Socioeconomic Background and Commercial Health Plan Spending

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abstract

BACKGROUND: Risk-adjustment algorithms typically incorporate demographic and clinical variables to equalize compensation to insurers for enrollees who vary in expected cost, but including information about enrollees' socioeconomic background is controversial.

METHODS: We studied 1 182 847 continuously insured 0 to 19-year-olds using 2008–2012 Blue Cross Blue Shield of Massachusetts and American Community Survey data. We characterized enrollees' socioeconomic background using the validated area-based socioeconomic measure and calculated annual plan payments using paid claims. We evaluated the relationship between annual plan payments and geocoded socioeconomic background using generalized estimating equations (γ distribution and log link). We expressed outcomes as the percentage difference in spending and utilization between enrollees with high and low socioeconomic backgrounds.

RESULTS: Geocoded socioeconomic background had a significant, positive association with annual plan payments after applying standard adjusters. Every 1 SD increase in socioeconomic background was associated with a 7.8% (95% confidence interval, 7.2% to 8.3%; $P < .001$) increase in spending. High socioeconomic background enrollees used higher-priced outpatient and pharmacy services more frequently than their counterparts from low socioeconomic backgrounds (eg, 25% more outpatient encounters annually; 8% higher price per encounter; $P < .001$), which outweighed greater emergency department spending among low socioeconomic background enrollees.

CONCLUSIONS: Higher socioeconomic background is associated with greater levels of pediatric health care spending in commercially insured children. Including socioeconomic information in risk-adjustment algorithms may address concerns about adverse selection from an economic perspective, but it would direct funds away from those caring for children and adolescents from lower socioeconomic backgrounds who are at greater risk of poor health.

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WHAT'S KNOWN ON THIS SUBJECT: Including socioeconomic information in risk-adjustment payment algorithms is controversial, but little is known about what its actual effect on providers might be.

WHAT THIS STUDY ADDS: Health care spending is higher among children and adolescents from higher (rather than lower) socioeconomic backgrounds. Including socioeconomic information in risk-adjustment algorithms may thus direct funds away from providers caring for lower socioeconomic populations.

Risk-adjustment for annual spending is a statistical approach used to manage a market of competing health insurance plans. Among community-rated plans (ie, those in which everyone pays the same premium), risk adjustment's goal is that plans with more expensive or complex patients should receive more resources compared with those with fewer, thereby attempting to minimize the insurers' incentive to attract favorable risks (ie, patients who are likely to be less expensive or complex).[1,2] Adequate risk adjustment is essential for the efficient functioning of health insurance exchanges across the United States. Health care providers use similar approaches to evaluate risk-bearing contracts they enter with health plans (eg, accountable care contracts).[3–5]

Risk-adjustment algorithms for annual spending typically include patients' demographics (age and sex) and clinical information (claims-based diagnoses). However, existing risk-adjustment algorithms generally do not include information about socioeconomic background (eg, educational attainment and income) or living circumstances (eg, area-based health risks), although background is thought to contribute substantially to risk for poor health and the complexity of caring for patients.[6–9] Progress in understanding the effects of including socioeconomic information in risk-adjustment algorithms has been impeded because insurers and health care providers do not systematically gather socioeconomic information from enrollees and patients.[10]

Geocoding (ie, mapping enrollees' addresses to their home census tracts and then linking the tracts to socioeconomic information collected by the US census) is 1 method to examine the socioeconomic circumstances in which patients live.[11] Geocoded socioeconomic information has

been shown to reflect individuals' health risks.[12–15] Composites of geocoded socioeconomic information, such as the validated area-based socioeconomic measure (ABSM),[13] have been shown to be representative of area-based health risks (eg, lead exposure and communicable diseases).[13,16–23] Thus, geocoded socioeconomic data can potentially explain differences in individual-level health plan spending after adjustment for other factors typically included in risk-adjustment algorithms. If spending differences exist, one can explore the degree to which differences are due to differential utilization or to unit prices for outpatient, pharmacy, emergency, and inpatient services.

