JAMA Internal Medicine | Original Investigation | HEALTH CARE REFORM

Social Determinants of Health in Managed Care Payment Formulas

Arlene S. Ash, PhD; Eric O. Mick, ScD; Randall P. Ellis, PhD; Catarina I. Kiefe, PhD, MD; Jeroan J. Allison, MD, MS; Melissa A. Clark, PhD

Invited Commentary

Supplemental content

IMPORTANCE Managed care payment formulas commonly allocate more money for medically complex populations, but ignore most social determinants of health (SDH).

OBJECTIVE To add SDH variables to a diagnosis-based payment formula that allocates funds to managed care plans and accountable care organizations.

DESIGN, SETTING, AND PARTICIPANTS Using data from MassHealth, the Massachusetts Medicaid and Children's Health Insurance Program, we estimated regression models predicting Medicaid spending using a diagnosis-based and SDH-expanded model, and compared the accuracy of their cost predictions overall and for vulnerable populations. MassHealth members enrolled for at least 6 months in 2013 in fee-for-service (FFS) programs (n = 357 660) or managed care organizations (MCOs) (n = 524 607).

EXPOSURES We built cost prediction models from a fee-for-service program. Predictors in the diagnosis-based model are age, sex, and diagnoses from claims. The SDH model adds predictors describing housing instability, behavioral health issues, disability, and neighborhood-level stressors.

MAIN OUTCOMES AND MEASURES Overall model explanatory power and overpayments and underpayments for subgroups of interest for all Medicaid-reimbursable expenditures excepting long-term support services (mean annual cost = $5590 per member).

RESULTS We studied 357 660 people who were FFS participants and 524 607 enrolled in MCOs with a combined 806 889 person-years of experience. The FFS program experience included more men (49.6% vs 43.6%), older patients (mean age of 26.1 years vs 21.6 years), and sicker patients (mean morbidity score of 1.16 vs 0.89) than MCOs. Overall, the SDH model performed well, but only slightly better than the diagnosis-based model, explaining most of the spending variation in the managed care population (validated R^2 = 62.4) and reducing underpayments for several vulnerable populations. For example, raw costs for the quintile of people living in the most stressed neighborhoods were 9.6% ($537 per member per year) higher than average. Since greater medical morbidity accounts for much of this difference, the diagnosis-based model underpredicts costs for the most stressed quintile by about 2.1% ($130 per member per year). The expanded model eliminates the neighborhood-based underpayment, as well as underpayments of 72% for clients of the Department of Mental Health (observed costs of about $30 000 per year) and of 7% for those with serious mental illness (observed costs of about $16 000 per year).

CONCLUSIONS AND RELEVANCE Since October 2016, MassHealth has used an expanded model to allocate payments from a prespecified total budget to managed care organizations according to their enrollees' social and medical risk. Extra payments for socially vulnerable individuals could fund activities, such as housing assistance, that could improve health equity.

JAMA Intern Med. doi:10.1001/jamainternmed.2017.3317
Published online August 7, 2017.

Author Affiliations: Department of Quantitative Health Sciences, University of Massachusetts Medical School, Worcester (Ash, Mick, Kiefe, Allison, Clark); Department of Economics, Boston University, Boston, Massachusetts (Ellis).

Corresponding Author: Arlene S. Ash, PhD, Department of Quantitative Health Sciences, University of Massachusetts Medical School, 368 Plantation St, ASC 9.2071, Worcester, MA 01605 (arlene.ash@umassmed.edu).

