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Brian W Powers

Jose F Figueroa

Melanie Canterbury

Suhas Gondi

Stephanie M Franklin

See next page for additional authors

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Authors

Brian W Powers, Jose F Figueroa, Melanie Canterbury, Suhas Gondi, Stephanie M Franklin, William H Shrank, and Karen E Joynt Maddox



Original Investigation

Association Between Community-Level Social Risk and Spending Among Medicare Beneficiaries

Implications for Social Risk Adjustment and Health Equity

Brian W. Powers, MD, MBA; Jose F. Figueroa, MD, MPH; Melanie Canterberry, PhD; Suhas Gondi, MD, MBA; Stephanie M. Franklin, MPS; William H. Shrank, MD, MSHS; Karen E. Joynt Maddox, MD, MPH

Abstract

IMPORTANCE Payers are increasingly using approaches to risk adjustment that incorporate community-level measures of social risk with the goal of better aligning value-based payment models with improvements in health equity.

OBJECTIVE To examine the association between community-level social risk and health care spending and explore how incorporating community-level social risk influences risk adjustment for Medicare beneficiaries.

DESIGN, SETTING, AND PARTICIPANTS Using data from a Medicare Advantage plan linked with survey data on self-reported social needs, this cross-sectional study estimated health care spending health care spending was estimated as a function of demographics and clinical characteristics, with and without the inclusion of Area Deprivation Index (ADI), a measure of community-level social risk. The study period was January to December 2019. All analyses were conducted from December 2021 to August 2022.

EXPOSURES Census block group-level ADI.

MAIN OUTCOMES AND MEASURES Regression models estimated total health care spending in 2019 and approximated different approaches to social risk adjustment. Model performance was assessed with overall model calibration (adjusted R^2) and predictive accuracy (ratio of predicted to actual spending) for subgroups of potentially vulnerable beneficiaries.

RESULTS Among a final study population of 61 469 beneficiaries (mean [SD] age, 70.7 [8.9] years; 35 801 [58.2%] female; 48 514 [78.9%] White; 6680 [10.9%] with Medicare-Medicaid dual eligibility; median [IQR] ADI, 61 [42-79]), ADI was weakly correlated with self-reported social needs ($r = 0.16$) and explained only 0.02% of the observed variation in spending. Conditional on demographic and clinical characteristics, every percentile increase in the ADI (ie, more disadvantage) was associated with a \$11.08 decrease in annual spending. Directly incorporating ADI into a risk-adjustment model that used demographics and clinical characteristics did not meaningfully improve model calibration (adjusted $R^2 = 7.90\%$ vs 7.93%) and did not significantly reduce payment inequities for rural beneficiaries and those with a high burden of self-reported social needs. A postestimation adjustment of predicted spending for dual-eligible beneficiaries residing in high ADI areas also did not significantly reduce payment inequities for rural beneficiaries or beneficiaries with self-reported social needs.

(continued)

Key Points

Question What is the association between community-level social risk factors and spending among Medicare beneficiaries, and how does this influence approaches to social risk adjustment?

Findings In this cross-sectional study of 61 469 Medicare beneficiaries, community-level social risk explained little variation in health care spending, was negatively correlated with spending conditional on demographics and clinical characteristics, and was poorly correlated with self-reported social risk factors.

Meaning Incorporating community-level social risk factors into Medicare risk adjustment may not address payment disparities for many beneficiaries with high-levels of social risk.

+ Supplemental content

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Abstract (continued)

CONCLUSIONS AND RELEVANCE In this cross-sectional study of Medicare beneficiaries, the ADI explained little variation in health care spending, was negatively correlated with spending conditional on demographic and clinical characteristics, and was poorly correlated with self-reported social risk factors. This prompts caution and nuance when using community-level measures of social risk such as the ADI for social risk adjustment within Medicare value-based payment programs.

