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Evaluating Area-Based Socioeconomic Status Indicators for Monitoring Disparities within Health Care Systems: Results from a Primary Care Network

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Associated Data

Supplementary Materials

Abstract

Tracking "prevailing disparities in health care delivery as it relates to racial factors and socioeconomic factors in priority populations" is a public health priority (Agency for Healthcare Research and Quality 2012a,b). However, there are considerable challenges to implementing the systems needed to monitor for health care inequalities within health care networks. Information to determine membership in populations of interest must be obtained routinely and reliably, and be stable over time or updated periodically. Identifying race/ethnicity for patients may be relatively straightforward; many systems capture information on racial/ethnic identity with a single, self-report item that does not change over the course of a patient's association with the health care system. However, the situation is more complicated for socioeconomic status (SES). SES is a multidimensional construct with many possible indicators (Liberatos, Link, and Kelsey 1988; Braveman et al. 2005). Many systems do not routinely collect SES information. Further, some indicators, such as income, are sensitive topics and may be uncomfortable for patients to report or for health care systems to collect (Liberatos, Link, and Kelsey 1988), and they may change over time.

For these reasons, the use of area-based SES indicators obtained from address data linked to geocoded census information is sometimes used as an alternative to self-report indicators (Bonito et al. 2012). Area-based SES indicators are convenient, as patient home addresses

are routinely collected and updated by health care systems for administrative and clinical purposes. Geocode linkage can often be accomplished expeditiously and at low cost (Krieger et al. 2002a, 2003b), and census data are in the public domain. Previous studies have examined the use of area-based SES measures in monitoring disparities as part of public health surveillance (Krieger et al. 2002a, 2003a,b, 2005). Despite this, there is little evidence identifying which area-based SES indicators may be best for monitoring inequalities within other health care delivery systems. Unanswered questions include the following: How well do area-based indicators correlate with self-report indicators such as educational attainment? Which geographic level is optimal? From which domain of SES, such as income, education, or occupation (Braveman et al. 2005), should an indicator be chosen? Do single-item indicators perform as well as multidimensional indices?

Our goal was to identify the best area-based SES measures from the perspective of a primary care delivery system in terms of accuracy and ease of obtaining and maintaining data for ongoing surveillance. To accomplish this, we compared commonly used area-based indicators to each other and to self-reported educational attainment. Based on previous work in the public health setting (Krieger et al. 2005), we hypothesized that area-based SES measures would correlate well with self-reported educational attainment, that the census tract would provide data for the most patients with the greatest specificity, that area-based indicators related to income would best predict health care outcomes, and that single-item indicators would perform as well as multidimensional indices.

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Methods

Study Setting and Population

We examined a cohort of adult (age <18 years) patients who were known to receive most of their care in one of 18 practices in our primary care network from January 1, 2009, to December 31, 2011, using a previously validated algorithm (Atlas et al. 2009). These practice settings included an academic, hospital-based clinic, community health centers, and private practices. The Partners HealthCare institutional review board approved the use of patient data for this study.

Assigning Geocodes

Patient address information was obtained from electronic registration data. We attempted to link each address to a specific geographic area ("geocode") at each of three levels: census block group (BG), census tract (CT), and ZIP code (ZIP). Census block groups are small, relatively homogenous areas of approximately 1,000 persons (U.S. Bureau of the Census 1994). Census tracts aggregate several block groups, and represent approximately 4,000 persons (U.S. Bureau of the Census 1994). As their name implies, both BGs and CTs are constructed by the U.S. Bureau of the Census for the purpose of assessing population demographics. By contrast, ZIP codes are constructed by the U.S. Post Office, for purposes of mail delivery, and may include more socioeconomic heterogeneity than BG or CT defined areas (Krieger et al. 2005). Previous studies have reported that ZIP code-based SES indicators detect weaker associations between SES and health outcomes, and sometimes even reverse the direction of association, compared to BG and CT defined areas (Krieger et al. 2002b, 2005). To provide more demographically meaningful zip code data, beginning with the 2000 census, the U.S. Census began assigning ZIP Code Tabulation Areas (US Bureau of the Census 2013), which often, but not always, correspond to the ZIP code of the mailing address. Assigning a ZIP code tabulation area requires the use of geocoding software to obtain a Federally Information Processing Standard code for an address, rather than simply using the ZIP code in an address field from patient records. This requires extra time and expense, but it may yield greater accuracy. We wanted to know how indicators constructed using the simpler process of taking ZIP codes in the address field to define the geographic region (and using ZIP Code Tabulation Area data provided by the census) would compare to the more complicated process of formally linking an address to a specific BG or CT.

