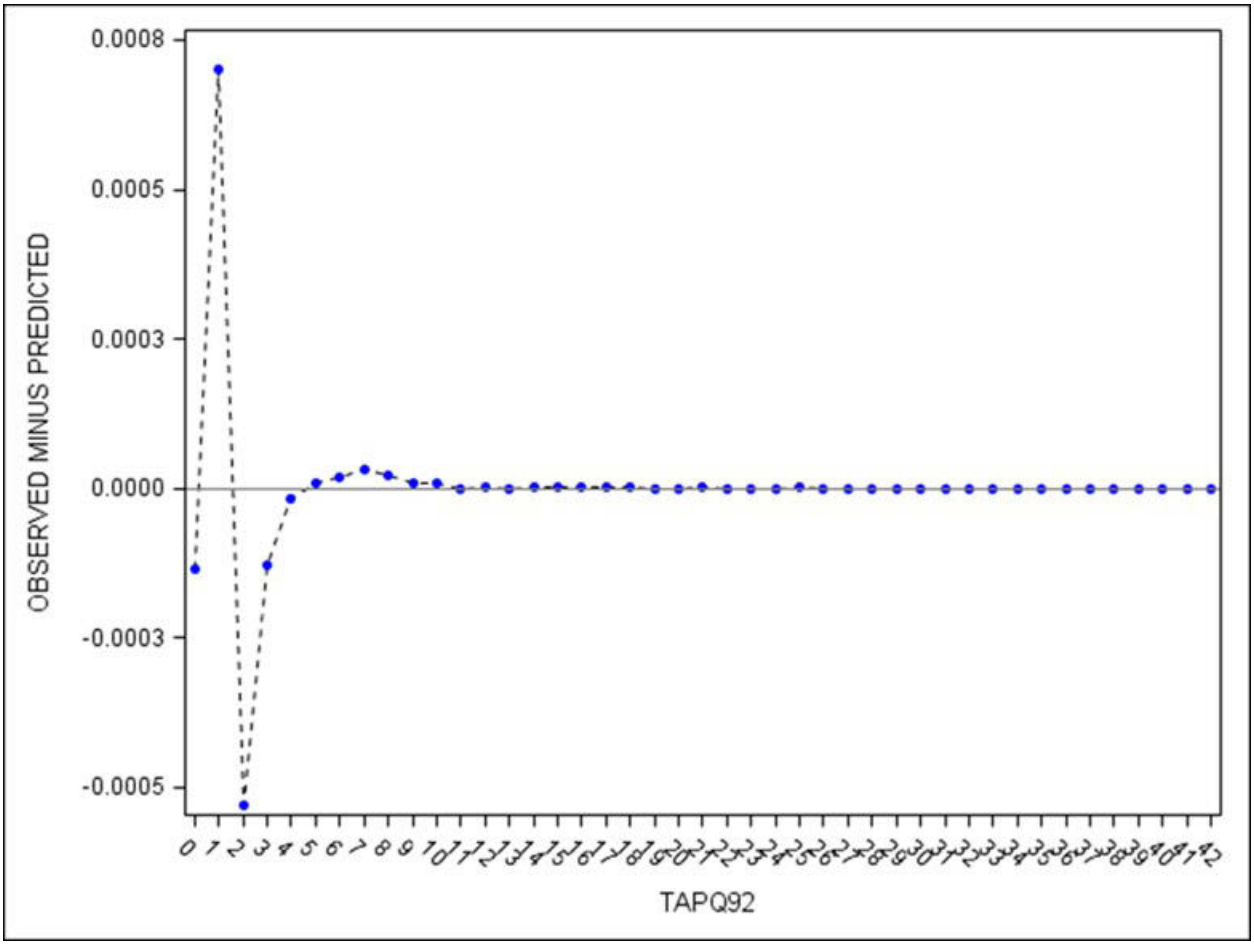
### 2. Cross-year validation

We also refit the ZINB models using the same risk factors on the 2009 HCBS user population. Although nearly two-thirds of HCBS users are in the 2009 and 2010 populations, this

test gives us a chance to validate the stability of the risk factors and model performance. As previously shown in Figures III.1 and III.2, state-level observed rates of acute and chronic composites are moderately correlated between 2009 and 2010.

As expected, we find that the 2009 model performs similarly to the 2010 model. The ZINB again closely predicts the number of observed events, with miniscule differences observed in the overall sample (Figure VI.2 uses the chronic composite for MME users as an example). In addition, the risk factors with the largest positive coefficients are very similar between 2009 and 2010. For example, spinal cord injury, mobility impairment, and multiple sclerosis have the largest coefficients in part two of the acute composite model for Medicaid-only beneficiaries in both 2009 and 2010.

**Figure VI.2. Observed-to-predicted chronic ACSC events among the 2009 MME HCBS population**




Source: Mathematica analysis of 2009 HCBS users. Data sources included the 2009 MAX PS, OT, and IP files, MedPAR file, and MBSF.

Note: TAPQ92 = Chronic ACSC composite count.

### 3. Sensitivity to time of HCBS enrollment

As we explain in Section III.B, the duration of HCBS use cannot be directly included in the model because of endogeneity. The TEP recommended that we evaluate the sensitivity of model results to persons who move in and out of HCBS in the given year ("churners"). We assessed the sensitivity of the model to these individuals by removing their information and refitting the model.

When restricting the model to persons continually using HCBS in calendar year 2010, the model fit improves substantially as evidenced by the substantially lower AIC and BIC of the model when non-continuous HCBS users are omitted. However, the magnitude and direction of risk factors are similar in both models.

We will bring these findings to the TEP for further consideration. During the initial meeting, the TEP supported including all HCBS users in the model regardless of time and continuity of use, but when reporting results, providing rates for the continuous or non-continuous subgroups.

### 4. State effects

Based on discussion with the TEP, we ultimately elected to exclude state effects from the model. The two reasons to include state effects are to account for state-level factors influencing the relationship between risk factors at ACSC events or to reliability-adjust the composite rates. Both of these reasons are compelling, and preliminary tests suggest that including state fixed-effects results in a better fit compared with models that exclude them.

Despite this conceptual and empirical rationale, we decided to exclude state effects for two reasons. First, our goal is to develop models which could be applied to subpopulations, and it is possible that the state effects vary by subpopulation. Second, we intend to reliability-adjust the HCBS composites using a two-part approach consistent with the other AHRQ quality indicators. We will bring these findings to the TEP for their final consideration.

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# VII. STATE-LEVEL HCBS COMPOSITE RESULTS

Using the finalized risk-adjustment models, we produced risk-adjusted HCBS composite rates for each state. The final risk-adjusted rates are indirectly standardized by dividing the observed number of acute or chronic events divided by the model-predicted number of events, creating an observed-to-expected rate (O/E) ratio. The process for this calculation was:

1. For each state, sum the observed number of ACSC events across MME and Medicaid-only HCBS users.
2. For each state, sum the predicted number of ACSC events across MME and Medicaid-only HCBS users.
3. For each state, divide the total number of observed and expected events calculated in steps 1 and 2 above.

Instead of transforming the O/E ratio into an indirectly-standardized rate, we can use the O/E ratio directly to assess state performance. An O/E ratio below 1.0 indicates that a state is performing better than average, and a ratio above 1.0 indicates worse-than-average performance; however, the point estimate alone is insufficient to determine whether a state's performance is statistically different from a benchmark. Assessing statistical significance of state O/E ratios is the subject of a future report.

## A. 2010 HCBS user population

Risk adjustment shifts the ranking of state acute and chronic composite performance for the 2010 HCBS user population (Table VII.1). Observed rates show substantial variation across states, but some of this variation may be due to different HCBS populations in each state. For example, New Mexico's acute composite observed rate is five times lower than the rate in Mississippi, but Mississippi's population has a generally higher level of chronic conditions compared with New Mexico's. Thus, ranking on observed rates alone may lead to inaccurate conclusions about the quality of care within the HCBS population.

Risk-adjusted HCBS composites (as depicted by O/E ratios) are highly correlated with observed rates, but some important differences emerge (Table VI.1). For example, Vermont's observed rate is 25 percent lower than the national chronic composite rate, which is 6,524 events per 100,000 HCBS users. Yet, Vermont's O/E ratio indicates that Vermont's observed performance is similar to what is expected based on its case mix. Across states, observed and expected rates were moderately correlated for the acute composite (rho = 0.74) and the chronic composite (rho = 0.85). The distribution of expected rates had similar range and shape as the observed rate distribution.

These results also show the potential relationship between outlier performance and the size of the state's HCBS population. Idaho, for example, has a small HCBS fee-for-service user population, and its results are substantially lower than the national average. Many states with smaller HCBS populations have noticeably different performance than average, which points to the potential importance of reliability adjustment to facilitate fair comparisons of the HCBS composites.

## Table VII.1. 2010 Observed and risk-adjusted HCBS composite rates, by state

| | Acute composite | | Chronic composite | |
|---|---|---|---|---|
| State | Observed rate[a] | O/E ratio | Observed rate | O/E ratio |
| National | 4,221 | 1.00 | 6,524 | 1.00 |
| Alaska | 3,705 | 0.92 | 4,981 | 0.81 |
| Alabama | 4,073 | 0.90 | 6,403 | 0.80 |
| Arkansas | 6,438 | 1.24 | 8,202 | 1.03 |
| California | 2,651 | 0.77 | 5,056 | 0.94 |
| Colorado | 3,836 | 0.90 | 3,969 | 0.67 |
| Connecticut | 5,006 | 1.13 | 6,712 | 0.99 |
| District of Columbia | 3,739 | 0.89 | 10,879 | 1.40 |
| Delaware | 5,363 | 1.23 | 5,430 | 0.88 |
| Florida | 5,151 | 1.13 | 6,102 | 1.14 |
| Georgia | 2,822 | 0.70 | 3,782 | 0.57 |
| Iowa | 4,795 | 1.10 | 5,873 | 0.84 |
| Idaho | 550 | 0.27 | 579 | 0.17 |
| Illinois | 4,606 | 1.04 | 8,481 | 1.30 |
| Indiana | 5,456 | 1.38 | 6,688 | 1.17 |
| Kentucky | 4,828 | 0.97 | 7,035 | 0.79 |
| Louisiana | 5,520 | 1.30 | 8,254 | 1.08 |
| Massachusetts | 4,747 | 1.19 | 6,223 | 1.18 |
| Maryland | 4,361 | 1.04 | 4,657 | 0.91 |
| Michigan | 4,473 | 1.00 | 9,055 | 1.13 |
| Minnesota | 2,324 | 0.75 | 3,289 | 0.77 |
| Missouri | 4,703 | 0.94 | 8,230 | 0.91 |
| Mississippi | 7,570 | 1.31 | 10,401 | 1.05 |
| Montana | 3,760 | 1.12 | 3,018 | 0.65 |
| North Carolina | 4,859 | 0.99 | 7,862 | 0.91 |
| North Dakota | 2,777 | 0.88 | 2,863 | 0.73 |
| Nebraska | 4,618 | 1.21 | 4,618 | 0.88 |
| New Hampshire | 4,976 | 1.25 | 6,167 | 1.00 |
| New Jersey | 4,343 | 0.93 | 8,084 | 1.24 |
| New Mexico | 1,625 | 0.72 | 956 | 0.60 |
| Nevada | 4,841 | 1.05 | 7,133 | 1.00 |
| New York | 4,049 | 0.93 | 6,792 | 1.07 |
| Ohio | 5,704 | 1.06 | 8,764 | 1.03 |
| Oklahoma | 6,636 | 1.13 | 10,392 | 0.86 |
| Oregon | 3,876 | 0.96 | 4,350 | 0.81 |
| Pennsylvania | 5,536 | 1.36 | 8,218 | 1.40 |
| Rhode Island | 3,709 | 0.92 | 5,152 | 0.88 |
| South Carolina | 5,967 | 1.35 | 6,079 | 0.95 |
| South Dakota | 4,175 | 1.50 | 2,840 | 0.93 |
| Tennessee | 2,137 | 1.25 | 427 | 0.70 |
| Texas | 4,974 | 1.18 | 7,508 | 1.14 |

