Integration of Social Determinants of Health into Medicaid Managed Care Risk Adjustment: Considerations and Financial Impacts

JUNE | 2025

Health Care Cost Trends

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Considerations and Financial Impacts

AUTHOR Rong Yi, PhD
Principal, Data Science Modeling Practice
Milliman, Inc

Jeffrey Milton-Hall, FSA MAAA
Principal and Consulting Actuary
Milliman, Inc.

Nicholas R. Gersch, FSA MAAA,
Actuary

Brian Merkey, PhD
Manager, Data and Analytics
Milliman, Inc.

Megan Nicholson, MS
Senior Data Scientist
Milliman, Inc.

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There is increasing recognition of the impact of social determinants of health (SDOH) on health outcomes, leading to new approaches for care and resource distribution that can help to optimize those outcomes. Risk adjustment is an actuarial mechanism aimed at reallocating healthcare resources using predetermined criteria to better align available resources with specific policy goals. In recent years, healthcare payers have started to explore and implement risk-adjustment payment methodologies that incorporate SDOH. For example, the Massachusetts Medicaid program uses a combination of morbidity risk scores and community- and beneficiary-level SDOH to risk adjust program payments to contracted Medicaid accountable care organizations (ACOs), prompting interest from other state Medicaid programs and risk-holding entities regarding its financial outcomes and market dynamics.

This study aims to explore how actuaries and state Medicaid programs may incorporate SDOH into risk adjustment. It examines the variations in financial outcomes between traditional morbidity-based risk adjustment and those that include SDOH. This report also touches on policy implications, including whether and how risk adjustment might be a useful tool for addressing differences in care and considerations for ensuring that risk adjustment does not perpetuate or exacerbate those differences.

While the study does not address best practices, it aims to serve as a foundation for future research and program design as states and healthcare organizations consider the integration of SDOH in Medicaid risk adjustment.

Executive Summary

To evaluate the impact of SDOH risk adjustment on financial outcomes for Medicaid ACOs and managed care organizations (MCOs, which the authors refer to interchangeably with ACOs in this report), the authors calibrated risk-adjustment models with the addition of SDOH risk factors and then they simulated financial outcomes for ACOs/MCOs across synthetic state Medicaid managed care markets with and without SDOH risk adjustment.

Integration of SDOH into Medicaid risk adjustment was found to provide a small but measurable reduction in volatility and variation of financial results versus a recalibrated model without SDOH (morbidity-only). The improvement in fit, while modest, is greatest for populations with below-average morbidity risk and above-average SDOH-related risk. Prospective risk scores for these beneficiaries were too low under morbidity-only models but closer to parity after incorporating SDOH, suggesting that SDOH risk factors may help right-size revenue for populations with costs that reflect utilization of services below their healthcare needs as indicated by prior-year diagnoses.

However, the authors also found that the SDOH risk factors in their models explained much less variation in estimated risk than existing Chronic Illness and Disability Payment System with Pharmacy (CDPS+Rx) condition categories, and that the financial impacts of SDOH risk-adjustment integration were effectively undetectable under an alternate sampling method that doesn't explicitly stratify MCOs by SDOH risk.

Several important lessons from this analysis and the study results included the following:

- Defining and measuring SDOH is challenging, and there are many different ways to do so.
- National individual-level SDOH data sources are hard to come by and are currently not reliably populated.
- Empirical approaches based on historical claims data—such as risk adjustment—have limitations that make them a less-than-ideal tool for identifying and addressing the basis for differences in care, and whether those are caused by differences in access to care or underlying health needs.
- Integration of SDOH into risk adjustment offers an opportunity for payers to address policymaker objectives of incentivizing the provision of appropriate care that enhances the health outcomes of all of its members. However, its success will depend on ensuring that SDOH risk factors have a meaningful impact on revenue allocation and align with MCOs' ability to implement effective interventions. In this focused research study, the influence of community-level SDOH as separate risk factors on revenue allocation was determined to be limited. There may be different interpretations.
    - Recent studies[1] have shown that disease prevalence rates are correlated with SDOH. The impact of SDOH on determining underlying member morbidity may have been partially captured through the condition categories, hence adding SDOH as separate risk factors would not contribute significantly relative to the condition categories. Or,

[1] For an example on the relationship between community-level SDOH and disease prevalence, see Benavidez, G. A., Zahnd, W. E., Hung, P., et al. (2024) Chronic Disease Prevalence in the US: Sociodemographic and Geographic Variations by Zip Code Tabulation Area. *Preventing Chronic Disease*, vol. 21, doi:10.5888/pcd21.230267. For an example on the relationship between individual-level SDOH and disease prevalence, see Kunnath, A. J., Sack, D. E., and Wilkins, C. H. (2024) Relative Predictive Value of Sociodemographic Factors for Chronic Diseases Among All of Us Participants: A Descriptive Analysis. *BMC Public Health*, vol. 24, Article no. 405, doi:10.1186/s12889-024-17834-1.

- The methodology design used in this study does not fully capture the complex interplay between SDOH and morbidity. Or,
- Community-level SDOH data lacks granularity. It is likely that individual-level SDOH may show more predictive value in risk adjustment.

There may well be other interpretations. Further research and additional data are needed to better understand this important topic.

- Risk adjustment, as a research methodology, a payment mechanism, and policy instrument, is constantly evolving. SDOH risk adjustment may hold the potential to drive meaningful change, but its full impact may take time to emerge as the interplay between coding incentives, care delivery, and the data informing risk scores and capitation rates continues to evolve.
- Rather than viewing SDOH risk adjustment as a standalone remedy, it is more prudently considered as one component of a comprehensive approach to appropriately address the needs of the entire population.

Finally, several opportunities for refinement in future research were identified including the following:

- Integrating individual-level SDOH risk factors. As of January 2024, a new CPT code G0136 became effective[2] to pay for administering an SDOH risk assessment. It is possible that individual-level SDOH data will become more widely available in the near future.
- Attempting to tease out access from need through a methodology design that first predicts access to care using non-claim risk factors and then predicts expected cost conditional on receipt of care.
- Expanding the current analysis to encompass additional data years and states to incorporate populations outside of the current cohort, such as dual eligibles, pregnant women, and recipients of long-term services and supports.
- Improving statistical power and generalizability of the calibrated SDOH risk-adjustment models.

[2] Centers for Medicare and Medicaid Services, Medicare Learning Network (October 2024). Annual Wellness Visit, Social Determinants of Health Risk Assessment. Retrieved February 28, 2025, from: https://www.cms.gov/files/document/mm13486-annual-wellness-visit-social-determinants-health-risk-assessment.pdf

Section 1: Introduction to Study

The World Health Organization (WHO) defines SDOH as "…the non-medical factors that influence health outcomes. They are the conditions in which people are born, grow, work, live, and age, and the wider set of forces and systems shaping the conditions of daily life. These forces and systems include economic policies and systems, development agendas, social norms, social policies and political systems."[3] This general description has been broadly accepted by the healthcare industry as the framework for measuring SDOH.

A growing body of research supports claims that SDOH have a substantial influence on variation in population morbidity, access to healthcare, and health outcomes.[4] Populations receiving benefits through state Medicaid and Children's Health Insurance Program (CHIP) programs are among the most vulnerable to economic and social factors such as housing instability, food insecurity, and access to transportation. However, addressing the underlying causes of variability in SDOH for Medicaid/CHIP populations and differences in the provision of care has proven to be a multifaceted challenge requiring creative policy and program design across multiple fronts. In this study, the authors explored the potential of risk adjustment as one such mechanism for addressing these issues.

Risk adjustment is a commonly used actuarial mechanism for aligning healthcare resource (re)allocation with specific policy goals. Risk-adjustment methodologies have evolved along with health reforms, policy priorities, data, and business operations. While today's healthcare landscape is evolving with a growing recognition of the significant impact of SDOH on health outcomes, approaches to improve the distribution of healthcare services and resource allocation to all members through risk adjustment are still relatively new and represent a complex, still-emerging practice area. MassHealth, the Massachusetts Medicaid program, is the first in the country that has implemented SDOH risk adjustment in ACO/MCO payments. The ensuing financial outcomes and market dynamics have been closely watched by many state Medicaid programs and ACO/MCOs.

With this study, considerations for actuaries and state Medicaid programs that wish to integrate SDOH measures into risk adjustment were explored, and variations in ACO/MCO financial outcomes were illustrated when such integration occurs (versus traditional morbidity-based risk adjustment), and observed variation in the contributions of SDOH measures and morbidity to modeled risk across programs and aid categories were evaluated.

Actuaries and other professionals may be able to use the findings from this study to understand how SDOH risk-adjustment models might work in practice, the actuarial and practical challenges such models may present, and the financial implications for ACO/MCOs of different population and SDOH mixes. Furthermore, they can use the technical details and the methodology to recalibrate SDOH risk-adjustment models to their own populations.

Notably, this research does not purport to settle questions of actuarial best practice nor provide definitive quantitative answers regarding accuracy and goodness of fit. Instead, the sole intent of this study is to provide a starting point for future inquiry and comparison as states and healthcare entities consider

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[3] World Health Organization. Social determinants of health. Retrieved February 28, 2025, from: https://www.who.int/health-topics/social-determinants-of-health#tab=tab_1

[4] A large body of research on SDOH is available. Several leading academic journals and professional and research organizations have aggregated SDOH related publications, data, and tools for public access, such as the World Health Organization and *Health Affairs*.

integrating SDOH measures into Medicaid risk adjustment and look to understand the potential impacts this may have on policy objectives, financial outcomes, and volatility.

1.1 STATE AND FEDERAL PROGRAMS ADDRESSING SOCIAL DETERMINANTS OF HEALTH

In this section, several pre-existing state and federal programs that adjust payment rates to risk-holding entities based on SDOH risk factors were examined.

MASSACHUSETTS

The state of Massachusetts has been a leader in integrating SDOH into its Medicaid ACO care model since 2018. This initiative was designed to prevent care avoidance for high-need beneficiaries and ensure that individuals with social risk factors receive adequate healthcare. The care model includes flexible services, such as non-medical interventions to address social needs, allowing ACOs to provide services like housing support and nutrition assistance. This approach is supported by Delivery System Reform Incentive Payment (DSRIP) funds, which help build infrastructure for community-based partnerships and improve care coordination. Program payment is risk adjusted using a risk-adjustment model that includes SDOH factors at the individual beneficiary level and census block group level, morbidity, and the interaction between SDOH factors and morbidity.[5]

MINNESOTA

In 2018, Minnesota updated its Medicaid ACO model, called Integrated Health Partnerships (IHPs), to include social risk factors in its payment system. This model adjusts payments based on both medical and social risk factors, such as income level and homelessness. The state uses data from Medicaid claims and administrative records to develop its risk-adjustment methodology. By incorporating social risk into the payment system, Minnesota aims to better support activities that Medicaid typically does not reimburse, recognizing that social challenges like poverty and housing insecurity can significantly impact health outcomes.