If address information cannot be linked to a BG, CT, or ZIP, then an area-based SES indicator cannot be constructed. This type of missingness is generally greater for smaller (e.g., BG) geographic areas, as opposed to larger ones (e.g., ZIP). Furthermore, due to privacy concerns and nonresponse for various census items, the U.S. Census does not release information for every geographical area (U.S. Bureau of the Census 2003). This is also more likely to occur in smaller geographical areas, and thus ZIP code defined areas may be more likely to have information for a given indicator, than BG or CT areas (U.S. Bureau of the Census 2003). However, if a ZIP code does not overlap a ZIP code tabulation area, there will be no data for that ZIP code. We used Census 2000 data (US Bureau of the Census 2003), because Census 2010 data was not yet available for all variables of interest. We used ArcGIS software to geocode addresses from our cohort (Esri, Redlands, CA, USA).

Socioeconomic Status Indicators

We assessed several socioeconomic status indictors in our study. Self-reported educational attainment was obtained from patient registration records. Educational attainment was categorized as less than high school diploma (<HS) or high school diploma or higher (≥HS). Self-reported educational attainment is a widely used indicator of SES and has been associated with many disparities in health (Braveman et al. 2005). We also examined several established area-based SES indicators which reflect different dimensions of SES, including income, education, and occupation (Krieger et al. 2002a, 2003a,b, 2005; Braveman et al. 2005). We constructed these indicators at all three geographic levels (BG, CT, and ZIP) based on patient address information.

Area-based SES indictors can be constructed as "quantiles," where geographic areas are ranked within the study sample and grouped. However, a quantile approach may produce categorizations that vary across space and time. For example, a BG median household income which is in the lowest quantile in a sample that largely contains wealthier areas might be in the highest quantile within a more impoverished sample. Therefore, we also employed an a priori categorical cut point approach, which used previously defined thresholds to assign groups. However, some area-based indicators, as described below, did not have well-defined cut points, and thus only the quantile approach could be used.

After examining a range of area-based SES indicators (data available upon request), we report on those that represented the best performance within each domain. For income-based indicators, we used (1) median household income, categorized into four groups using a priori cut points based on a government definition of low-income areas (Department of Housing and Urban Development 2013) (<60 percent state-wide median household income [the worst-off group], 60–100 percent state-wide median household income, <100–140 percent state-wide median household income, and <140 percent state-wide median household income[the best-off group]); (2) median household income, as quartiles (with the lowest median household income quartile representing the worst-off group and the highest representing the best-off group); (3) percent of area persons living in poverty, categorized into four groups based on previously established cut points (Krieger et al. 2005; Department of Housing and Urban Development 2013) (<20 percent [the worst-off group], <10–20, 5–10, and <5 percent [the best-off group]); and (4) percent of area persons living in poverty, as quartiles (with the quartile with the highest percent living in poverty representing the worst-off group and the lowest percent living in poverty representing the best-off group).

For education-based indicators, we used percent of area individuals with college degree or higher educational attainment by quartiles (with the lowest quartile representing the worst-off group), as there was no established cut point.

With regards to occupation-based indicators, we constructed one based on percent of area individuals unemployed, using a governmental definition of high unemployment areas (Employment Training Panel 2011) to categorize using the following cut points: <125 percent the state-wide unemployment rate (the worst-off group), <100–125 percent the state unemployment rate, 75–100 percent the state-wide unemployment rate, and <75 percent the state-wide unemployment rate (the best-off group).

Finally, we used two previously validated multidimensional indices that were constructed from several different census indicators (Figure S1): the Neighborhood Deprivation Index (Messer et al. 2006; O'Campo et al. 2008; Schempf et al. 2011) (NDI) (with the highest quartile representing the worst-off group) and an index created by the Agency for Healthcare Research and Quality (AHRQ; Bonito et al. 2012) (with the lowest scoring quartile representing the worst-off group).