Rather than individuals paying for each medical service they use, health insurance creates a pooled budget to pay for a population's health care; the money can be used to pay bills directly (fee-for-service [FFS]) or to contract with managed care organizations (MCOs), with each MCO receiving a "global payment" to care for its enrolled population. Higher-than-average payments are made for needier patients through risk adjustment; otherwise, MCOs with costlier patients would go broke. Most risk models account for medical problems (diagnoses on claims), age, and sex. However, since social determinants of health (SDH) such as poverty and limited education also affect the ability to seek medical care, adhere to medical recommendations[1-3] and achieve good outcomes, risk formulas should consider SDH.[4,5] Accounting for social risk in value-based purchasing addresses root causes of poor health and high costs, such as housing, nutritional, and behavioral health needs.[6] Comprehensive risk models also bolster the business case for health equity.[7]

MassHealth encompasses Massachusetts' Medicaid and Children's Health Insurance Program. Until 2016, MassHealth relied solely on a refinement of the Department of Health and Human Services' Hierarchical Condition Category (HHS-HCC) model used for the federal Health Insurance Marketplace[8] and for risk adjusting Affordable Care Act (ACA) Marketplace payments. We describe MassHealth's first-in-nation payment model to include SDH variables, implemented in October 2016 for MCOs—and for "accountable care organizations" (ACOs) now being organized.

Inadequate risk adjustment takes money from vulnerable patients and their clinicians, and generates unearned profits for plans that shun needier patients. Risk adjustment *adjusts payments* to each MCO or ACO *to the risk* (that is, expected needs) *of the particular individuals* it enrolls. Extra SDH-based dollars can, for example, address a woman's repeated respiratory hospitalizations by housing her if she is homeless, or by buying an air conditioner or removing allergens at her home.

Key Points

Question Can social determinants of health (SDH) be included in Medicaid payment formulas so as to pay more equitably for the care of socially vulnerable individuals?

Findings Using data from more than 350 000 Massachusetts 2013 Medicaid beneficiaries, we developed a payment model that adds readily available SDH variables to medical diagnoses, age and sex, eliminating or significantly reducing underpayments for several vulnerable subgroups: for example, clients of mental health services, persons with 3 or more addresses during the year, and those living in distressed neighborhoods.

Meaning Massachusetts Medicaid implemented this SDH model in 2016, potentially enabling clinicians to better meet the needs of socially vulnerable patients.

Methods

Overview

Risk adjustment has many applications; herein, we use it to allocate a Medicaid budget among MCOs. We use person-level data to predict medical spending ("expected cost"). In actual contracting with MCOs, payments also account for inflation, regional differences in labor and capital costs, and other factors. This work was an operations project that relied on deidentified data; thus, it was not considered to be human subjects research, and the University of Massachusetts Medical School institutional review board was not involved.

From 2010 to 2016, MassHealth calculated risk from a diagnosis-based Hierarchical Condition Category (DxCG-HCC)[9] relative risk score (RRS); we call this the RRS model. We sought an expanded SDH model that might better tailor predictions to costs for SDH-defined subgroups (eg, race, disability, and factors associated with housing or neighborhood). We measured how well a model fits a group using the predictive ratio: the group's average actual (observed) cost divided by its average model-predicted (expected) cost. A predictive ratio greater than 1.0 indicates underpayment; less than 1.0, overpayment. Predictive ratios near 1.0 represent good fit.

Data

MassHealth's Primary Care Clinician Plan is its FFS program. We used 2013 data for MassHealth enrollees in both FFS and MCO programs. Because "per member per time enrolled" payment is poorly suited to short-term enrollees, we modeled costs for members present for at least 183 days. The resulting "modeling population" excluded 8.4% and 22.0% of FFS and MCO person-years, respectively. All percentages cited for subgroups of people refer to their contribution to total person-years.

Population Studied

The Medicare Advantage program and the ACA Marketplace build MCO payment models on FFS data[10] because claims are considered more accurate than encounter records (dummy bills) provided by MCOs. Similarly, we used FFS data in 2013 to build the SDH model, then examined its ability to predict cost in 2013 FFS and MCO populations.

