Updating the Chronic Illness and Disability Payment System

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Background: Of the 38 Medicaid programs that risk adjust payments to Medicaid managed care organizations (MCOs), 33 of them use the Chronic Illness and Disability Payment System (CDPS). There has been recent interest in adding social determinants of health (SDH) into risk-adjustment models.

Objective: To update the CDPS models using recent MCO data based on the International Classification of Diseases version 10 coding system and to explore whether indicators of SDH are predictive of expenditures.

Research Design: Data from 3 national Medicaid MCOs and 8 states are used to update the CDPS model. We test whether spending on Medicaid beneficiaries living in economically and socially deprived communities is greater than spending on similar beneficiaries in less deprived communities.

Subjects: Medicaid beneficiaries with full benefits and without dual eligibility under Medicare enrolled in Medicaid MCOs in 8 states during 2017–2019, including 1.4M disabled beneficiaries, 9.2M children, and 6.4M adults.

Measures: Health care eligibility and claims records. Indicators based on the Social Deprivation Index were used to measure SDH.

Results: The revised CDPS model has 52 CDPS categories within 19 major categories. Six major categories of CDPS were revised: Psychiatric, Pulmonary, Renal, Cancer, Infectious Disease, and Hematological. We found no relationship between health care spending and the Social Deprivation Index.

Conclusions: The revised CDPS models and regression weights reflect the updated International Classification of Diseases-10 coding system and recent managed care delivery. States should choose alternative payment strategies to address disparities in health and health outcomes.

Of the 38 Medicaid programs that risk adjust payments to Medicaid managed care organizations (MCOs), 33 of them use the Chronic Illness and Disability Payment System (CDPS) or a related model (Table 1). Risk-adjustment models typically use diagnosis or pharmaceutical codes from claims or encounter data to measure illness burden among groups of beneficiaries enrolled in managed care plans. The resulting risk scores are then used to adjust capitation payments received by the plans to account for differences in the severity of illness in their enrolled populations. The CDPS model maps International Classification of Disease (ICD) codes to CDPS categories.[1] Medicaid Rx is a pharmacy-based system that uses National Drug Classification (NDC) data from claims and encounters to develop profiles based on types of pharmacotherapy.[2] CDPS+Rx is a combination of the CDPS and Medicaid Rx (MRX) models.

The CDPS model focuses on conditions more common among Medicaid beneficiaries including persons with disabilities. In this way, CDPS differs from other risk-adjustment models such as the Centers for Medicare & Medicaid Services-Hierarchical Coexisting Conditions (CMS-HCC) model that was developed for Medicare using Medicare data[3] or the HHS-HCC model developed for the state health exchanges using commercial claims and encounter data.[4] CDPS was originally designed to be predictive of spending while being resistant to gaming and over coding. Thus, the original CDPS model included 58 categories within 19 hierarchies compared with 76 categories used in the V22 version of the CMS-HCC model and 127 HHS-HCCs.

The CDPS was initially developed in 2000 using data from 7 fee-for-service (FFS) state Medicaid programs. The model received major updates in 2009, using national FFS Medicaid data from 2002 to 2005, and in 2014, using national FFS Medicaid data from 2011. In 2016, ICD-10 codes were incorporated into CDPS using the CMS General Equivalence Mappings. CDPS has received regular annual updates to include the most recent ICD and NDC codes.

This paper describes an update to the CDPS models. We used data from 3 national Medicaid MCOs to update the mapping of diagnoses to CDPS categories, taking advantage of the revised ICD coding system and reflecting changes in health care practice over time as well as any differences in practice in MCOs. To the extent that new treatments and technology have changed how patients are treated, the relative weights estimated with 2011 data may not accurately reflect the relative cost in 2019. In 2020, 72%

of Medicaid beneficiaries were enrolled in managed care plans.[5] To the extent that treatment patterns differ across managed care and FFS, the relative weights estimated in earlier versions of CDPS may not accurately reflect the treatment patterns in MCOs.