Health Outcomes

We selected outcomes that encompassed multiple domains of health care quality and in which SES gradients were expected (Agency for Healthcare Research and Quality 2012a,b). Our dimensions of health and health care quality (Agency for Healthcare Research and Quality 2012a,b) included disease prevalence, chronic disease management and effectiveness of care, preventive service provision, resource utilization, and patient centeredness of care. For disease prevalence, we used the prevalence of diabetes, as defined by a previously validated algorithm (Grant et al. 2012). While disease prevalence may not be a valid indicator of health care quality in general, several studies demonstrating effective diabetes prevention efforts in the health care setting (Tuomilehto et al. 2001; Knowler et al. 2002) support examining this condition. For chronic disease management and effectiveness of care, we assessed the proportion of patients with coronary heart disease and/or diabetes mellitus whose most recent low density lipoprotein cholesterol in the prior year was <100 mg/dL (Agency for Healthcare Research and Quality 2012a,b). For preventive service provision, we assessed the proportion of eligible adults (those aged 52–75 years without prior total colectomy) who had completed colorectal cancer screening within the recommended interval (Centers for Disease Control and Prevention 2011). For health service resource utilization, we assessed the proportion of patients considered "frequent utilizers" of the emergency department, with greater than three visits in 12 months (Liu et al. 2013). For patient centeredness of care, we assessed the proportion of patients who reported poor communication with their health care provider (defined as reporting that their provider sometimes or never explained things in a way that was easy to understand, listened carefully, showed respect for what they had to say, or spent enough time with them) in a subset of sample population who received the Consumer Assessment of Healthcare Providers and Systems (CAHPS) survey (Agency for Healthcare Research and Quality 2012a,b).

Data Analysis

We first performed descriptive statistics of our study cohort. We then examined the missing data for each SES indicator and further characterized the area-based indicators' missing data into two groups: missing because an address could not be assigned to a given geographical level, and missing because census data for that indicator was not reported for the geographic area. We compared group missingness using logistic regression with generalized estimating equations to account for repeated subjects (SAS PROC GENMOD). Next, to understand how closely associated our self-report SES indicator, educational attainment, was with our area-based SES indicators, we calculated a regression based metric, the Relative Index of Inequality (RII), for each of our comparisons, similar to prior studies (Krieger et al. 2003a; Khang et al. 2004). An alternative to the risk ratio (RR) between the worst-off and best-off groups, the RII has the advantage of incorporating all the available data in its calculation and may be less affected by extremes in high and low categories with low numbers of patients (Wagstaff, Paci, and van Doorslaer 1991; Krieger et al. 2003a; Regidor 2004). Following the standard calculation method (The Public Health Disparities Geocoding Project 2004; Khang, Yun, and Lynch 2008), each area-based SES group was assigned a ridit score, between 0 and 1, which represented the midpoint of the group's position in the cumulative distribution from worst-off (1) to best-off (0), using the entire network sample. We calculated the RII and 95 percent Confidence Interval (95 percent CI) using log-Poisson regression with robust error variance (SAS PROC GENMOD) (Zou 2004). We selected this method because the RIIs presented can be interpreted as prevalence ratios (Kunst and Mackenbach 1994; Khang, Yun, and Lynch 2008), which is more interpretable than odds ratios given that many of our outcomes occur with high frequency, and because Poisson regression is preferred for this purpose (Khang, Yun, and Lynch 2008). In our study, the RII reported represents the prevalence ratio of a given outcome between a group having the worst-off and best-off status. We also conducted sensitivity analyses using traditional RRs and RIIs calculated with log-binomial regression, and the results were not substantially different (data available upon request).

To determine if a particular geographic level, BG, CT, or ZIP consistently detected the larger gradients, we performed all analyses at each of these geographic levels. While we report nominal 95 percent confidence intervals for ease of interpretation, we were concerned about multiple comparisons. Thus, for significance testing, we compared RIIs derived from the regression equations using an alpha = .00025 level of significance, which preserves a type 1 error rate of 5 percent across 200 comparisons, using the Bonferroni correction (Pocock, Geller, and Tsiatis 1987). Comparisons were made within the same indicator by geographic level, and across indicators at the same geographic level. All analyses were performed using *SAS*, version 9.3 (Cary, NC, USA).

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Results

The study cohort included 142,659 adult patients seen in our network between January 1, 2009, and December 31, 2011, and linked to a specific primary care provider or practice. The median age was 50.2 years, 57.5 percent were women, 69.0 percent had commercial insurance, and 7.6 percent had less than a high school diploma (Table(Table11).