Table VII.1 (continued)

| State | Acute composite | | Chronic composite | |
|---|---|---|---|---|
| | Observed rate[a] | O/E ratio | Observed rate | O/E ratio |
| Utah | 2,708 | 0.85 | 1,219 | 0.37 |
| Virginia | 5,476 | 0.98 | 6,114 | 0.83 |
| Vermont | 4,760 | 1.24 | 4,807 | 1.01 |
| Washington | 3,668 | 0.98 | 4,600 | 0.84 |
| Wisconsin | 2,867 | 0.86 | 2,884 | 0.67 |
| West Virginia | 6,952 | 1.52 | 11,584 | 1.28 |
| Wyoming | 5,288 | 1.35 | 4,824 | 0.84 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

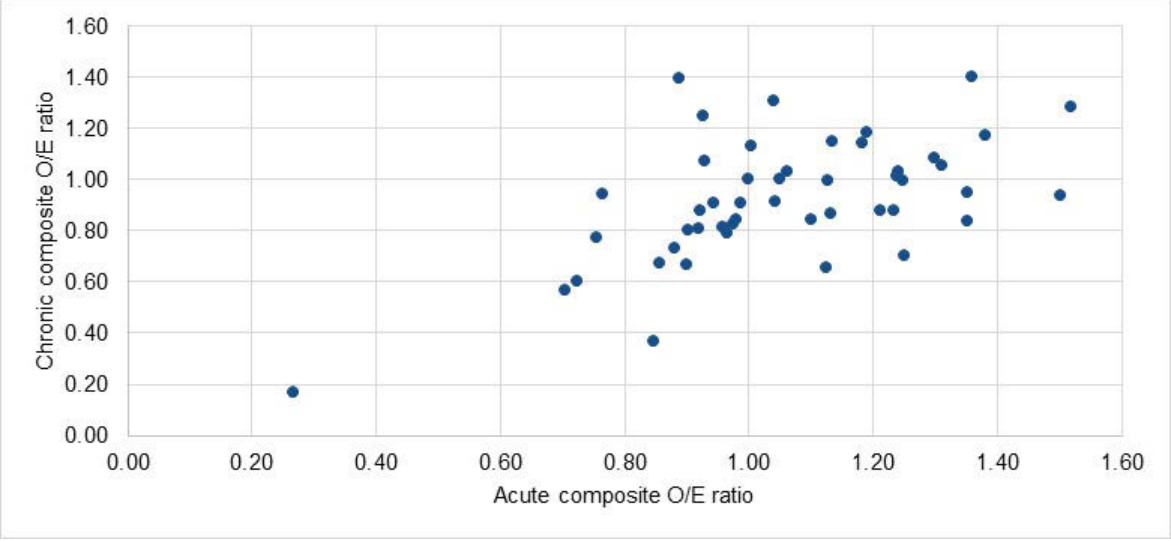
Notes: Observed rate is presented as acute or chronic ACSC events per 100,000 HCBS users. MME and Medicaid-only beneficiaries are combined for each state.

[a] This reporting of observed rates uses the number of HCBS users in the denominator, which is different from early tables. We report observed rates with this denominator because the O/E ratio does not account for months of HCBS use.

O/E ratio = observed-to-expected ratio.

The acute and chronic O/E ratios are also moderately correlated at the state level (Figure VII.1). Most of the states have similar ranking on the two composites (rho = 0.58). Among the 47 states with HCBS composite rates, approximately two-thirds (32 states) exhibit consistently higher or lower than average performance on both the acute and chronic composites. Although the composites are correlated, the acute and chronic composites provide different information on the HCBS user population's experience. Given that the acute and chronic composites convey different information, we will ask the TEP whether the combined overall composite would produce useful information, or potentially mask important variation in hospitalizations due to acute versus chronic events.

**Figure VII.1. Relationship between acute and chronic O/E ratios**




Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF.

O/E ratio = observed-to-expected rate ratio.

## B. 2009 HCBS user population

We then applied the 2010 model coefficients to the 2009 HCBS user population, which allows us to compare performance over time. Because most HCBS users are found in both the 2009 and 2010 populations, expected rates for each state are strongly correlated (acute composite, rho = 0.94, chronic composite, rho = 0.96). In addition, because disability and health status generally worsen over time, we found that expected rates are slightly lower in 2009 compared with 2010—in other words, risk is increasing over time.

Applying these models to the 2009 data yielded similar ranking of state performance in 2009 and 2010 (Table VII.2). As hypothesized, the national O/E ratio in 2009 is greater than 1.0, and because the observed rate is similar between years, the 2009 population has a lower expected rate compared with 2010. States that make large changes over time are often smaller (for example, the District of Columbia) or have implemented large changes to their Medicaid programs between 2009 and 2010 (for example, Georgia and Tennessee). The jump in rates between states further motivates reliability adjustment.

### Table VII.2. O/E ratios for 2009 and 2010 populations

| | Acute O/E ratio | | Chronic O/E ratio | |
|---|---|---|---|---|
| State | 2009 | 2010 | 2009 | 2010 |
| National | 1.17 | 1.00 | 1.00 | 1.23 |
| Alaska | 1.07 | 0.93 | 0.75 | 0.92 |
| Alabama | 0.97 | 0.91 | 0.79 | 0.99 |
| Arkansas | 1.50 | 1.24 | 1.07 | 1.29 |
| California | 0.91 | 0.77 | 0.97 | 1.19 |
| Colorado | 1.11 | 0.89 | 0.67 | 0.82 |
| Connecticut | 1.24 | 1.12 | 1.00 | 1.22 |
| District of Columbia | 1.20 | 0.87 | 1.45 | 1.80 |
| Delaware | 1.37 | 1.27 | 0.91 | 1.10 |
| Florida | 1.25 | 1.14 | 1.03 | 1.25 |
| Georgia | 1.36 | 0.68 | 0.79 | 0.97 |
| Iowa | 1.24 | 1.10 | 0.81 | 0.99 |
| Idaho | 1.14 | 0.29 | 0.70 | 0.85 |
| Illinois | 1.20 | 1.03 | 1.33 | 1.66 |
| Indiana | 1.55 | 1.40 | 1.11 | 1.36 |
| KS | 1.46 | N/A | 0.95 | 1.17 |
| Kentucky | 1.07 | 0.95 | 0.72 | 0.89 |
| Louisiana | 1.51 | 1.29 | 1.07 | 1.32 |
| Massachusetts | 1.30 | 1.18 | 1.19 | 1.46 |
| Maryland | 1.13 | 1.04 | 0.91 | 1.10 |
| Michigan | 1.15 | 1.01 | 1.19 | 1.47 |
| Minnesota | 1.01 | 0.75 | 0.78 | 0.98 |
| Missouri | 1.15 | 0.94 | 0.89 | 1.10 |
| Mississippi | 1.50 | 1.30 | 1.04 | 1.27 |
| Montana | 1.42 | 1.13 | 0.79 | 0.96 |
| North Carolina | 1.15 | 1.00 | 0.89 | 1.11 |

Table VII.2 (continued)

| State | Acute O/E ratio | | Chronic O/E ratio | |
|---|---|---|---|---|
| | 2009 | 2010 | 2009 | 2010 |
| North Dakota | 1.00 | 0.86 | 0.68 | 0.80 |
| Nebraska | 1.48 | 1.22 | 0.77 | 0.93 |
| New Hampshire | 1.22 | 1.26 | 0.90 | 1.11 |
| New Jersey | 1.03 | 0.92 | 1.22 | 1.47 |
| New Mexico | 1.53 | 0.71 | 0.38 | 0.46 |
| Nevada | 1.17 | 1.07 | 0.95 | 1.17 |
| New York | 1.07 | 0.94 | 1.07 | 1.30 |
| Ohio | 1.21 | 1.05 | 0.96 | 1.17 |
| Oklahoma | 1.37 | 1.14 | 0.86 | 1.06 |
| Oregon | 1.01 | 0.96 | 0.79 | 0.94 |
| Pennsylvania | 1.61 | 1.34 | 1.34 | 1.63 |
| Rhode Island | 0.95 | 0.91 | 0.86 | 1.05 |
| South Carolina | 1.58 | 1.36 | 0.94 | 1.14 |
| South Dakota | 1.78 | 1.52 | 1.15 | 1.37 |
| Tennessee | 1.92 | 1.12 | 0.74 | 0.99 |
| Texas | 1.33 | 1.16 | 1.13 | 1.38 |
| Utah | 0.90 | 0.83 | 0.34 | 0.41 |
| Virginia | 1.09 | 0.96 | 0.80 | 0.96 |
| Vermont | 1.32 | 1.23 | 0.91 | 1.10 |
| Washington | 1.16 | 0.98 | 0.94 | 1.14 |
| Wisconsin | 1.05 | 0.84 | 0.62 | 0.76 |
| West Virginia | 1.84 | 1.53 | 1.20 | 1.49 |
| Wyoming | 1.59 | 1.37 | 1.12 | 1.37 |

Source: Mathematica analysis of 2009 and 2010 HCBS users. Data sources included the 2009 and 2010 MAX PS, OT, and IP files, MedPAR file, and MBSF. Data are unavailable for Kansas in 2010.

O/E ratio = observed-to-expected rate ratio.

## C. MFP and non-MFP populations

Two primary subgroups of interest in this analysis are the HCBS transitioner populations: individuals leaving institutional care with the assistance of the Money Follows the Person (MFP) demonstration, and a comparison group of those who transitioned from institutional care without MFP (non-MFP). These subpopulations are generally small, making their risk-adjusted rates unstable. As a first step to risk-adjusting the HCBS composites for these populations, we tried to refit the same ZINB model applied to the 2009 and 2010 populations, but due to the complexity of the model and limited sample, the model failed to converge.