NORTH CAROLINA

North Carolina has taken a proactive approach through its Healthy Opportunities Pilot (HOP), which is part of the state's Medicaid transformation initiative. This program, launched in 2022, is the first in the nation to fund non-medical services through Medicaid to address SDOH such as housing, transportation, and food insecurity. By integrating community-based organizations (CBOs) into care delivery and providing payments for social care services, the state aims to reduce healthcare costs while improving outcomes for members with additional non-medical needs. North Carolina has also implemented standardized SDOH screening tools and created a state-level interactive map that tracks social indicators across regions to better inform community health investments.

ARIZONA

Arizona has also been actively incorporating SDOH into its Medicaid risk-adjustment models. The state uses factors like housing instability, food insecurity, and transportation barriers to adjust payments for its MCOs. Arizona's model examines how these social risk factors impact medical costs and adjusts payments

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[5] Commonwealth of Massachusetts (2017). MassHealth Risk Adjustment Methodology. Retrieved February 28, 2025, from: https://www.mass.gov/lists/masshealth-risk-adjustment-methodology

accordingly, aiming to improve alignment of the healthcare system with the health needs of the population. The incorporation of SDOH in Arizona's Medicaid program has allowed the state to fine-tune how resources are allocated, focusing on high-risk populations and improving outcomes for beneficiaries.

Section 2: Data

At a high level, the authors sought to evaluate the integration of social determinants of health (SDOH) into Medicaid risk adjustment by first calibrating a set of risk-adjustment models with morbidity and community-level SDOH risk factors to individual-level Medicaid enrollment and claims data. The next step was to use the same data source to simulate risk-adjusted financial outcomes under different population morbidity and SDOH profiles, comparing results for traditional morbidity-based risk-adjustment approaches to those incorporating SDOH factors.

In this section, the key data sources—claims and SDOH—used in the analysis were outlined. Inclusion and exclusion criteria applied to define the study population were also described, along with the rationale behind these decisions, to ensure data consistency and relevance for risk-adjustment modeling.

MEDICAID CLAIMS AND ENROLLMENT

The Authors obtained access to the Transformed Medicaid Statistical Information System (T-MSIS) through the CMS Research Data Assistance Center Chronic Conditions Warehouse Virtual Research Data Center (VRDC). T-MSIS is a national dataset that captures detailed enrollment and claims/encounter information for 100% of Medicaid and CHIP beneficiaries. Data has been submitted to T-MSIS by state Medicaid agencies (fee-for-service Medicaid/CHIP beneficiaries) and by managed care plans. As such, data quality varies by state and by data submitter.

COMMUNITY-LEVEL SDOH

In the United States, several community-level SDOH measures have been developed, including:

- Area Deprivation Index (ADI): Measures neighborhood disadvantage using factors like income, education, employment, and housing quality. Useful for understanding differences at the community-level. (https://www.nimhd.nih.gov)
- Social Vulnerability Index (SVI): Developed by the Centers for Disease Control and Prevention, this index identifies communities vulnerable to external stresses, such as natural disasters, based on socioeconomic and housing data. (https://www.atsdr.cdc.gov/place-health/php/svi/index.html)
- Social Deprivation Index (SDI): Aggregates factors such as income, education, and housing to identify communities facing social disadvantages affecting health. (https://www.graham-center.org)
- Neighborhood Stress Score (NSS7): Developed by University of Massachusetts and used in Massachusetts to measure neighborhood-level social and economic stress. The score incorporates seven indicators: percentage of families below the poverty level, percentage of adults without a high school diploma, percentage of households with single parents, percentage of residents unemployed, percentage of households receiving public assistance, percentage of residents who are non-English speakers, and percentage of occupied housing units that are renter-occupied. (https://www.mass.gov/doc/social-determinants-of-health-sdh-faq-1/download)
- Child Opportunity Index (COI): Evaluates conditions supporting healthy child development, including education, health, and social context, across neighborhoods. (https://www.diversitydatakids.org/child-opportunity-index)

Rather than using any of the indices as-is, the authors instead chose to adapt the component census measures underlying the CDC's SVI (see Table 1), both to model the independent risk contribution of these component measures and because demographic and language measures are included that are not incorporated in other SDOH indices.

Table 1

COMMUNITY-LEVEL SDOH MEASURES ADAPTED FROM CDC-SVI

	SVI - Component Census Measures		Action in Modeling	Final Measure Name
Socioeconomic Status	EP_POV	% below poverty	Drop - High collinearity with most other variables	n/a
	EP_UNEMP	% unemployed	Use unmodified	EP_UNEMP
	EP_PCIK	per capita income in $1K	Flip sign for consistency with other measures (higher = greater vulnerability). Measure in units of $10,000 from a center point of 0 for $40,000 in income.	EP_PCI10K
	EP_NOHSDP	% no high school diploma, age 25+	Use unmodified	EP_NOHSDP
Household Composition & Disability	EP_AGE65	% age 65 and older	Drop - Statistically insignificant	EP_NONWORK
	EP_AGE17	% age 17 and younger	Use unmodified	
	EP_DISABL	% noninstitutionalized disabled	Use simple average with EP_GROUPQ to create new housing-related variable	EP_DISABL
	EP_SNGPNT	% single parent households with children under 18	Use simple average with EP_CROWD to create new housing-related variable	EP_SNGPNT
Racial and Ethnic Minority Status & Language	EP_MINRTY	% minority (non-white)	Drop - Statistically insignificant	EP_MINRTY
	EP_LIMENG	% speaking English less well, age 5+	Use unmodified	EP_LIMENG
Housing Type & Transportation	EP_MUNIT	% in housing structures w 10+ units	Drop - Statistically insignificant	n/a
	EP_MOBILE	% mobile homes	Use unmodified	EP_MOBILE
	EP_CROWD	% housing units with more people than rooms	Use simple average with EP_GROUPQ to create new housing-related variable	EP_CROWD_GQ
	EP_GROUPQ	% in group quarters	Use simple average with EP_CROWD to create new housing-related variable	
	EP_NOVEH	% households with no vehicle	Use unmodified	EP_NOVEH

Source: Agency for Toxic Substances and Disease Registry (July 2024). Social Vulnerability Index. https://www.atsdr.cdc.gov/place-health/php/svi/index.html. Decisions on how to use the census measures in modeling are included in the last two columns.

The SVI-based census measures were calculated at the census tract level, where census tracts were inferred using the enrollment data in T-MSIS.[6] In modeling, modifications were made to the list of SVI measures. This will be discussed in greater detail in the Methodology section.

INDIVIDUAL-LEVEL SDOH

Ideally, both community and beneficiary-level SDOH risk factors would be measured. However, even where the T-MSIS data contains relevant information on SDOH, such as race and ethnicity fields in the T-MSIS enrollment files, such data fields are often missing, rendering them unusable for the purpose of this study.

For example, the ICD-10-CM codes included in categories Z55-Z65 (Z codes) identify aspects of individuals' socioeconomic situations that may influence health status and healthcare, including education and literacy, employment, housing, and lack of adequate food or water. However, the prevalence of Z codes on

[6] The T-MSIS geographic granularity, based on ZIP Code (ZIP 5), may not align precisely with individual census tracts. This could introduce limitations to the geographic specificity of the findings.

encounter data in the United States tends to be low, with variation attributable not only to patient-level SDOH characteristics but also to substantial differences in coding patterns across providers and regions.

The authors explored using ICD-10-CM code Z59.0 (homelessness) paired with frequency information on the number of times an individual's address changes within a year (by ZIP Code) to infer the presence of housing instability, but they ultimately declined to include these or other individual-level SDOH factors in the final model and analysis. These items will be discussed in greater detail in the Methodology section.

TIMEFRAME

The years 2018 and 2019 were chosen for this study to ensure that the analysis is based on the most recent available data not influenced by the disruptions of the COVID-19 pandemic and changes in Medicaid enrollment from maintenance of effort (and subsequent redeterminations) during the Public Health Emergency (PHE).

STATE SELECTION

In order to select states to study, several factors were considered, including:

- Good data quality
- Adequate sample size by broad eligibility category
- Recency of data, prioritizing calendar years 2018 and 2019 immediately prior to the public health emergency
- Medicaid program fee-for-service data with no or very little managed care penetration/interaction. This is a key consideration because (1) it eliminates concerns about the impact of managed care provider contracts on financial outcomes, and (2) it removes the need to reprice claims to account for pricing variations associated with managed care.

Upon reviewing the available state data, Connecticut and Montana fee-for-service program data were selected based on the above-stated considerations. Several other subpopulations with non-standard benefits or non-homogenous risk characteristics were excluded from the final analysis, which is discussed in greater detail in the Methodology section.

Section 3: Methodology

3.1 DATA STAGING

PROSPECTIVE RISK-ADJUSTMENT DESIGN

For this research, a prospective risk-adjustment methodology was employed, which uses demographic and claims data from a base year (Year 1) to predict healthcare spending in a future year (Year 2). This approach is widely utilized in Medicaid managed care contracting to estimate costs and allocate resources effectively.

BENEFICIARIES AND CLAIMS CHOSEN FOR ANALYSIS

Data from Connecticut and Montana (along with other states not included in the final analysis) were reviewed for data quality and credibility, making sure it was fully populated and appropriate for the purposes of this study.

Several populations were not incorporated in the study for reasons of non-standard benefits and acute risks typically financed through mechanisms other than capitation and prospective risk adjustment (e.g., kick payments) to avoid drawing inappropriate conclusions due to claims credibility, large claims, volatility from other payors, and unmodeled sources of cost variation. The following populations were left out:

- Dual eligible enrollees.
- Infants (Medicaid enrollees under one year of age).
- Pregnancy: Pregnant beneficiaries whose eligibility was based on their being pregnant were left out. Beneficiaries who were enrolled for other reasons but became pregnant during the program year were kept in.
- Beneficiaries with restricted/limited benefits.
- Beneficiaries receiving long-term services and supports (LTSS): Such claims are typically paid on a per diem basis, may substitute for healthcare costs that would otherwise be provided through the acute benefit, and fall outside risk-adjusted capitation arrangements.