Commercial insurers are an important source of insurance for youth, insuring nearly 60% of children and adolescents in the United States, including those with significant health conditions and those from low-income backgrounds.[24] Some might hypothesize that insurers spend more on youth living in lower socioeconomic areas because this population is at greater risk for many physical and mental health problems (eg, neighborhood violence)[6–8,23,25–29]; they may correspondingly use more services. Alternatively, others might hypothesize that insurers spend more on youth from higher socioeconomic backgrounds because their parents may have an easier time accessing services.[30–32] To our knowledge, no one has examined how spending may vary among those from different socioeconomic backgrounds.

In this study, we use geocoding to ascertain the socioeconomic background of commercially insured youth. We then examine the relationship between enrollees' geocoded socioeconomic background and their annual claims-based spending. We also compare the rates at which youth from low versus high

socioeconomic backgrounds utilize outpatient, pharmacy, inpatient, and emergency health care services and the degree to which the unit prices for these services differ between the 2 populations.

METHODS

Study Design and Data Sources

We conducted a cross-sectional study with person-year–level claims by linking Blue Cross Blue Shield of Massachusetts (BCBSMA) data to the US Census Bureau's American Community Survey.[11,33] Boston Children's Hospital's Institutional Review Board approved the study.

We included the years 2008 to 2012, which represented the period when Massachusetts achieved near universal health insurance coverage after the 2006 Massachusetts Health Care Reform. This period also spanned the Patient Protection and Affordable Care Act of 2010.

The BCBSMA data included enrollee information (eg, census tract) and claims for outpatient, pharmacy, and inpatient services. Rolling 5-year American Community Survey aggregates provided estimates considered representative of the United States.[33]

Study Population

We included each person-year that BCBSMA enrollees 0 to 19 years old had full pharmacy and mental health benefits, lived in New England (93% were Massachusetts residents), and were continuously covered during each calendar year (or were continuously covered from their date of birth to the end of their birth calendar year) between 2008 and 2012.

Geocoded Socioeconomic Information

We used established methods to calculate each child's ABSM and oriented the ABSM so that

more positive values represented higher socioeconomic background (Supplemental Table 4).[11,34,35] For example, living in a census tract with an ABSM value 1 SD above the enrollee mean corresponds to a child living in a tract with a median household income of ~\$100 000 and with 58% of those ≥25 years old with a bachelor's degree or higher. The corresponding numbers for a census tract with an ABSM 1 SD below are ~\$28 000 and 10%.

Annual Spending

We measured annual health care spending using paid claims, which reflect spending incurred by insurers on behalf of individual patients and excludes administrative costs and payments that insurers may have made to providers via bonuses or shared savings and delivered at an aggregate (not individual) level.[5] Our primary analysis calculated annual plan payments, which included BCBSMA claim payment amounts exclusive of patient out-of-pocket spending. We excluded patient payments because the intent of risk adjustment is to level the playing field for competing insurers for their portion of provider billings. We conducted a sensitivity analysis of annual payments to providers, which combined BCBSMA claim payment amounts with patient out-of-pocket spending. To compare spending across years, we adjusted dollar values to 2010 dollars by using the Consumer Price Index for urban consumers.[36] We used Current Procedural Terminology codes to classify utilization and associated prices paid for outpatient, inpatient, and emergency department (ED) care; we used National Drug Codes to examine the number of distinct classes of drugs filled by this population.[37,38]

Geocoded Socioeconomic Background and Spending

We examined the relationship between enrollees' geocoded socioeconomic background and annual plan payments adjusting for variables typical in health plan risk-adjustment payment models (age, sex, and diagnoses by using the Agency for Healthcare Research and Quality's Chronic Condition Indicator classification system[39]). We excluded prior utilization from the base risk-adjustment model because such spending reflects patient utilization while insured; including prior utilization would effectively reimburse the insurer for a portion of prior-year spending for those who continued enrollment. We included a variable for insurer sponsorship type (employer or self-insured) and benefit design (eg, health maintenance organization) in base models because both factors could explain spending variation. We lacked more detailed data on benefit design.

