RISKY BUSINESS: COMPARATIVE MODELING OF COMMERCIAL-POPULATION RISK ADJUSTMENT EQUATIONS JUSTIN KIEL, MS; LAURA NASUTI, MPH, PhD; DAVID AUERBACH, PhD

INTRODUCTION

Risk scores are intended to be a measure of health risk among a given population and have been increasingly used in payment and quality measures. In previous research, the Massachusetts Health Policy Commission (HPC) has found that risk scores are rising roughly 2-3% per year overall, and that much of this growth is inflationary due to coding behavior rather than true changes in patient health status.¹

Disproportionate increases in patient population risk therefore have a higher potential for overcoding.² scores that do not accurately reflect true patient pop-

ulation health can undermine payment systems and quality measures that make use of risk scores and risk adjustment throughout health systems.

Risk adjustment formulas are not standardized: there is a great variety of different methods, variables, and equations to estimate and calculate risk scores. Those that rely on diagnostic coding information are more susceptible to payer and provider manipulation and

OBJECTIVES

Because coding intensity distorts performance evaluation metrics that use risk scores, the HPC has sought to identify comparable alternate risk adjustment equations and methods that are less prone to distortion. Additionally, risk adjustment is increasingly being used to counter disparities in access to care among more marginalized populations by incorporating factors associated with this lack of access (such as education, race/ethnicity, housing status, etc.) and deliberately increasing risk scores for these factors if necessary

(they often are negatively associated with spending because of lack of access to care, which would penalize providers or insurers for covering these patients if the coefficients are not adjusted out-of-model).

Thus, to meet these objectives, the HPC has estimated various risk score equations to calculate risk scores using alternative risk adjustment variables and inputs, including social determinants of health.

STUDY DESIGN

The study population for this analysis included 931,963 commercially insured members from five Massachusetts health plans in 2019. All patients had continuous medical and prescription coverage for 12 months and were between the ages of 0 and 64.

As a baseline, the HPC regressed annual individual total spending on diagnosis-based risk scores (using The Johns Hopkins ACG[®] System © 1990, 2017, Johns Hopkins University. All Rights Reserved.) for the study population. Several alternative models were then tested.

In one of these models, social determinants of health were included. This included geographic region and

variables associated with the individual's zip code: income decile, median family income, home value, percent of white collared workers, percent of single parent households, unemployment percentage, percent of population with a high school diploma, percent of population on FS/SNAP, and the percent in the same house in 12 months. These added variables did not appreciably change the R-squared.

One model included only diagnostic health condition categories that are less likely to be influenced by coding practices, twelve restrictive health conditions: AIDS/HIV, asthma, arthritis, cancer, cardiovascular issues, diabetes, epilepsy, hypertension, mood disorder, multiple sclerosis, psychosis, and renal failure.

RESULTS

Exhibit 1. Comparative Modeling of Risk Adjustment Equations to Predict **2019 Commercial Massachusetts Spending Variation**



Source: Traditional risk adjustment model estimated using The Johns Hopkins ACG® System 1990, 2017, Johns Hopkins University. All Rights Reserved. HPC analysis of Center for Health Information and Analysis Massachusetts All-Payer Claims Database, 2019.

Exhibit 2. Comparative Modeling of Alternative and Traditional Risk Adjustment **Equations to Predict 2019 Commercial Massachusetts Spending Variation**

| COMPREHENSIVE RISK ADJUSTMENT MODEL | TRADITIONAL RISK ADJUSTMENT MODEL |
|-------------------------------------|-----------------------------------|
| R-Squared: 0.23 | R-Squared: 0.21 |
| Age | ACG© Risk Score |
| Sex | |
| Age-Sex Interaction | |
| 10 Social Determinants of Health | |
| 12 Diagnostic Health Conditions | |
| Inpatient Admission | |

Source: Traditional risk adjustment model estimated using The Johns Hopkins ACG[®] System © 1990, 2017, Johns Hopkins University. All Rights Reserved. HPC analysis of Center for Health Information and Analysis Massachusetts All-Payer Claims Database, 2019.