Modeling Approach

We predict total cost on a per-member per-time-enrolled basis including all inpatient, outpatient, and pharmacy costs, but excluding long-term services and supports (LTSS), which are paid for separately. LTSS includes nursing home care, adult daycare, home health and personal care services, transportation, supported employment, family-caregiver assistance, and care planning and coordination. Following the federal Marketplace approach,[7] we used a "concurrent frame," predicting 2013 cost from 2013 patient diagnoses and SDH characteristics. We annualized cost (eg, letting a person with $3000 of costs over 6 months contribute one-half of a person-year of experience at the rate of $6000 annually). In practice, MCO payments are made monthly, based on number of days enrolled, and recalibrated quarterly using the most recent 12 months of data available. We top-coded costs at $125 000 (replacing larger spending with $125 000) to prevent outliers from distorting the model. Top-coding was used in developing the RRS and the Medicare Advantage and ACA Marketplace risk adjustment models; it is consistent with "reinsurance," in which plans buy policies that cover health care costs for individuals when they exceed a prespecified threshold. Top-coding removed 1.8% and 3.9% of costs in the FFS and MCO programs, respectively.

Predictors

The RRS model predicted cost from medical conditions recorded as *International Classification of Diseases, Ninth Revision (ICD-9),* diagnoses, age, and sex as summarized in a DxCG-HCC (version 4.2, Verscend) concurrent Medicaid relative risk score. This score was developed on the MarketScan Medicaid Managed Care Research Database with individual-level data from about 10 Medicaid states in 2008 to 2009; the model uses a comprehensive 394-condition category classification, but otherwise resembles the Center for Medicare and Medicaid Services' Hierarchical Condition Category (CMS-HCC) model,[8] calculating expected costs from age, sex, and diagnoses grouped into condition categories with hierarchies. For example, chronic lung disease dominates cough; when both are present, the latter is ignored. We used existing Medicaid claims and enrollment files to identify potentially useful variables: race/ethnicity; disability (disability-based entitlement, and clients qualifying for specialized services for mental health or developmental disabilities); housing issues (unstable housing, ≥3 addresses within a year), homelessness (by *ICD* code); substance use disorders; serious mental illness; and 20 age-sex category indicators.[11,12] The substance use disorder and serious mental illness indicators were based on diagnosis codes for conditions such as "drug dependence" and "major depression" (see eAppendix and eReferences in the Supplement).

A key innovation was using enrollee addresses to calculate a "neighborhood stress score" (NSS). We assigned addresses to US Census block groups with American Community Survey neighborhood-level variables.[13] We then used principal components analysis to identify 7 indicators of economic stress (percentage of families with incomes <100% of the federal poverty level [FPL], percentage with <200% of FPL, percentage of unemployed adults, percentage of households receiving public assistance, percentage of households with no car, percentage of single parents among households with children, and percentage of people ≥25 years with no high school degree). We created the NSS by standardizing each variable (to have a mean [SD] of 0 [1]), taking their average, and restandardizing this across the combined FFS and MCO populations (eAppendix in the Supplement). We set NSS = 0 for those members (6.0% of FFS and 5.1% of MCO) with nongeocodable addresses. The NSS ranged from −1.8 to 3.3 and averaged 0.030 among MCO members and −0.044 in FFS.

We also examined variables such as race/ethnicity, extreme poverty (family income ≤86% of FPL), homelessness as identified in administrative records, and problems with the English language. Reasons for rejecting variables included many missing values (eg, nearly 40% of values for race were missing), redundancy with other information (having a coefficient near zero), and potentially subtracting money from patient populations whose use of additional resources (eg, translation services for people with limited English) is not captured in claims or encounter records.

Similar to modeling for the federal ACA Marketplace,[8] we wanted predictors to statistically significantly predict cost; be reliably measured for nearly all members; and satisfy feasibility, fairness, and transparency considerations. Hence, for fairness, we set NSS to its average value of 0 rather than use "address could not be geocoded" as a predictor (which would have subtracted about $90 from the annual payment for each such person). Another consideration was how the model would work in a dynamic marketplace where stakeholders can "game" variables to trigger a larger payment than justified. For example, we considered 3 potentially relevant "flags" for housing-related risks: a homeless designation in state administrative records; a "homelessness" *ICD* diagnosis code during some medical encounter; and having 3 or more residential addresses in a year (ie, ≥2 moves). These identified 2.3%, 0.7%, and 11.5% of FFS members, respectively, and were associated with radically different incremental costs: about $0, $7000, and $600, respectively. We discarded the noninformative administrative flag. Also, we were reluctant to put $7000 on a diagnosis code that is currently rarely and inconsistently used. Reasoning that homelessness conferred at least as much risk as repeated moves, we used the increment of about $600 for any member with either 3 or more addresses or an *ICD* code for homelessness.