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Introduction

As health care payments shift from fee-for-service toward value-based models that reward improving quality and controlling spending,^{1,2} it is necessary to ensure that these models also advance health equity. Doing so requires approaches to risk adjustment that do not disincentivize providing care for vulnerable beneficiaries and that facilitate investments to improve care for these groups.²⁻⁴ Growing evidence, much of it from the traditional Medicare program, suggests that failing to account for social factors in risk adjustment can lead to inaccurate performance assessments and potentially perpetuate inequities.³⁻¹⁵ Amid these concerns, there is an increasing focus on social risk adjustment—the practice of incorporating social risk factors into risk adjustment frameworks.^{4,8,12,13,16-18}

One approach to social risk adjustment gaining traction is the use of community-level social risk indices to calculate payments and spending targets under value-based payment models. The Centers for Medicare & Medicaid Services (CMS) has implemented this approach within the Accountable Care Organization Realizing Equity, Access, and Community Health (ACO REACH) program¹⁹ and is considering related approaches in the Shared Savings Program²⁰ and in Medicare Advantage.²¹ Unlike self-reported data on individual-level social risk, community-level measures are widely available and relatively easy to implement. Yet recent studies raise concern that community-level social risk may be an inaccurate proxy for individual social needs,^{22,23} and that incorporating measures of disadvantage into risk adjustment may reinforce structural inequities.²⁴⁻²⁶ As experimentation with social risk adjustment intensifies, it is important to understand the impacts of different approaches.

In this study, we used data from a large, national Medicare Advantage plan, linked with survey data on self-reported social risk, to investigate the association between community-level social risk and spending and to explore how incorporating community-level social risk influences risk adjustment, especially for potentially vulnerable subgroups of Medicare beneficiaries.

Methods

Study Population

Our study population was drawn from a sample of 431 476 beneficiaries enrolled in Medicare Advantage plans offered by a large, national insurer who were surveyed on their individual social risk factors using an adapted version of the CMS Accountable Health Communities Health-Related Social Needs Screening Tool.²⁷ This survey, which has been described previously,^{28,29} had a response rate of 25% and no evidence of nonresponse bias on observable characteristics (see the eMethods and eTable 1 in Supplement 1 for more detail). We limited our analysis to beneficiaries who completed the entire survey to ensure there were no missing data on individual-level social risk factors among our study population. We further restricted the sample to beneficiaries who were not contractually excluded from research; not attributed to primary organizations that delegate claims processing to a third party; continuously enrolled from January 1, 2019, to December 31, 2019; and did not have end-stage kidney disease, become institutionalized, or enroll in hospice in 2019.

This study was reviewed by the Humana Healthcare Research Human Subject Protection Office and deemed not human participants research; therefore, informed consent was waived. The study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines for cross-sectional studies.

Primary Outcome

Our primary outcome of interest was raw, unadjusted total medical spending in 2019, calculated using all paid Part A and B claims.

Beneficiary Characteristics

We extracted the following demographic characteristics from enrollment files: age, sex, race, dual eligibility, disability, Part D low-income subsidy eligibility, and principal address, all as of January 1, 2019. Race was assessed according to the CMS beneficiary race code, which reflects data reported to the Social Security Administration, and categorized as Black, White, Unknown, and Other (Asian, Hispanic, North American Native, and Other). We used address data to assign beneficiaries to a census block group, to classify the zip code-level population density of their residence, and to determine the average 2018 Part A and B traditional Medicare spending in their county of residence.³⁰

For each beneficiary, we obtained monthly Hierarchical Condition Category (HCC) risk scores from January 2019 to December 2019 from CMS, and averaged these scores to construct an average annual value for 2019.³¹ The HCC score is a diagnosis-based measure of comorbidity burden used across most Medicare value-based payment programs. These 2019 HCC scores reflected comorbidities documented in 2018 and did not include contributions from demographic variables.

Our primary exposure variable was the 2019 Area Deprivation Index (ADI) of a beneficiary's census block group.^{32,33} The ADI is a measure of neighborhood socioeconomic disadvantage that has been associated with adverse outcomes in Medicare populations³⁴⁻³⁶ and is being used, or being considered, for social risk adjustment across a number of Medicare programs.¹⁹⁻²¹ The ADI uses US Census data in the domains of income, education, employment, and housing quality to calculate a neighborhood's level of socioeconomic disadvantage and assigns each census block group a national percentile rank (1-100), with higher numbers representing more disadvantage.

