

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

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) program (n=357,660) or managed care organizations (MCOs) (n=524,607).

Exposures: We built cost prediction models from 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 Outcome 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=\$5,590 per member).

Results: We studied 357660 people who were FFS participants and 524607 enrolled in MCOs with a combined 806889 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 diagnosed-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 under predicts 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 \$30000 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.

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

Background

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 recommendationⁱ⁻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 encompassed 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 Marketplaceⁱⁱ 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.

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 de-identified 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 data¹⁰ 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 day-care, home health and personal care services, transportation, supported employment, family-caregiver assistance, and care planning and coordination. Following the federal Market-place 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 12months of data available. We top-coded costs at \$125000 (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 (CMSHCC) 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 re-standardizing 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 $\leq 86\%$ 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 non-informative 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 regression⁸ 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 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 would allocate the same budget by paying \$5157 per RRS unit (average RRS is \$1.164, and $\$6000 = \$1.164 \times \$5157$). The rightmost 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 $\$299 + 596 + (3 \times 3582) + (2 \times 46) = \$11\,733$. 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 \$125000, we set the minimum and maximum payments at around \$15 and \$125000, 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 (\$30000) 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 \$35000 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 \$34000 (\$21000+ \$13000) out of about \$42000 (= \$29000 + \$13000) in *total costs*.

Costs for residents of the most stressed neighborhoods were more than 23% higher than those in the least stressed 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 \$100000 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 only modeled members with at least 6 months of experience. However, in Massachusetts, longer-term members contribute the vast majority of program experience, as measured in person years. In the spirit of making global payments that both encourage and allow systems of care to use their own best judgment to allocate money between strictly medical and other services, we wanted to model “all” costs, including those for long-term support services, but – having no reliable way to measure the need for those other services – that work remains for another day. It would also be better if our SDH model could account for additional important social risks, such as “social isolation” and “limited English proficiency.” However, we could only use predictors that we could derive from our State’s administrative records. 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); regardless, they will need to develop a model that reflects the relationship between patient characteristics and costs that applies for them. Our work demonstrates that a good start on such modeling is feasible without waiting for ideal data, and this paper provides guidance about how to do that and what is likely to be gained.

Conclusion

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.

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Table 1. MassHealth 2013 Member Characteristics by Program*

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.

*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*

Characteristic or Program	Primary Care Clinician Plan (FFS)				MCOs			
	Member-years	%	Mean		Member-years	%	Mean	
			Cost, \$	RRS			Cost, \$	RRS
Age and sex								
Age ≤18 y	148396	45.5	3195	0.53	263317	54.8	2725	0.44
Female	164619	50.4	5804	1.21	270862	56.4	5063	0.97
Race/ethnicity								
White/non-Hispanic	122968	37.7	6960	1.46	165566	34.5	5711	1.10
Black/non-Hispanic	33744	10.3	5545	1.16	48682	10.1	4453	0.83
Hispanic	32004	9.8	5391	1.13	60494	12.6	4157	0.81
Other non-Hispanic	20331	6.2	3182	0.62	21828	4.5	3202	0.59
Missing/unknown	117454	36.0	4638	0.96	183819	38.3	4194	0.78
Unstable housing								
Homeless, by ICD-9 coding	2191	0.7	32 647	6.19	76	0.03	745	5.93
≥3 Addresses in a year	37694	11.5	8441	1.67	55250	11.5	6734	1.25
Other								
Family income ≤86% of FPL	243290	74.5	6342	1.33	334027	69.5	5240	1.00
Client of DMH	4817	1.5	28150	3.39	2110	0.4	20419	2.79
Client of DDS (not DMH)	8022	2.5	11647	2.42	5067	1.1	9648	1.89
Other disabled	58802	18.0	12503	2.82	51294	10.7	13132	2.66
Serious mental illness	46962	14.4	15570	3.02	49038	10.2	13277	2.67
Substance use disorder	31401	9.6	16488	3.46	29697	6.2	15667	3.15
Persistent LTSS use	10955	3.4	26943	4.54	7426	1.5	26231	3.68
Could not be geocoded	19650	6.0	6267	1.33	24454	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.