Further, we test whether spending on Medicaid beneficiaries living in economically and socially deprived communities is greater than spending on similar beneficiaries in less deprived communities. This work contributes to the growing literature exploring whether and how risk adjustment can be used to address the disparities in health and health outcomes experienced by patients with greater social needs.[6–9]

METHODS

Data and Setting

Health care eligibility and claims records were provided by 3 national Medicaid MCOs. The data covered 3 years, 2017–2019, and 8 states: Florida, Illinois, Kansas, Kentucky, Louisiana, Michigan, New Jersey, and Washington. The data were limited to Medicaid beneficiaries with full benefits and without dual eligibility under Medicare. The data included disabled beneficiaries and nondisabled child (age below 19) and adult (age 19 years or above) beneficiaries, including those covered under Medicaid expansions. Eligibility data included demographics (age and sex), aid category, and months enrolled during the year. Claims data included the year of service, procedure, ICD and NDC codes, and the amounts paid by the organizations to providers for their services. The resulting data include just over 17M person-year observations: 1.4M disabled beneficiaries, 9.2M children, and 6.4M adults.

CDPS Analysis Methods

The 2000 CDPS model was developed using an iterative process that combined clinical and economic expertise. ICD codes were initially ordered within major categories corresponding to body systems or types of disease. These codes were then combined, typically at the 3-digit level, into stage 1 groups. Linear regression of stage 1 group indicators on health expenditures was used to generate estimated coefficients for these stage 1 groups. Linear regression was chosen in favor of alternatives, including nonlinear regression, multipart, or machine-learning models. Linear regression has traditionally been used in risk adjustment, and introducing a new modeling approach would add complexity to the interpretation of the coefficients and application of the models to adjust payment. In addition, the CDPS algorithm was developed using linear regression, and it is not clear if the linear function form of CDPS could be accurately applied using nonlinear models.

Two specifications of expenditures are used in the CDPS model. Concurrent expenditures are those that occur within the year that the diagnoses are assigned to CDPS categories. Prospective expenditures are those that occur within the following year. In the concurrent model, at least 6 months of enrollment is required to establish stable CDPS profiles. The prospective model additionally requires at least 1 month of enrollment in the following year. The dependent variable is the ratio of monthly health care expenditures to average expenditures by category of enrollment. Beneficiaries without any expenditures in the year are included in the

TABLE 1. Risk-Adjustment Efforts by State

State	Population Covered	Year Implemented	Classification System
Arizona	SSI + TANF + EXP	2020	CDPS+Rx
California	SSI + TANF + EXP	2009	Medicaid Rx
Colorado	SSI + TANF	1997	CDPS
Delaware	SSI + TANF + EXP	2000	CDPS+Rx
District of Columbia	SSI + TANF	2014	CDPS+Rx
Florida	SSI + TANF	2006	CDPS+Rx
Georgia	TANF	2017	CDPS+Rx
Hawaii	SSI + TANF + EXP	2014	CDPS+Rx
Illinois	SSI + TANF + EXP	2011	CDPS+Rx
Indiana	SSI + TANF + EXP	2015	CDPS+Rx
Iowa	SSI + TANF + EXP	2016	CDPS+Rx
Kansas	SSI + TANF + CHIP	2018	CDPS+Rx
Kentucky	SSI + TANF + EXP	2019	CDPS+Rx
Louisiana	SSI + TANF + EXP	2012	ACG
Maryland	SSI + TANF	1997	ACG
Massachusetts	SSI + TANF	2009	DxCG
Michigan	SSI + TANF + EXP	2000	CDPS+Rx
Minnesota	TANF + EXP + BHP + SSI	2000	CDPS+Rx
Mississippi	SSI + TANF	2017	CDPS+Rx
Missouri	TANF	2012	CDPS+Rx
Nebraska	SSI + TANF	2018	CDPS+Rx
Nevada	TANF + EXP	*	CDPS+Rx
New Hampshire	SSI+ TANF + EXP	2014	CDPS+Rx
New Jersey	SSI + TANF + EXP	2000	CDPS+Rx
New Mexico	SSI + TANF + EXP	2021	CDPS+Rx
New York	SSI + TANF	2008	CRG
North Carolina	SSI + TANF	2021	CDPS+Rx
Ohio	SSI + TANF	2006	CDPS+Rx
Oregon	SSI + TANF + EXP	1998	CDPS+Rx
Pennsylvania	SSI + TANF + EXP	2003	CDPS+Rx
South Carolina	SSI + TANF	2009	CDPS+Rx
Tennessee	SSI + TANF	2000	ACG
Texas	SSI + TANF + CHIP	2007	CDPS+Rx
Utah	SSI	1998	CDPS
Virginia	SSI + TANF + EXP	2003	CDPS
Washington	SSI + TANF + CHIP + EXP	2003	CDPS+Rx
Wisconsin	SSI + TANF	2011	CDPS+Rx
Puerto Rico	SSI + TANF + EXP	2018	CDPS+Rx