We also constructed measures of social risk at the individual level. Using responses to the aforementioned survey, we identified a beneficiary's aggregate burden of social needs as well as the presence of the following individual needs: financial strain, food insecurity, utility insecurity, unreliable transportation, housing insecurity, and loneliness (see the eMethods in Supplement 1 for additional detail). We used these individual-level social risk measures to explore payment inequities, as described below.

Statistical Analysis

We compared the characteristics of beneficiaries living in the highest and lowest ADI quintiles using standardized mean differences (SMDs), with SMDs greater than 0.1 considered to represent meaningful differences.³⁷ We assessed the correlation between ADI and both spending and self-reported social need burden using correlation coefficients.

To explore the association between ADI and spending, we constructed a series of beneficiary-level ordinary least squares regression models. The dependent variable for all models was 2019 spending. For the first model, we included as independent variables the demographic and clinical characteristics commonly used for risk adjustment in Medicare programs: age, sex, dual eligibility, disability, and HCC score. Since most approaches to setting risk-adjusted payments and spending benchmarks in Medicare programs account for regional variation in spending, we also included average county-level traditional Medicare spending as an independent variable. The second model included these same independent variables, but with the addition of ADI. Finally, we modeled the association between ADI and spending alone, without any additional covariates. Our primary

analyses modeled this association using a beneficiary-level ordinary least squares regression model, but we conducted additional analyses using hierarchical linear regression models to estimate the proportion of variance in spending explained by ADI after clustering beneficiaries at the census block group or county level.

These regression models also allowed us to explore different approaches with community-level social risk adjustment using ADI. The first regression model served as an approximation of approaches to risk adjustment that use demographic and clinical characteristics. The second regression model approximated an approach to community-level social risk adjustment that directly adjusts for ADI, treating ADI similarly to demographic and clinical variables. An alternative approach to community-level social risk adjustment is to perform a postestimation adjustment, wherein spending is predicted based on demographic and clinical characteristics, and then adjusted upward or downward based on ADI. This is the approach that CMS has taken with the health equity benchmark adjustment (HEBA) in the ACO REACH model.¹⁹ To approximate this approach, we implemented methods similar to the HEBA. We assigned each beneficiary a numerical score equal to their ADI (for non-dual eligible beneficiaries) or their ADI plus 25 (for dual eligible beneficiaries) and then ranked beneficiaries into deciles based on these scores. Beneficiaries in the top decile received an upward adjustment of \$360 to the annual spending predicted from the first regression model, and those in the bottom 5 deciles received a \$72 downward adjustment.

We compared the performance of these 3 approaches to risk adjustment in 2 ways. The first was overall model calibration, assessed using adjusted R^2 and mean absolute error (MAE), measures of individual-level fit commonly used to assess the accuracy of risk-adjustment models. The second was predictive accuracy, assessed using predictive ratios (ie, the ratio of predicted to actual spending). Unlike R^2 and MAE, predictive ratios can be used to compare how effectively risk adjustment models equalize risk at the population level. Further, predictive ratios allow for comparisons of payment equity across different risk-adjustment approaches.^{38,39} We classified predictive ratios less than 1—predicted spending lower than actual spending—as payment inequities. We calculated predictive ratios among the following strata of beneficiaries: race (Black and White only due to inaccuracies in classification for other beneficiaries⁴⁰), population density, low-income subsidy eligibility, ADI quintile, self-reported social need burden, and the presence of individual self-reported social needs. As described above, none of these demographic or socioeconomic variables were included as independent variables in the regression models.

Analyses were conducted using SAS Enterprise Guide, version 8.2 (SAS Institute) from December 2021 to August 2022. We used regression coefficients to calculate marginal effects, and report 95% CIs using standard errors calculated at the individual level to reflect random survey sampling. We used bootstrapped samples ($n = 1000$) to report 95% CIs for predictive ratios. Statistical significance was set at the $P < .05$ level.