We excluded "persistent use of LTSS" (commonly, nursing home care, and defined here as at least $500 of LTSS in each of 3 consecutive months), although average costs for such people were $7000 more than we could otherwise predict. Why? Because models should encourage cost-efficiency by capturing the *need* for, rather than *use* of, services. If we paid for "persistent LTSS," a plan could trigger $7000 in extra payments simply by spending $500 of LTSS on a person in 3 consecutive months, even if better options were available.

Estimation

Following Medicare Advantage, Part D, and the ACA Marketplace, we used simple, weighted, least-squares regression[8] to predict 2013 cost from 2013 patient characteristics for MassHealth FFS members. We then tweaked the regression outputs to conform to policy considerations, such as setting a minimum positive prediction for everyone. Analyses were performed with Stata statistical software (version 14.1; StataCorp Inc).

Results

In the 2013 modeling population, the FFS program included more men (49.6% vs 43.6%), older patients (mean age of 26.1 years vs 21.6 years), and sicker patients (mean morbidity score of 1.16 vs 0.89) than MCO members. See **Table 1** and **Table 2**. MCO members had higher proportions of children (≤18 years; 54.8% vs 45.5%) and women, but fewer white/non-Hispanic members (34.5% vs 37.7%). Although both programs had 11.5% of members with at least 3 addresses during the year, most social risks were less prevalent among MCO enrollees; fewer had

Table 1. MassHealth 2013 Member Characteristics by Program[a]

Characteristic	Primary Care Clinician Plan (FFS)	MCOs
Members	357 660	524 607
Member-years	326 501	480 389
Population statistics, mean (SD) [median]		
Enrollment duration, mo	11.2 (1.5) [12.0]	11.2 (1.4) [12.0]
Age, y	26.1 (18.6) [22.0]	21.6 (17.0) [22.0]
Cost, $	5590 (11 684) [1719]	4694 (10 395) [1475]
Relative risk score	1.164 (2.29) [0.42]	0.889 (1.88) [0.33]
Neighborhood stress score	−0.044 (1.03) [−0.10]	0.030 (1.06) [−0.03]

Abbreviations: FFS, fee-for-service; MCO, managed care organization.

[a] All statistics are weighted (WGT) (fraction of the year during which the member was eligible) and include only those enrolled for at least 183 days, representing 91.6% and 78.0% of all enrolled months for FFS and MCO members, respectively. Cost excludes long-term services and supports (LTSS) and is annualized by dividing by WGT and then top-coded at $125 000. Relative risk score (RRS) is the diagnosis-based Hierarchical Condition Category, version 4.2, concurrent model 312 risk score used to summarize the combined effect of all medical conditions listed as diagnoses on claims or encounter records and is normalized to have mean = 1 in the combined 2013 FFS/MCO population.

Table 2. MassHealth 2013 Costs and Medical Risk Scores by Member Characteristics and Program[a]