For all beneficiaries, costs for nonstandard benefits such as non-emergency transportation and dental and vision care were left out of the analysis.

To ensure data quality for model development, several adjustments were made to the dataset. Beneficiaries whose county or ZIP Code values were outside the covered states, high-risk beneficiaries with unusually low claim costs, beneficiaries whose ages were negative, and beneficiaries whose diagnosis information was incompatible with their age and sex were all left out

RATE CELLS – AID CATEGORIES, DEMOGRAPHIC GROUPINGS, AND REGIONS

The included Connecticut and Montana fee-for-service beneficiaries were grouped into the following six aid categories shown in Table 2:

Table 2
AID CATEGORIES

Aid Category	Description
CHIP	Children (through age 18) eligible for coverage through the state Children's Health Insurance Program
Disabled	Aged, blind, or disabled children and adults not receiving LTSS and without dual Medicare eligibility
Expansion	Adults eligible for coverage through the expansion of state Medicaid coverage under the Patient Protection and Affordable Care Act
Foster Care	Children (through age 18) eligible for Medicaid coverage through state foster care and adoption assistance programs.
TANF Adult	Parents, caretakers, and other adults eligible for state Medicaid coverage outside of the preceding aid categories
TANF Child	Children (through age 18) eligible for Medicaid coverage outside of the preceding aid categories

Beneficiaries were further subdivided into demographic groupings by aid category, age range, and sex for the purpose of market simulations and financial modeling. Please refer to Table 12 in Appendix A.

Credibility and industry standards were considered when formulating rate cells (aid category, demographic, and regional groupings). The regions selected are based on the public health regions in Montana[7] as well as the former Medicaid managed care regions in Connecticut's Husky Health program (at the county level of detail in the state). Please refer to Table 13 in Appendix A.

ELIGIBILITY DURATION IN THE BASE YEAR

In Medicaid risk adjustment, a minimum enrollment duration threshold is commonly used to ensure that claims data are credible enough to accurately calculate beneficiary risk scores. Beneficiaries enrolled beyond this threshold are scored using a morbidity model, while those with shorter enrollment durations are assessed based on demographic factors.

The determination of the duration threshold involves balancing both statistical and policy considerations. This includes ensuring adequate sample size, maintaining the model's predictive accuracy and stability, and aligning with program incentives. Beneficiaries with brief enrollment may differ significantly from those with longer enrollment periods. For example, longer enrollment allows time for pent-up healthcare demand to manifest, while short-term beneficiaries might be intrinsically healthier, leading to lower utilization rates. Using an average demographic factor for short-term enrollees could overestimate their healthcare needs, introducing inaccuracies into program payment and causing unintended consequences in the market.

To address this, the statistical performance of the original CDPS+Rx models on the Connecticut data was evaluated using minimum enrollment durations of seven months and four months in 2018. The model's performance remained stable when the threshold was reduced from seven to four months, and doing so increased the sample size by a substantial amount. Considering the enhanced sample size, stable model performance, and policy implications, a four-month threshold for risk score credibility was chosen for both Connecticut and Montana's data. Please refer to Table 18 in the Appendix C.

[7] Montana.gov. Montana Health Planning Regions. Retrieved February 28, 2025, from: https://dphhs.mt.gov/qad/licensure/healthcarefacilitylicensure/certificateofneed/healthplanningregions

3.2 RISK-ADJUSTMENT MODEL DESIGN AND CALIBRATION

The CDPS+Rx methodology was selected as the starting point for SDOH risk-adjustment integration and for modeling individual-level morbidity due to its wide acceptance and extensive use in Medicaid programs across many states. In addition, the CDPS+Rx methodology is open source, offering transparency and adaptability for the study's design.

A stepwise approach was used to develop the risk-adjustment models. Throughout the process, statistical performance measures such as model R^2, mean absolute prediction error (MAPE), and predictive ratio (predicted divided by actual at the group level) were evaluated.

STEP 1: UNMODIFIED CDPS+RX MODELS

The first step was to attach CDPS+Rx Version 7.1 condition categories and prospective weights as-is to the 2018 claims, predicting 2019 spending truncated at $250,000 after annualization, by population type—SSI, child, and adult—for Connecticut and Montana separately.

STEP 2: RECALIBRATED WEIGHTS

As part of common actuarial practice, recalibration is often used to make the risk-adjustment model more specific to the population, data, and other characteristics of the project for which it is being used.

Restricted linear regressions were used through an iterative process to recalibrate the CDPS+Rx risk weights by population type and only included factors with sufficient volume in the training data and for which the final coefficients were both statistically significant and nonnegative. This was to ensure that having a risk factor would not reduce program payment.

Under the final models, each beneficiary was assigned a prospective morbidity risk score for 2019 if they had at least four months of enrollment in 2018. For beneficiaries not part of the 2018 data or with a shorter 2018 enrollment duration, an average expected risk score was assigned based on demographics and aid category.

STEP 3: FULL MODEL

In this step, full models with SDOH were produced by pairing the recalibrated morbidity risk scores from Step 2 with a modified set of community-level SDOH measures adapted from the SVI to again predict annualized 2019 total cost truncated at $250,000. Multiplicative interaction factors between the morbidity risk score and each of the community-level census measures were also considered. In an iterative process, statistically significant factors were incorporated into a constrained version of the full model—excluding risk factors with negative coefficients.

After this step, the resulting beneficiary risk scores were decomposed from various models into components for each of demographic and morbidity (from the recalibrated CDPS+Rx model), SDOH, and the interaction of SDOH with demographics/morbidity.

Please see Table 19 in the Appendix C for the final model coefficients. The high-level model performance statistics are included in Table 3.

Table 3

MODEL R^2 AND MEAN ABSOLUTE PREDICTION ERROR

	CDPS+Rx V7.1 Unmodified		Recalibrated Weights		Full model		Full Model Constrained	
	R-sq	MAPE	R-sq	MAPE	R-sq	MAPE	R-sq	MAPE
Connecticut								
Adult	21.6%	963.06	24.2%	801.66	24.6%	795.00	24.8%	799.65
Child	8.9%	331.06	25.5%	307.05	25.7%	305.83	25.6%	306.34
SSI	14.5%	400.60	31.3%	360.94	31.4%	354.51	31.3%	355.12
Montana								
Adult	18.2%	5,633.91	21.9%	5,998.44	22.5%	5,647.81	22.4%	6,102.49
Child	4.4%	2,422.68	13.7%	2,313.58	14.2%	2,128.03	13.9%	2,373.42
SSI	6.5%	1,188.37	25.7%	1,601.90	25.9%	1,613.79	25.7%	1,609.59

Risk scores from each of the models under consideration were then referenced —including unmodified CDPS+Rx, recalibrated CDPS+Rx, and full models with SDOH (with and without negative coefficients)—as inputs for the risk-adjusted Medicaid managed care market financial outcome simulations.

STEP 4: HOMELESSNESS Z CODE AND UNSTABLE HOUSING EXPLORATION

The ICD-10-CM codes ranging from Z55 to Z65 were introduced by the Centers for Medicare and Medicaid Services (CMS) in 2016. They are used to document SDOH that can impact a patient's health status and interactions with the healthcare system. Currently there are 11 major categories of Z codes encompassing a broad spectrum of SDOH, including problems related to homelessness, food insecurity, upbringing, and family and support group issues. By incorporating Z codes into medical records and claims data, healthcare providers can gain a more comprehensive understanding of a patient's overall health needs and address factors that may contribute to unfavorable health outcomes for those patients.

The prevalence of Z code usage remains relatively low in claims data. For instance, in a recent study[8] that utilized national data for the commercial and Medicaid populations, the prevalence rate of Z codes is estimated to be 1.6% for the Medicaid population and 1.0% for the commercial population. Another recent study[9] which used data from two Medicaid managed care states found roughly 0.6% members had a Z code for homelessness, and an additional 2% of members were coded with at least one Z code other than homelessness. Coding patterns and gaps in data capture vary by provider, service, and coverage types. Given this, including Z codes in risk adjustment may be premature as it may reflect coding patterns as opposed to underlying population characteristics.

For exploratory purposes in risk-adjustment modeling, a variable was included to indicate whether or not a beneficiary had ever been homeless or had unstable housing during the program year. Homelessness was identified using the diagnosis code Z59.0 in the 2018 claims data. For unstable housing, beneficiaries with three or more ZIP Codes in their 2018 membership records were flagged. Beneficiary counts and prevalence rate of homelessness or unstable housing for Connecticut and Montana are included in Table 4, as well as the coefficients and P-values in the risk-adjustment models.

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[8] Gibbons, J.B., Cram P, Meiselbach, M.K., et al. (December 2023). Comparison of social determinants of health in Medicaid vs commercial health plans, *Health Affairs Scholar*, Volume 1, Issue 6, qxad074. Retrieved February 28, 2025, from: https://doi.org/10.1093/haschl/qxad074

[9] Larson, A., Baird E., et al, (December 2024) Applying an equity lens to Medicaid risk adjustment. Milliman whitepaper, from https://www.milliman.com/en/insight/applying-equity%20lens%20medicaid%20risk%20adjustment

Table 4
ADDING HOMELESSNESS AND UNSTABLE HOUSING INDICATORS

		Connecticut		Montana	
		% Members	Sign	% Members	Sign
Homelessness or Unstable Housing	Adult	0.51%	+	0.64%	+
Interaction, (Homelessness or Unstable Housing)*(Risk Score)	Adult		+		-
Homelessness or Unstable Housing	Child	0.03%		0.04%	
Interaction, (Homelessness or Unstable Housing)*(Risk Score)	Child				
Homelessness or Unstable Housing	SSI	1.27%	+	1.03%	
Interaction, (Homelessness or Unstable Housing)*(Risk Score)	SSI		-		

Notes:
Positive sign (+): Positive and significant coefficient; Negative sign (-): Negative and significant coefficient; Empty cells: statistically insignificant

In light of the low and inconsistent prevalence of these indicators on the beneficiary-level data used for the analysis, homelessness or unstable housing was not included as a factor in the SDOH risk-adjustment models.