Exhibit 3. Ten Social Determinants of Health and Twelve Select Medical Conditions for Alternative Risk Adjustment Modeling

| SOCIAL DETERMINANTS OF HEALTH | DIAGNOSTIC HEALTH CONDITIONS |
|--|------------------------------|
| Region | AIDS/HIV |
| Income Decile | Asthma |
| Median Family Income | Arthritis |
| Home Value | Cancer |
| Percent of White Collared Workers | Cardiovascular Disease |
| Percent of Single Parent Households | Diabetes |
| Unemployment Percentage | Epilepsy |
| Percent of Population with HS Diploma | Hypertension |
| Percent of Population on FS/SNAP | Mood Disorder |
| Percent in the Same House in 12 Months | Multiple Sclerosis |
| | Psychosis |
| | Renal Failure |

Source: HPC analysis of Center for Health Information and Analysis Massachusetts All-Payer Claims Database, 2019.

The baseline model (the ACG[®] risk score model) predicted the variance of spending with an R-Squared of 0.21. The first alternative model was purely demographic including only age, sex, and age-sex interaction terms. The model had a much lower R-squared of 0.01. Including social determinants of health did not appreciably add to the R-squared value.

The third model combined the age and sex variables with the restrictive list of twelve diagnostic health conditions, resulting in a larger R-squared of 0.15. The fourth model, using only age, sex, and a binary variable for any inpatient admission during 2019, also had an R-squared of 0.15, which is comparative to the diagnosis-based health conditions model.

In risk adjustment literature, there is strong evidence that a health condition that is recorded or registered from prescription use data rather than subjective diagnosis is less susceptible to risk score inflation.^{3,4} Using prescription claims data, the HPC replicated five of these twelve diagnostic health conditions (HIV/AIDS, asthma, diabetes, cancer, and psychosis) to compare the efficacy of a prescription-based model to a diagnosis-based model. Restricting the original diagnostic model to just these five health conditions from the original twelve had an R-squared of 0.06. The comparative prescription-based model also had an R-squared of 0.06, identical in predictive power to estimate spending variation.

The sixth and fully comprehensive alternative model (with age/sex, social determinants of health, the twelve health conditions, and inpatient admission) resulted in an R-squared of 0.23, which is marginally greater than the ACG[®] diagnosis-based risk adjustment model.

Risk adjustment models that do not rely on gameable variable, since inpatient admissions are strongly prevariables, like diagnosis-based risk scores, offer alterdictive of spending. While it is important not to incentivize marginal hospital admissions, such a variable natives that are less susceptible to coding intensity. Using only a few diagnosis categories for specific, might also be less susceptible to gaming than relying high-cost health conditions such as HIV/AIDS, cancer, on diagnosis codes. or renal failure, can be preferable to using a great-Social determinants of health are important to consider number of health conditions through a traditional er and include in any risk adjustment model. While they diagnosis-based risk adjustment method. Certain may have limited predictive power, payment formulae diagnoses can also be replaced with more empirical that include risk adjustment should not be solely beprescription data to predict spending, with prescription holden to regression equations that predict spending tions acting as an internal validation check that the payers and policymakers should place significant condition is merited and being medically treated. weight on these variables in payment and performance Simple measures can also have a good deal of premetrics that incorporate risk adjustment for health dictive power, such as a binary inpatient admission equity reasons.

Risk-adjusted annual spending growth is a key meametrics, and policies and ensure payers and providers sure of performance employed in numerous private are rewarded for efficient provision of care and not for their ability to manipulate diagnosis codes. Reduccontracts and by government agencies. Less gameing inflationary trends in risk score growth can help able risk adjustment methods, in addition to or instead of traditional diagnosis-based risk score models can prevent unsustainable growth in health care which is improve the accuracy of spending growth evaluation, ultimately borne by consumers and patients.

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CONCLUSIONS

POLICY IMPLICATIONS

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