	Primary Care Clinician Plan (FFS)				MCOs			
			Mean				Mean	
Characteristic or Program	Member-years	%	Cost, $	RRS	Member-years	%	Cost, $	RRS
Age and sex								
Age ≤18 y	148 396	45.5	3195	0.53	263 317	54.8	2725	0.44
Female	164 619	50.4	5804	1.21	270 862	56.4	5063	0.97
Race/ethnicity								
White/non-Hispanic	122 968	37.7	6960	1.46	165 566	34.5	5711	1.10
Black/non-Hispanic	33 744	10.3	5545	1.16	48 682	10.1	4453	0.83
Hispanic	32 004	9.8	5391	1.13	60 494	12.6	4157	0.81
Other non-Hispanic	20 331	6.2	3182	0.62	21 828	4.5	3202	0.59
Missing/unknown	117 454	36.0	4638	0.96	183 819	38.3	4194	0.78
Unstable housing								
Homeless, by *ICD-9* coding	2191	0.7	32 647	6.19	76	0.0	29 745	5.93
≥3 Addresses in a year	37 694	11.5	8441	1.67	55 250	11.5	6734	1.25
Other								
Family income ≤86% of FPL	243 290	74.5	6342	1.33	334 027	69.5	5240	1.00
Client of DMH	4817	1.5	28 150	3.39	2110	0.4	20 419	2.79
Client of DDS (not DMH)	8022	2.5	11 647	2.42	5067	1.1	9648	1.89
Other disabled	58 802	18.0	12 503	2.82	51 294	10.7	13 132	2.66
Serious mental illness	46 962	14.4	15 570	3.02	49 038	10.2	13 277	2.67
Substance use disorder	31 401	9.6	16 488	3.46	29 697	6.2	15 667	3.15
Persistent LTSS use	10 955	3.4	26 943	4.54	7426	1.5	26 231	3.68
Could not be geocoded	19 650	6.0	6267	1.33	24 454	5.1	5643	1.07

Abbreviations: DDS, Department of Developmental Services (serving the intellectually disabled); Disabled, Medicaid eligibility is for disability; DMH, Department of Mental Health; FPL, Federal Poverty Level; *International Classification of Diseases, Ninth Revision (ICD-9)*; persistent LTSS use, at least $500 of long-term services and supports spending in each of 3 consecutive months; RRS, the diagnosis-based Hierarchical Condition Category, version 4.2, concurrent model 312 risk score, normalized to have mean = 1 in the combined 2013 fee-for-service/managed care organization population and used to summarize the combined effect of all medical conditions listed as diagnoses on claims or encounter records.

[a] All statistics are weighted (WGT) (fraction of the year during which the member was eligible) and include only those enrolled for at least 183 days; Cost is annualized by dividing by WGT and then top-coded at $125 000; it excludes LTSS.

extremely low family income (69.5% vs 74.5%), were clients of the Departments of Mental Health (0.4% vs 1.5%) or Developmental Services (1.1% vs 2.5%), or were flagged for homelessness (0.02% vs 0.67%), disability (12.2% vs 21.9%), serious mental illness (10.2% vs 14.4%), or substance use disorders (6.2% vs 9.6%). And, among members defined by every single one of these social risk factors, mean medical risk (RRS) was lower for those enrolled in MCO programs.

Table 3 shows the mean-only (constant), RRS (diagnosis-based), and SDH model coefficients in the 2013 FFS population, rescaled to illustrate payments where the mean-only model pays $6000 for each member-year. The RRS model

Table 3. Coefficients and R^2s for Models Predicting 2013 Cost for 357 660 Fee-for-Service Members[a]

Predictor	%, Mean	Model, $		
		Constant[b]	RRS[c]	SDH[d]
Intercept, mean	1.000	6000	0	0
RRS[c]	1.164	0	5157	3582
20 Age-sex categories[d]	0	0	0	Various
Disability markers, %				
DMH client	1.5	0	0	14 817
Developmental services (not DMH) client	2.5	0	0	2758
All other disabled	18.0	0	0	1533
Serious mental illness, %	14.4	0	0	2463
Substance use disorder, %	9.6	0	0	2162
Unstable housing, %[e]	11.9	0	0	596
Neighborhood stress score	−0.44	0	0	46
Model R^2 (×100)		0.0	53.5	57.2

Abbreviations: DDS, Department of Developmental Services; DMH, Department of Mental Health; LTSS, long-term services and supports; MMIS, MassHealth Medicaid Management Information System; NNS, Neighborhood Stress score; RRS, relative risk score; SDH, social determinants of health.