Sensitivity Analyses

We conducted a sensitivity analysis to better understand the generalizability of our findings to beneficiaries enrolled in traditional Medicare by replicating the above analysis, restricting our population to the 16 164 beneficiaries enrolled in preferred provider organization products (as opposed to health management organization products) and attributed to primary care organizations reimbursed under fee-for-service contracts (as opposed to value-based contracts). This created a subcohort of beneficiaries where spending patterns would be expected to more closely reflect those in traditional Medicare, an open network insurance product with significantly lower rates of value-based contracts than the Medicare Advantage plans included in this analysis.^{1,41} To explore whether our findings were sensitive to the assumption of linearity implicit to modeling ADI as a continuous variable, we repeated our core regression model with indicator variables for ADI decile.

Results

Patient Sample and Characteristics

Our study population included 61 469 beneficiaries (mean [SD] age, 70.7 [8.9] years; 35 801 [58.2%] female; 48 514 [78.9%] White; 6680 [10.9%] with Medicare-Medicaid dual eligibility; median [IQR] ADI, 61 [42-79]; see eTable 2 in Supplement 1 for participant flow through the study) residing in 42 078 census block groups. Compared with beneficiaries residing in the lowest ADI quintile, beneficiaries in the highest ADI quintile (most disadvantaged) were more likely to be younger, Black, dual eligible, low income, disabled, reside in rural areas, and have a higher burden of self-reported social needs (Table 1). The ADI was weakly correlated with spending ($r = 0.01$) as well as the burden

Table 1. Characteristics of the Study Population

Characteristic	No. (%)			SMD ^a
	Overall	Lowest	Highest	
No.	61 469	12 590	12 082	
Age, y ^b				
<65	11 027 (17.9)	1315 (10.4)	2953 (24.4)	.38
65-74	30 443 (49.5)	6523 (51.8)	5864 (48.5)	.07
75-84	16 611 (27.0)	3909 (31.0)	2745 (22.7)	.19
≥85	3388 (5.5)	843 (6.7)	520 (4.3)	.11
Sex ^b				
Female	35 801 (58.2)	6822 (54.2)	7335 (60.7)	.13
Male	25 668 (41.8)	5768 (45.8)	4747 (39.3)	.13
Dual Medicare and Medicaid eligible ^b	6680 (10.9)	1024 (8.1)	2945 (24.4)	.45
Original reason for Medicare entitlement ^b				
Age-in	42 867 (69.7)	10 300 (81.8)	7116 (58.9)	.52
Disability	18 602 (30.3)	2290 (18.2)	4966 (41.1)	.52
Race ^c				
Black	10 400 (16.9)	1156 (9.2)	3573 (29.6)	.53
White	48 514 (78.9)	10 598 (84.2)	8151 (67.5)	.40
Other	1843 (3.0)	588 (4.7)	275 (2.3)	.13
Unknown	712 (1.2)	248 (2.0)	83 (0.7)	.11
Population density				
Urban	37 164 (60.5)	9527 (75.7)	6502 (53.8)	.47
Suburban	15 843 (25.8)	2315 (18.4)	3011 (24.9)	.16
Rural	7284 (11.8)	411 (3.3)	2366 (19.6)	.53
Unknown		337 (2.7)	203 (1.7)	.07
Medicare low-income subsidy eligibility	14 163 (23.0)	1607 (12.8)	4356 (36.1)	.56
Total spending in 2019, \$, median (IQR)	2289 (959-6370)	2185 (929-5844)	2358 (980-6615)	.03
ADI, median (IQR) ^b	61 (42-79)	27 (19-33)	91 (87-96)	2.78
No. of self-reported health-related social needs				
0	28 429 (46.2)	7964 (63.3)	4864 (40.3)	.47
1	14 361 (23.4)	2459 (19.5)	2962 (24.5)	.12
≥2	18 679 (30.4)	2167 (17.2)	4256 (35.2)	.42
Individual self-reported health-related social needs				
Financial strain	23 377 (38.0)	3372 (26.8)	5837 (48.3)	.46
Food insecurity	14 114 (23.0)	1784 (14.2)	3845 (31.8)	.43
Utility insecurity	6250 (10.2)	977 (7.8)	1494 (12.4)	.15
Unreliable transportation	5333 (8.7)	734 (5.8)	1450 (12.0)	.22
Housing insecurity	4073 (6.6)	711 (5.6)	912 (7.5)	.08
Loneliness	4333 (7.0)	628 (5.0)	981 (8.1)	.13
HCC score, median (IQR) ^b	0.41 (0.00-0.98)	0.32 (0.00-0.83)	0.52 (0.10-1.10)	.22

Abbreviations: ADI, Area Deprivation Index; HCC, Hierarchical Condition Category; SMD, standardized mean difference.