Table 1

Demographics

Characteristics	**% (*n*) or Median (IQR)**
	***N* = 142,659**
Age (y)	50.2 (37.2–63.7)
Female	57.5 (81,955)
Race/ethnicity	

Characteristics	% (*n*) or Median (IQR)
	***N* = 142,659**
Non-Hispanic white	78.3 (110,074)
Non-Hispanic black	6.1 (8,610)
Hispanic	9.5 (13,401)
Asian	6.0 (8,365)
Other/multi	0.1 (133)
Insurance	
None/self/free care	3.5 (5,005)
Commercial	69.0 (98,432)
Medicare	18.7 (26,734)

Characteristics	% (*n*) or Median (IQR)
	***N* = 142,659**
Medicaid	8.7 (12,467)
<High school diploma	7.6 (10,490)
Non-English primary language	8.9 (12,661)

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Completeness of SES Indicators

With regards to SES indicator data, missing data were low overall (Table(Table2).2). Ninety-six percent of patients had self-reported educational attainment and 99 percent of patients had ZIP-level SES indicators. For CT and BG level indicators, missing data was more common, with only 89–91 percent, of patients, depending on the indicator, assigned to these levels. Using median household income census data, significantly more patients could be assigned a ZIP-level SES indicator than a CT- ($p < .0001$) or BG- ($p < .0001$) level indicator. Additionally, significantly more patients had ZIP-level median household income data than educational attainment data ($p < .0001$). Similarly, ZIP-level data had significantly lower missingness than CT, BG, and educational attainment for all other SES indicators studied (data not shown). With regards to the reason for missing data, ZIP-level data were more likely to be missing due to missing census data, as opposed to inability to assign a patient to that level. For example, using median household income data, 86 percent of patients could not be assigned a ZIP-level indicator due to missing census data, compared to 52 percent for CT and 54 percent for BG ($p < .0001$ for both comparisons). Results were similarly significant for all other census data (available upon request).

Table 2

Assignment and Missing Data for SES Indicators

		Assigned		Missing		Reason for Missing Data: Could Not Be Assigned to Level		Reason for Missing Data: Missing Census Info	
Indicator	**Level**	***N***	**%**	***N***	**%**	***N***	**%**	***N***	**%**
Education	Individual	137,647	96	5,012	4	n/a	n/a	n/a	n/a
Median household income	BG	129,385	91	13,274	9	6,110	46	7,164	54
	CT	129,813	91	12,846	9	6,110	48	6,736	52
	ZIP	141,122	99	1,537	1	215	14	1,322	86
Poverty	BG	129,344	91	13,315	9	6,110	46	7,205	54
	CT	129,812	91	12,847	9	6,110	48	6,737	52
	ZIP	141,112	99	1,547	1	215	14	1,332	86

						Reason for Missing Data			
		Assigned		Missing		Could Not Be Assigned to Level		Missing Census Info	
Indicator	**Level**	***N***	**%**	***N***	**%**	***N***	**%**	***N***	**%**
%≥ College	BG	129,366	91	13,293	9	6,110	46	7,183	54
	CT	129,813	91	12,846	9	6,110	48	6,736	52
	ZIP	141,107	99	1,552	1	215	14	1,337	86
Unemployed	BG	129,368	91	13,291	9	6,110	46	7,181	54
	CT	129,813	91	12,846	9	6,110	48	6,736	52
	ZIP	141,122	99	1,537	1	215	14	1,322	86
NDI	BG	127,154	89	15,505	11	6,110	39	9,395	61

						Reason for Missing Data			
		Assigned		Missing		Could Not Be Assigned to Level		Missing Census Info	
Indicator	**Level**	***N***	**%**	***N***	**%**	***N***	**%**	***N***	**%**
	CT	126,831	89	15,828	11	6,110	39	9,718	61
	ZIP	140,887	99	1,772	1	215	12	1,557	88
AHRQ	BG	127,154	89	15,505	11	6,110	39	9,395	61
	CT	129,775	91	12,884	9	6,110	47	6,774	53
	ZIP	140,894	99	1,765	1	215	12	1,550	88

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Comparing Patient-Reported Educational Attainment and Area-Based SES Indicators

Overall, area-based SES indicators were strongly associated with educational attainment (Table(Table3).3). For example, using the quantile-based median household income indicator, the prevalence of having <HS educational attainment was 46, 55, and 46 times higher in the worst-off, compared to the best-off, group at the BG, CT, and ZIP level, respectively. Results were similar for the other area-based indicators (data not shown), and no geographic level was consistently more strongly associated with educational attainment.