3.3 MCO/ACO SIMULATION

To evaluate the financial impacts of integrating SDOH into Medicaid risk adjustment, a series of synthetic Medicaid managed care markets was constructed first, each comprised of a set of MCOs (or, equivalently for this analysis, ACOs) that vary along various dimensions of interest. The simulated MCOs were defined by their attributed membership, which were sampled in a semi-random fashion from the 2019 T-MSIS Medicaid (and CHIP) populations in each of Connecticut and Montana.

For each state, 100 simulation iterations were performed across two different sampling methods, totaling 400 simulated markets each comprised of between three and nine MCOs. Each such simulated MCO is in turn comprised of exactly 10,000 individuals sampled with replacement from the set of fee-for-service beneficiaries in the 2019 T-MSIS data for that state. The count of enrollees was kept constant to eliminate unnecessary variation and ensure consistent interpretation of volatility across scenarios.

In order to broaden the observations and test how well they generalize, two different sampling methods were used for defining synthetic MCOs: one that prioritizes interpretability and another that attempts to approximate real-world variation in population risk.

MCO SAMPLING METHOD 1: SIMULATED RISK PROFILES

The first sampling method prioritizes interpretability by simulating nine MCOs per iteration that vary systematically with respect to their morbidity and SDOH-related population risk profiles. For each of the morbidity and SDOH risk factors, sampling weights were adjusted to alter each MCO's population mix toward a lower, representative, or higher distribution of risk factors, resulting in nine combinations of low-, medium-, and high-risk profiles.

Table 5
MCO RISK PROFILES

		SDOH-Related Risk		
		Low	Medium	High
Morbidity Risk	Low	MCO **A**	MCO **B**	MCO **C**
	Medium	MCO **D**	MCO **E**	MCO **F**
	High	MCO **G**	MCO **H**	MCO **I**

After quantifying the morbidity and SDOH risk for each enrollee in the data, the set of all enrollees was used to build a distribution from which sampling (with replacement) could be done to build synthetic MCOs aligned with the risk profiles described in Table 5. Furthermore, by modifying the sampling weight assigned to each individual the distribution could be adjusted to skew more strongly toward a desired overall risk profile.

To do this, enrollees were first divided within each rate cell into five quintiles of equal size based on morbidity-related risk (using risk scores from the recalibrated CDPS+Rx model) and again (separately) based on SDOH-related risk (using the SDOH component score from the full model). Then, starting from a default probability weight of 1.0, the probability weight used for sampling enrollees from the 2019 T-MSIS population was multiplicatively adjusted up or down based on the combination of beneficiaries' morbidity quintiles and corresponding MCO morbidity risk profile, and then again based on the combination of beneficiaries' SDOH quintiles and corresponding MCO SDOH-related risk profile.

Table 6 shows the multiplicative sampling weight adjustment factors used by profile and quintile. The final relative sampling weight for an enrollee equals the product of the applicable morbidity weight adjustment factor and applicable SDOH weight adjustment factor based on intersections of beneficiary quintiles and MCO risk profiles.

Table 6
MULTIPLICATIVE SAMPLING WEIGHT ADJUSTMENT FACTORS BY BENEFICIARY AND MCO RISK

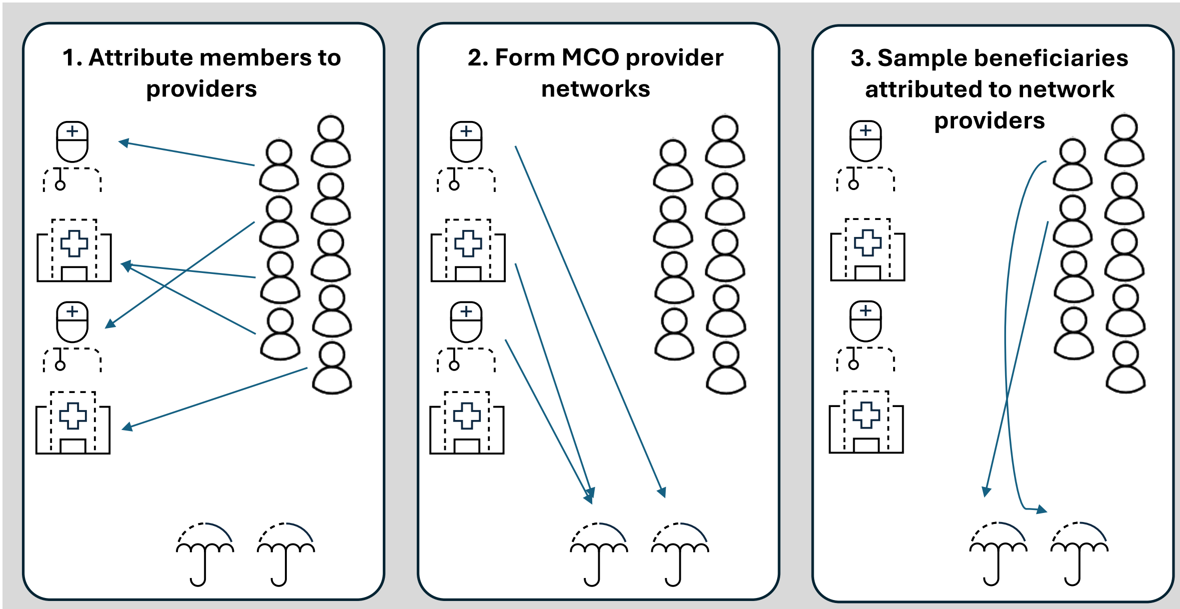
		Beneficiary Risk Quintile (within Rate Cell)				
		1 - Lowest	2 - Second Lowest	3 - Middle	4 - Second Highest	5 - Highest
MCO Risk Profile	Low	1.50	1.25	1.00	0.75	0.50
	Medium	1.00	1.00	1.00	1.00	1.00
	High	0.50	0.75	1.00	1.25	1.50

The advantage of this first sampling method is to provide a clean (if artificial) window into how risk-adjusted loss ratios may vary across risk-adjustment models and MCO population profiles.

MCO SAMPLING METHOD 2: SIMULATED NETWORKS

The second sampling method simulates provider networks as the basis for correlated risk among assigned beneficiaries with the intent of approximating a more realistic form of variation in MCO risk profiles than the explicit risk stratification applied in Method 1. In each simulation iteration under this method, provider networks were randomly defined for three synthetic MCOs, and then sampled members (with replacement) for each MCO from the pool of members attributed to providers in that MCO's network (Figure 1).

Figure 1
NETWORK SIMULATION ILLUSTRATION



To do this, the first step was to attribute individuals to a managing primary care provider physician group or outpatient facility based on which physician group performed the plurality of evaluation and management (E&M) visits for that beneficiary in 2019 (if applicable) or which facility performed the plurality of outpatient visits (otherwise). Physician groups were identified and distinguished by tax identification number (TIN) and facilities by CMS Certification Number (CCN). This initial attribution step was performed once, deterministically, for each of Connecticut and Montana. The remaining steps include random elements that were caused to vary for iteration of the simulation.

Next, any beneficiaries not yet attributed were randomly assigned to a provider in the first step (due to insufficient 2019 utilization experience) to a physician group or facility provider with a probability equal to that provider's share of attributed beneficiaries among all attributed beneficiaries residing in the same county as the unattributed beneficiary.

Once all beneficiaries were attributed to a provider (physician group or facility), provider networks were randomly defined for each of three synthetic MCOs within each of the defined geographic rating areas. This was done by first establishing a target network share of attributed beneficiaries between 40% and 60% and then randomly assigning physician provider groups and facilities to each MCO's network until the providers in its network represent a share of attributed beneficiaries equal to or greater than its target share within that rating area. Information from the Milliman MedInsight Provider Registry[10] was also used to model system affiliations between providers and ensure that if one provider from a system is assigned to a synthetic network, then all physician groups and facilities for that system within that rating area would also be assigned together.

[10] Milliman MedInsight (2025). Provider Registry. Retrieved February 28, 2025, from: https://medinsight.com/healthcare-data-analytics-software/data-intelligence/provider-registry/

The next step was to sample 10,000 beneficiaries uniformly with replacement from the set of beneficiaries attributed to providers within each MCO's network, producing three preliminary synthetic MCO populations, each with 10,000 beneficiaries.

As a final step to improve interpretability and ensure some degree of systematic differentiation in risk between the three MCOs under this method, beneficiary populations were shuffled between MCOs at the rating area level to produce three "re-assigned" MCOs with a consistent ranking of population risk. Beneficiaries were then grouped together from the lowest-risk preliminary MCO in each rating area (out of the three simulated MCO populations per rating area per iteration, using regional MCO risk-adjustment factors from the full model with SDOH) as the "low-risk" re-assigned MCO, beneficiaries from the highest-risk preliminary MCO in each rating area as the "high-risk" re-assigned MCO, and the remainder as the "medium-risk" re-assigned MCO.

The advantage of this second sampling method is to provide a more realistic basis for defining synthetic MCOs (i.e., provider networks as opposed to the simulated risk profiles in Method 1) that still captures an important source and correlate of real-world variation in population risk.

3.4 RATE STRUCTURE AND FINANCIAL OUTCOME SIMULATION

The final step taken was to simulate financial outcomes for each MCO within a synthetic Medicaid managed care market using actual 2019 benefit expenditures and a simplified capitation rate structure with revenue-neutral risk adjustment.

CAPITATION RATE STRUCTURE

A set of base rates and rating factors was developed with the intent of approximating a typical Medicaid managed care rate structure. Base rates and multiplicative region factors were set by state, region, and aid category based on average observed 2019 benefit expenditures per member per month (PMPM). The next step was to set demographic factors by state, aid category, and demographic grouping (but not region) so that the product of base rates and demographic factors would match observed 2019 benefit expenditures PMPM at that level of detail. (See Tables 11, 12, and 14 in Appendix A for base rates, demographic factors, and region factors for Connecticut and Montana.)

Capitation rates were established deterministically, once per state, using actual 2019 benefit expenditures and enrollment across all beneficiaries included in the analysis. No projection factors or trend assumptions were required, since capitation rates were developed using data for the same year to which they are applied.

Allowances for non-benefit expenses or underwriting margin were omitted, and therefore loss ratios (claims divided by revenue) are referred to as "claims ratios," where a claims ratio of 100% indicates that benefit expenditures are exactly offset by simulated revenue.