*Unknown.
ACG indicates Ambulatory Care Groups; CDPS, Chronic Illness and Disability Payment System; CHIP, Children's Health Insurance Program; CRG, Clinical Risk Groups; DxCG, Diagnostic Cost Groups; EXP, Medicaid expansion population; SSI, disabled Medicaid beneficiaries; TANF, Medicaid eligibility under temporary aid to needy families or other family categories.

analysis with a ratio of zero. Regressions are weighted by months of enrollment. Separate models are estimated for the disabled, children, and adults.

Multiple iterations of these regressions were reviewed by a team of clinical experts and health service researchers. The results were used to combine stage 1 groups into CDPS categories and to create hierarchies within major categories. Combining the stage 1 groups into CDPS categories and categories into hierarchies helps to reduce the potential overfitting of the model to the data and reduces the incentive and ability for upcoding and gaming the algorithm to maximize reimbursement. Diagnoses were excluded if they are not associated with costs or if they were clinically not well defined. Diagnoses from laboratory or radiology claims were

TABLE 2. Concurrent CDPS Model

CDPS	CDPS description	SSI	TANF child	TANF adult	SSI N	TANF child N	TANF adult N
Baseline	Intercept	0.018	0.159	0.066	1,438,330	9,246,704	6,417,719
CARVH	Cardiovascular, very high	2.535	94.17	7.210	12,841	1476	7599
CARM	Cardiovascular, medium	0.580	8.486	1.469	138,967	38,222	192,901
CARL	Cardiovascular, low	0.159	2.963	0.512	152,303	134,182	323,763
CAREL	Cardiovascular, extra low	0.068	0.583	0.120	338,525	48,853	1,127,054
PSYH	Psychiatric, high	0.776	5.839	2.033	73,896	2763	35,375
PSYM	Psychiatric, medium	0.545	2.721	1.087	26,082	30,946	52,120
PSYL	Psychiatric, low	0.269	1.206	0.363	547,021	903,702	1,310,917
SKCM	Skeletal, medium	0.706	1.776	2.336	78,613	178,683	115,682
SKCL	Skeletal, low	0.182	0.714	0.509	178,464	354,555	442,149
SKCVL	Skeletal, very low	0.041	0.167	0.226	103,037	48,727	280,369
CNSH	CNS, high	1.924	15.12	8.246	16,393	2875	9055
CNSM	CNS, medium	0.273	2.270	1.312	47,191	13,570	38,667
CNSL	CNS, low	0.273	2.209	0.637	250,565	134,202	345,727
PULVH	Pulmonary, very high	2.398	64.31	7.490	28,426	7078	15,563
PULH	Pulmonary, high	1.596	6.583	2.647	5960	20,423	4971
PULM	Pulmonary, medium	0.754	4.487	1.645	87,675	68,431	133,525
PULL	Pulmonary, low	0.089	0.488	0.256	283,555	818,127	572,755
GIH	Gastro, high	1.508	27.979	4.131	25,576	9663	18,043
GIM	Gastro, medium	0.341	4.612	0.980	71,167	19,189	162,910
GIL	Gastro, low	0.121	0.602	0.346	252,498	369,009	651,483
DIA1	Diabetes, type 1	0.796	5.951	1.928	27,790	14,176	50,078
DIA2	Diabetes, type 2	0.247	0.428	0.463	226,426	9320	493,269
SKNH	Skin, high	1.281	21.289	5.443	11,773	1007	6580
SKNL	Skin, low	0.416	4.418	1.342	18,496	1952	22,267
SKNVL	Skin, very low	0.132	0.410	0.257	110,561	333,866	364,461
RENEH	Renal, extra high	2.585	154.3	7.521	9241	278	4207
RENM	Renal, medium	0.170	3.227	0.918	66,143	6921	72,275
RENL	Renal, low	0.170	0.583	0.453	87,216	86,449	124,946
SUBL	Substance abuse, low	0.283	5.584	0.964	85,008	13,602	269,156
SUBVL	Substance abuse, very low	0.000	1.393	0.291	31,655	4102	84,225
CANVH	Cancer, very high	3.641	32.19	11.00	12,893	441	10,908
CANH	Cancer, high	1.352	9.926	4.557	20,321	4792	22,871
CANM	Cancer, medium	0.400	4.995	1.151	16,238	4608	27,357
CANL	Cancer, low	0.000	0.933	0.377	19,285	1793	38,289
DDM	DD, medium	0.287	3.711	4.807	6053	367	191
DDL	DD, low	0.075	3.661	0.957	53,914	21,540	6558
GENEL	Genital, extra low	0.059	0.932	0.273	66,038	74,100	331,776
METH	Metabolic, high	0.936	5.278	1.189	36,738	44,356	61,586
METM	Metabolic, medium	0.446	4.950	0.832	96,893	25,325	190,138
PRGCMP	Pregnancy, complete	0.338	2.327	1.180	14,030	17,714	488,479
PRGINC	Pregnancy, incomplete	0.023	0.709	0.178	4538	8285	119,729
EYEL	Eye, low	0.333	2.624	0.559	10,859	5809	23,365
EYEVL	Eye, very low	0.055	0.421	0.282	77,661	41,208	121,812
CERM	Cerebrovascular, medium	0.413	7.697	2.576	21,265	1334	13,690
INFVH	Infectious, very high	4.717	29.05	7.281	1,915	938	2195
INFH	Infectious, high	2.305	13.72	4.871	18,223	2966	37,666
INFM	Infectious, medium	1.100	1.473	2.437	52,775	101,033	95,030
INFL	Infectious, low	0.000	0.426	0.213	42,274	6291	100,388
HEMEH	Hematological, extra high	13.16	40.34	19.87	582	1115	762
HEMVH	Hematological, very high	2.292	40.34	5.894	8,190	1716	7315
HEMM	Hematological, medium	0.836	2.416	1.224	17,557	28,484	25,937
HEML	Hematological, low	0.638	2.416	1.224	28,573	28,219	58,004
MRX13	Rare diseases	26.57	145.5	70.6	429	302	224
R-squared	—	—	0.26	0.11	0.39	—	—