^a We considered SMDs greater than 0.10 to reflect meaningful differences between groups.³⁷

^b Demographic and clinical characteristics used as independent variables in regression models used to simulate different approaches to risk adjustment. Other demographic and clinical characteristics were used to stratify beneficiaries when calculating predictive ratios under different approaches to risk adjustment.

^c Race was assessed according to the Centers for Medicare & Medicaid Services beneficiary race code, which reflects data reported to the Social Security Administration. The Other category includes the following races: Asian, Hispanic, North American Native, and other.

of self-reported social needs ($r = 0.16$). The majority of beneficiaries (53.8%) reported at least 1 social need, with financial strain and food insecurity being the most commonly reported (38.0% and 23.0% of beneficiaries, respectively).

Association Between ADI and Spending

The ADI explained 0.02% of the observed variation in spending (Table 2; full regression results in eTable 3 in Supplement 1). When clustering beneficiaries by geography using hierarchical models, ADI explained 0.61% of the variation in spending at the census block group level and did not account for any variation at the county level. The proportion of total variation in spending explained by ADI was 0.01% in both hierarchical models.

Considered alone, ADI was significantly associated with increased spending, with every 1-point increase in ADI (ie, more disadvantage) associated with an \$8.77 increase in annual spending. Conditional on demographic and clinical characteristics, ADI remained significantly associated with spending, but the direction of the association reversed, with every 1-point increase in ADI associated with a \$11.08 decrease in spending. Findings were similar when considering ADI in deciles rather than as a continuous variable (eFigure in Supplement 1).

Calibration of Different Risk-Adjustment Approaches

The model approximating risk adjustment with demographic and clinical characteristics had an adjusted R^2 of 7.90% and a MAE of \$7293 (Table 2). Directly incorporating ADI into this model did not meaningfully change overall model calibration (adjusted $R^2 = 7.93\%$ and MAE = \$7292).

Predictive Accuracy of Different Risk-Adjustment Approaches

The model approximating risk adjustment with demographics and clinical characteristics resulted in payment inequities (predictive ratio less than 1) for the following subgroups of beneficiaries: White (predictive ratio [95% CI], 0.97 [0.96-0.98]), suburban (0.96 [0.93-0.99]), rural (0.95 [0.90-0.99]), low ADI quintiles (eg, 0.94 [0.91-0.98] for quintile 1), and those with a high burden of self-reported social needs (eg, 0.95 [0.93-0.97] for those with ≥ 2 social needs) (Table 3). There were also payment inequities for beneficiaries reporting several individual social needs: financial strain (0.93 [0.92-0.95]), food insecurity (0.97 [0.94-0.99]), unreliable transportation (0.90 [0.86-0.95]), and loneliness (0.94 [0.89-0.99]).

Table 2. Association Between Demographic, Clinical, and Community-Level Social Risk Characteristics and Spending

Characteristic	Independent variables used in regression model		
	Demographics and clinical characteristics	Demographics, clinical characteristics, and ADI	ADI alone
Marginal effect on spending (95% CI), \$ ^a			
Age, y	-40.36 (-57.93 to -22.80)	-40.96 (-58.52 to -23.39)	NA ^b
Female sex	-233.54 (-486.37 to 19.29)	-210.94 (-463.98 to 42.10)	NA ^b
Dual eligible	-95.08 (-458.62 to 268.46)	-13.64 (379.28 to 352.00)	NA ^b
Disabled	634.29 (285.84 to 982.74)	709.88 (359.55 to 1060.21)	NA ^b
HCC score	4968.69 (4825.82 to 5111.56)	4979.48 (4836.53 to 5122.42)	NA ^b
County FFS spending, \$	1.98 (-1.62 to 5.58)	1.29 (-2.32 to 4.91)	5.61 (1.85 to 9.37)
ADI (percentile)	NA ^b	-11.08 (-16.46 to -5.70)	8.77 (3.31 to 14.24)
Model calibration			
Adjusted R^2 , %	7.90	7.93	0.02
MAE	7292.72	7291.79	7940.16

Abbreviations: ADI, Area Deprivation Index; FFS, fee-for-service; HCC, Hierarchical Condition Category; MAE, mean absolute error; NA, not applicable.