The next step for these subpopulations is to produce risk-adjusted rates using the model fit on the 2010 population. By applying the coefficients from the 2010 HCBS population, we can directly compare the HCBS composites for the transitioner populations to the broader population of HCBS users. However, because of the small number of transitioners in each state, reliability adjustment will be important for making comparisons. Thus, we do not report state-level rates for transitioner populations in this report. Volume 2 will present risk- and reliability-adjusted HCBS composite rates for the MFP and non-MFP populations.

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# VIII. DISCUSSION AND NEXT STEPS

We fit risk-adjustment models for the acute and chronic HCBS composites, using the 2010 HCBS user population as our development sample. The final models used a zero-inflated negative binomial structure to account for a large proportion of HCBS users with no events and a highly dispersed HCBS composite distribution. The final models were fit separately for MME and Medicaid-only beneficiaries, accounting for chronic health conditions, mental health conditions, mobility limitations, substance use disorders, and demographics. Using split-sample, external-sample, and subsample approaches, we validated our model to understand how sensitive our results were to the underlying data and populations. Overall, the risk-adjustment models fit well, but more guidance is needed from the TEP on how to ultimately use these models to support Medicaid-based quality improvement efforts.

Risk adjustment had a meaningful effect on state rates, with some states moving above or below average as a result of accounting for underlying case mix. In general, each state's risk-adjusted HCBS composite rate was similar in 2009 and 2010, with the largest differences occurring in smaller states where rates may be unreliable. We were unable to refit the model on the MFP and non-MFP population data because of model complexity, but even if we had done so successfully, the resulting rates would be unstable and therefore need reliability adjustment.

This report shows that risk adjustment has an impact on state HCBS composite rates, but more work is needed if these methods are to be used by states and stakeholders, namely:

**Reliability adjustment.** Although state rates represent information on all HCBS users enrolled in fee-for-service Medicaid and Medicare, some states have variable estimates because of their small populations. Reliability adjustment can reduce this variation by shrinking state rates toward the national rate. Reliability-adjusted rates are ideal for comparisons to a benchmark, but some states may not be comparable to others (discussed in detail under peer grouping below).

**Comparison framework**. HCBS composite rates are estimates subject to statistical uncertainty. Thus, when comparing rates against a benchmark, it is important to incorporate uncertainty to determine whether differences are statistically meaningful. Going beyond simple ranking, frequentist or Bayesian methods are available for comparisons.

**Setting the benchmark.** The goal of the HCBS composites is to allow states to compare their rates with a meaningful benchmark. Such benchmarks may include national rates, peer group rates, or an achievement-oriented benchmark such as the mean among the top five states. By making this comparison, states can assess their performance and determine whether intervention is needed. Our analyses revealed that some states have highly unique HCBS populations and therefore may not be comparable to others. In such cases, it may be necessary to establish benchmarks that are relevant to the state based on their HCBS population's characteristics.

**Peer grouping.** Descriptive statistics on HCBS population demographics and comorbidities identified a handful of unique states that may not be comparable to all other states. Tennessee, for example, emerged as a state where most HCBS users had intellectual disabilities, an

uncommon prevalence compared with all other states. When developing reliability-adjustment models, the comparison framework, or benchmarks, it may be necessary to create peer groups based on HCBS populations as opposed to comparing all states nationally.

**Display and use.** Quality measures are intended to assist stakeholders in making decisions on how to improve quality. The HCBS composites are useful for assessing the quality of care experienced by the HCBS population, but these tools must be carefully used to improve quality. This effort will try to draw on existing tools available to states, such as MONAHRQ.

We will continue refinement of the HCBS composite measures during our next TEP meeting to finalize how these measures are used. The TEP will discuss the issues described above and follow up on key issues from the first meeting: (1) incorporation of HCBS duration and (2) reporting rates by subgroups. As we continue the development process, we will also consider the most recent developments in the PQIs, quality measures for HCBS populations, and risk-adjustment models built for ACSC measures. The TEP will help to finalize the approach to estimation and use of HCBS composite measures through reliability adjustment, setting benchmarks, and recommending methods for comparing results. The TEP will also recommend how these measures should be used by Medicaid programs to drive quality improvement.

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# APPENDIX A

# HCBS COMPOSITE TEP MEETING 1 SUMMARY

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On March 23rd, 2015, Mathematica Policy Research (Mathematica) convened the first of two Technical Expert Panels (TEP) held on behalf of the Centers for Medicare & Medicaid Services (CMS), and the Office of the Assistant Secretary for Planning and Evaluation (ASPE) to solicit input on the development of risk- and reliability-adjustment models for three composite measures intended to measure quality of care among Medicaid beneficiaries using Home- and Community-Based Services (HCBS). The three composite measures, which act as indicators of potentially avoidable hospitalizations and are adapted from the AHRQ prevention quality indicators (PQIs), include (1) a chronic conditions composite, (2) an acute conditions composite, and (3) an overall composite that includes components from both the chronic conditions and acute conditions composites. During this TEP, Mathematica presented strategies for building risk-adjustment models of the three composite measures that account for person-level risk factors, and asked the TEP members to provide input on the following topics:

- Risk adjusting the overall composite
- Selection of risk factors
- Adjustment for past outcomes
- Accounting for changes in enrollment status

The TEP participants included Robert Applebaum, Ph.D. of Scripps Gerontology Center, Arlene Ash, Ph.D. of University of Massachusetts Medical School, Julie Bershadsky, Ph.D. of Human Services Research Institute, Peter Boling, M.D. of Virginia Commonwealth University School of Medicine, Alison Cuellar, Ph.D., M.B.A. of George Mason University, Lynda Flowers, J.D., MSN, R.N. of AARP, Sara Galantowicz, M.P.H. of Abt Associates, Teresa Johnson, M.B.A. of National Adult Day Services Association, Alice Lind, M.P.H., BSN of Washington State Health Care Authority, Abby Marquand, M.P.H. of Paraprofessional Healthcare Institute, Thomas Meehan, M.D., M.P.H. of Qualidigm, Chris Murtaugh, Ph.D., M.P.A. of Visiting Nurse Service of New York, Cheryl Phillips, M.D. of LeadingAge, Jonathan Shaw, M.D., M.S. of Stanford University, and Michael Shwartz, Ph.D., M.B.A. of Boston University.[11]

The remainder of this memo summarizes the TEP's feedback and recommendations, and concludes with immediate next steps for this measure development effort.

## A. Risk Adjusting the Overall Composite

The TEP first discussed the best method for developing a risk-adjustment model for the overall HCBS composite measure, which includes all component measures in both the acute and chronic HCBS composite measures. The options presented by Mathematica were: 1) to develop the overall HCBS measure model independently from the development of the acute and chronic models, or 2) develop the overall model by combining the acute and chronic models, without constructing an independent model. In both cases models would be developed at the person-level, and then aggregated up for state-level reporting. The first option has the advantages of

[11] Lynda Flowers, Alice Lind, Thomas Meehan, and Cheryl Phillips could not attend the teleconference, but were given the opportunity to provide feedback via email and/or separate individual calls. Their input is also included in this summary.

convenience and an expected increase in model reliability. However, the second option may be preferable because the effect of key risk factors may vary between acute and chronic events, and the first option may obscure these differences. In addition, while state-level rates for the acute and chronic measures are strongly correlated overall, there can be marked variation in a given state, and the associated policy and quality improvement implications are likely very different.

Based on the resulting discussion, most TEP members supported employing Option 2. The following points were raised for Mathematica's consideration:

- One essential aspect of a composite measure is to be able to trace it backwards to its individual components to get a better sense of its make-up. This may be lost if the overall composite is modeled independently.
- Modeling the overall composite by combining the acute and chronic composites is preferable, because the component measure events are not evenly distributed. Basing the overall composite on a combination of the acute and chronic composites would provide context, and also illuminate variation between states. For example, two states might have similar overall composite rates, but the acute and chronic components making up the overall composite may differ markedly.
- It's important to remember that the chronic composite measure actually captures acute events tied to chronic conditions; since these two types of events (acute and chronic) are so intertwined it may make sense to model the overall composite independently.
- In many states there is considerable within-state variation with regards to Activities of Daily Living (ADL) supports needed, availability of family support, and other features not typically captured in claims data. Such variation is important to factor into the models, if possible. Because only a limited subset of the HCBS population have ADL or family support data available via recent assessments (i.e., MDS or OASIS), it may be useful to validate the model's performance using assessment data for this subgroup.
- The question of whether or not to model the overall composite independently boils down to asking if it is an additive model of the acute and chronic measures.
- An argument in opposition to employing Option 2 was that building each model independently will generate models that are more specific to the individual measures they capture.

## B. Selecting Risk Factors and Stratifiers

The TEP's second topic of discussion was the selection of risk factors and stratifiers. Both risk factors and stratifiers are important to the model, because they enable comparisons across states; however their purposes differ. Risk factors are characteristics related to the probability of having an acute or chronic event. In contrast, stratifying variables serve to distinguish subgroups that are unique from the overall population for reasons such as health needs, eligibility for certain programs, or relationship between risk factors and acute or chronic events (i.e. an effect modifier or interaction term).

## Risk Factors

Mathematica presented two options for selecting risk factors: 1) to use a uniform set of risk factors for all three composites, or 2) to allow risk factors to vary between the different composites. In addition, the presentation highlighted that there is no established convention for determining which risk factors to include in models such as these. For example, some similar models will include all risk factors with clinical rational, while others will include only risk factors that improve model fit or are significant. To guide the conversation, two specific questions were posed:

1. Are there any strong concerns with using different risk factors for the acute and chronic composites?
2. Are there concerns about the approach (retain statistically or clinically significant risk factors unless multicollinearity issues arise, or coefficients are both large and opposite of the expected direction) to selecting risk factors?

In general, the expert panel agreed that the criteria for selecting risk factors to include in the models should depend on both statistical and clinical significance. They provided the following suggestions and reasoning for blending clinical and statistical rational:

- One way to blend statistical and clinical relevance when selecting risk factors would be to retain statistically significant factors, but also include risk factors with higher p values than would usually be included in cases where there is a very strong clinical rational for inclusion. Or in other words, one could base the threshold for significance of risk factors off their clinical rational for inclusion.
- Due to the large sample size being used to create the models it is likely that almost all risk factors will look statistically significant, thus clinical significance should play a large role in selecting risk factors for inclusion in the model.
- One of the limitations of basing the model on claims data is that risk factors that are theoretically significant may not always effect the model as expected due to the coding of claims data. Choosing risk factors based on both clinical and statistical significance allows one to disregard unexpected behavior and thus create a more accurate model.

## Stratification

Mathematica proposed two subgroups of interest on which to stratify: dual eligible, and transitioner (for instance, people participating in the Money Follows the Person demonstration) populations. Mathematica asked if the panel had any concerns with stratifying on these two populations; if they represent the most important subgroups of interest; and if any other subgroups should be considered based on identifiers such as enrollment in or use of services through a specific 1915(c) waiver,[12] chronic conditions, disability-related conditions, behaviors, demographics, or duration of HCBS use.