High Versus Low Geocoded Socioeconomic Background, Utilization, and Unit Prices

We considered enrollees to have a high or low geocoded socioeconomic background if their ABSM score was +1 SD above or below the study population mean, respectively. We used unique service dates and corresponding billing codes to determine the unique annual number of outpatient encounters, prescriptions, inpatient admissions, lengths of stay, and ED visits. We used paid claims for the unique service dates and corresponding billing codes to determine unit prices for services. We describe prescription use by counting the number of unique drug classes filled by enrollees using BCBSMA's National Drug Code-based drug directory.[38]

Statistical Analysis

Person-year is the unit of analysis. We modeled the mean of annual plan payments and annual plan plus patient payments using generalized estimating equations (γ distribution and log link) to account for the distribution of the outcomes (normal on a log scale with expected tails with a right skew) and within-enrollee correlation. Independent variables included age, sex, Chronic Condition Indicator count, insurer sponsorship type, benefit design, year, and ABSM score. Our single-level model clustered on enrollees using an exchangeable correlation structure and robust variance estimates. We also ran the single-level model while clustering on tracts rather than enrollees to examine the degree to which within tracts correlation might affect our findings. We included both those with positive annual spending (97% of enrollees) and those remaining with 0 annual spending (3% of enrollees). We presented the model results by exponentiating the coefficients for each independent variable and converting them to percentage change. We calculated adjusted predictions by taking the mean of enrollees' predicted annual plan payments while ABSM scores were fixed at specified levels (−3, −2, −1, 0, +1, +2, and +3 SDs from the enrollee mean). For utilization outcomes (eg, the number of outpatient visits and lengths of stay), we used negative binomial distributions to fit the models described above and compared those with high versus low geocoded socioeconomic backgrounds. We used 2-tailed tests and set our significance level at 0.05. We used Stata version 13.1 for all analyses (StataCorp, College Station, TX).

RESULTS

Study Population

We studied 1 182 847 person-years of enrollees aged 0 to 19 years with ≥1 full year of BCBSMA insurance between 2008 and 2012 (Table 1, Fig 1). The average enrollee age was 10 years (SD 5.8), 51% were male, and 54% had no chronic conditions. Most children and adolescents were insured by an employer-sponsored

health plan (68%) and had health maintenance organization benefits (73%). By using the ABSM, 15% and 13% of enrollees came from high and low geocoded socioeconomic backgrounds, respectively; ABSM values ranged from −28 to +27.

Spending Descriptions

Almost all enrollees (97%) incurred health care spending during each calendar year (96% of enrollees incurred outpatient expenses, and 57%, 15%, and 6% incurred prescription drug, ED, and inpatient spending, respectively) (Table 1). Results were essentially the same when patient out-of-pocket payments were added (Supplemental Tables 5-7, Supplemental Figure 2).

Overall, per child annual plan payments were right-skewed with a median of $795 and a mean of $2607 with considerable variation (SD $13 828, range $0–$3 225 485). Each of the following components of annual plan payments was right-skewed: outpatient services (median $644, mean $1616, SD $6949, range $0–$2 191 095); pharmacy services (median $6, mean $263, SD $1751, range $0–$467 969); ED services (median $0, mean $39, SD $154, range $0–$14 793); and inpatient services (median $0, mean $689, SD $10 523, range $0–$3 211 813).

Geocoded Socioeconomic Background and Spending

Observations were distributed normally across a full range of values for both the ABSM predictor and the annual plan payments outcome (individual dots within Fig 1).