Demographic indicators and interaction terms for disabled children are not shown.

All coefficients are significant at $P < 0.0001$.

SSI indicates disabled Medicaid beneficiaries; TANF Child, children (age < 19) eligible under temporary aid to need families or other family categories; TANF adult, adults (age 19+) eligible under temporary aid to need families or other family categories or Medicaid expansion.

excluded since they are sometimes listed as "rule-out" diagnoses. The 2000 model had 58 CDPS categories within 19 major categories. Categories higher in the hierarchy had greater coefficients and generally lower numbers of beneficiaries than categories lower in the hierarchy.

A similar approach was used in the 2022 revision. An initial run of the 2000 model using newer data from 3 national Medicaid MCOs showed that some of the hierarchies were not maintained. Stage 1 groups were recreated using ICD-10 codes for each of the affected major categories. Linear

regression analyses were conducted by each major category after replacing the respective CDPS categories with stage 1 groups. These regression results were reviewed to determine which stage 1 groups should be reordered to improve the hierarchy while maintaining clinical accuracy. The updated CDPS model was re-estimated after each reordering. If the hierarchy still appeared insufficient, then the stage 1 groups were revisited and reordered. Iterations of this process were continued until each major category had an acceptable hierarchy.

In developing the 2000 model, to avoid overfitting the data, we used a split-sample design, whereby we developed the model on a 75% sample of the data and compared the result when applying the resulting algorithm to the remaining 25% of the data. In this revision, we decided against using a split-sample approach for the reason that this revision did not involve as much adding diagnoses as it did reordering diagnoses. Thus, we were less concerned with overfitting than we were with having an adequate sample size to revise and re-estimate the model.

MRX Analysis Methods

An initial run of the MRX model showed that the model was relatively stable over time. However, some MRX categories had very low or negative coefficients. Some of these categories were dropped from the model. Others were restricted to classes of medications appropriate for the most serious manifestations of disease in that category. Several MRX categories related to infectious diseases were incorporated into a hierarchy. Finally, a new category was created for Rare Diseases. This category includes medications that are used in patients with a disease state prevalence of fewer than 20,000 in the United States and in which the drug cost is $150,000 or more for the average weight and dosing.