[12] 1915(c) waivers used in this work include: aged/disabled, aged only, disabled only, traumatic brain injury, HIV/AIDS, intellectual disability/developmentally disabled, mental illness, technologically dependent, unspecified waiver, or autism.

Several experts held the opinion that stratification depends on data availability, and cannot be decided upon until the model is run and compared on potential subgroups of interest. In addition, one person raised the point that selecting strata depends largely on the end goal and intended audience of the measure. Several experts cautioned against over-adjusting the model and thus masking state effects by employing both risk-adjustment and stratification. Despite these concerns, experts largely agreed that stratification on dual eligibility was appropriate. Reasons included the following:

- Dual and non-dual populations are fundamentally and vastly different; thus a rate based on the two together is not as meaningful as rates specific to each group.
- The availability of comorbidity information from Medicare claims for the dual eligible population may help improve model fit under a stratified approach. Medicare data are generally more standardized and complete than Medicaid data, where standardization and completion varies by state.

After considering characteristics on which to stratify in addition to dual eligibility, it was clear that some panel members believed stratification based on waiver status would be detrimental to the measure. Key points to these arguments were:

- Using waiver status as a stratifier would "muddy" the measures, because of the vast between-state differences in waiver availability and waiver eligibility criteria.
- Comorbidities are typically not well captured by waiver enrollment, and thus would be missed if waiver status was used as a stratifier. However, using waiver information as a stratifier would be an effective way to identify the Intellectual/Developmental Disability (IDD) population, which is not always well identified in claims data.
- Several TEP members suggested stratifying for populations under and over age 65, and comparing those results to results stratified on dual eligibility. In general, a lot of dual eligibles are under 65 (for example, people with long-term disabilities, or intellectual disabilities), while non-dual eligibles tend to be under 65. Thus stratifying based on age could be a way to stratify for dual eligibility independently of waiver status.

## C. Adjustment for Past Outcomes

In 2013, an Expert Workgroup was asked whether or not past outcomes (i.e., potentially preventable hospitalizations) should be included in the models. The group provided mixed feedback on this topic, noting that while past outcomes are a strongly predictive of current outcomes, adjusting for them could potentially adjust-away poor quality of care. This is supported by preliminary Mathematica analyses which show that past outcomes are highly significant predictors of current outcomes and can improve model fit (evidenced by lower Akaike and Bayesian information criteria), and affect coefficients of comorbidity and demographic risk factors. However, inclusion of past outcomes is resource intensive and introduces new challenges. For instance, historical data is not always available for HCBS users that are newly Medicaid or Medicare eligible, and availability of data varies greatly by state. In addition, past outcomes did not necessarily occur during HCBS enrollment.

The majority of TEP members agreed that because the end goal of these measures is state-to-state comparisons, and not comparison within a state over time, past outcomes should not be included in the adjusted models.

## D. Accounting for Changes in Enrollment Status

The final topic of discussion addressed challenges associated with the dynamic nature of the HCBS population. Two challenges were outlined. First, HCBS use is both endogenous and exogenous with the measured outcomes. On one hand, longer HCBS use increases the chances of observing an acute or chronic event, but on the other hand, an acute or chronic event can lead to death or transition to institutional long-term care or rehab and reduce future HCBS use. Second, HCBS use varies by state and is not always continuous; average months of HCBS enrollment by state range from 7.6 months in North Dakota to 11.1 months in New Mexico. Moreover, roughly 90 percent of HCBS users have continuous use, but states have different proportions of institutional care use before, during, or after HCBS.

Mathematica outlined the three most promising options for accounting for HCBS enrollment and use:

1. Modify the denominator with a minimum enrollment exclusion
2. Create stratum based on time of enrollment, and recent institutional care use
3. Consider only hospitalizations that occurred during HCBS use

Overall, experts agreed that the measure will need to be adjusted for length of HCBS enrollment, because the population of individuals enrolled in HCBS for only a few months is fundamentally different from the population of long-term HCBS users. A few experts raised concerns with adjusting based on length of HCBS enrollment—they worried that it would obscure quality of care issues in states with high levels of movement in and out of HCBS. A measure unadjusted for movement in and out of HCBS could highlight states in which this is a problem, and since the goal of the measure is state-to-state comparison it may be advantageous to highlight when this is occurring. The high level of movement is something states can address with policy changes. The discussion included the follow rationales:

- Estimated measure outcomes for individuals with only one month of HCBS enrollment is particularly noisy.
- People who are enrolled in HCBS for very short time spans are typically in times of crisis, and thus have very different needs than people who have been enrolled long-term.
- A clinical expert added the point that more and more often he sees HCBS recipients admitted to hospitals in a state of crisis, because their family can no longer handle their care needs. These people often end up institutionalized after their hospital stay.
- Medical needs are not the only cause of movement in and out of HCBS. Incorrect or missing paper work, for example, can cause disenrollment.

Suggestions for adjusting the measure included:

- Keep individuals with only one-month of HCBS enrollment in the denominator of the measure, but only include claims in the numerator occurring after one month of enrollment. For example, if someone enrolls in June, only include claims from July in the numerator. Similarly, include any claims occurring within one month of disenrollment from HCBS in the numerator. So, for instance, if someone were to disenroll in July, include that person's claims through August.
- Run parallel analyses for different categories of HCBS utilization. One category could be what TEP members referred to as "in-and-out" or "churning" HCBS users, and another would be long-term HCBS users. Afterwards, compare the two analyses to see if the differences warrant stratification based on length of enrollment.
- Mathematica noted that one option is to change the measure calculation to be quarter based, instead of year based. A lot of experts were receptive to this idea and felt that it would improve the measure.

## E. Next Steps for Measure Development

Based on the TEP's feedback, Mathematica, CMS and ASPE anticipate taking the following next steps in the risk-adjustment modeling process:

- Developing the overall composite model by combining the chronic and acute composite models
- Selecting risk factors based on both clinical and statistical significance
- Acknowledging the lack of information on ADLs and family support available for risk-adjustment, and considering how to validate risk-adjustment by comparing the claims-based risk factors with assessment data (for example, MDS or OASIS) available for certain subpopulations (for example, MFP transitioners)
- Stratifying results by Dual eligibility status at a minimum, and exploring the potential for stratifying by age 65+, IDD waiver enrollment, and transitioner status
- Evaluating model sensitivity to HCBS "churning" by evaluating model results for HCBS users with: 1) continuous HCBS use or enrollment; or 2) only 1-3 months of continuous HCBS use or enrollment
- Considering numerator or denominator restrictions based on a minimum of 2 months of HCBS use or enrollment
- Exploring whether producing results by quarter, rather than by year, will address the issues of non-continuous HCBS use and enrollment

# APPENDIX B

# MODEL COEFFICIENTS AND P-VALUES

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## Table B.1. Acute composite Medicaid-only model coefficients and P-values

| Risk Factor | Part I: Zero-Inflated | | Part II: Count | | Joint Relative Risk |
|---|---|---|---|---|---|
| | Coefficient | P-Value | Coefficient | P-Value | |
| Female | 0.18 | 0.04 | 0.16 | 0.00 | 1.01 |
| Ages 18 to 24 | 0.68 | 0.00 | 0.35 | 0.00 | 0.80 |
| Ages 25 to 44 | 0.21 | 0.30 | 0.23 | 0.01 | 1.07 |
| Ages 45 to 64 | -1.45 | 0.00 | 0.04 | 0.60 | 2.63 |
| Ages 75 to 84 | -0.75 | 0.02 | -0.19 | 0.10 | 1.42 |
| Age 85 and older | -0.14 | 0.69 | -0.05 | 0.72 | 1.06 |
| Alcohol Use | -0.58 | 0.01 | -0.10 | 0.07 | 1.40 |
| Alzheimer's Disease and Related Disorders or Senile Dementia | -0.94 | 0.00 | 0.08 | 0.14 | 2.08 |
| Anxiety disorders | -0.35 | 0.01 | 0.01 | 0.75 | 1.32 |
| Asthma | -0.53 | 0.00 | 0.27 | 0.00 | 1.94 |
| Bipolar disorder | 0.33 | 0.04 | 0.09 | 0.11 | 0.84 |
| Breast Cancer | -1.42 | 0.03 | 0.14 | 0.12 | 2.88 |
| Cystic fibrosis and other metabolic developmental disorders | -1.20 | 0.03 | 0.16 | 0.19 | 2.63 |
| Congestive Heart Failure | -3.08 | 0.01 | 0.20 | 0.00 | 4.95 |
| Chronic Kidney Disease | -1.50 | 0.00 | 0.50 | 0.00 | 4.27 |
| Chronic Obstructive Pulmonary Disease and Bronchiectasis | -0.94 | 0.00 | 0.49 | 0.00 | 3.15 |
| Cerebral palsy | -0.94 | 0.00 | 0.29 | 0.00 | 2.58 |
| Sensory: deafness and hearing impairment | -0.53 | 0.03 | -0.06 | 0.45 | 1.40 |
| Depression | 0.17 | 0.18 | 0.21 | 0.00 | 1.08 |
| Diabetes | -0.62 | 0.00 | 0.00 | 0.90 | 1.58 |
| Epilepsy | -0.42 | 0.00 | 0.07 | 0.12 | 1.47 |
| Hip/Pelvis Fracture | -2.32 | 0.22 | -0.18 | 0.17 | 2.90 |
| Benign prostatic hyperplasia | -1.21 | 0.15 | -0.09 | 0.31 | 1.32 |
| Hypertension | -0.44 | 0.00 | -0.05 | 0.14 | 1.22 |
| Intellectual disabilities and related conditions | -0.05 | 0.67 | 0.16 | 0.01 | 4.37 |
| Mobility impairments | -1.38 | 0.00 | 0.58 | 0.00 | 4.61 |
| Multiple sclerosis and transverse myelitis | -1.62 | 0.00 | 0.52 | 0.00 | 1.51 |
| Other developmental delays | -0.94 | 0.00 | -0.24 | 0.06 | 1.32 |
| Post-traumatic stress disorders | -0.10 | 0.78 | -0.11 | 0.35 | 0.97 |
| Schizophrenia and other psychotic disorders | 0.44 | 0.00 | -0.10 | 0.05 | 0.63 |
| Spinal cord injuries | -1.89 | 0.00 | 1.05 | 0.00 | 8.67 |
| Spina bifida and other congenital abnormalities of the nervous system | -0.94 | 0.00 | 0.50 | 0.00 | 3.17 |
| Stroke/Transient Ischemic Attack | -1.19 | 0.00 | -0.12 | 0.01 | 1.97 |
| Substance abuse | 0.23 | 0.22 | 0.29 | 0.00 | 1.12 |
| Traumatic brain injury and nonpsychotic mental disorders due to brain damage | -0.38 | 0.49 | -0.24 | 0.05 | 1.05 |
| Tobacco use disorders | -0.69 | 0.00 | 0.05 | 0.18 | 1.74 |
| Intercept | 1.32 | 0.00 | -3.88 | 0.00 | 1.0 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, MBSF, and CCW flags.