Table 3

Associations between Self-Reported Educational Attainment and Area-Based SES Indicators

Area-Based SES Indicators	Level	<HS Educational Attainment	
		RII*	**95% CI**
Median household income (cut points)	BG	41.16	37.68–44.96
	CT	53.07	48.25–58.36
	ZIP	50.56	46.11–55.45
Median household income (quartiles)	BG	46.31	42.02–51.03
	CT	54.56	49.30–60.39
	ZIP	45.68	41.48–50.31
Poverty (cut points)	BG	25.93	23.87–28.16
	CT	35.72	32.82–38.87

Area-Based SES Indicators	Level	<HS Educational Attainment	
		RII*	95% CI
	ZIP	31.65	29.11–34.43
Poverty (quartiles)	BG	25.50	23.15–28.10
	CT	36.85	33.43–40.61
	ZIP	23.39	21.61–25.32
College and higher	BG	62.64	56.24–69.77
	CT	56.31	50.56–62.73
	ZIP	48.21	43.58–53.34
Unemployed (cut points)	BG	5.21	4.84–5.60
	CT	9.28	8.61–10.00

Area-Based SES Indicators	Level	<HS Educational Attainment	
		RII*	95% CI
	ZIP	16.91	15.70–18.21
NDI	BG	77.13	68.95–86.27
	CT	70.16	62.99–78.14
	ZIP	62.85	56.80–69.54
AHRQ	BG	85.29	76.24–95.42
	CT	75.76	67.88–84.55
	ZIP	61.90	55.88–68.58

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*Relative Index of Inequality (RII) represents the prevalence ratio between the worst-off and the best-off status.

Association among Area-Based SES Indicators and Health Care Outcomes

Area-based SES indicators consistently detected associations between low SES and poor clinical outcomes that were in the same direction as and similar in magnitude to associations detected by self-reported educational attainment (Table(Table4).4). For example, with regard to patients reporting poor provider communication, the RII for the worst-off, compared to best-off, self-reported educational attainment groups was 2.66 (95 percent CI: 1.92–3.69), meaning that the prevalence of poor communication would be 266 percent higher in the worst-off compared to the best-off group. By comparison, the RII in the worst-off, compared to the best-off, group using median household income cut points at the ZIP level was 2.79 (95 percent CI: 1.72–4.50), 2.29 (95 percent CI: 1.36–3.87) for the groups defined by percent with college degree at the BG level, and 2.51 (95 percent CI: 1.51–4.18) for the group defined by the AHRQ index at the CT level. Overall, RIIs were smaller for area-based indicators than self-reported educational attainment for most outcomes, but the differences were small: the RII of at least one area-based SES indicator was not statistically significantly different from the RII of self-reported educational attainment for every outcome except diabetes prevalence, and for both the chronic disease management and patient centeredness outcomes, several area-based SES indicators detected larger disparities than self-reported educational attainment.

Table 4

Associations among Area-Based SES Indicators and Clinical Outcomes

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
Education		7.64	7.00–8.35	1.10	0.94–1.28	1.91	1.72–2.13	11.48	8.20–16.07	2.66	1.92–3.69

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
Median household income (cut points)	BG	3.33	3.12–3.56	1.40	1.26–1.55	1.63	1.54–1.73	9.32	7.00–12.39	2.87	1.76–4.69
	CT	3.50	3.27–3.74	1.43	1.28–1.59	1.66	1.56–1.76	7.43	5.64–9.79	3.06	1.81–5.20
	ZIP	3.14	2.95–3.35	1.48	1.33–1.63	1.68	1.59–1.78	4.88	3.84–6.19	2.79	1.72–4.50
Median household	BG	3.39	3.18–3.62	1.41	1.27–1.57	1.63	1.53–1.73	8.27	6.23–10.99	2.41	1.49–3.91