REVENUE-NEUTRAL RISK ADJUSTMENT

The next step was to calculate and apply a set of risk-adjustment factors (RAFs) to simulated MCOs on a revenue-neutral basis within each Medicaid managed market simulation iteration for each of the four scenarios (simulated risk profiles and simulated networks for each of Connecticut and Montana).

Preliminary risk-adjustment factors (RAFs) were then calculated for each MCO, aid category, and region (but not demographic grouping) equal to the ratio of observed risk scores for that MCO versus expected risk scores for the same mix of enrollees by aid category and demographic grouping. Risk scores for unscored beneficiaries (i.e., fewer than four months of exposure in 2018) were set to the expected average for scored beneficiaries with the same aid category and demographic grouping, with the exception of SDOH risk factors, which were calculated for unscored members using their 2019 area of residence.

Next, multiplicative RAFs were normalized by MCO, aid category, and region (but not demographic grouping) to be revenue neutral such that simulated revenue by aid category and region is unchanged in total (across simulated MCOs for a given scenario iteration) before and after RAFs are applied.

Financial outcomes net of risk-adjusted revenue were reported using RAFs for each of the following models:

1. No risk adjustment (base capitation only)
2. SDOH risk factors only (no CPDS+Rx condition categories)
3. CPDS+Rx version 7.1 (unmodified weights)
4. Recalibrated weights (retained subset of CPDS+Rx condition categories, with modified weights)
5. Full model (two-stage model with morbidity factor using recalibrated CDPS+Rx weights, community-level SDOH factors, and morbidity x SDOH interaction factors, including factors with negative coefficients)
6. Full model constrained (full model, constrained and iteratively recalibrated after excluding factors with negative coefficients)

SAMPLING CALIBRATION FACTORS

Due to the way that the two sampling methodologies were designed, some members were slightly more likely than others to be sampled or omitted from any given market simulation iteration, resulting in a slight deviation from capitation rate setting (which assumes equal weight for all member months of experience in the 2019 Connecticut and Montana T-MSIS data). To correct for this potential source of distortion, an additional set of sampling calibration factors was calculated and applied to simulate claims and revenue, which were then varied by aid category, state, and simulation method (risk profiles or network), but otherwise held constant across all MCOs for all iterations to offset any systematic distortions introduced by the sampling process used. See Table 7 for the range and median of these calibration factors (across aid categories) for each of claims and revenue, by state and simulation method:

Table 7

SAMPLING CALIBRATION FACTOR SUMMARY STATISTICS

		Connecticut		Montana	
		Claims	Revenue	Claims	Revenue
Levels	Median	100.0%	100.0%	100.0%	100.0%
	Range	98.7% - 101.0%	100.0% - 100.1%	99.5% - 100.4%	100.0% - 100.0%
Network	Median	99.7%	100.0%	99.3%	99.9%
	Range	97.6% - 102.9%	99.3% - 100.2%	97.1% - 100.1%	99.5% - 100.2%

Section 4: Results

4.1 SIMULATED RISK PROFILES

Table 8 summarizes risk profile simulation results for Connecticut. Results are similar for Montana (see Table 15 in Appendix B), and all qualitative observations below apply to both states unless noted otherwise.

Table 8

SUMMARY RESULTS – SIMULATED RISK PROFILES, CONNECTICUT

		Simulated MCOs by Risk Profile										
	Morbidity	Low			Med			High				
	SDOH Risk	Low	Med	High	Low	Med	High	Low	Med	High		
Risk-adjustment Model		A	B	C	D	E	F	G	H	I	Total Market	Any Carrier
Average Monthly Members		8,954	8,749	8,554	8,996	8,789	8,596	9,024	8,820	8,627	79,109	8,790
Average Claims Ratio	1. N/A (Base Capitation Only)	76%	78%	81%	98%	100%	102%	120%	122%	122%	100%	100%
	2. SDOH Risk Factors Only	77%	79%	80%	100%	100%	101%	122%	121%	119%	100%	100%
	3. CDPS+Rx (Original)	101%	102%	102%	100%	100%	100%	99%	99%	99%	100%	100%
	4. Recalibrated Weights	103%	106%	110%	98%	100%	103%	95%	97%	98%	100%	100%
	5. Full Model (Recalibrated + SDOH)	102%	103%	103%	100%	100%	100%	98%	98%	98%	100%	100%
	6. Full Model Constrained (Non-Negative)	102%	103%	103%	100%	100%	100%	98%	98%	98%	100%	100%
Coef. of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	2.8%	2.7%	2.6%	2.7%	2.7%	2.4%	2.3%	2.5%	2.4%	1.0%	17.9%
	2. SDOH Risk Factors Only	2.7%	2.7%	2.6%	2.7%	2.7%	2.3%	2.3%	2.5%	2.4%	1.0%	17.3%
	3. CDPS+Rx (Original)	2.5%	2.5%	2.8%	2.4%	2.4%	2.4%	2.1%	2.2%	2.3%	1.0%	2.6%
	4. Recalibrated Weights	2.3%	2.5%	2.7%	2.5%	2.3%	2.2%	2.1%	2.2%	2.2%	1.0%	5.1%
	5. Full Model (Recalibrated + SDOH)	2.3%	2.5%	2.6%	2.4%	2.3%	2.1%	2.1%	2.2%	2.2%	1.0%	3.0%
	6. Full Model Constrained (Non-Negative)	2.3%	2.5%	2.6%	2.4%	2.3%	2.1%	2.1%	2.2%	2.2%	1.0%	3.0%

Table 8 presents average claims ratios (the ratio of observed expenditures to risk-adjusted “revenue” under the simplified capitation rate structure that was used) for each of nine MCO profiles (A through I) and six risk-adjustment scenarios (1 through 6), as averaged across all 100 iterations of the risk profile simulation methodology for Connecticut. A claims ratio below 100% implies that MCO costs fall below simulated revenue on average, a ratio of 100% implies perfect calibration (recall that simulated revenue is calibrated to expected benefit costs with no non-benefit allowance), and a ratio above 100% implies that MCO costs exceed revenue on average.

The bottom section presents the coefficient of variation for claims ratios (i.e., standard deviation of observed MCO-average claims ratios over the average across all 100 iterations) by MCO risk profile and risk-adjustment scenario. The coefficient of variation can be thought of as a measure of expected volatility of MCO results across iterations.

The final two columns on the far right represent results (claims ratios and coefficient of variation) across iterations for the overall market ("Total Market," representing average results for the market as a whole after aggregating experience across all nine MCO profiles) and for "Any Carrier": results for a single MCO (rather than the whole market) across all 100 iterations and nine risk profiles.

Claims ratios average out to 100% (perfectly calibrated) for MCO risk profile E (medium morbidity risk x medium SDOH risk) but systematically diverge from 100% for other profiles. The greatest divergences are observed for MCOs with low or high morbidity profiles in the absence of risk adjustment (e.g., MCO profiles each of A through C and G through I for model 1, base capitation only) or when risk adjustment excludes condition category risk factors (the same MCO profiles for model 2, SDOH risk factors only). Smaller divergences can be observed when varying MCO SDOH risk profiles (e.g., D and F) and for models that include condition category risk factors (models 3 through 6).

Volatility is almost uniformly lower when the MCO risk profile is known in advance (i.e., coefficient of variation of claims ratios for risk profiles A through I) than when the MCO risk profile is also randomized ("Any Carrier").

Integration of SDOH into risk adjustment provides a small but measurable reduction in volatility and variation of financial results across risk profiles, versus a recalibrated model without SDOH. This can be observed by comparing the coefficient of variation of the claims ratio for the "Any Carrier" risk profile (a measure of volatility in MCO financial results) for models 5 and 6 (which include SDOH, both 3.0%) versus model 4 (which only includes demographic and condition category risk factors, 5.1%).

The improvement in fit, while modest, is greatest for populations with below-average morbidity risk and above-average SDOH-related risk (i.e., MCO profile C). Prospective risk scores for these beneficiaries are too low under the morbidity-only recalibrated model (model 4, average claims ratio of 110%) but closer to parity after incorporating SDOH (models 5 and 6, average claims ratio of 103% for both), suggesting that SDOH risk factors may help right-size revenue for populations whose healthcare needs are greater than otherwise indicated by prior-year diagnoses.

The reduction in volatility from introducing SDOH risk factors to risk adjustment (models 5 and 6 versus 4, model 2 versus 1) is much less than the impact from introducing CPDS+Rx condition categories (models 3 and 4 versus 1).

The unmodified CPDS+Rx version 7.1 model does a better job of addressing volatility in expected claims by MCO profile than the recalibrated model before incorporating SDOH risk factors and performs similarly to the recalibrated models with SDOH risk factors. The authors discuss reasons for doing this in Section 5 and propose methods such as partial recalibration with penalized ridge regression that future researchers and program designers may employ to obtain the benefits of recalibration without discarding relevant information already embedded in original model weights.

Table 9
"ANY CARRIER" VOLATILITY BY AID CATEGORY – SIMULATED RISK PROFILES

	Risk-adjustment Model	CHIP	Foster Care	TANF Adult	TANF Child	Expan-sion	Disabled (Non-Dual)	All Aid Categories
	Connecticut							
	Average Monthly Members	236	93	1,956	3,198	3,162	195	8,840
Coef. of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	24.8%	36.0%	17.1%	17.2%	19.3%	20.6%	17.9%
	2. SDOH Risk Factors Only	24.7%	35.4%	16.8%	17.1%	18.7%	18.6%	17.3%
	3. CDPS+Rx (Original)	18.6%	24.4%	4.8%	4.8%	3.7%	10.2%	2.6%
	4. Recalibrated Weights	18.1%	24.9%	7.5%	4.5%	6.8%	10.7%	5.1%
	5. Full Model (Recalibrated + SDOH)	18.1%	25.0%	5.4%	4.5%	3.9%	10.0%	3.0%
	6. Full Model Constrained (Non-Negative)	18.1%	25.0%	5.4%	4.5%	3.8%	9.9%	3.0%
	Montana							
	Average Monthly Members	932	250	670	2,793	3,403	362	8,409
Coef. of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	15.0%	24.2%	15.8%	14.1%	16.1%	18.2%	15.3%
	2. SDOH Risk Factors Only	15.1%	24.0%	15.5%	13.8%	15.9%	18.1%	15.2%
	3. CDPS+Rx (Original)	9.3%	13.5%	8.6%	6.0%	4.5%	12.1%	3.8%
	4. Recalibrated Weights	9.1%	12.4%	8.8%	5.3%	5.8%	9.8%	4.2%
	5. Full Model (Recalibrated + SDOH)	9.3%	12.0%	7.0%	4.3%	3.9%	9.2%	3.2%
	6. Full Model Constrained (Non-Negative)	9.0%	12.1%	6.9%	4.0%	3.6%	9.1%	2.7%

As Table 9 shows, volatility of financial results was higher within each aid category than in total, with the level of volatility closely related to the average population size for each aid category. For example, simulated claims ratios were most volatile for the foster care and adoption assistance aid category, which had the fewest assigned beneficiaries in both states, and least volatile for the expansion adult population, which is the largest aid category in Montana and a close second to TANF Child in Connecticut.