*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.

Table 3. Coefficients and R²s for Models Predicting 2013 Cost for 357 660 Fee-for-Service Members*

Predictor	%, Mean	Model, \$		
		Constant**	RRS***	SDH****
Intercept, mean	1.000	6000	0	0
RRS***	1.164	0	5157	3582
20 Age-sex categories****	0	0	0	Various
Disability markers, %				
DMH Client	1.5	0	0	14817
Developmental service (not DMH) client	2.5	0	0	2758
All other disabled	18	0	0	1533
Serious mental illness, %	14.4	0	0	2463
Substance use disorder, %	9.6	0	0	2162
Unstable housing, %*****	11.9	0	0	596
Neighborhood stree 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.

*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.

**Pays \$6000, the population mean, for each person

***Pays \$5157 times each person’s RRS.

****The Social Determinants of Health model assigns “intercept” dollars to 20 age-sex categories; see eTable in the [Supplement](#).

*****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, non-representative subset of those who are homeless, we used the model-derived \$596 coefficient for those with multiple addresses for the pooled category.

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

		N (%)	Mean Cost, \$	Model Predictive Ratio*		
				Constant**	RRS***	SDH****
Subgroups identified by SDH Model predictors						
Sex and Age, y						
	Female, age 0 - 17	73899 (20.7)	3044	0.51	1.26	1.00
	Female, age 18 - 44	67784 (18.7)	6951	1.16	0.97	1.00
	Female, age >45	38023 (10.9)	11030	1.84	0.93	1.00
	Male, age 0 - 17	79157 (22.3)	3764	0.63	1.28	1.00
	Male, age 18 - 44	60064 (16.4)	5747	0.96	0.97	1.00
	Male, age >45	38733 (11.0)	9858	1.64	0.87	1.01
Disability Status						
	DMH Client	5036 (1.5)	30216	5.04	1.72	1.00
	Developmental Services (but not DMH) Client	8298 (2.5)	12502	2.08	1.01	1.00
	All other disabled	61556 (18.0)	13421	2.24	0.93	1.00
Behavioral Health						
	Serious mental illness	50041 (14.4)	16713	2.79	1.07	1.01
	Substance use disorder	34160 (9.6)	17698	2.95	0.99	1.02
Housing						
	Homelessness by diagnostic code	2396 (0.7)	35044	5.84	1.11	1.24
	>=3 Addresses in a year	42938 (11.5)	9061	1.51	1.06	1.01
	Least stressed neighborhood quintile	74251 (20.8)	5325	0.89	0.97	1.00
	Most stressed neighborhood quintile	67195 (18.8)	6577	1.10	1.02	1.00
Selected other (non-modeled) subgroups						
Race/Ethnicity						
	White/Non-Hispanic	133142 (37.7)	7471	1.25	0.99	1.01
	Black/Non-Hispanic	37308 (10.3)	5952	0.99	0.99	0.98
	Hispanic	35163 (9.8)	5787	0.96	1.00	0.98
	Other/Non-Hispanic	21873 (6.2)	3416	0.57	1.06	1.00

	Missing/unknown	130174 (36.0)	4979	0.83	1.01	1.00
LTSS						
	Persistent LTSS use	11426 (3.4)	28921	4.82	1.27	1.36
	Some LTSS use, not persistent	26907 (7.7)	13822	2.30	0.95	1.08
Medical Conditions						
	Any behavioral health use	88747 (25.5)	13263	2.21	1.11	1.08
	Schizophrenia	6343 (1.9)	27569	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.

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

**Constant pays the average for each person.

***RRS pays a multiple of this score that reflects age, sex and diagnoses

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

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