Note: Joint Relative Risk compares the predicted number of ACSC events for a 65 to 75-year old male with vs. without the risk factor using part I and part II of the model. Numbers above 1.0 indicate greater risk associated with a risk factor.

## Table B.2. Acute composite MME model coefficients and P-values

| Risk Factor | Part I: Zero-Inflated | | Part II: Count | | Joint Relative Risk |
|---|---|---|---|---|---|
| | Coefficient | P-Value | Coefficient | P-Value | |
| Female | -0.01 | 0.74 | 0.16 | 0.00 | 1.00 |
| Ages 18 to 24 | 1.90 | 0.00 | 0.18 | 0.20 | 1.18 |
| Ages 25 to 44 | 1.61 | 0.00 | 0.16 | 0.00 | 0.26 |
| Ages 45 to 64 | 0.36 | 0.00 | -0.19 | 0.00 | 0.33 |
| Ages 75 to 84 | -0.50 | 0.00 | 0.13 | 0.00 | 0.65 |
| Age 85 and older | -1.72 | 0.00 | 0.22 | 0.00 | 1.53 |
| Conduct disorders and hyperkinetic syndrome | 0.36 | 0.00 | 0.01 | 0.88 | 0.79 |
| Alcohol Use | -0.08 | 0.51 | -0.16 | 0.00 | 0.90 |
| Alzheimer's Disease and Related Disorders or Senile Dementia | -0.64 | 0.00 | 0.16 | 0.00 | 1.69 |
| Anxiety disorders | -0.11 | 0.08 | 0.13 | 0.00 | 1.22 |
| Autism spectrum disorders | 0.24 | 0.29 | 0.15 | 0.35 | 0.99 |
| Asthma | -0.55 | 0.00 | 0.07 | 0.00 | 1.48 |
| Bipolar disorder | -0.08 | 0.30 | 0.05 | 0.10 | 1.11 |
| Sensory: blindness and visual impairment | 0.07 | 0.51 | 0.13 | 0.00 | 1.09 |
| Breast Cancer | -0.36 | 0.02 | 0.04 | 0.36 | 1.29 |
| Cystic fibrosis and other metabolic developmental disorders | -0.61 | 0.05 | 0.09 | 0.32 | 1.54 |
| Congestive Heart Failure | -0.62 | 0.00 | 0.15 | 0.00 | 1.65 |
| Chronic Kidney Disease | -0.41 | 0.00 | 0.13 | 0.00 | 1.45 |
| Chronic Obstructive Pulmonary Disease and Bronchiectasis | -1.21 | 0.00 | 0.34 | 0.00 | 2.54 |
| Cerebral palsy | -0.39 | 0.00 | 0.36 | 0.00 | 1.80 |
| Colorectal cancer | -1.11 | 0.00 | 0.04 | 0.38 | 1.83 |
| Depression | -0.19 | 0.00 | 0.20 | 0.00 | 1.38 |
| Diabetes | -0.27 | 0.00 | 0.06 | 0.00 | 1.26 |
| Endometrial Cancer | -0.71 | 0.15 | 0.10 | 0.37 | 1.64 |
| Epilepsy | -0.47 | 0.00 | 0.10 | 0.00 | 1.45 |
| Hip/Pelvis Fracture | -0.97 | 0.00 | -0.03 | 0.37 | 1.61 |
| Benign prostatic hyperplasia | 0.06 | 0.61 | 0.19 | 0.00 | 1.17 |
| Hypertension | 0.17 | 0.00 | 0.06 | 0.00 | 0.96 |
| Intellectual disabilities and related conditions | -0.30 | 0.00 | 0.26 | 0.00 | 1.55 |
| Learning disabilities | 0.33 | 0.21 | 0.06 | 0.70 | 0.85 |
| Mobility impairments | -1.40 | 0.00 | 0.17 | 0.00 | 2.30 |
| Multiple sclerosis and transverse myelitis | -1.12 | 0.00 | 0.63 | 0.00 | 3.30 |
| Personality disorders | -0.13 | 0.39 | -0.20 | 0.00 | 0.89 |
| Post-traumatic stress disorders | 0.25 | 0.20 | -0.13 | 0.13 | 0.74 |
| Schizophrenia and other psychotic disorders | 0.08 | 0.19 | 0.10 | 0.00 | 1.05 |
| Spinal cord injuries | -1.08 | 0.00 | 0.85 | 0.00 | 4.06 |
| Spina bifida and other congenital abnormalities of the nervous system | -0.68 | 0.00 | 0.31 | 0.00 | 1.99 |
| Stroke/Transient Ischemic Attack | -0.52 | 0.00 | 0.08 | 0.00 | 1.46 |
| Substance abuse | -0.14 | 0.15 | 0.22 | 0.00 | 1.36 |
| Tobacco use | -0.11 | 0.12 | 0.04 | 0.07 | 1.12 |
| Intercept | 0.57 | 0.00 | -3.05 | 0.00 | 1.00 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, MBSF, and CCW flags.

Note: Joint Relative Risk compares the predicted number of ACSC events for a 65- to 75-year old male with vs. without the risk factor using part I and part II of the model. Numbers above 1.0 indicate greater risk associated with a risk factor.

## Table B.3. Chronic composite Medicaid-only model coefficients and P-values

| Risk Factor | Part I: Zero-Inflated | | Part II: Count | | Joint Relative Risk |
|---|---|---|---|---|---|
| | Coefficient | P-Value | Coefficient | P-Value | |
| Female | -0.10 | 0.06 | -0.03 | 0.38 | 1.26 |
| Ages 18 to 24 | 1.87 | 0.00 | 1.40 | 0.00 | 0.26 |
| Ages 25 to 44 | 0.57 | 0.00 | 0.67 | 0.00 | 0.40 |
| Ages 45 to 64 | -0.61 | 0.00 | 0.26 | 0.00 | 0.72 |
| Ages 75 to 84 | -0.07 | 0.76 | -0.33 | 0.01 | 1.26 |
| Age 85 and older | -0.03 | 0.94 | -0.48 | 0.01 | 1.80 |
| Conduct disorders and hyperkinetic syndrome | -0.07 | 0.72 | -0.24 | 0.09 | 0.84 |
| Atrial Fibrillation | -0.56 | 0.00 | 0.11 | 0.02 | 1.89 |
| Alzheimer's Disease and Related Disorders or Senile Dementia | 0.27 | 0.02 | -0.10 | 0.09 | 0.70 |
| Acute Myocardial Infarction | -0.70 | 0.00 | 0.23 | 0.00 | 2.40 |
| Anxiety disorders | 0.01 | 0.88 | 0.16 | 0.00 | 1.16 |
| Asthma | -1.02 | 0.00 | 0.37 | 0.00 | 3.63 |
| Bipolar disorder | 0.17 | 0.08 | -0.06 | 0.27 | 0.80 |
| Cystic fibrosis and other metabolic developmental disorders | 0.40 | 0.15 | 0.06 | 0.69 | 0.72 |
| Congestive Heart Failure | -0.96 | 0.00 | 0.47 | 0.00 | 3.82 |
| Chronic Kidney Disease | -0.92 | 0.00 | 0.27 | 0.00 | 3.05 |
| Chronic Obstructive Pulmonary Disease and Bronchiectasis | -1.03 | 0.00 | 0.37 | 0.00 | 3.68 |
| Cerebral palsy | 0.55 | 0.01 | -0.26 | 0.15 | 0.45 |
| Sensory: deafness and hearing impairment | 0.11 | 0.50 | -0.35 | 0.00 | 0.63 |
| Depression | -0.02 | 0.72 | 0.05 | 0.12 | 1.08 |
| Diabetes | -1.53 | 0.00 | 0.03 | 0.37 | 3.97 |
| Epilepsy | 0.38 | 0.00 | 0.03 | 0.52 | 0.72 |
| Hip/Pelvis Fracture | 0.24 | 0.43 | -0.01 | 0.95 | 0.79 |
| Hypertension | -0.31 | 0.00 | -0.01 | 0.82 | 1.32 |
| Intellectual disabilities and related conditions | 0.42 | 0.00 | -0.27 | 0.00 | 0.51 |
| Ischemic Heart Disease | -0.12 | 0.08 | 0.26 | 0.00 | 1.45 |
| Learning disabilities | -0.14 | 0.75 | -0.42 | 0.25 | 0.75 |
| Muscular dystrophy | -1.27 | 0.00 | -0.96 | 0.00 | 1.20 |
| Mobility impairments | -0.01 | 0.91 | -0.13 | 0.02 | 0.89 |
| Multiple sclerosis and transverse myelitis | 0.57 | 0.02 | -0.25 | 0.09 | 0.45 |
| Personality disorders | 0.29 | 0.10 | 0.17 | 0.09 | 0.90 |
| Post-traumatic stress disorders | 0.50 | 0.02 | -0.12 | 0.35 | 0.55 |
| Schizophrenia and other psychotic disorders | 0.31 | 0.00 | -0.12 | 0.01 | 0.66 |
| Spinal cord injuries | 0.34 | 0.29 | -0.45 | 0.03 | 0.46 |
| Spina bifida and other congenital abnormalities of the nervous system | -0.25 | 0.40 | -0.44 | 0.03 | 0.81 |
| Stroke/Transient Ischemic Attack | 0.02 | 0.85 | -0.04 | 0.39 | 0.94 |
| Substance abuse | -0.15 | 0.05 | 0.36 | 0.00 | 1.65 |
| Tobacco use | -0.42 | 0.00 | 0.20 | 0.00 | 1.81 |
| Intercept | 2.82 | 0.00 | -2.54 | 0.00 | 1.0 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, MBSF, and CCW flags.

Note: Joint Relative Risk compares the predicted number of ACSC events for a 65 to 75-year old male with vs. without the risk factor using part I and part II of the model. Numbers above 1.0 indicate greater risk associated with a risk factor.