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
income (quartiles)	CT	3.48	3.26–3.72	1.39	1.25–1.54	1.64	1.55–1.74	8.07	6.12–10.63	3.08	1.85–5.12
	ZIP	3.27	3.07–3.48	1.43	1.29–1.58	1.69	1.60–1.79	4.61	3.64–5.86	3.12	1.93–5.07
Poverty (cut points)	BG	2.49	2.33–2.66	1.36	1.23–1.52	1.50	1.41–1.60	5.39	4.06–7.15	2.38	1.44–3.92
	CT	2.81	2.64–3.00	1.37	1.23–1.52	1.56	1.46–1.66	6.16	4.70–8.07	2.37	1.44–3.91

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
	ZIP	2.45	2.30–2.61	1.43	1.29–1.58	1.57	1.48–1.67	5.32	4.16–6.79	2.57	1.62–4.09
Poverty (quartiles)	BG	2.46	2.30–2.62	1.31	1.18–1.45	1.47	1.38–1.56	4.26	3.18–5.71	1.98	1.22–3.24
	CT	2.70	2.53–2.88	1.43	1.29–1.58	1.55	1.46–1.64	5.88	4.42–7.81	2.68	1.65–4.35
	ZIP	2.31	2.17–2.45	1.44	1.30–1.59	1.53	1.45–1.62	4.69	3.64–6.02	2.64	1.68–4.16

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
College and higher	BG	4.29	4.02–4.59	1.47	1.32–1.63	1.61	1.52–1.71	5.41	4.06–7.22	2.29	1.36–3.87
	CT	4.22	3.95–4.52	1.37	1.23–1.52	1.58	1.48–1.68	4.04	3.05–5.35	2.19	1.29–3.73
	ZIP	4.15	3.89–4.42	1.42	1.28–1.57	1.52	1.43–1.61	3.03	2.35–3.92	2.73	1.67–4.49
Unemployed (cut points)	BG	1.72	1.61–1.84	1.30	1.17–1.44	1.27	1.19–1.35	2.64	2.02–3.46	1.16	0.71–1.90

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
	CT	2.03	1.90–2.16	1.31	1.18–1.45	1.35	1.27–1.43	3.29	2.52–4.29	2.28	1.41–3.69
	ZIP	2.09	1.97–2.22	1.46	1.33–1.62	1.44	1.36–1.52	3.24	2.56–4.09	2.71	1.73–4.24
NDI	BG	3.89	3.64–4.16	1.46	1.31–1.63	1.67	1.57–1.78	7.12	5.30–9.57	2.24	1.34–3.76
	CT	3.85	3.60–4.11	1.42	1.28–1.59	1.67	1.57–1.78	7.10	5.34–9.44	2.23	1.34–3.72

Area-Based SES Indicators	Level	Chronic Disease Prevalence		Chronic Disease Management		Preventive Services		Resource Utilization		Patient Centeredness	
		Presence of Diabetes		LDL <100		Have Not Completed CRC Screening		Had <3 ED Visits in Last 12 months		Report Poor Communication with PCP	
		RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI	RII*	95% CI
	ZIP	3.53	3.32–3.77	1.46	1.32–1.62	1.69	1.60–1.79	4.71	3.67–6.05	2.74	1.69–4.41
AHRQ	BG	4.28	4.01–4.58	1.48	1.33–1.65	1.70	1.60–1.80	7.58	5.69–10.11	2.54	1.50–4.30
	CT	4.24	3.97–4.53	1.45	1.30–1.61	1.68	1.58–1.78	6.52	4.94–8.61	2.51	1.51–4.18
	ZIP	4.11	3.85–4.38	1.47	1.33–1.63	1.65	1.56–1.74	3.80	2.96–4.88	3.00	1.86–4.87

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*Relative Index of Inequality (RII) represents the prevalence ratio between the worst-off and the best-off status.

With regard to geographic level, comparisons of BG-, CT-, and ZIP-based indicators revealed very similar RIIs. Comparing ZIP to BG/CT (Table(Table4),4), there was no statistically significant difference in 69 of 80 (86 percent) comparisons. The BG- or CT-level indicator detected a greater RII in 10 percent, and the ZIP indicator detected a larger RII in 4 percent. Compared to other ZIP-level indicators, ZIP median household income with a priori cut points was not statistically significantly different in 27/35 comparisons. ZIP median household income with a priori cut points detected a statistically significantly greater RII than other ZIP-level indicators in 5/35 comparisons, and a significantly smaller RII in 3/35 comparisons.