After adjusting for demographics and diagnoses representative of chronic diseases, geocoded socioeconomic background had a significant positive association with annual plan spending, and these findings were robust to clustering at either the enrollee or census tract level. With ABSM added to the risk-adjustment model as a continuous variable

to express the marginal effect of ABSM at each integer of the ABSM, annual plan payments increased 1.1% (95% confidence interval [CI], 1.1% to 1.2%) (Table 2). In terms of SDs rather than integers, every 1 SD increase in ABSM is associated with a 7.8% (95% CI, 7.2% to 8.3%)

increase in annual plan payments (gray squares in Fig 1). When comparing children and adolescents with the highest geocoded socioeconomic backgrounds (+3 SDs above the enrollee average) with those with the lowest (−3 SDs below), this difference amounts to a
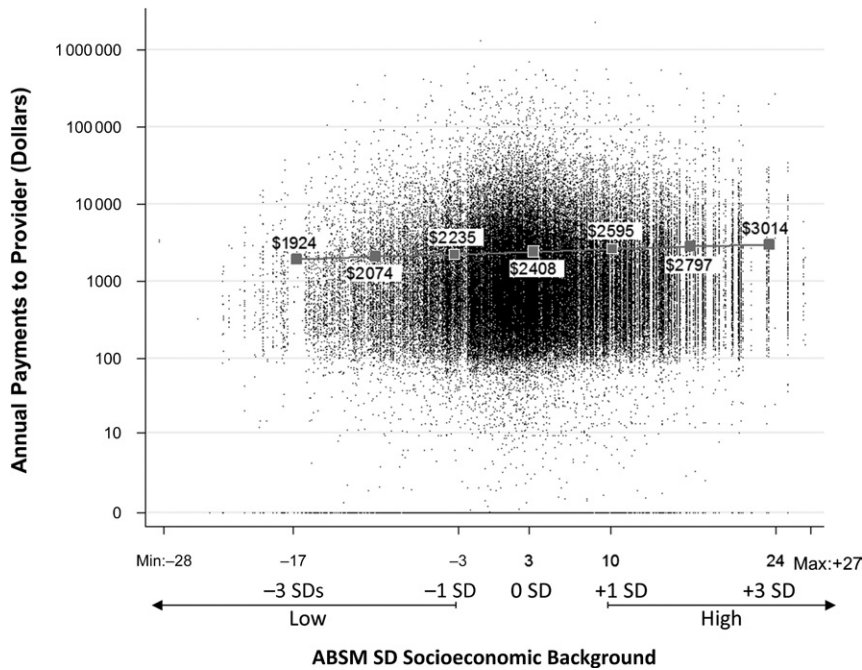
TABLE 1 Enrollee Characteristics: BCBSMA 2008–2012

		N			%	
Person-years		1 182 847			100	
Unique enrollees		458 168			39	
Age, y						
0–1		110 973			9	
2–6		261 104			22	
7–12		355 119			30	
13–17		323 591			27	
18–19		132 060			11	
Male		604 204			51	
No. of chronic conditions[a]						
0		636 687			54	
1		340 363			29	
2		135 700			11	
≥3		70 097			6	
Health plan type[b]						
Employer insured		807 966			68	
Self-insured		374 881			32	
Basic benefit design[c]						
Health maintenance organization		868 809			73	
Preferred provider organization		253 040			21	
Point of service		60 998			5	
Geocoded socioeconomic background via the ABSM[d]						
High (ABSM >1 SD above enrollee mean)		181 350			15	
Medium		850 804			72	
Low (ABSM <1 SD below enrollee mean)		150 693			13	
Proportion with any spending in category		1 143 293			97	
Outpatient		1 136 404			96	
Prescription medications		671 109			57	
ED		173 227			15	
Inpatient		72 326			6	
Per person annual, $	N	Median	Mean	SD	Min	Max
Annual plan payments	1 182 847	795	2607	13 828	0	3 225 485
Outpatient	1 182 847	644	1616	6949	0	2 191 095
Prescription medications	1 182 847	6	263	1751	0	467 969
ED	1 182 847	0	39	154	0	14 793
Inpatient	1 182 847	0	689	10 523	0	3 211 813

[a] Per the Agency for Healthcare Research and Quality Chronic Condition Indicator for the *International Classification of Diseases, Ninth Revision, Clinical Modification*.[39]

[b] Employer sponsored is when the employer purchases health insurance from a health plan on behalf of employees, and the insurer takes the financial risk. Self-insured means that the employer designs and funds his or her own health plan for employees; the employer takes the financial risk and may pay health plan fees to administer the health plan (eg, process claims).