CDPS+Rx Analysis Methods

The CDPS+Rx model includes all CDPS categories and a subset of 15 restricted MRX categories that we consider to be the least affected by variations in physician prescribing patterns. An initial run of the model included each of these categories along with CDPS. The resulting coefficients were examined to determine where the MRX categories would be most appropriately included in the CDPS hierarchies. An algorithm was developed to integrate the 15 MRX categories into CDPS.

Social Deprivation Index

Indicators based on the Social Deprivation Index (SDI) were used to examine whether spending on Medicaid beneficiaries living in economically and socially deprived communities is greater than spending on similar beneficiaries in less deprived communities.[10] The SDI is a composite measure of disparity that uses place-based data on education, employment, income, density, car and home ownership, and family structure to assign an index value to a geographic area. We used the zip code of residence to assign each beneficiary an SDI value and included these values as a set of categorical indicators (rounded up to the tens place) into the CDPS regression analysis. We considered using information on

beneficiary race and ethnicity and using Z-codes to identify unhoused beneficiaries, but concerns from our MCO partners, which we shared, about incomplete and inconsistent coding caused us to use area characteristics as a measure of disadvantage. This approach follows the recommendations of a committee report from the National Academy of Medicine.[3]

RESULTS

The revised CDPS+Rx model is shown in Table 2. The revised model has 52 CDPS categories within 19 major categories. Six CDPS major categories were revised: psychiatric, pulmonary, renal, cancer, infectious disease, and hematological. Table 3 provides counts for the 15 restricted MRX categories and shows where they were integrated into the CDPS model. The 15 restricted MRX indicators were included in 8 major CDPS categories and at every level of severity from extra high to extra low. The MRX category for Rare Diseases did not fit naturally within any of the CDPS major categories and thus remained as an independent category with relatively few individuals but very high-estimated coefficients. More detail on changes made in updating the models is available on the CDPS website: https://hwsph.ucsd.edu/research/programs-groups/cdps.html.

The revised CDPS models result in similar predictions to the earlier versions. For the CDPS model, the correlation coefficient between the prediction with the most recent 2000 model and the prediction with the 2020 model ranges from 0.98 to 0.99 by aid category for concurrent and prospective models. The R-square values increase slightly in the new CDPS models compared with the 2000 model: from 0.21 to 0.24 among the disabled and from 0.10 to 0.11 among

TABLE 3. Mapping of Restricted MRX Categories to CDPS

MRX	MRX description	CDPS mapping	SSI N	TANF adult N	TANF child N
MRX1	Anti-coagulants	CARM	45,668	1506	62,293
MRX2	Cardiac	CAREL	507,791	39,823	1,230,917
MRX3	Psychosis/ bipolar/ depression	PSYL	486,185	253,063	1,151,716
MRX4	Diabetes	DIA2	202,757	30,113	443,812
MRX5	Hemophilia/von Willebrands	HEMEH	211	444	195
MRX6	Hepatitis	INFM	5563	53	10,005
MRX7	HIV	INFM	10,646	1061	31,818
MRX8	Infections, high	INFH	5318	935	6856
MRX9	Inflammatory/ autoimmune	SKCM	13,284	6150	34,048
MRX10	Malignancies	CANM	18,260	4671	26,921
MRX11	Multiple sclerosis/ paralysis	CNSH	3849	206	5159
MRX12	Parkinsons/ tremor	CNSL	57,954	2192	53,765
MRX13	Rare diseases	MRX13	429	302	224
MRX14	Seizure disorders	CNSL	60,805	25,400	50,393
MRX15	Tuberculosis	INFL	2024	1845	5988