## Table B.4. Chronic composite MME model coefficients and P-values

| Risk Factor | Part I: Zero-Inflated | | Part II: Count | | Joint Relative Risk |
|---|---|---|---|---|---|
| | Coefficient | P-Value | Coefficient | P-Value | |
| Female | -0.24 | 0.00 | 0.03 | 0.02 | 1.26 |
| Ages 18 to 24 | 2.60 | 0.00 | 1.12 | 0.00 | 0.26 |
| Ages 25 to 44 | 1.62 | 0.00 | 0.60 | 0.00 | 0.40 |
| Ages 45 to 64 | 0.44 | 0.00 | 0.06 | 0.00 | 0.72 |
| Ages 75 to 84 | -0.42 | 0.00 | -0.12 | 0.00 | 1.26 |
| Age 85 and older | -1.09 | 0.00 | -0.26 | 0.00 | 1.80 |
| Conduct disorders and hyperkinetic syndrome | 0.15 | 0.26 | -0.07 | 0.44 | 0.82 |
| Atrial Fibrillation | -0.50 | 0.00 | 0.14 | 0.00 | 1.75 |
| Alcohol Use | 0.03 | 0.67 | 0.08 | 0.01 | 1.06 |
| Alzheimer's Disease and Related Disorders or Senile Dementia | 0.27 | 0.00 | -0.16 | 0.00 | 0.68 |
| Acute Myocardial Infarction | -0.33 | 0.00 | 0.14 | 0.00 | 1.51 |
| Anxiety disorders | 0.12 | 0.00 | 0.25 | 0.00 | 1.15 |
| Autism spectrum disorders | 0.71 | 0.01 | 0.27 | 0.27 | 0.69 |
| Asthma | -0.82 | 0.00 | 0.32 | 0.00 | 2.65 |
| Bipolar disorder | 0.01 | 0.87 | -0.09 | 0.00 | 0.91 |
| Sensory: blindness and visual impairment | -0.37 | 0.00 | 0.04 | 0.11 | 1.43 |
| Cystic fibrosis and other metabolic developmental disorders | 0.05 | 0.83 | -0.06 | 0.50 | 0.90 |
| Congestive Heart Failure | -0.83 | 0.00 | 0.55 | 0.00 | 3.40 |
| Chronic Kidney Disease | -1.28 | 0.00 | 0.13 | 0.00 | 3.01 |
| Chronic Obstructive Pulmonary Disease and Bronchiectasis | -1.54 | 0.00 | 0.31 | 0.00 | 4.25 |
| Cerebral palsy | 0.41 | 0.01 | -0.35 | 0.00 | 0.49 |
| Sensory: deafness and hearing impairment | 0.36 | 0.00 | -0.10 | 0.00 | 0.66 |
| Depression | -0.09 | 0.02 | 0.01 | 0.32 | 1.10 |
| Diabetes | -1.18 | 0.00 | 0.12 | 0.00 | 2.80 |
| Epilepsy | 0.20 | 0.00 | 0.02 | 0.57 | 0.85 |
| Hip/Pelvis Fracture | 0.00 | 0.98 | -0.20 | 0.00 | 0.81 |
| Hypertension | 0.02 | 0.54 | -0.02 | 0.28 | 0.96 |
| Intellectual disabilities and related conditions | 0.46 | 0.00 | -0.22 | 0.00 | 0.53 |
| Ischemic Heart Disease | -0.13 | 0.00 | 0.24 | 0.00 | 1.41 |
| Learning disabilities | 0.50 | 0.11 | 0.18 | 0.43 | 0.77 |
| Muscular dystrophy | -1.01 | 0.00 | -0.56 | 0.00 | 1.27 |
| Mobility impairments | 0.05 | 0.34 | -0.10 | 0.00 | 0.86 |
| Multiple sclerosis and transverse myelitis | 0.37 | 0.01 | -0.42 | 0.00 | 0.48 |
| Other developmental delays | 0.51 | 0.00 | 0.14 | 0.29 | 0.73 |
| Personality disorders | 0.13 | 0.27 | -0.07 | 0.24 | 0.83 |
| Post-traumatic stress disorders | -0.08 | 0.62 | -0.37 | 0.00 | 0.74 |
| Schizophrenia and other psychotic disorders | 0.19 | 0.00 | -0.13 | 0.00 | 0.74 |
| Spinal cord injuries | 0.00 | 0.98 | -0.39 | 0.00 | 0.68 |
| Spina bifida and other congenital abnormalities of the nervous system | 0.10 | 0.67 | -0.27 | 0.05 | 0.70 |
| Stroke/Transient Ischemic Attack | -0.17 | 0.00 | -0.06 | 0.00 | 1.08 |
| Substance abuse | -0.21 | 0.00 | 0.14 | 0.00 | 1.38 |
| Traumatic brain injury and nonpsychotic mental disorders due to brain damage | 0.13 | 0.40 | -0.15 | 0.06 | 0.77 |
| Tobacco use | -0.34 | 0.00 | 0.28 | 0.00 | 1.77 |
| Intercept | 1.83 | 0.00 | -2.29 | 0.00 | 1.0 |

Source: Mathematica analysis of 2010 HCBS users. Data sources included the 2010 MAX PS, OT, and IP files, MedPAR file, MBSF, and CCW flags.

Note: Joint Relative Risk compares the predicted number of ACSC events for a 65 to 75-year old male with vs. without the risk factor using part I and part II of the model. Numbers above 1.0 indicate greater risk associated with a risk factor.

# APPENDIX C

# CHRONIC CONDITIONS WAREHOUSE INDICATORS

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We applied the Chronic Conditions Warehouse (CCW) algorithms for chronic conditions, disability-related conditions, mental health conditions, and substance use disorders in Tables C.1 through C.3 below. With the exception of the substance use disorders, these CCW algorithms were taken from the CCW website (www.ccwdata.org) on September 2014. The substance use algorithms were provided by CMS, and reflect public comments on the proposed definitions for these conditions published in April 2014. The CCW algorithms were developed for use with Medicare and Medicaid administrative data using International Classification of Disease, 9th revision, Clinical Modification (ICD-9) codes. Each CCW indicator has a look-back period and rules specifying the number and types of claims and ICD-9 codes that indicate a condition. Future analysis using ICD-10 data will need to apply a revised set of definitions. In our work, we identify HCBS users who met each CCW indicator definition at any point before the beginning of the calendar year, or for the transitioner populations, before the date of transition.

The original CCW algorithm was expanded to consider diagnostic information contained in Medicaid claims for the following types of services: transportation services, personal care services, targeted case management, rehabilitation services, PT, OT, speech, hearing services, hospice benefits, nurse midwife services, nurse practitioner services, private duty nursing, non-waiver personal care, non-waiver private duty nursing, non-waiver adult day, non-waiver home health, non-waiver residential care, non-waiver rehab for aged/disabled, non-waiver targeted case management, non-waiver transportation, non-waiver hospice, non-waiver DME, waiver any other service, waiver personal care, waiver private duty nursing, waiver adult day, waiver home health, waiver residential care, waiver rehab, waiver targeted case management, waiver transportation, waiver hospice, or waiver DME. Inclusion of these claim types was judged to be particularly important for the HCBS population, increasing the prevalence of conditions by up to 10 percent. For persons with Medicare and Medicaid eligibility, we used the Medicare claims sources listed in Tables C1 to C.3. The indicators did not use information on Medicare assessments.

All CCW algorithms use mutually exclusive sets of ICD-9 codes to identify conditions or disorders, with the exception of two sets of indicators with overlapping definitions: Alzheimer's and depression. In our models, we used the more inclusive definitions that consider a broader set of ICD-9 codes, meaning that we used the Alzheimer's disease and related disorders or senile dementia and depression indicators listed under Chronic Conditions (Table C.1).