[c] Health maintenance organization and point of service benefit designs typically require enrollees to designate a primary care provider who directs care within a designated network for which there are no or limited patient out-of-pocket costs; out-of-pocket costs rise if patients seek out-of-network care. In health maintenance organizations, patients must involve their primary care providers in directing care to a greater extent than in point of service plans. In preferred provider organization plans, primary care providers are not required to direct care, and enrollees typically pay some out-of-pocket amounts for the care they seek.

[d] As a continuous variable, ABSM has a mean of 3.4 and an SD of 6.7.

FIGURE 1
Geocoded socioeconomic background and annual plan payments: observed and adjusted. ● = observed; ■ = adjusted.

difference of $1089 (95% CI, $1016 to $1162) in terms of annual plan payments per enrollee. Consistent with studies of adults, there was a moderate correlation (0.23) of year-to-year plan spending for enrollees.[40]

Other variables within spending risk-adjustment algorithms, including age, sex, and clinical conditions, were also statistically significant. Children ≥2 years old (versus <2), girls (versus boys), and children with no chronic conditions (versus those with ≥1 chronic condition) incurred significantly less spending. By using adjusted predictions, we found an average of $182 more in spending for every 1 SD increase in enrollees' ABSM score.

High Versus Low Geocoded Socioeconomic Background: Utilization and Unit Prices

Enrollees from high socioeconomic backgrounds used outpatient and pharmacy services at higher rates than enrollees from low socioeconomic backgrounds but were less likely to have a hospital

admission or ED visit (Table 3). On average, over 1 year, enrollees from high socioeconomic backgrounds had 1.5 (95% CI, 1.4 to 1.6), or 23% (95% CI, 22% to 24%), more outpatient visits in 1 year than enrollees from low socioeconomic backgrounds (P < .001). Children from high socioeconomic backgrounds also filled drug prescriptions from 0.20 (95% CI, 0.18 to 0.21), or 13% (95% CI, 12% to 14%), more prescription classes than their counterparts from low socioeconomic backgrounds (P < .001). In contrast, enrollees from high socioeconomic backgrounds were 12% (95% CI, 9% to 15%) less likely to be admitted to the hospital and 19% (95% CI, 17% to 21%) less likely to visit the ED than enrollees from low socioeconomic backgrounds (P < .001 for both). For hospital stays, however, enrollees from high and low socioeconomic backgrounds were not significantly different with respect to the lengths of their hospital stays (P = .77).

Enrollees from high socioeconomic backgrounds used services with

significantly higher unit prices than those from low socioeconomic backgrounds with respect to outpatient encounters, prescription medications, and ED visits but not hospital admissions. The mean unit price for an outpatient encounter was $17 (95% CI, $14 to $20), or 8% (95% CI, 7% to 10%), more per visit for enrollees from high socioeconomic backgrounds than for those from low socioeconomic backgrounds (P < .001). Similarly, the mean unit price for a prescription drug class was $37 (95% CI, $28 to $47), or 36% (95% CI, 26% to 46%), more for enrollees from high versus low socioeconomic backgrounds (P < .001). The mean unit price paid for an ED visit for enrollees from high versus low socioeconomic backgrounds was $30 (95% CI, $27 to $34), or 17% (95% CI, 15% to 19%), more per visit (P < .001). The unit price for inpatient admissions was not different between socioeconomic groups (95% CI, −11% to 1%; P = .10).