^a Compared with referent group for categorical variables (male sex, not dual eligible, not disabled) or with 1 unit change for continuous variables (age = 1 year; HCC score = 1

unit; county FFS spending = \$1; ADI = 1 percentile). Further information on variable scaling is provided in the Methods. Full regression output, including standardized estimates, is provided in eTable 3 in Supplement 1.

Directly incorporating ADI into a risk adjustment model using demographics and clinical characteristics did not significantly reduce inequities for rural beneficiaries or those with self-reported social needs (Table 3). Doing so also decreased predicted spending for Black beneficiaries and those in high-ADI (ie, more disadvantaged) areas. A postestimation adjustment for ADI and dual eligibility modeled after the HEBA adjustment in the ACO REACH program did not significantly reduce payment inequities for rural beneficiaries or those with self-reported social needs.

Sensitivity Analyses

Restricting the study population to beneficiaries enrolled in preferred provider organization plans and cared for under fee-for-service contracts did not meaningfully change our findings (eTable 4 and eTable 5 in Supplement 1), nor did modeling ADI using indicator variables for ADI decile rather than as a continuous variable (eTable 6 in Supplement 1).

Discussion

In this cross-sectional study of Medicare beneficiaries, we examined the association between community-level social risk and health care spending and evaluated the potential effect of incorporating community-level social risk indices into risk adjustment models used to set payments and benchmarks under value-based payment programs in Medicare. We found that the ADI of a

Table 3. Predictive Ratios for Population Subgroups Under Different Approaches to Risk Adjustment^a

Characteristic	Beneficiaries, No. (%)	Predictive ratio (95% CI)		
		Demographics and clinical characteristics	Direct adjustment for ADI	Postestimation adjustment for ADI
Race				
Black	10 400 (16.9)	1.11 (1.06-1.15)	1.10 (1.05-1.14)	1.12 (1.07-1.16)
White	48 514 (78.9)	0.97 (0.96-0.98)	0.97 (0.97-0.98)	0.97 (0.96-0.98)
Population density				
Urban	37 164 (60.5)	1.03 (1.01-1.04)	1.03 (1.02-1.05)	1.03 (1.01-1.04)
Suburban	15 843 (25.8)	0.96 (0.93-0.99)	0.96 (0.93-0.98)	0.96 (0.93-0.99)
Rural	7284 (11.9)	0.95 (0.90-0.99)	0.93 (0.89-0.97)	0.95 (0.91-0.99)
Unknown	1178 (1.9)	1.00 (0.88-1.11)	1.00 (0.88-1.12)	1.00 (0.87-1.11)
Medicare low-income subsidy eligibility				
ADI, quintile				
1 (Least disadvantage)	12 590 (20.5)	0.94 (0.91-0.98)	1.00 (0.97-1.02)	0.93 (0.90-0.96)
2	11 900 (19.4)	0.98 (0.94-1.01)	1.00 (0.96-1.03)	0.97 (0.94-1.00)
3	12 470 (20.3)	1.01 (0.97-1.04)	1.01 (0.97-1.04)	1.00 (0.97-1.04)
4	12 427 (20.2)	1.03 (1.00-1.06)	1.01 (0.98-1.04)	1.04 (1.01-1.07)
5 (Most disadvantage)	12 082 (19.7)	1.04 (1.00-1.07)	0.99 (0.97-1.02)	1.06 (1.02-1.09)
No. of self-reported health-related social needs				
0	31 495 (51.2)	1.06 (1.05-1.08)	1.07 (1.05-1.09)	1.06 (1.04-1.08)
1	13 849 (22.5)	0.96 (0.93-0.99)	0.96 (0.93-0.99)	0.96 (0.93-0.99)
≥2	16 125 (26.2)	0.95 (0.93-0.97)	0.94 (0.92-0.97)	0.95 (0.93-0.97)
Individual self-reported health-related social needs				
Financial strain	23 377 (38.0)	0.93 (0.92-0.95)	0.93 (0.91-0.95)	0.94 (0.92-0.95)
Food insecurity	14 114 (23.0)	0.97 (0.94-0.99)	0.97 (0.94-0.99)	0.98 (0.95-1.00)
Utility insecurity	6250 (10.2)	0.96 (0.92-1.01)	0.96 (0.92-1.01)	0.97 (0.92-1.01)
Unreliable transportation	5333 (8.7)	0.90 (0.86-0.95)	0.90 (0.86-0.94)	0.91 (0.87-0.95)
Housing insecurity	4073 (6.6)	0.95 (0.88-1.00)	0.95 (0.88-1.00)	0.95 (0.89-1.01)
Loneliness	4333 (7.1)	0.94 (0.89-0.99)	0.94 (0.90-0.99)	0.95 (0.90-1.00)