Despite the greater observed volatility at the aid category level, the ordinal ranking of models with respect to observed volatility is relatively consistent across aid categories and states.

4.2 SIMULATED NETWORKS

Table 10 summarizes network simulation results for Connecticut. Results are again similar for Montana (see Table 16 in Appendix B), and all qualitative observations again apply to both states unless noted otherwise.

Table 10
SUMMARY RESULTS – SIMULATED NETWORKS, CONNECTICUT

		Simulated MCOs by Network Risk Profile				
		Lowest	Median	Highest	Total Market	Any Carrier
	Average Monthly Members	8,954	8,749	8,554	26,520	8,840
Average Claims Ratio	1. N/A (Base Capitation Only)	95%	100%	105%	100%	100%
	2. SDOH Risk Factors Only	95%	100%	105%	100%	100%
	3. CDPS+Rx (Original)	99%	100%	101%	100%	100%
	4. Recalibrated Weights	99%	100%	101%	100%	100%
	5. Full Model (Recalibrated + SDOH)	99%	100%	101%	100%	100%
	6. Full Model Constrained (Non-Negative)	99%	100%	101%	100%	100%
Coef. Of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	2.8%	2.8%	3.4%	2.0%	5.0%
	2. SDOH Risk Factors Only	2.8%	2.8%	3.3%	2.0%	4.9%
	3. CDPS+Rx (Original)	2.8%	2.7%	2.8%	2.0%	2.9%
	4. Recalibrated Weights	2.8%	2.6%	2.9%	2.0%	2.9%
	5. Full Model (Recalibrated + SDOH)	2.7%	2.6%	2.9%	2.0%	3.0%
	6. Full Model Constrained (Non-Negative)	2.7%	2.6%	2.9%	2.0%	3.0%

Variation of financial results between simulated MCOs is muted when using randomly assigned provider networks as the basis for varying MCO risk compared to explicit simulation of different risk profiles. For example, claims ratios before risk adjustment (model 1, above) only vary +/-5% from the median for the lowest- and highest-risk re-assigned MCO networks, versus more than +/- 20% under the previous method (Table X from earlier). This is also evident in less variation in financial outcomes when the MCO profile is not known in advance under network simulation (5.0% coefficient of variation for “Any Carrier” claims ratios under model 1) versus under risk profile simulation (17.9%). This expected result may represent a more realistic measure of model effectiveness, since actual MCOs are also unlikely to be subject to explicit risk stratification of the sort used when simulating risk profiles.

Notably, the financial impacts of incorporating SDOH factors into risk adjustment (models 5 and 6 versus 4, model 2 versus 1) are negligible under the simulated networks method, suggesting that any beneficial effects of incorporating SDOH measures into risk adjustment may be neutralized to the extent that MCOs don’t differ materially in the SDOH composition of their member population within a given rating area.

For simulated networks volatility results by aid category, see Table 17 in Appendix B.

Section 5: Discussion

5.1 LESSONS LEARNED

Integrating SDOH into risk adjustment presents both challenges and opportunities. Through the analysis that was performed, several key lessons have emerged:

Defining and measuring SDOH is difficult: SDOH encompasses a broad range of factors, and operationalizing these within a risk-adjustment framework is inherently complex. There is no consensus on the best way to define or measure SDOH for risk-adjustment purposes.

National SDOH data sources are poor/limited: Reliable, individual-level SDOH data sources at the national level are scarce and often incomplete. The use of proxy measures, such as census-based variables, provides some insights but lacks the granularity needed for precise modeling.

Limits of an empirical approach: Risk adjustment based on historical claims data has inherent limitations. These models often fail to distinguish between differences in access to care and actual healthcare needs, which can exacerbate inaccuracies rather than address them.

Populations not fully integrated into the healthcare system and negative coefficients: Historical claims data often underrepresents populations not fully integrated into the healthcare system due to lower utilization. This can lead to unexpected model behaviors, such as negative coefficients for certain SDOH variables, which contradict objectives by reducing risk-based capitation payments for individuals with higher SDOH needs.

Distinguishing access from need: A major challenge lies in disentangling differences in access to care from differences in underlying health needs. Without careful adjustments, risk-adjustment models may conflate the two, undermining their utility to appropriately fund the healthcare needs of all members..

Effective interventions may require time: The full impact of SDOH risk adjustment may take years to materialize. Coding incentives, care delivery patterns, and data quality will evolve over time, gradually influencing outcomes.

Impacts might be too small to influence behavior: The analysis that was conducted indicates that, compared with morbidity-based risk adjustment in which medical conditions may have already captured some of the SDOH variability, adding community-level SDOH as separate risk factors has limited impact on revenue allocation. Such small-scale effects may not be sufficient to incentivize substantial behavioral changes among MCOs.

Risk adjustment as one policy ingredient: SDOH risk adjustment is more prudently viewed as part of a broader set of potential policy options rather than as a standalone solution. It complements other initiatives, such as direct funding for populations with limited access to healthcare and incentivizes SDOH data collection.

5.2 LIMITATIONS

The study conducted faced several limitations to consider when interpreting the findings:

Absence of individual SDOH data: The lack of reliable individual-level SDOH data constrained the ability to accurately assess personalized social needs and their impact on healthcare outcomes.

Imprecision of census-based SDOH variables: Census-level SDOH proxies, while useful for broad analyses, lack the granularity required to fully capture nuanced health-related social needs at the individual level. This limitation could reduce the model's precision in reflecting the social determinants impacting healthcare utilization.

Limited data for recalibration: Access to updated and longitudinal data for recalibrating the risk-adjustment model was insufficient, limiting the model's ability to respond to emerging trends and changes in population dynamics.

Statistical bias in calibration and validation: The enrollment and claims data from Connecticut and Montana was not large enough to support both a recalibration and a rigorous validation, especially when separate risk weights needed to be developed for adults, children, and beneficiaries on SSI. The use of the same dataset for both calibration and validation may have introduced statistical bias, potentially inflating the model's performance metrics and reducing its robustness.

Risk factors not Analyzed: Certain risk factors were not included in the analysis due to statistical insignificance or low data volume, which could have affected the comprehensiveness of the model.

Collinear variables: High collinearity among some SDOH variables posed challenges in isolating their unique effects on health outcomes, potentially impacting the accuracy of the model’s predictions.

Variability across states: Risk-adjustment models can perform differently across states due to variations in demographics, healthcare delivery systems, and policy environments, limiting the generalizability of the findings.

Use of pre-pandemic data: The analysis relied on data from 2018 through 2019, which does not account for the significant shifts in healthcare utilization and social needs caused by the COVID-19 pandemic.

Key subpopulations not studied: Certain high-need populations, including dual-eligible individuals, maternity cases, and neonates, were removed from the analysis, reducing the applicability of the findings to these critical groups.

Assumptions in simulating Medicaid managed care: The use of fee-for-service data to simulate Medicaid managed care involved assumptions that may not fully align with real-world managed care dynamics.

Limited geographic scope: The study was based on data from only two states, which limits the statistical power and generalizability of the results to broader populations and settings.

5.3 OPPORTUNITIES FOR FUTURE RESEARCH AND POTENTIAL POLICY IMPLEMENTATIONS

The study’s findings suggest several promising directions for advancing research and potential policy interventions:

Two-stage risk-adjustment methodology: A two-stage risk-adjustment approach could better address access and morbidity differences. The first stage would predict the likelihood of an individual seeking care, using individual and community-level socioeconomic factors that influence access to affordable care in their community. The second stage would then apply a morbidity and SDOH risk-adjustment model, similar to the one presented in this research study. Importantly to enhance impact, the factors used in each stage would differ: the first stage would focus on access and availability challenges, while the second stage would emphasize care patterns, healthcare utilization, and health outcomes.

Incorporating additional SDOH measures and data sources: The study that was conducted explored a limited set of SDOH factors. Expanding to include more comprehensive measures and alternative data sources could improve the model's granularity and effectiveness. Currently, the model relies on community-level SDOH data, which may not capture individual-level variability. For some members in communities with a high degree of SDOH variability, individual-level SDOH data is far more informative for predicting individual healthcare spending than aggregate community-level data. The industry is progressing toward collecting more individual-level SDOH data, as evidenced by embedded SDOH screening tools in major electronic health record systems and the introduction of new CPT codes for capturing health-related social needs.

Expanding the scope of analysis: Due to exploratory constraints and data quality concerns, this study utilized data from only two states. Broadening the analysis to include more states, years, populations, and benefit structures would significantly enhance the generalizability of findings. Such expansions could provide a clearer understanding of how SDOH risk adjustment performs across a broad array of healthcare landscapes.

Enhancing statistical power and calibration generalizability: Employing advanced statistical methods could strengthen model robustness and improve generalizability. For example, partial credibility methods, such as adjusting CDPS weights with a ridge regression penalty, could balance model performance across all populations and reward consistency across states.[11] Such approaches could refine the calibration process, ensuring more reliable and actionable results.

Exploring policy avenues beyond and complementary to risk adjustment: Risk adjustment is just one tool for aligning healthcare resource allocation with policy goals. Given its current limitations, results would likely be enhanced by considering complementary initiatives, such as increasing funding for populations with limited access to healthcare, developing targeted access interventions, and incentivizing the collection of richer and more detailed SDOH data. A recent industry study[12] also suggested strategies such as making community investments, developing enhanced benefits to offer in-lieu-of services and value-added benefits, and providing financial incentives that are tied to ensuring that all members have adequate access to healthcare providers. These strategies can amplify the impact of risk-adjustment efforts and address provider access issues more comprehensively.