Examining differences in cut point versus quantile approaches to indicator construction, the RIIs were again similar (Table(Table4).4). When compared to the cut point-based indicator at the same geographic level, there was no statistically significant difference in the RII detected by quantile-defined indicators. For example, ZIP-level median household income by cut point detected an RII of 3.14 (95 percent CI: 2.95–3.35) for diabetes prevalence, compared to an RII of 3.27 (95 percent CI: 3.07–3.48) for the quantile-based indicator.

Finally, we examined differences in the use of single-item indicators versus indices (Table (Table4).4). Compared to NDI and AHRQ indices constructed at the same geographic level, there was no statistically significant difference for the RIIs detected by cut point-based median household income for all outcomes except diabetes prevalence, where the AHRQ group-based indicator detected a significantly larger RII at the BG, CT, and ZIP levels, and the NDI- based indicator detected a significantly larger RII at the BG level. For example, the ZIP median household income by cut points indicator detected an RII of 1.58 (95 percent CI: 1.59–1.78) for colorectal cancer screening completion, and the ZIP NDI and AHRQ indicators detected RIIs of 1.69 (95 percent CI: 1.60–1.79) and 1.65 (95 percent CI: 1.56–1.74), respectively.

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Discussion

We sought to identify which area-based SES indicator should be used to monitor health disparities from the perspective of a primary care delivery system in terms of accuracy, ease of determination, completeness, and ongoing maintenance. First, area-based SES indicators demonstrated little missing data, especially using ZIP codes, with no consistent difference in magnitude of the RII by geographic level. Second, area-based SES indicators were strongly correlated with self-reported educational attainment, a widely used and well-validated SES indicator (Braveman et al. 2005). Third, patient-reported educational attainment and a variety of area-based SES indicators detected similar differences across a range of clinical outcome categories. Finally, cut point-based indicators performed as well as quantile-based indicators, and single-item area-based SES indicators performed as well as indicators constructed from multidimensional indices. These results suggest that area-based SES indicators such as median household income or percent living in poverty from ZIP code tabulation areas may represent a simple, easy-to-obtain way to track the impact of SES disparities on health outcomes in primary care practice networks.

Area-based SES indicators constructed using data from small geographic areas, such as BG and CT, were associated with greater missing data. In addition, we did not find that the BG or CT consistently detected substantially greater health care disparities than ZIP-level indicators. For some outcomes, such as frequent ED utilization, BG and CT did detect greater disparities, but for others the opposite was true. Despite the statistically significant difference in some cases, it is not clear that the magnitudes would be importantly different from the perspective of a health care system user—either a CT- or ZIP-based indicator in these cases would still highlight an important inequality and suggest further investigation regarding whether it could and should be resolved. Thus, for interpretation, the qualitative similarities across indicators are of greater importance than quantitative differences. Supporting this view, we found no cases of a *qualitative* change where a ZIP-level measure detected a gradient in the opposite direction of that detected at the BG or CT level. This is opposite of what we expected based on prior studies, which used public health data (Krieger et al. 2002b), and did find several of these qualitative changes. There are several possible explanations for this finding. First, BG- or CT-defined areas are thought to contain more demographically homogenous groups. While more homogenous demographics may be useful if trying to impute area values for individuals, BG and CT areas are also smaller, and a person may spend more time away from this exposure. ZIP-defined areas, which are larger, may represent greater exposure to deprivation. The relative contribution of individual characteristics (to the extent this is estimated by an area-based SES indicator) and neighborhood context may vary by outcome category, reflecting both compositional and contextual effects of SES on health outcomes. For example, the associations among area-based SES indicators and frequent ED utilization were generally larger for BG- and CT-level indicators, though not always statistically significantly, than ZIP-level indicators, but the reverse was true for patients reporting poor communication (Table(Table4).4). Because BG and CT levels are more demographically homogenous than ZIP, this may indicate that composition, that is, who are the people in that area, is more important than context, that is, what is that area like, with regard to this particular outcome. Second, BG and CT areas had more missing data. If this missingness was not random, particularly if less-well-off areas were under-represented, then this may have introduced bias which "cancelled out" some of the beneficial effect of greater demographic homogeneity.