[a] Analyses are weighted (WGT) (fraction of the year during which the member was eligible) and include only those enrolled for at least 183 days. Cost was first top-coded at an annualized rate of $125 000, that is, cost = minimum (dollars spent/WGT, 125 000); it was then rescaled (from a mean of $5590 to $6000) for ease of interpretability. Risk is the diagnosis-based Hierarchical Condition Category (version 4.2, Verscend) concurrent model 312 risk score, normalized to have mean = 1 in the combined 2013 FFS–managed care organization population and used to identify medical conditions; NSS is a standardized measure (mean [SD], 0 [1]) summarizing 7 US Census block–level (when not available, tract-level) variables. All predictions are bottom- and top-coded at approximately $15 and $125 000.

[b] Pays $6000, the population mean, for each person.

[c] Pays $5157 times each person's RRS.

[d] The Social Determinants of Health model assigns "intercept" dollars to 20 age-sex categories; see eTable in the Supplement.

[e] Unstable housing refers to those with either an *International Classification of Diseases (ICD)* diagnosis code for homelessness or at least 3 addresses during the year. Because *ICD* coding for homelessness currently flags a small, nonrepresentative subset of those who are homeless, we used the model-derived $596 coefficient for those with multiple addresses for the pooled category.

would allocate the same budget by paying $5157 per RRS unit (average RRS is $1.164, and $6000 = $1.164 × $5157). The right-most column shows SDH model predictors and coefficients. Each RRS unit adds $3582, and the 3 disability categories add $14 817, $2758, and $1533, respectively. Unstable housing (≥3 addresses and/or an *ICD* code for homelessness) adds $596. Each 1-unit increase in NSS increases payment for those in more stressed neighborhoods by $46. Thus, for example, to calculate the SDH model payment for a 40-year-old homeless woman with RRS = 3 who lived in a fairly stressed neighborhood (NSS = 2) and had no other risk factors we would find the demographic contribution for a 40-year-old woman ($299, see the eTable in the Supplement), and calculate $299 + 596 + (3 × 3582) + (2 × 46) = $11 733. Such "raw" dollar payment calculations using the SDH formula can be unreasonably large or small. To recognize that care management costs something (even if only to ensure that nothing is needed), and that the costs that we predict never exceed $125 000, we set the minimum and maximum payments at around $15 and $125 000, respectively.

The SDH model's explanatory power (R^2) for predicting 2013 FFS costs from same-year predictors was 57.2% (vs 53.5% for the RRS model). When applied to the 2013 MCO data, the SDH model R^2 was 62.4%. However, in practice, the model will be less accurate when used prospectively—to pay for "next year." We used 2014 data (not shown) to estimate the prospective R^2 as 38%, which is at the high end of best-performing prospective models in US populations.[14]

The principal goal of risk models is to make payments track large, predictable variations in spending of readily identified subgroups, such as those seen in **Table 4**. Thus, examining predictive ratios (PRs, actual cost/model-predicted cost) for vulnerable subgroups is key. Costs in the most expensive groups exceed 5 times the average, whereas females younger than 18 years cost about half of the average. The RRS model tracks variations in cost fairly well (PRs are near 1), especially for racial/ethnic groups. For clients of the Department of Mental Health, with costs 5 times average, the RRS model has a predictive ratio of 1.72. That is, the RRS model would provide substantial resources to a plan—on average, $17 567 (= $30 216/1.72)—for Department of Mental Health clients, but only the SDH model pays their full ($30 000) cost.

The SDH model's payments are close to costs for most subgroups shown, but not for people with a homelessness diagnosis code, for whom it would pay about $28 000 of their $35 000 costs ($28 178 = $35 044/1.24). Another seriously underpaid group is persistent users of LTSS, with mean medical costs of $28 921. Note that the State of Massachusetts additionally paid about $13 000 per person for LTSS, beyond the global payment. Thus, the SDH model predictive ratio of 1.36 for persistent users of LTSS means that the global budget includes $21 265 for their *medical* costs. Thus, it pays about $34 000 ($21 000 + $13 000) out of about $42 000 (= $29 000 + $13 000) in *total costs*.