Abbreviation: ADI, Area Deprivation Index.

^a Predictive ratios represent the ratio of predicted to actual spending. For example, a predictive ratio of 0.97 indicates that predicted spending is 3% below observed spending for beneficiaries in that group. Should such a risk-adjustment approach be used to set a spending benchmark or capitated payment, it would be expected to result in an underpayment to a risk-bearing plan or care delivery organization of 3%. We classified predictive ratios less than 1—predicted spending lower than actual spending—as payment inequities. As discussed in the Methods, none of these demographic and socioeconomic characteristics were included in the regression models simulating different approaches to risk adjustment.

beneficiary's residence, a commonly used measure of community-level social risk, was weakly correlated with health care spending, explaining only 0.02% of the variation in spending observed among beneficiaries in 2019. This suggests that incorporating community-level social risk factors, even at the granular census block group level, may not meaningfully improve the calibration of risk adjustment models among Medicare beneficiaries. Whereas we believe our study is the first to evaluate this association in a Medicare Advantage population and using the ADI, prior research has found measures of community-level social risk to be poor proxies for individual social needs.^{22,23}

Although relatively weak in magnitude, there was a significant association between ADI and health care spending. Considered alone, increases in ADI (ie, more disadvantage) were associated with increased spending. Conditional on demographic and clinical characteristics, however, increases in ADI were associated with decreased spending. One explanation of this pattern is that, as observed in our study, high-cost beneficiaries disproportionately reside in disadvantaged areas, such that ADI serves as a proxy for higher spending. But when conditioned on demographic and clinical characteristics, ADI serves more as a proxy for structural access barriers and is therefore associated with lower spending, as has been shown for other markers of structural access barriers.²⁴⁻²⁶

This association prompts caution and nuance when using measures of community-level social risk—and the ADI specifically—for social risk adjustment. To the extent that risk-adjustment models underpredict spending for specific subgroups of beneficiaries, payers and care delivery organizations face a disincentive to serve these beneficiaries and may have fewer resources to invest in their care, potentially creating or exacerbating disparities and inequities. We found that directly incorporating ADI into risk-adjustment models using demographic and clinical characteristics reduced predicted spending for beneficiaries in more disadvantaged areas. While this reflects more accurate spending predictions, it runs counter to the aims of health equity. Importantly, we also found that directly incorporating ADI into risk-adjustment models would reduce predicted spending for Black, low-income, and rural beneficiaries, as well as those with self-reported social needs.

Direct adjustment is not the only approach for incorporating community-level social risk into risk-adjusted payments and spending benchmarks. An alternative approach is to perform a postestimation adjustment, wherein spending is predicted based on demographic and clinical characteristics and then adjusted based on community-level social risk. This is the approach that CMS has taken with the HEBA in the ACO REACH model.¹⁹ Our study simulated a HEBA-like adjustment and found that this approach, by design, increased predicted spending for beneficiaries in high-ADI areas. However, it did not lead to significant changes in payment inequities for rural beneficiaries or those with self-reported social needs. These findings suggest that postestimation adjustments for community-level social risk are effective at increasing payments and spending benchmarks for beneficiaries living in disadvantaged areas, but inefficient or ineffective at addressing payment disparities and inequities for many beneficiaries with individual social risk factors.