Source: Authors' analyses of data from 3 national Medicaid Managed Care plans.
MRX indicates Medicaid Rx model; SSI, disabled Medicaid beneficiaries; TANF Child, children (age < 19) eligible under temporary aid to need families or other family categories; TANF adult, adults (age 19+) eligible under temporary aid to need families or other family categories or Medicaid expansion.
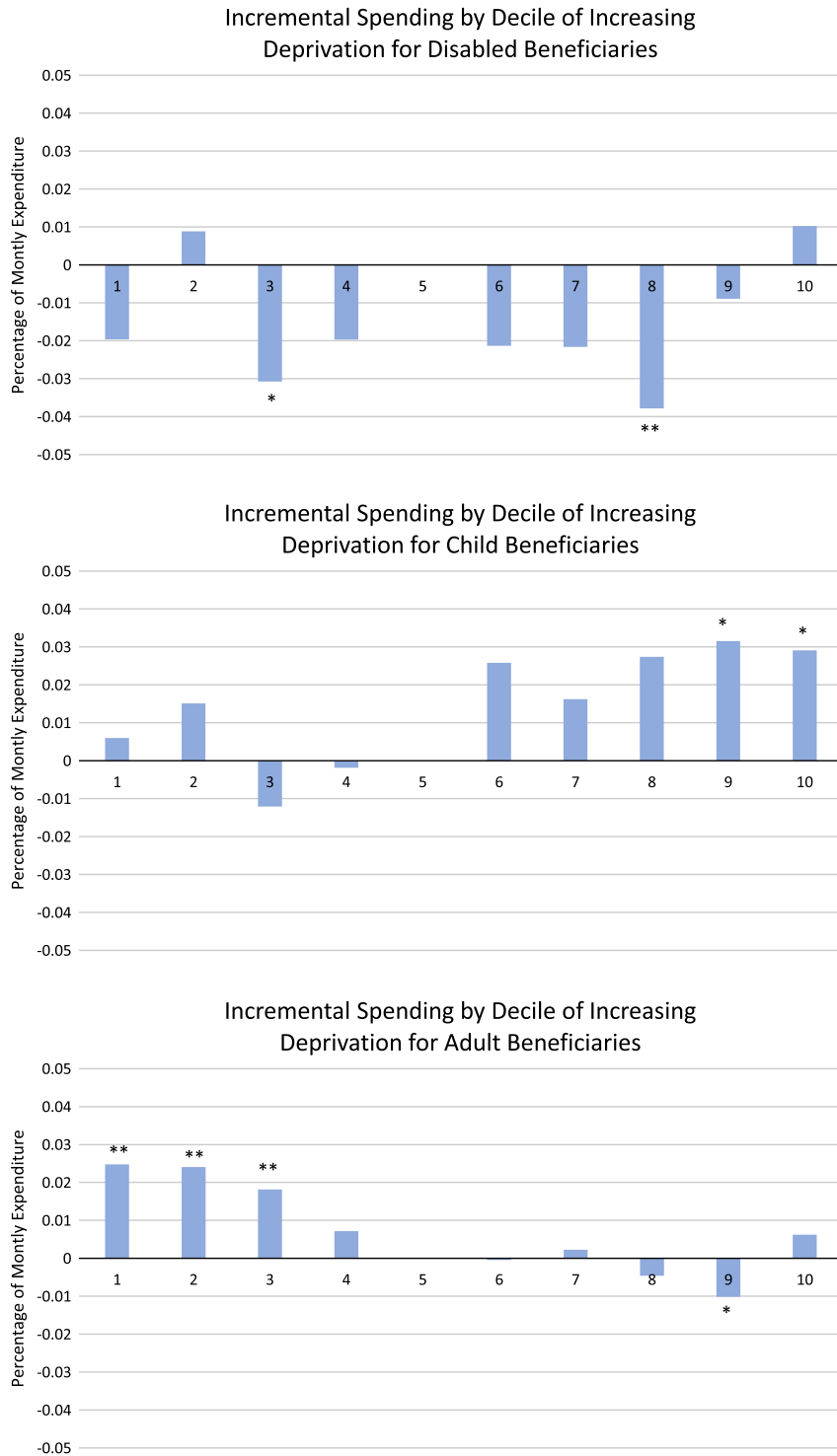
FIGURE 1. Social Deprivation Index Category Coefficients. Plotted data are regression coefficients from 3 concurrent Chronic Illness and Disability Payment System regressions, including state indicators and categories based on the Social Deprivation Index. An SDI between 50 and 59 serves as the reference category. An * indicates that the coefficient is statistically significantly different from 0 at $P < 0.05$, and ** indicates statistical significance at $P < 0.01$.

children, while the R-square in the adult model is the same at 0.35 (data not shown). Correlation coefficients between the most recent and revised MRX models are lower than for the CDPS model: 0.78–0.87, likely as a result of the continuous introduction of new drugs. It is challenging to interpret changes in R-square values among versions of the MRX and

CDPS+Rx models since there have been significant changes in pharmacy codes over time.