## Table C.1. Chronic condition algorithms

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify[b] | Exclusions |
|---|---|---|---|---|
| Acquired Hypothyroidism | 1 year | DX 244.0, 244.1, 244.2, 244.3, 244.8, 244.9, (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| Acute Myocardial Infarction | 1 year | DX 410.01, 410.11, 410.21, 410.31, 410.41, 410.51, 410.61, 410.71, 410.81, 410.91 (ONLY first or second DX on the claim) | At least 1 inpatient claim with DX codes during the 1-yr period | |
| Alzheimer's Disease | 3 years | DX 331.0 (any DX on the claim) | At least 1 inpatient, SNF, HHA, HOP or Carrier claim with DX codes during the 3-yr period | |
| Alzheimer's Disease and Related Disorders or Senile Dementia | 3 years | DX 331.0, 331.11, 331.19, 331.2, 331.7, 290.0, 290.10, 290.11, 290.12, 290.13, 290.20, 290.21, 290.3, 290.40, 290.41, 290.42, 290.43, 294.0, 294.10, 294.11, 294.20, 294.21, 294.8, 797 (any DX on the claim) | At least 1 inpatient, SNF, HHA, HOP or Carrier claim with DX codes during the 3-yr period | |
| Anemia | 1 year | DX 280.0, 280.1, 280.8, 280.9, 281.0, 281.1, 281.2, 281.3, 281.4, 281.8, 281.9, 282.0, 282.1, 282.2, 282.3, 282.40, 282.41, 282.42, 282.43, 282.44, 282.45, 282.46, 282.47, 282.49, 282.5, 282.60, 282.61, 282.62, 282.63, 282.64, 282.68, 282.69, 282.7, 282.8, 282.9, 283.0, 283.10, 283.11, 283.19, 283.2, 283.9, 284.01, 284.09, 284.11, 284.12, 284.19, 284.2, 284.81, 284.89, 284.9, 285.0, 285.1, 285.21, 285.22, 285.29, 285.3, 285.8, 285.9 (any DX on the claim) | At least 1 inpatient, SNF, HHA, OP or Carrier claim from any source (inpatient, home health, skilled nursing facility, outpatient or Part B with DX codes during the 1-year time period | |
| Asthma | 1 year | DX 493.00, 493.01, 493.02, 493.10, 493.11, 493.12, 493.20, 493.21, 493.22,493.81, 493.82, 493.90, 493.91, 493.92, (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| Atrial Fibrillation | 1 year | DX 427.31 (ONLY first or second DX on the claim) | At least 1 inpatient claim or 2 HOP or Carrier claims with DX code during the 1-yr period | |
| Benign Prostatic Hyperplasia | 1 year | DX 600.00, 600.01, 600.10, 600.11, 600.20, 600.21, 600.3, 600.90, 600.91 (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | If any of the qualifying claims also have a diagnosis of 222.2, then EXCLUDE |
| Cataract | 1 year | DX 366.01, 366.02, 366.03, 366.04, 366.09, 366.10, 366.12, 366.13, 366.14, 366.15, 366.16, 366.17, 366.18, 366.19, 366.20, 366.21, 366.22, 366.23, 366.30, 366.45, 366.46, 366.50, 366.51, 366.52, 366.53, 366.8, 366.9, 379.26, 379.31,379.39, 743.30, 743.31, 743.32, 743.33, V43.1, (ONLY principal DX on the claim) | At least 1 HOP or Carrier claim with DX codes during the I-yr period | |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify[b] | Exclusions |
|---|---|---|---|---|
| Chronic Kidney Disease | 2 years | DX 016.00, 016.01, 016.02, 016.03, 016.04, 016.05, 016.06, 095.4, 189.0, 189.9, 223.0, 236.91, 249.40, 249.41, 250.40, 250.41, 250.42, 250.43, 271.4, 274.10, 283.11, 403.01, 403.11, 403.91, 404.02, 404.03, 404.12, 404.13, 404.92, 404.93, 440.1, 442.1, 572.4, 580.0, 580.4, 580.81, 580.89, 580.9, 581.0, 581.1, 581.2, 581.3, 581.81, 581.89, 581.9, 582.0, 582.1, 582.2, 582.4, 582.81, 582.89, 582.9, 583.0, 583.1, 583.2, 583.4, 583.6, 583.7, 583.81, 583.89, 583.9, 584.5, 584.6, 584.7, 584.8, 584.9, 585, 585.1, 585.2, 585.3, 585.4, 585.5, 585.6, 585.9, 586, 587, 588.0, 588.1, 588.81, 588.89, 588.9, 591, 753.12, 753.13, 753.14, 753.15, 753.16, 753.17, 753.19, 753.20, 753.21, 753.22, 753.23, 753.29, 794.4 (any DX on the claim) | At least 1 inpatient, SNF or HHA claim or 2 HOP or Carrier claims with DX codes during the 2-yr period | |
| Chronic Obstructive Pulmonary Disease and Bronchiectasis | 1 year | DX 490, 491.0, 491.1, 491.8, 491.9, 492.0, 492.8, 491.20, 491.21, 491.22, 494.0, 494.1, 496 (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| Depression | 1 year | DX 296.20, 296.21, 296.22, 296.23, 296.24, 296.25, 296.26, 296.30, 296.31, 296.32, 296.33, 296.34, 296.35, 296.36, 296.51, 296.52, 296.53, 296.54, 296.55, 296.56, 296.60, 296.61, 296.62, 296.63, 296.64, 296.65, 296.66, 296.89, 298.0, 300.4, 309.1, 311 (any DX on the claim) | At least 1 inpatient, SNF, HHA, HOP or Carrier claim with DX codes during the 1-yr period | |
| Diabetes | 2 years | DX 249.00, 249.01, 249.10, 249.11, 249.20, 249.21, 249.30, 249.31, 249.40, 249.41, 249.50, 249.51, 249.60, 249.61, 249.70, 249.71, 249.80, 249.81, 249.90, 249.91, 250.00, 250.01, 250.02, 250.03, 250.10, 250.11, 250.12, 250.13, 250.20, 250.21, 250.22, 250.23, 250.30, 250.31, 250.32, 250.33, 250.40, 250.41, 250.42, 250.43, 250.50, 250.51, 250.52, 250.53, 250.60, 250.61, 250.62, 250.63, 250.70, 250.71, 250.72, 250.73, 250.80, 250.81, 250.82, 250.83, 250.90, 250.91, 250.92, 250.93, 357.2, 362.01, 362.02, 362.03, 362.04, 362.05, 362.06, 366.41 (any DX on the claim) | At least 1 inpatient, SNF or HHA claim or 2 HOP or Carrier claims with DX codes during the 2-yr period | |
| Glaucoma | 1 year | DX 362.85, 365.00, 365.01, 365.02, 365.03, 365.04, 365.10, 365.11, 365.12, 365.13, 365.15, 365.20, 365.21, 365.22, 365.23, 365.24, 365.31, 365.32, 365.41, 365.42, 365.43, 365.51, 365.52, 365.59, 365.60, 365.61, 365.62, 365.63, 365.64, 365.65, 365.81, 365.82, 365.83, 365.89, 365.9, 377.14 (ONLY principal DX on the claim) | At least 1 Carrier claim with DX codes during the 1-yr period | |
| Heart Failure | 2 years | DX 398.91, 402.01, 402.11, 402.91, 404.01, 404.11, 404.91, 404.03, 404.13, 404.93, 428.0, 428.1, 428.20, 428.21, 428.22, 428.23, 428.30, 428.31, 428.32,428.33, 428.40, 428.41, 428.42, 428.43, 428.9 (any DX on the claim) | At least 1 inpatient, HOP or Carrier claim with DX codes during the 2-yr period | |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify[b] | Exclusions |
|---|---|---|---|---|
| Hip/Pelvic Fracture | 1 year | DX 733.14, 733.15, 733.96, 733.97, 733.98, 808.0, 808.1, 808.2, 808.3, 808.41, 808.42, 808.43, 808.44, 808.49, 808.51, 808.52, 808.53, 808.54, 808.59, 808.8, 808.9, 820.00, 820.01, 820.02, 820.03, 820.09, 820.10, 820.11, 820.12, 820.13, 820.19, 820.20, 820.21, 820.22, 820.30, 820.31, 820.32, 820.8, 820.9 (any DX on the claim) | At least 1 inpatient or SNF claim with DX code during the 1-yr period | |
| Hyperlipidemia | 1 year | DX 272.0, 272.1, 272.2, 272.3, 272.4 (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| Hypertension | 1 year | DX 362.11, 401.0, 401.1, 401.9, 402.00, 402.01, 402.10, 402.11, 402.90, 402.91, 403.00, 403.01, 403.10, 403.11, 403.90, 403.91, 404.00, 404.01, 404.02, 404.03, 404.10, 404.11, 404.12, 404.13, 404.90, 404.91, 404.92, 404.93, 405.01, 405.09, 405.11, 405.19, 405.91, 405.99, 437.2 (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| Ischemic Heart Disease | 2 years | DX 410.00, 410.01, 410.02, 410.10, 410.11, 410.12, 410.20, 410.21, 410.22, 410.30, 410.31, 410.32, 410.40, 410.41, 410.42, 410.50, 410.51, 410.52, 410.60, 410.61, 410.62, 410.70, 410.71, 410.72, 410.80, 410.81, 410.82, 410.90, 410.91, 410.92, 411.0, 411.1, 411.81, 411.89, 412, 413.0, 413.1, 413.9, 414.00, 414.01, 414.02, 414.03, 414.04, 414.05, 414.06, 414.07, 414.12, 414.2, 414.3, 414.4, 414.8, 414.9 (any DX on the claim) | At least 1 inpatient, SNF, HHA, HOP or Carrier claim with DX codes during the 2-yr period | |
| Osteoporosis | 1 year | DX 733.00, 733.01, 733.02, 733.03, 733.09 (any DX on the claim) | At least 1 inpatient, SNF, HHA or 2 HOP or Carrier claims with DX codes during the 1-yr period | |
| RA/OA (Rheumatoid Arthritis/ Osteoarthritis) | 2 years | DX 714.0, 714.1, 714.2, 714.30, 714.31, 714.32, 714.33, 715.00, 715.04, 715.09, 715.10, 715.11, 715.12, 715.13, 715.14, 715.15, 715.16, 715.17, 715.18, 715.20, 715.21, 715.22, 715.23, 715.24, 715.25, 715.26, 715.27, 715.28, 715.30, 715.31, 715.32, 715.33, 715.34, 715.35, 715.36, 715.37, 715.38, 715.80, 715.89, 715.90, 715.91, 715.92, 715.93, 715.94, 715.95, 715.96, 715.97, 715.98, 720.0, 721.0, 721.1, 721.2, 721.3, 721.90, 721.91 (any DX on the claim) | At least 2 inpatient, SNF, HHA, HOP or Carrier claim with DX codes during the 2-yr period. Any combination of claims at least one day apart. | |
| Stroke / Transient Ischemic Attack | 1 year | DX 430, 431, 433.01, 433.11, 433.21, 433.31, 433.81, 433.91, 434.00, 434.01, 434.10, 434.11, 434.90, 434.91, 435.0, 435.1, 435.3, 435.8, 435.9, 436, 997.02 (any DX on the claim) | At least 1 inpatient claim or 2 HOP or Carrier claims with DX codes during the 1-yr period | If any of the qualifying claims have:<br>800 <= DX Code <= 804.9, 850 <= DX Code <= 854.1 in any DX position OR DX V57xx as the principal DX code, then EXCLUDE. |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify[b] | Exclusions |
|---|---|---|---|---|
| Female/Male Breast Cancer | 1 year | DX 174.0, 174.1, 174.2, 174.3, 174.4, 174.5, 174.6, 174.8, 174.9, 175.0, 175.9, 233.0, V10.3 (any DX on the claim) | At least 1 inpatient, SNF or 2 HOP or Carrier claims with DX codes during the 1-year time period (Any combination of 2 HOP/Carrier claims at least one day apart) | |
| Colorectal Cancer | 1 year | DX 153.0, 153.1, 153.2, 153.3, 153.4, 153.5, 153.6, 153.7, 153.8, 153.9,154.0,154.1, 230.3, 230.4, V10.05, V10.06 (any DX on the claim) | At least 1 inpatient, SNF or 2 HOP or Carrier claims with DX codes during the 1-year time period (Any combination of 2 HOP/Carrier claims at least one day apart) | |
| Prostate Cancer | 1 year | DX 185, 233.4, V10.46 (any DX on the claim) | At least 1 inpatient, SNF or 2 HOP or Carrier claims with DX codes during the 1-year time period (Any combination of 2 HOP/Carrier claims at least one day apart) | |
| Lung Cancer | 1 year | DX 162.2, 162.3, 162.4, 162.5, 162.8, 162.9, 231.2, V10.11 (any DX on the claim) | At least 1 inpatient, SNF or 2 HOP or Carrier claims with DX codes during the 1-year time period (Any combination of 2 HOP/Carrier claims at least one day apart) | |
| Endometrial Cancer | 1 year | DX 182.0, 233.2, V10.42 (any DX on the claim) | At least 1 inpatient, SNF or 2 HOP or Carrier claims with DX codes during the 1-year time period (Any combination of 2 HOP/Carrier claims at least one day apart) | |

[a]Effective dates of these codes vary. Researchers may be interested in confirming the code(s) of interest in accompanying claims or assessment data files.

[b]Carrier claims refers to RIC "O" claims (not DMERC RIC "M" claims), and excludes any claims for which line item Berenson-Eggers Type of Service [BETOS] variable equals D1A, D1B, D1C, D1D, D1E, D1F, D1G, or O1A. The categories with D1 in the first two positions are DME categories. The O1A category includes ambulance services. The intent of the algorithm is to exclude claims where the services do not require a licensed health care professional. SNF refers to skilled nursing facility; HHA refers to home health agency; HOP refers to hospital outpatient.