Costs for residents of the most stressed neighborhoods were more than 23% higher than those in the least stressed

Table 4. Prevalence, Costs, and Predictive Ratios for Policy-Relevant Subgroups of FFS Members in 2013

			Model Predictive Ratio[a]		
Characteristic	No. (%)	Mean Cost, $	Constant[b]	RRS[c]	SDH[d]
Subgroups Identified by SDH Model Predictors					
Sex and age, y					
Female, age 0-17	73 899 (20.7)	3044	0.51	1.26	**1.00**
Female, age 18-44	67 784 (18.7)	6951	1.16	**0.97**	**1.00**
Female, age >45	38 023 (10.9)	11 030	1.84	0.93	**1.00**
Male, age 0-17	79 157 (22.3)	3764	0.63	1.28	**1.00**
Male, age 18-44	60 064 (16.4)	5747	**0.96**	**0.97**	**1.00**
Male, age >45	38 733 (11.0)	9858	1.64	0.87	**1.01**
Disability status					
DMH client	5036 (1.5)	30 216	5.04	1.72	**1.00**
Developmental services (but not DMH) client	8298 (2.5)	12 502	2.08	**1.01**	**1.00**
All other disabled	61 556 (18.0)	13 421	2.24	0.93	**1.00**
Behavioral health					
Serious mental illness	50 041 (14.4)	16 713	2.79	1.07	**1.01**
Substance use disorder	34 160 (9.6)	17 698	2.95	**0.99**	**1.02**
Housing					
Homeless by diagnostic code	2396 (0.7)	35 044	5.84	1.11	1.24
≥3 Addresses in a year	42 938 (11.5)	9061	1.51	1.06	**1.01**
Least stressed neighborhood quintile	74 251 (20.8)	5325	0.89	**0.97**	**1.00**
Most stressed neighborhood quintile	67 195 (18.8)	6577	1.10	**1.02**	**1.00**
Selected Other (Nonmodeled) Subgroups					
Race/ethnicity					
White/non-Hispanic	133 142 (37.7)	7471	1.25	**0.99**	**1.01**
Black/non-Hispanic	37 308 (10.3)	5952	**0.99**	**0.99**	**0.98**
Hispanic	35 163 (9.8)	5787	**0.96**	**1.00**	**0.98**
Other/non-Hispanic	21 873 (6.2)	3416	0.57	1.06	**1.00**
Missing/unknown	130 174 (36.0)	4979	0.83	**1.01**	**1.00**
LTSS[c]					
Persistent LTSS use	11 426 (3.4)	28 921	4.82	1.27	1.36
Some LTSS use, not persistent	26 907 (7.7)	13 822	2.30	0.95	1.08
Medical conditions					
Any behavioral health use	88 747 (25.5)	13 263	2.21	1.11	1.08
Schizophrenia	6343 (1.9)	27 569	4.59	1.31	1.09

Abbreviations: DDS, Department of Developmental Services; disabled, eligible owing to disability; DMH, Department of Mental Health; FFS, fee-for-service; LTSS, long-term services and supports; RRS, relative risk score; SDH, social determinants of health.

[a] Predictive ratios that differ by less than 5% from the average are highlighted in bold, and reflect good model performance.

[b] Constant pays the average for each person.

[c] RRS pays a multiple of this score that reflects age, sex and diagnoses.

[d] SDH pays on age, sex, RRS, and the other 7 variables listed in Table 2.

neighborhoods (1.10/0.89 = 1.23). The RRS model mostly corrected this, with costs being just 3% less and 2% more than predicted for those living in the least and most stressed neighborhoods, respectively. The SDH model eliminated the remaining difference.

Discussion

We augmented Massachusetts' diagnosis-based Medicaid payment model with available SDH and other data, modestly improving overall explanatory power and dramatically improving the match of payments to costs for several categories of vulnerable members. This model, used by MassHealth since October 2016, allocates payments within a fixed budget accounting for socioeconomic and psychosocial as well as medical risk.