Medicaid beneficiaries living in zip codes with high levels of deprivation as measured by the SDI did not have consistently higher spending than beneficiaries living in zip codes with lower levels of deprivation. Figure 1 shows regression coefficients for SDI variables from concurrent CDPS regressions. Higher deciles of SDI indicate higher levels of deprivation. The coefficients were small (< 0.05 of mean expenditure), and only 8 of 27 reached statistical significance, despite the large sample size. Only among children was there any positive relationship between deprivation and spending: among the 2 highest deciles, spending was about 3% higher than in the fifth decile ($P < 0.05$). Among adults, spending was negatively associated with deprivation: among the 3 lowest deciles, spending was 1.8%–2.5% higher than the fifth decile (reference group, $P < 0.01$ each). Among the disabled, deciles 3 and 8 were associated with lower spending ($P < 0.05$ each).

The lack of systematic relationship between spending and area deprivation held across multiple model specifications: concurrent versus prospective, with and without state indicators, and in CDPS, MRX, and CDPS+RX (data not shown). Results were similar in regressions restricted to beneficiaries from a single state; in none of the states in our analytic sample were expenditures consistently higher for beneficiaries in more deprived zip codes (data not shown). Further, even in regression models without CDPS indicators as explanatory variables (ie, with demographic and state indicators only), there is little indication that spending is higher on beneficiaries living in more deprived zip codes (data not shown).

DISCUSSION

We report on revisions to the CDPS family of models that reflect patterns of care delivered by 3 national Medicaid MCOs in 2017–2019 based on updated ICD-10 coding. Predicted risk scores using the revised models are similar to risk scores from the original models but can be used with greater confidence by state Medicaid programs and Medicaid MCOs. One limitation of this work is that the regression weights are based on the patterns of care in 3 large Medicaid MCOs and 8 states. It is at least possible that weights would be different if data from other states or other MCOs were available. However, the states included in the analysis encompass all geographic regions and a wide range of Medicaid programs.

We found no relationship between health care spending and social deprivation as measured by the SDI. Our results differ slightly from those of Ash et al[7], who find that spending on Massachusetts Medicaid beneficiaries living in the quintile of neighborhoods that are most stressed are 2.1% greater than predicted by a diagnosis-based model. The difference between the 2% finding in Ash and colleagues and our null result may be due to differences in spending patterns between Massachusetts and the states in our analysis or to the fact that Ash and colleagues used census-tract data on neighborhood characteristics, while our analysis was limited to zip code level data.

The lack of relationship between area deprivation and spending may reflect access barriers; beneficiaries living in more deprived areas might need more care than beneficiaries in less deprived areas but might be less able to obtain needed care because of supply constraints. However, if supply constraints were the main reason that there is no gradient between area deprivation and spending, we might have expected to see some evidence of a positive gradient in states with less restrictive Medicaid programs. However, we did not see a positive gradient between area deprivation and spending in our state-specific results.

Our study sample consists entirely of Medicaid beneficiaries, all of whom, by definition, are low income and many of whom, regardless of where they live, face substantial economic and social challenges to good health and obtaining good health care. It should not be surprising that within a Medicaid population, there is no relationship between measures of area deprivation and spending. Notwithstanding this empirical result, states could still choose to employ their Medicaid programs to address disparities in health and health outcomes. If so, we do not recommend attempting to operationalize these efforts using risk adjustment. Instead, we offer 2 alternative approaches currently being pursued in California.

One approach is to pay directly for services that address health disparities. In California, the Department of Health Care Services is addressing health disparities through their CalAIM section 1115 waiver by paying directly for services such as enhanced care management for Medi-Cal beneficiaries with high needs, community supports to help homeless beneficiaries secure and maintain housing, and targeted services for those who are justice involved before release.[11] Paying directly for services requires that these services be prespecified. However, it also ensures that additional payments are used to address the identified disparities.

Another approach is to invest in community-based organizations to address health disparities. The Los Angeles County Department of Mental Health is using this approach to build community capacity to address trauma.[12] Trauma is a significant public health issue, negatively impacting a range of health outcomes that disproportionately impact vulnerable populations. Recognizing the widespread experience of trauma in the community, as well as their limited ability to address community-wide trauma within traditional community mental health centers, Los Angeles County Department of Mental Health has funded 9 regionally based, community-embedded partnerships with the goal of building capacity to address trauma within their communities. Paying community organizations to address disparities relinquishes some control of funding but leverages community knowledge and trust and can more effectively engage community members in developing sustainable solutions.[13]

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