[11] Parkes, S. and Armstrong, B. (July 2015). Calibrating Risk Score Model with Partial Credibility. Society of Actuaries. Article from Forecasting and Futurism. Retrieved February 28, 2025, from: https://www.soa.org/globalassets/assets/Library/Newsletters/Forecasting-Futurism/2015/July/ffn-2015-iss11-parkes-armstrong.pdf
[12] Anders, Applying an equity lens to Medicaid risk adjustment, 16.

Section 6: Disclosures and Qualifications

The Society of Actuaries Research Institute (SOA) retained Milliman, Inc. to conduct data-driven research into considerations and potential impacts associated with integration of social determinants of health into Medicaid risk adjustment.

The research performed relied on information and data provided by CMS, including research identifiable Medicaid enrollment and claims data from the CMS Research Data Assistance Center (ResDAC), and population survey data from the Census Bureau. A limited review of the data and other information was performed, and it was also checked for reasonableness and consistency. No material defects were found in the data or information used. If there are material defects in the data or other information, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or for relationships that are materially inconsistent. Such a review was beyond the scope of this assignment.

Models used in preparation of the analysis conducted were applied consistently with their intended use. Where reliance was placed on models developed by others, such as the Chronic Illness and Disability Payment System and component factors from the CDC Social Vulnerability Index, a reasonable effort was made by the authors to understand the intended purpose, general operation, dependencies, and sensitivities of those models. The authors relied on input, review, and validation by other experts in the development of their models.

The estimates included in this document are not predictions of the future; they are estimates based on the assumptions and data analyzed at a point in time. Actual results will vary due to both random and non-random factors.

Guidelines issued by the American Academy of Actuaries require actuaries to include their professional qualifications in actuarial communications. Jeff Milton-Hall and Nicholas Gersch are members of the American Academy of Actuaries and meet its qualification standards to perform the analysis and render any actuarial opinions contained herein.

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Section 7: Acknowledgments

The authors’ deepest gratitude goes to those without whose efforts this project could not have come to fruition: the volunteers who generously shared their wisdom, insights, advice, guidance, and arm’s-length review of this study prior to publication. Any opinions expressed may not reflect their opinions nor those of their employers. Any errors belong to the authors alone.

Project Oversight Group:

Joan Barrett, FSA, MAAA

Max Billings, FSA, MAAA

Craig Cartossa, ASA, MAAA

Reese Dai, FSA, MAAA

Samuel Driscoll, FSA, MAAA

Ian Duncan, FSA, FIA, FCIA, MAAA, FCA

Wendy Feng, FSA, MAAA

Thomas Lemire, ASA, MAAA

Pei Pei, ASA, PHD

Tanvi Tilloo, MPP

Rodger Yan, FSA, MAAA

Jing Zhang, FSA, MAAA

At the Society of Actuaries Research Institute:

Achilles Natsis, FSA, MAAA, FHLI, Health Research Actuary

Barbara Scott, Senior Research Administrator

Appendix A: Additional Descriptive Data Tables

Table 11

2019 T-MSIS ENROLLMENT AND SIMULATED CAPITATION "BASE RATE" BY STATE AND AID CATEGORY

Aid Category	Connecticut		Montana	
	Included MMs	Base Rate PMPM	Included MMs	Base Rate PMPM
CHIP	235,896	$196	313,055	$362
Disabled	197,862	$2,031	121,695	$1,879
Expansion	3,136,362	$622	1,136,410	$545
TANF Adult	1,923,151	$483	223,032	$471
TANF Child	3,223,661	$274	929,384	$271
Foster Care	91,119	$482	83,905	$663

Table 12

DEMOGRAPHIC GROUPINGS AND SIMULATED "RATE FACTORS" BY AID CATEGORY

Aid Category	Age Lower Bound	Age Upper Bound	Sex	Connecticut Rate Factor	Montana Rate Factor
CHIP	1	3	All	0.943	0.763
CHIP	4	14	All	0.887	0.876
CHIP	15	18+	Female	1.384	1.772
CHIP	15	18+	Male	1.215	1.225
Disabled	1	18	All	2.299	0.952
Disabled	19	99	All	0.961	1.014
Expansion	19	29	Female	0.608	0.789
Expansion	19	29	Male	0.507	0.521
Expansion	30	44	Female	1.231	1.061
Expansion	30	44	Male	0.870	0.842
Expansion	45	99	Female	1.473	1.475
Expansion	45	99	Male	1.436	1.323
TANF Adult	19	29	Female	0.897	1.045
TANF Adult	19	29	Male	0.485	0.496
TANF Adult	30	44	Female	1.089	1.172
TANF Adult	30	44	Male	0.703	0.746
TANF Adult	45	99	Female	1.356	1.366
TANF Adult	45	99	Male	1.074	1.019
TANF Child	1	3	All	0.978	0.742
TANF Child	4	14	All	0.961	0.945
TANF Child	15	18+	Female	1.207	1.523
TANF Child	15	18+	Male	1.057	1.209
Foster Care	1	3	All	0.923	0.550
Foster Care	4	14	All	1.017	1.027
Foster Care	15	18+	Female	1.004	1.115
Foster Care	15	18+	Male	0.961	1.039

Table 13
STATE RATING REGIONS

State	Region	Counties
CT	Fairfield	Fairfield
CT	Hartford	Hartford
CT	Litchfield	Litchfield
CT	Middlesex	Middlesex
CT	New Haven	New Haven
CT	New London	New London
CT	Tolland	Tolland
CT	Windham	Windham
MT	Region 1	Rosebud, Custer Fallon, Power River, Carter, Prairie, Wibaux, Dawson, McCone, Richland, Roosevelt, Garfield, Sheridan, Danield, Valley, Phillips, Treasure
MT	Region 2	Blaine, Hill, Chouteau, Liberty, Toole, Cascade, Glacier, Pondera, Teton
MT	Region 3	Petroleum, Fergus, Judith Basin, Golden Valley, Wheatland, Musselshell, Yellowstone, Stillwater, Sweet Grass, Big Horn, Carbon
MT	Region 4	Park, Gallatin, Madison, Beaverhead, Broadwater, Jefferson, Silver Bow, Deer Lodge, Granite, Powell, Meagher, Lewis and Clark
MT	Region 5	Ravalli, Missoula, Mineral, Sanders, Lake, Flathead, Lincoln

Table 14
SIMULATED CAPITATION REGIONAL "RATE FACTORS" BY STATE, REGION, AND AID CATEGORY

		Regional Rate Factor by Aid Category					
State	Region	CHIP	Disabled	Expansion	TANF Adult	TANF Child	Foster Care
Connecticut	Fairfield	1.001	0.994	0.951	0.930	0.947	0.956
Connecticut	Hartford	1.030	0.970	0.968	0.982	1.027	1.009
Connecticut	Litchfield	1.005	0.850	1.001	0.995	1.025	1.329
Connecticut	Middlesex	0.966	1.027	0.977	1.014	1.088	0.896
Connecticut	New Haven	1.009	1.060	1.056	1.055	1.009	1.028
Connecticut	New London	0.892	0.961	1.063	1.038	0.956	0.856
Connecticut	Tolland	1.062	0.829	0.976	1.026	1.058	1.275
Connecticut	Windham	0.917	1.038	1.007	1.039	1.044	0.762
Montana	1	0.871	0.994	1.256	1.316	1.230	0.977
Montana	2	0.925	1.016	1.121	1.131	1.067	0.858
Montana	3	0.956	0.979	1.027	0.951	0.911	0.928
Montana	4	1.078	0.954	0.901	0.891	1.029	1.167
Montana	5	1.021	1.036	0.937	0.937	0.939	1.046

Appendix B: Additional Simulation Results

Table 15
SUMMARY RESULTS – SIMULATED RISK PROFILES, MONTANA

		Simulated MCOs by Risk Profile										
	Morbidity	Low			Med			High				
	SDOH Risk	Low	Med	High	Low	Med	High	Low	Med	High		
Risk-adjustment Model		A	B	C	D	E	F	G	H	I	Total Market	Any Carrier
Average Monthly Members		8,164	8,195	8,201	8,229	8,263	8,264	8,258	8,293	8,293	74,160	8,240
Average Claims Ratio	1. N/A (Base Capitation Only)	79%	81%	84%	98%	100%	102%	116%	118%	120%	100%	100%
	2. SDOH Risk Factors Only	82%	82%	82%	101%	100%	99%	119%	118%	117%	100%	100%
	3. CDPS+Rx (Original)	102%	104%	106%	99%	100%	101%	97%	98%	98%	100%	100%
	4. Recalibrated Weights	103%	105%	107%	99%	100%	101%	96%	97%	97%	100%	100%
	5. Full Model (Recalibrated + SDOH)	104%	103%	102%	101%	100%	99%	99%	98%	97%	100%	100%
	6. Full Model Constrained (Non-Negative)	102%	102%	102%	101%	100%	99%	100%	99%	98%	100%	100%
Coef. of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	2.6%	2.6%	2.6%	2.3%	2.3%	2.2%	2.3%	2.4%	2.2%	0.8%	15.3%
	2. SDOH Risk Factors Only	2.6%	2.6%	2.6%	2.3%	2.3%	2.2%	2.3%	2.3%	2.2%	0.8%	15.2%
	3. CDPS+Rx (Original)	2.5%	2.6%	2.9%	2.5%	2.6%	2.7%	2.4%	2.3%	1.9%	0.8%	3.8%
	4. Recalibrated Weights	2.4%	2.4%	2.6%	2.3%	2.2%	2.2%	2.0%	2.1%	1.9%	0.8%	4.2%
	5. Full Model (Recalibrated + SDOH)	2.4%	2.5%	2.5%	2.2%	2.2%	2.1%	2.0%	2.1%	1.9%	0.8%	3.2%
	6. Full Model Constrained (Non-Negative)	2.4%	2.4%	2.5%	2.2%	2.2%	2.1%	2.0%	2.1%	1.9%	0.8%	2.7%