Paying about $50 per standard deviation-sized increment in "neighborhood stress" can give clinicians who serve 1000 or 2000 people in a socioeconomically distressed neighborhood $100 000 or more per year to support innovations that address social complexity. These might include finding housing, or making existing houses safer for people with breathing problems; teaching groups of Caribbean men to prepare diabetes-friendly dishes that they will enjoy eating; or creating internet technology infrastructure to link (as he arrives at the emergency department for the fifth time) a young man with very little medically wrong with him to a community health worker to help him address root causes of his recurrent health emergencies. Such programs could draw more people with complex problems—those who have the most to gain from coordinated care—into managed care. Such incentives seem necessary, since in 2013, the sickest and most vulnerable members remained underrepresented in managed care programs.

As another example, while paying $600 annually for coded homelessness is far less than needed for members who received this code in 2013, it will both support useful services now and encourage the more comprehensive coding needed to accurately price homelessness in the future.

Even when a risk model does not fully match payments to costs for some subgroups, the model diagnostics illustrated here, which compare costs with model-based predictions through predictive ratios, can identify issues that need addressing. For example, MassHealth will separately reimburse MCOs or ACOs for each birth, and subsidize some high costs associated with valuable emergent expenses, such as for curative hepatitis C therapy. We are working on "SDH 2.0."

Limitations

We modeled only enrollees of at least 6 months. However, in Massachusetts, such members contribute most person-years' experience. While global payments should enable systems of care to allocate money wisely between strictly medical and other services, we could not reliably measure the need for those LTSS, and modeled only non-LTSS costs. An SDH model should probably account for additional important social risks, such as "social isolation" and "limited English proficiency." However, we could use only readily available predictors. Other states may not be able to identify the exact same variables—for example, "client of the Department of Mental Health" (a designation that requires rigorous vetting), and their risk models will need to reflect the relations between patient characteristics and cost in their own data. Our work takes a first step, demonstrating that SDH modeling is feasible and providing guidance for how to do it.

Conclusions

A payment formula that accounts for medical problems but ignores social risk can underpay for vulnerable populations, potentially exacerbating inequality. MassHealth's social determinants of health payment model uses existing Medicaid data and reproducible methods to support care for vulnerable members and improve payment equity.

ARTICLE INFORMATION

Accepted for Publication: May 31, 2017.

Published Online: August 7, 2017. doi:10.1001/jamainternmed.2017.3317

Author Contributions: Dr Mick had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.
Study concept and design: Ash, Mick, Ellis, Allison.
Acquisition, analysis, or interpretation of data: Ash, Mick, Kiefe, Clark.
Drafting of the manuscript: Ash, Mick, Ellis, Allison, Clark.
Critical revision of the manuscript for important intellectual content: Ash, Mick, Ellis, Kiefe, Allison.
Statistical analysis: Ash, Mick, Ellis.
Obtained funding: Ash.
Administrative, technical, or material support: Clark.
Study supervision: Ash, Ellis.

Conflict of Interest Disclosures: For some years, terminating in 2016, Drs Ash and Ellis had contract relationships with the company (now called Verscend Technologies) that licenses the DxCG model used in this research. No other disclosures are reported.

Additional Contributions: Many people contributed to this work. At UMass, we thank Georgia Willis, PhD, and Franny Eanet, MA, MS, for project management, Jianying Zhang, MPH, and Jeff Williams, BS, for analytic support, and Judith Steinberg, MD, MPH, for executive leadership. MassHealth collected the data for this study, was consulted during its design and conduct, and approved the manuscript for submission. We especially wish to thank David Garbarino, MPA, John Boney, MS, Julie Fondurulia, MS, Ann Marie Bayer, MBA, and Monique Bertic-Cohen, MPH, MPA, at MassHealth for sharing their extensive knowledge of their program. Everyone is thanked for sustained and passionate commitment to health equity.

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