DISCUSSION

In this study, we make 2 key observations with policy or interventional implications. First, because geocoded socioeconomic information explains a significant, albeit small, amount of variation in insurer spending, including this information in risk-adjustment algorithms could potentially help address concerns about selection (ie, plan efforts to attract the less costly and thus more profitable youth) when running health insurance exchanges and creating value-based or accountable care contracts. However, doing so would direct funds toward those plans and providers caring for patients with fewer (rather than greater) risks of poor health.[10,35] Insofar as policy makers and payers seek to direct funds toward providers caring for more children of lower income

TABLE 2 Geocoded Socioeconomic Information Within a Typical Risk-Adjustment Model

Effect on Annual Plan Payments	Percent Change	95% CI, %		P
Geocoded socioeconomic background via the ABSM as a continuous measure	+1.1	+1.1	+1.2	<.001
Age, y (0–1 as referent)				
2–6	−69	−69	−68	<.001
7–12	−75	−75	−74	<.001
13–17	−68	−68	−67	<.001
18–19	−65	−66	−65	<.001
Sex (male as referent)				
Female	−6	−7	−5	<.001
No. of chronic conditions[a] (0 as referent)				
1	+156	+153	+159	<.001
2	+366	+362	+376	<.001
3	+685	+669	+708	<.001
4	+1233	+1181	+1287	<.001
≥5	+3312	+3019	+3597	<.001
Health plan type[b] (employer insured as referent)				
Self-insured	+13	+12	+14	<.001
Basic benefit design[c] (HMO as referent)				
Preferred provider organization	−6	−7	−5	<.001
Point of service	+8	+6	+11	<.001
Study year (2008 as referent)				
2009	−1	−2	0	.009
2010	+4	+3	+5	<.001
2011	+7	+6	+8	<.001
2012	+6	+5	+8	<.001

HMO, health maintenance organization.

[a] Per the Agency for Healthcare Research and Quality Chronic Condition Indicator for the *International Classification of Diseases, Ninth Revision, Clinical Modification.*[41]

[b] Employer sponsored is when the employer purchases health insurance from a health plan on behalf of employees, and the insurer takes the financial risk. Self-insured means that the employer designs and funds his or her own health plan for employees; the employer takes the financial risk and may pay health plan fees to administer the health plan (eg, process claims).

[c] Health maintenance organization and point of service benefit designs typically require enrollees to designate a primary care provider who directs care within a designated network for which there are no or limited patient out-of-pocket costs; out-of-pocket costs rise if patients seek out-of-network care. In health maintenance organizations, patients must involve their primary care providers in directing care to a greater extent than in point of service plans. In preferred provider organization plans, primary care providers are not required to direct care, and enrollees typically pay some out-of-pocket amounts for the care they seek.

backgrounds, they should think carefully about the tension between that goal and the goal of minimizing selection when considering whether to include geocoded socioeconomic information in risk-adjustment algorithms for spending.

Second, on balance, health care spending was higher among youth living in higher socioeconomic areas than those in lower socioeconomic areas in a commercially insured population.[42–45] The spending difference appears to be driven by a combination of differences in the type, volume, and prices paid for services. Greater outpatient and pharmacy use and unit prices among youth from higher socioeconomic backgrounds outweighed spending for more frequent ED visits and inpatient admission rates among youth from low socioeconomic backgrounds. Policy makers, payers, and physicians who are frequently concerned with whether ED use among youth of low-income backgrounds is appropriate may want to consider such appropriateness of questions among youth from high socioeconomic backgrounds as well.[31]

Researchers of future studies can investigate whether youth from higher socioeconomic backgrounds are overutilizing care, those from lower socioeconomic backgrounds are underutilizing care, and whether care quality is comparable across all groups. Overutilization of care can be targeted in a variety of ways (eg, decision support tools, quality improvement, or nonpayment); underutilization can be investigated for when the breakdowns occur (eg, patients having difficulty accessing clinicians or clinicians facing challenges recognizing patients' socioeconomically or area-based health risks). It may also help us investigate care quality under accountable care contracts, develop strategies for identifying underutilizers, or assess concerns about cherry-picking (eg, insurers who might market more extensively in lower-spending groups). To link payment information with clinical care, researchers of such studies would need to collect primary data or create novel connections between claims and medical records.