Table 16

SUMMARY RESULTS – SIMULATED NETWORKS, MONTANA

		Simulated MCOs by Risk Profile				
		Lowest	Median	Highest	Total Market	Any Carrier
Average Monthly Members		**8,368**	**8,454**	**8,405**	**25,228**	**8,409**
Average Claims Ratio	1. N/A (Base Capitation Only)	98%	100%	102%	100%	100%
	2. SDOH Risk Factors Only	98%	100%	102%	100%	100%
	3. CDPS+Rx (Original)	100%	100%	100%	100%	100%
	4. Recalibrated Weights	100%	100%	100%	100%	100%
	5. Full Model (Recalibrated + SDOH)	100%	100%	100%	100%	100%
	6. Full Model Constrained (Non-Negative)	100%	100%	100%	100%	100%
Coef. of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	2.4%	2.6%	2.8%	1.6%	3.2%
	2. SDOH Risk Factors Only	2.4%	2.7%	2.8%	1.6%	3.1%
	3. CDPS+Rx (Original)	2.5%	2.9%	2.7%	1.6%	2.7%
	4. Recalibrated Weights	2.3%	2.6%	2.7%	1.6%	2.5%
	5. Full Model (Recalibrated + SDOH)	2.2%	2.5%	2.7%	1.6%	2.5%
	6. Full Model Constrained (Non-Negative)	2.2%	2.5%	2.7%	1.6%	2.5%

Table 17

“ANY CARRIER” VOLATILITY BY AID CATEGORY – SIMULATED NETWORKS

	Risk-adjustment Model	CHIP	Foster Care	TANF Adult	TANF Child	Expan-sion	Disabled (Non-Dual)	All Aid Categories
	Connecticut							
	Average Monthly Members	236	93	1,956	3,198	3,162	195	8,840
Coef. Of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	22.5%	30.8%	6.2%	6.9%	6.0%	10.7%	5.0%
	2. SDOH Risk Factors Only	22.5%	30.8%	6.1%	6.9%	6.0%	10.7%	4.9%
	3. CDPS+Rx (Original)	19.8%	26.4%	4.9%	5.4%	4.1%	10.3%	2.9%
	4. Recalibrated Weights	20.6%	26.9%	4.8%	5.2%	4.0%	10.4%	2.9%
	5. Full Model (Recalibrated + SDOH)	20.4%	26.9%	4.8%	5.2%	4.2%	10.3%	3.0%
	6. Full Model Constrained (Non-Negative)	20.5%	26.9%	4.8%	5.2%	4.1%	10.2%	3.0%
	Montana							
	Average Monthly Members	932	250	670	2,793	3,403	362	8,409
Coef. Of Variation (Claims Ratio)	1. N/A (Base Capitation Only)	10.1%	15.2%	8.0%	4.8%	4.4%	8.3%	3.2%
	2. SDOH Risk Factors Only	10.0%	15.2%	8.0%	4.6%	4.3%	8.3%	3.1%
	3. CDPS+Rx (Original)	9.7%	14.6%	7.3%	4.6%	3.7%	8.9%	2.7%
	4. Recalibrated Weights	9.6%	13.3%	7.3%	4.3%	3.6%	8.0%	2.5%
	5. Full Model (Recalibrated + SDOH)	9.6%	13.3%	7.3%	4.1%	3.6%	7.9%	2.5%
	6. Full Model Constrained (Non-Negative)	9.6%	13.3%	7.3%	4.2%	3.6%	7.8%	2.5%

Appendix C: Additional Risk-adjustment Model Calibration Results

Table 18

BASE YEAR ENROLLMENT DURATION AND MODEL PERFORMANCE, CONNECTICUT CDPS+RX MODELS, V7.1 ELIGIBILITY-WEIGHTED MODEL R-SQUARED VALUES, PREDICTING UNTRUNCATED TOTAL ANNUALIZED SPENDING

2018 Enrollment Duration >=4 months

Eligibility Category	Unique Members	Total Member Months	Eligibility-Weighted R2, Untruncated
SSI	16,097	187,682	19.6%
Adult	137,757	1,573,144	22.2%
Child	291,883	3,368,194	15.9%
Expansion	193,595	2,190,694	19.9%

Table 19

FINAL FULL MODEL COEFFICIENTS

Connecticut - Full Model (Recalibrated + SDOH)

Model	Variable	Coefficient	t Value
Adult	constant	586.64	10.998
Adult	EP_CROWD_GQ	-3587.59	-3.24
Adult	EP_CROWD_GQ*RS interaction	5079.64	7.57
Adult	EP_MOBILE*RS interaction	-3853.23	-6.68
Adult	EP_PCI10K	-61.36	-4.22
Adult	EP_PCI10K*RS interaction	106.36	4.69
Adult	EP_SNGPNT	-1083.08	-2.81
Adult	EP_SNGPNT*RS interaction	1298.14	5.48
Adult	RS	5525.53	167.02
Child	constant	255.17	3.7
Child	EP_CROWD_GQ	-7379.62	-7.93
Child	EP_CROWD_GQ*RS interaction	8545.48	15.53
Child	EP_DISABL	-2537.74	-5.17
Child	EP_DISABL*RS interaction	1562.31	5.88
Child	EP_LIMENG	1992.46	3.69
Child	EP_LIMENG*RS interaction	-689.36	-2.26
Child	EP_MINRTY	733	11.01
Child	EP_MINRTY*RS interaction	-734.74	-6.18
Child	EP_MOBILE	2065.64	2.49
Child	EP_MOBILE*RS interaction	-2093.04	-4.52
Child	EP_NOHSDP	-1489.36	-6.18
Child	EP_NOHSDP*RS interaction	1074.68	2.45
Child	EP_NONWORK*RS interaction	689.82	3.97

Child	EP_NOVEH	1253.5	5.12
Child	EP_NOVEH*RS interaction	-736.34	-5.37
Child	EP_PCI10K	-61.02	-3.61
Child	EP_PCI10K*RS interaction	94.12	9.24
Child	EP_SNGPNT	-1588.81	-4.8
Child	EP_SNGPNT*RS interaction	799.41	4.06
Child	EP_UNEMP	3793.25	7.59
Child	EP_UNEMP*RS interaction	-4307.48	-15.13
Child	RS	2554.81	35.64
SSI	EP_CROWD_GQ*RS interaction	12691.94	2.27
SSI	RS	19142.34	91.96

Connecticut - Full Model Constrained (Non-Negative)

Model	Variable	Coefficient	t Value
Adult	constant	441.02	17.34
Adult	EP_CROWD_GQ*RS interaction	3577.57	7.08
Adult	EP_SNGPNT*RS interaction	792.17	5.69
Adult	RS	5559.23	220.61
Child	EP_CROWD_GQ*RS interaction	3623.99	10.19
Child	EP_PCI10K*RS interaction	24.63	4.7
Child	RS	2842.59	266.91
SSI	RS	19487.76	137.48

Montana - Full Model (Recalibrated + SDOH)

Model	Variable	Coefficient	t Value
Adult	constant	-207.85	-3.09
Adult	EP_CROWD_GQ	-6181.16	-3.72
Adult	EP_DISABL*RS interaction	2574.01	4.23
Adult	EP_LIMENG	-23563.02	-2.93
Adult	EP_LIMENG*RS interaction	35008.16	6.77
Adult	EP_MINRTY	4034.29	15.65
Adult	EP_MINRTY*RS interaction	1010.51	4.98
Adult	EP_MOBILE*RS interaction	2812.41	9.33
Adult	EP_NONWORK*RS interaction	-3991.26	-7.64
Adult	EP_SNGPNT*RS interaction	-3824.01	-6.21
Adult	EP_UNEMP*RS interaction	-3039.51	-3.61
Adult	RS	6640.3	32.76
Child	A_15_24M	-335.99	-3.73
Child	EP_CROWD_GQ	-6707.32	-5.07
Child	EP_LIMENG*RS interaction	12685.31	4.05
Child	EP_MINRTY	2636.22	12.78

Child	EP_NOHSDP*RS interaction	-1719.59	-3.04
Child	EP_NONWORK	-1852.63	-13.13
Child	EP_NONWORK*RS interaction	1422.45	3.34
Child	EP_NOVEH*RS interaction	1718.18	3.7
Child	EP_UNEMP	9587.26	8.79
Child	EP_UNEMP*RS interaction	-9131.85	-14.74
Child	RS	3095.4	18.29
SSI	EP_CROWD_GQ*RS interaction	-23852.01	-2.6
SSI	EP_NOHSDP*RS interaction	18188.99	2.16
SSI	EP_NONWORK*RS interaction	-16877.35	-3.56
SSI	EP_PCI10K*RS interaction	-1466.02	-2.98
SSI	RS	27443.54	14.7

Montana - Full Model Constrained (Non-Negative)

Model	Variable	Coefficient	t Value
Adult	EP_LIMENG*RS interaction	23433.54	6.03
Adult	EP_MINRTY	2924.97	20.88
Adult	EP_MOBILE*RS interaction	2877.85	10.25
Adult	RS	5028.01	139.67
Child	A_15_24M	-469.95	-5.28
Child	EP_LIMENG*RS interaction	11042.75	3.64
Child	EP_MINRTY	1568.63	16.3
Child	RS	3099.74	148.58
SSI	RS	19531.88	96.11

*RS – Recalibrated CDPS+Rx risk score

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Serving as the research arm of the Society of Actuaries (SOA), the SOA Research Institute provides objective, data-driven research bringing together tried and true practices and future-focused approaches to address societal challenges and your business needs. The Institute provides trusted knowledge, extensive experience and new technologies to help effectively identify, predict and manage risks.

Representing the thousands of actuaries who help conduct critical research, the SOA Research Institute provides clarity and solutions on risks and societal challenges. The Institute connects actuaries, academics, employers, the insurance industry, regulators, research partners, foundations and research institutions, sponsors, and non-governmental organizations, building an effective network that provides support, knowledge, and expertise regarding the management of risk to benefit the industry and the public.

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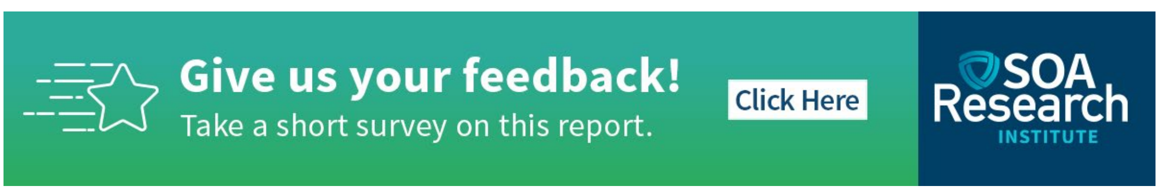
Society of Actuaries Research Institute
8770 W Bryn Mawr Ave, Suite 1000
Chicago, IL 60631
www.SOA.org



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