Prior studies have not been able to compare area-based indicators to patient self-report of educational attainment, a commonly used SES indicator. Area-based SES indicators were strongly associated with self-reported educational attainment, which suggests that they may identify similar patient groups. Perhaps because of this close association, both area-based indicators and educational attainment detected expected disparities across a wide range of health outcomes.

Finally, our results support the use of cut point-defined, single-item indicators, as opposed to quantile-defined or multidimensional indices. Factors that support their use include consistency over place and time compared to quantile approaches, and lower missing data compared to indices. In addition, indices rely on specific weighting among components, and so may not be applicable in settings or time-periods that are different from those in which they were derived (Braveman et al. 2005).

One concern with area-level SES indicators is the "Ecologic Fallacy" described by Robinson (Subramanian et al. 2009). This occurs when inference is made by imputing an aggregate-level value for an individual parameter and associating it with an individually measured outcome. For example, this could occur if we used the ZIP median household income to impute the income for a patient living in that ZIP, and then claimed an association between individual income and an outcome, say diabetes. Because we would not, in this case, know whether the individual with the outcome actually had the imputed income, the conclusion drawn, for example "low income is associated with increased risk of diabetes" could be erroneous. However, in this manuscript, we have not used area-level data to impute individual values, but rather used individual-level data, that is, the patient's address, to assign an exposure, namely residing in an area with particular features, which likely reflects a mix of both neighborhood composition, such as the characteristics of people in the neighborhood, and neighborhood context, such as available resources. Since both the exposure and the outcome were measured at an individual level, there is no danger of the ecologic fallacy (Krieger et al. 2005; Subramanian et al. 2009).

This study has several important limitations. Our results are representative of a health care system that serves a single metropolitan geographic area in the northeastern United States. Whether these results are applicable to other areas is not known. However, with regard to detecting health inequalities, our results are consistent with those derived from national samples (Agency for Healthcare Research and Quality 2012a,b), and there is a diversity of practice types within this system. Second, we have evaluated this tool for use in health care system monitoring, not for etiologic research. If attempting to "adjust" for the effect of SES on particular clinical outcomes, or establish the outcome's association with SES, self-report educational attainment, or income information, may be more useful. Finally, there is no "gold standard" indicator of SES to compare area-based SES indicators against. However, our technique of comparing area-based indicators to self-reported educational attainment and to area-based indicators from other domains allows a "ballpark" estimate of the "true" effect of low SES. While each indicator measures a different exposure, we found that the magnitude of the RIIs were generally similar. This simultaneous assessment of self-reported and area-based SES measures is an important strength compared to prior studies (Krieger et al. 2002b, 2003b, 2005).

These limitations are balanced by several strengths. Previous studies addressing the use of area-based SES indicators for monitoring disparities have used data from public health surveillance efforts, and while important, they may not translate to the health care delivery setting with different sources of data and different outcomes. In addition, the comparison of ZIP code-based indicators to ones defined using census geography (BG and CT) has practical implications for primary care networks. The ability to assign SES indicators to a high proportion of patients using ZIP codes, and have them perform similarly to BG- or CT-level SES indicators, increases the feasibility of monitoring SES inequalities within health care systems. Being able to construct indicators without having to use specific geocoding software significantly reduces the expense and complexity of indicator construction. Additionally, while we have focused on using area-based SES indicators for disparity surveillance, they may still be useful for research studies within practice-based research networks. For systems where researchers have access to educational attainment, or other patient-reported SES indicators, the addition of area-based SES indicators can allow for the use of multilevel frameworks when seeking to disentangle compositional and contextual effects of SES (Subramanian et al. 2009).

One important area of development in measuring SES using publicly available data is the construction of the HOUSES index (Butterfield et al. 2011). While not currently in widespread use, this method uses publicly available housing data for index construction. As this method develops, it will be useful to compare its performance in detecting SES disparities to other existing methods.

In conclusion, area-based SES indicators can be used to assess disparities in clinical outcomes in a large health care network. Almost all indicators detected similar disparities, so based on considerations of completeness, ease of use, and consistency over time and place, we recommend ZIP-level median household income or percent living in poverty, based on a priori cut points, for monitoring SES differences in health outcomes within a health care system.

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Acknowledgments

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Supporting Information

Appendix SA1: Author Matrix.

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Figure S1. Formulae Used to Calculate Area-Based Socioeconomic Status Indices.

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