To our knowledge, we present the first assessment of the use of census-tract–based socioeconomic information in risk-adjustment algorithms for annual spending, adult or pediatric. In pediatrics, studies of risk adjustment for annual spending date back to the 1990s, a time when neither self-reported nor geocoded socioeconomic information were available and when stakeholders were focused on adequately capturing the clinical conditions facing children.[46–48] More recently, several have examined the degree to which geocoded information may augment clinical information, especially as it pertains to assessing asthma risk factors and care.[41,49,50] In adult populations, the role that socioeconomic information (geocoded or otherwise) plays in explaining differential performance in pay-for-performance programs

TABLE 3 High and Low Geocoded Socioeconomic Backgrounds: Utilization and Prices for Outpatient, Inpatient, Pharmacy, and ED Services

Type of Service, Annual	Utilization									Prices, $								
	High Socioeconomic Background (ABSM >1 SD Above Enrollee Mean)				Low Socioeconomic Background (ABSM <1 SD Below Enrollee Mean)					High Socioeconomic Background (ABSM >1 SD Above Enrollee Mean)				Low Socioeconomic Background (ABSM <1 SD Below Enrollee Mean)				
	Median Observed	Mean Adjusted	95% CI		Median Observed	Mean Adjusted	95% CI		P	Median Observed	Mean Adjusted	95% CI		Median Observed	Mean Adjusted	95% CI		P
Outpatient encounters	5.0	7.9	7.9	8.0	4.0	6.4	6.4	6.5	<.001	103	223	221	225	102	206	204	208	<.001
Prescription drug classes	1.0	1.7	1.7	1.8	1.0	1.5	1.5	1.6	<.001	13	141	133	149	9	104	99	108	<.001
Inpatient Admissions	0.0	0.07	0.067	0.070	0.0	0.08	0.076	0.079	<.001	2711	9792	9295	10289	2657	10336	9706	10967	.10
Length of stay, d	2.0	4.3	4.2	4.4	2.0	4.3	4.2	4.5	.77	—	—	—	—	—	—	—	—	—
ED visits	0.0	0.18	0.18	0.19	0.0	0.23	0.22	0.23	<.001	148	212	210	215	145	182	180	184	<.001

—, not applicable.

or public reporting has been the focus of substantial empirical study.[15,51–54] Although many studies have been conducted, most must rely on Medicaid eligibility or zip code-based indicators, so more granular individual or area-based risk information is important for examining the degree to which care is appropriate for different patient populations and its corresponding spending consequences.[51–54]

Our study is potentially limited by its use of data from a single commercial insurer in Massachusetts, one with a 45% market share.[55] However, because the variance in annual payments to providers attributable to differences among commercial insurers with differing health benefits is extremely small (~0.25%), we expect other studies of plans in which the measure of spending is close to utilization to give a similar conclusion.[40] This study also relies on claims-based payments for individual care and does not include provider-level, quality-related bonus payments, such as those that BCBSMA introduced via Alternative Quality Contract payments.[3–5] We cannot estimate the degree to which provider-level bonus payments contribute to care quantity or quality at the individual level. Also, the effect of any single risk adjuster like the ABSM will depend on what other variables are in the model and what the risk-adjustment goals are. Our analysis has focused on capturing tract-level circumstances of enrollees rather than individual characteristics.[34] Also, youth in this study represent a full range of geocoded socioeconomic backgrounds. This breadth would not be present if we had studied government-insured patients only, but the role of socioeconomic information among Medicaid enrollees should also be evaluated.

On balance, among commercially insured youth, it appears that geocoded socioeconomic information may

indicate greater economic demand for or access to health care among families from higher (rather than lower) socioeconomic backgrounds. Researchers of future studies should examine the degree to which the patterns we observed among the commercially insured also exist among those insured by Medicaid. Although Medicaid-insured patients will not be as diverse as the commercially insured with respect to their geocoded socioeconomic background, there could still be an important socioeconomic gradient between those living above and below the federal poverty line.

CONCLUSIONS

Geocoded socioeconomic information explains variation in spending. Incorporating this information in risk adjustment could address concerns about adverse selection. However, doing so would direct more funds toward providers caring for patients with fewer (rather than greater) risks of poor health.

ABBREVIATIONS

ABSM: area-based socioeconomic measure
BCBSMA: Blue Cross Blue Shield of Massachusetts
CI: confidence interval
ED: emergency department

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