Limitations

This study has several limitations. First, we used data from a single, albeit large and national, Medicare Advantage plan, potentially limiting generalizability to other Medicare populations or individuals with other sources of coverage or no insurance coverage. We conducted a sensitivity analysis that provided reassurance around generalizability to beneficiaries enrolled in traditional Medicare. Replicating these analyses in other Medicare Advantage and traditional Medicare populations, and with other modeling approaches, should be prioritized. Relatedly, we analyzed 1 specific measure of community-level social risk, the ADI, because the ADI is widely studied and currently used for social risk adjustment by CMS.¹⁹ Prior research found that a different community-level social risk index—the Neighborhood Stress Score—was associated with higher spending conditional on demographic and clinical characteristics among Medicaid beneficiaries in Massachusetts.⁴² This underscores how the performance of social-risk adjustment approaches are sensitive to underlying measures and populations, and should be carefully evaluated in a context-specific manner before widespread implementation. Third, due to limitations in CMS race data, we

were unable to accurately analyze the potential impact of community-level social risk adjustment on non-Black and non-White beneficiaries. Fourth, we focused on the association between community-level social risk factors and spending. Further research is needed to understand the potential impact of community-level social risk adjustment on quality measurement. Fifth, our ascertainment of individual-level social risk factors was limited to those included in a single survey instrument and subject to nonresponse bias, though we found no evidence of such bias on observable characteristics. Finally, since we measured individual-level social risk factors in a period concurrent with our spending outcomes, we were unable to evaluate the role that these factors could play in prospective social risk adjustment, an important area for future research.

Conclusions

In this cross-sectional study of Medicare Advantage beneficiaries, we found that the ADI, a widely used measure of community-level social risk, explained little variation in health care spending, was negatively correlated with spending conditional on demographic and clinical characteristics, and was poorly correlated with self-reported social risk factors. This prompts caution and nuance when using the ADI for social risk adjustment and raises concern that adjusting for community-level social risk may not address payment disparities for many beneficiaries with high levels of social risk.

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Corresponding Author: Karen E. Joynt Maddox, MD, MPH, Washington University School of Medicine in St Louis, 660 S Euclid Ave, St Louis, MO 63130 (kjoyntmaddox@wustl.edu).

Author Affiliations: Tufts University School of Medicine, Boston, Massachusetts (Powers); MassGeneral Brigham, Boston, Massachusetts (Powers); Humana Inc, Louisville, Kentucky (Powers, Franklin, Shrank); Harvard T. H. Chan School of Public Health, Boston, Massachusetts (Figueroa); Harvard Medical School, Boston, Massachusetts (Figueroa, Gondi); Brigham and Women's Hospital, Boston, Massachusetts (Figueroa, Gondi); Humana Healthcare Research, Louisville, Kentucky (Canterberry); Washington University School of Medicine in St Louis, St Louis, Missouri (Joynt Maddox).

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Concept and design: Powers, Gondi, Shrank, Joynt Maddox.

Acquisition, analysis, or interpretation of data: Powers, Figueroa, Canterbury, Gondi, Franklin, Joynt Maddox.

Drafting of the manuscript: Powers, Canterbury, Gondi, Joynt Maddox.

Critical revision of the manuscript for important intellectual content: Powers, Figueroa, Franklin, Shrank, Joynt Maddox.

Statistical analysis: Powers, Canterbury.

Administrative, technical, or material support: Powers, Franklin, Shrank.

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SUPPLEMENT 1.

eMethods. Supplemental Methods

eTable 1. Comparison of Survey Respondents and Non-Respondents, Survey Completers and Non-Completers, and Survey Completers Included in the Analysis and Survey Completers Excluded from the Analysis

eTable 2. Participant Flow through the Study

eTable 3. Complete Regression Results

eTable 4. Predictive Ratios for Population Subgroups Under Different Approaches to Risk-Adjustment for Sensitivity Analysis Modeling ADI Deciles

eTable 5. Complete Regression Results for Sensitivity Analysis Restricting to Beneficiaries in PPO Products Attributed to Providers in FFS Payment Arrangements

eTable 6. Complete Regression Results for Sensitivity Analysis Modeling ADI Deciles

eFigure. Relationship between ADI Decile and Spending

eReferences

SUPPLEMENT 2.

Data Sharing Statement