## Table C.2. Disability-related condition algorithms

| Algorithms | Reference Time Period (# of years) | Valid ICD-9 Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Autism Spectrum Disorders | 2 years | 299.0, 299.00, 299.01, 299.1, 299.11, 299.8, 299.80, 299.81, 299.9, 299.90, 299.91 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Cerebral Palsy | 2 years | 333.71, 343, 343.0, 343.1, 343.2, 343.3, 343.4, 343.8, 343.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Cystic Fibrosis and Other Metabolic Developmental Disorders | 2 years | 243, 255.2, 269.2, 270.1, 270.2, 270.3, 270.4, 270.6, 270.7, 271.1, 277.0, 277.00, 277.01, 277.02, 277.03, 277.09, 277.81, 277.85, 277.6 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Epilepsy | 2 years | 345, 345.0, 345.00, 345.01, 345.1, 345.10, 345.11, 345.2, 345.3, 345.4, 345.40, 345.41, 345.5, 345.50, 345.51, 345.6, 345.60, 345.61, 345.7, 345.70, 345.71, 345.8, 345.80, 345.81, 345.9, 345.90, 345.91 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Intellectual Disabilities and Related Conditions | 2 years | 317, 318, 318.0, 318.1, 318.2, 319, 758, 758.0, 758.1, 758.2, 758.3, 758.31, 758.32, 758.33, 758.39, 758.5, 759.7, 759.81, 759.83, 759.89, 760.71 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Learning Disabilities | 2 years | 315, 315.01, 315.02, 315.09, 315.1, 315.2, 315.31, 315.32, 315.34, 315.35, 315.39, 315.4, | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Mobility Impairments | 2 years | 334.1, 342.00, 342.01, 342.02, 342.10, 342.11, 342.12, 342.80, 342.81, 342.82, 342.90, 342.91, 342.92, 344, 344.0, 344.00, 344.01, 344.02, 344.03, 344.04, 344.09, 344.1, 344.2, 344.3, 344.30, 344.31, 344.32, 344.4, 344.40, 344.41, 344.42, 344.5, 344.6, 344.60, 344.61, 344.8, 344.81, 344.89, 344.9, 438.20, 438.21, 438.22, 438.30, 438.31, 438.32, 438.40, 438.41, 438.42, 438.50, 438.51, 438.52, 438.53 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Multiple Sclerosis and Transverse Myelitis | 2 years | 340, 341, 341.0, 341.2, 341.20, 341.21, 341.22, 341.8, 341.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Muscular Dystrophy | 2 years | 359, 359.0, 359.1 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Other Developmental Delays | 2 years | 315.5, 315.8, 315.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9 Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Sensory – Deafness and Hearing Impairment | 2 years | 389, 389.1, 389.10, 389.11, 389.12, 389.13, 389.14, 389.15, 389.16, 389.17, 389.18, 389.2, 389.20, 389.21, 389.22, 389.7, 389.8, 389.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Sensory - Blindness and Visual Impairment | 2 years | 369, 369.0, 369.00, 369.01, 369.02, 369.03, 369.04, 369.05, 369.06, 369.07, 369.08, 369.1, 369.10, 369.11, 369.12, 369.13, 369.14, 369.15, 369.16, 369.17, 369.18, 369.2, 369.20, 369.21, 369.22, 369.23, 369.24, 369.25, 369.3, 369.4 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Spina Bifida and Other Congenital Anomalies of the Nervous System | 2 years | 740.0, 740.1, 740.2, 741, 741.0, 741.00. 741.01, 741.02, 741.03, 741.9, 741.90, 741.91. 741.92, 741.93, 742.0, 742.1, 742.2, 742.3, 742.4, 742.5, 742.51, 742.53, 742.59, 742.8, 742.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Spinal Cord Injury | 2 years | 349.39, 806.00. 806.01, 806.02, 806.03, 806.04, 806.05, 806.06, 806.07, 806.08, 806.09, 806.10, 806.11, 806.12, 806.13, 806.14, 806.15, 806.16, 806.17, 806.18, 806.19, 806.20, 806.21, 806.22, 806.23, 806.24, 806.25, 806.26, 806.27, 806.28, 806.29, 806.30, 806.31, 806.32, 806.33, 806.34, 806.35, 806.36, 806.37, 806.38, 806.39, 806.4, 806.5, 806.60, 806.61, 806.62, 806.69, 806.70, 806.71, 806.72, 806.79, 806.8, 806.9, 907.2, 952.00, 952.01, 952.02, 952.03, 952.04, 952.05, 952.06, 952.07, 952.08, 952.09, 952.10, 952.11, 952.12, 952.13, 952.14, 952,15, 952.16, 952.17, 952.18, 952.19, 952.2, 952.3, 952.4, 952.8, 952.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Traumatic Brain Injury and Nonpsychotic Mental Disorders due to Brain Damage | 2 years | 310, 310.0, 310.1, 310.2, 310.8, 310.81, 310.89, 907, 907.0, 907.1 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |

[a] Effective dates of these codes vary. Researchers may be interested in confirming the code(s) of interest in accompanying claims or assessment data files.

## Table C.3. Mental health conditions and substance use disorder algorithms

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Anxiety Disorders | 2 years | 293.84, 300.00, 300.01, 300.02, 300.09, 300.10, 300.20, 300.21, 300.22, 300.23, 300.29, 300.3, 300.5, 300.89, 300.9, 308.0, 308.1, 308.2, 308.3, 308.4, 308.9, 309.81, 313.0, 313.1, 313.21, 313.22, 313.3, 313.82, 313.83 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Bipolar Disorder | 2 years | 296.00, 296.01, 296.02, 296.03, 296.04, 296.05, 296.06, 296.10, 296.11, 296.12, 296.13, 296.14, 296.15, 296.16, 296.40, 296.41, 296.42, 296.43, 296.44, 296.45, 296.46, 296.50, 296.51, 296.52, 296.53, 296.54, 296.55, 296.56, 296.60, 296.61, 296.62, 296.63, 296.64, 296.65, 296.66, 296.7, 296.80, 296.81, 296.82, 296.89, 296.90, 296.99 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Conduct Disorders and Hyperkinetic Syndrome | 2 years | 312.00, 312.01, 312.02, 312.03, 312.10, 312.11, 312.12, 312.13, 312.20, 312.21, 312.22, 312.23, 312.30, 312.31, 312.32, 312.33, 312.34, 312.35, 312.39, 312.4, 312.81, 312.82, 312.89, 312.9, 314.00, 314.01, 314.1, 314.2, 314.8, 314.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Depressive Disorders | 2 years | 296.20, 296.21, 296.22, 296.23, 296.24, 296.25, 296.26, 296.30, 296.31, 296.32, 296.33, 296.34, 296.35, 296.36, 300.4, 311, V79.0 | At least one inpatient claim *OR* two other non-drug claims of any service type<br>AND<br>There must be at least one qualifying claim without a screening code (i.e.,V79.0) | None |
| Personality Disorders | 2 years | 301.0, 301.10, 301.11, 301.12, 301.13, 301.20, 301.21, 301.22, 301.3, 301.4, 301.50, 301.51, 301.59, 301.6, 301.7, 301.81, 301.82, 301.83, 301.84, 301.89, 301.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Post-Traumatic Stress Disorder (PTSD) | 2 years | 309.81 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Schizophrenia | 2 years | 295.00, 295.01, 295.02, 295.03, 295.04, 295.05, 295.10, 295.11, 295.12, 295.13, 295.14, 295.15, 295.20, 295.21, 295.22, 295.23, 295.24, 295.25, 295.30, 295.31, 295.32, 295.33, 295.34, 295.35, 295.40, 295.41, 295.42, 295.43, 295.44, 295.45, 295.50, 295.51, 295.52, 295.53, 295.54, 295.55, 295.60, 295.61, 295.62, 295.63, 295.64, 295.65, 295.70, 295.71, 295.72, 295.73, 295.74, 295.75, 295.80, 295.81, 295.82, 295.83, 295.84, 295.85, 295.90, 295.91, 295.92, 295.93, 295.94, 295.95 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Schizophrenia and Other Psychotic Disorders | 2 years | 293.81, 293.82, 295.00, 295.01, 295.02, 295.03, 295.04, 295.05, 295.10, 295.11, 295.12, 295.13, 295.14, 295.15, 295.20, 295.21, 295.22, 295.23, 295.24, 295.25, 295.30, 295.31, 295.32, 295.33, 295.34, 295.35, 295.40, 295.41, 295.42, 295.43, 295.44, 295.45, 295.50, 295.51, 295.52, 295.53, 295.54, 295.55, 295.60, 295.61, 295.62, 295.63, 295.64, 295.65, 295.70, 295.71, 295.72, 295.73, 295.74, 295.75, 295.80, 295.81, 295.82, 295.83, 295.84, 295.85, 295.90, 295.91, 295.92, 295.93, 295.94, 295.95, 297.0, 297.1, 297.2, 297.3, 297.8, 297.9, 298.0, 298.1, 298.2, 298.3, 298.4, 298.8, 298.9 | At least one inpatient claim *OR* two other non-drug claims of any service type | None |
| Tobacco Use | 2 years | 305.1, 649.00, 649.01, 649.02, 649.03, 649.04, 989.84, 99406, 99407 | At least one inpatient claim *OR* two other non-drug claims of any service type *OR* one procedure code claim of any type (i.e., 99406, 99407) | None |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Substance abuse | 2 years | 292, 292.0, 292.11, 292.12, 292.2, 292.8, 292.81, 292.82, 292.83, 292.84, 292.85, 292.89, 292.9, 304, 304.0 304.01, 304.02, 304.1, 304.11, 304.12, 304.2, 3042.0, 304.21, 304.22, 304.3, 304.30, 304.31, 304.32, 304.4, 304.40, 304.41, 304.42 , 304.5, 304.50, 304.51, 304.52, 304.6, 304.60, 304.61, 304.62, 304.7, 304.70, 304.71, 304.72, 304.8, 304.80, 304.81, 304.82, 304.9, 304.90, 304.91, 304.92, 305, 305.2, 305.20, 305.21, 305.22, 305.3, 305.30, 305.31, 305.32, 305.4, 305.40, 305.41, 305.42, 305.5, 305.50, 305.51, 305.52, 305.6, 305.60, 305.61, 305.62, 305.7, 305.70, 3057.1, 305.72 305.8, 305.80, 305.81, 305.82, 305.9, 305.90, 305.91 305.92, 648.3, 648.30, 648.31, 648.32, 648.33, 648.34, 655.5, 655.50, 655.51, 655.53, 760.72, 760.73, 760.75, 779.5, 965.0, 965.00, 965.01, 965.02, 965.09, V6542, 946, 946.4, 946.5, 946.6, 946.7, 946.8, 946.9, E850.0, E850.1, E850.2, E854.1, E935.0, E935.1 | At least one inpatient claim *OR* two other non-drug claims of any service type *OR* one procedure code claim of any type (i.e., 946, 946.4, 946.5, 946.6, 946.7, 946.8, 946.9) | |

| Algorithms | Reference Time Period (# of years) | Valid ICD-9/CPT4/HCPCS Codes[a] | Number/Type of Claims to Qualify | Exclusions |
|---|---|---|---|---|
| Alcohol abuse | 2 years | 291, 291.0, 291.1, 291.2, 291.3, 291.4, 291.5, 291.8, 291.81, 291.82, 291.89, 291.9, 303.0, 303.00, 303.01, 303.02, 303.9, 303.90, 303.91, 303.92, 305, 305.0, 305.00, 305.01, 305.02, 357.5, 425.5, 535.3, 535.30, 535.31, 571, 571.0, 571.1, 571.2, 571.3, 760.71 ,980, 980.0, V6542, V791, 946, 946.1, 946.2, 946.3, 946.7, 946.8, 946.9, E860.0 | At least one inpatient claim *OR* two other non-drug claims of any service type *OR* one procedure code claim of any type (i.e., 946, 946.4, 946.5, 946.6, 946.7, 946.8, 946.9) | |

[a] Effective dates of these codes vary. Researchers may be interested in confirming the code(s) of interest in accompanying claims or assessment data files.

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