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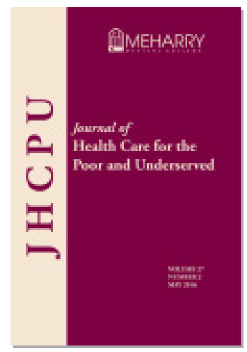

Journal of Health Care for the Poor and Underserved, Volume 27, Number 2, May 2016, pp. 663-684 (Article)

Published by Johns Hopkins University Press
DOI: https://doi.org/10.1353/hpu.2016.0091

ORIGINAL PAPER

Measuring Geographic "Hot Spots" of Racial/Ethnic Disparities: An Application to Mental Health Care

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Abstract: This article identifies geographic "hot spots" of racial/ethnic disparities in mental health care access. Using data from the 2001–2003 Collaborative Psychiatric Epidemiology Surveys(CPES), we identified metropolitan statistical areas(MSAs) with the largest mental health care access disparities ("hot spots") as well as areas without disparities ("cold spots"). Racial/ethnic disparities were identified after adjustment for clinical need. Richmond, Virginia and Columbus, Georgia were found to be hot spots for Black-White disparities, regardless of method used. Fresno, California and Dallas, Texas were ranked as having the highest Latino-White disparities and Riverside, California and Houston, Texas consistently ranked high in Asian-White mental health care disparities across different methods. We recommend that institutions and government agencies in these "hot spot" areas work together to address key mechanisms underlying these disparities. We discuss the potential and limitations of these methods as tools for understanding health care disparities in other contexts.

Key words: Racial/ethnic disparities, geographic variation, mental health care, statistical adjustment for health status, empirical Bayes shrinkage methods, small area estimation.

Two significant strains of health services literature over the past decade have identified disparities in health care by racial/ethnic group and by geographic location. For mental health services, previous studies have found racial/ethnic disparities in unmet need[1] and service use after adjusting for need,[2–4] and that Black-White and Latino-White disparities in mental health care access have not improved over time.[5] Regarding geographic variation, studies have focused on the area-level variation in

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Medicare spending for equivalent procedures and a concomitant lack of improvement in quality of care, access to care, health outcomes, or satisfaction.[6–8] The scant literature on geographic variation in mental health care shows that area-level characteristics are associated with increased mental health care use[9] and adequacy of mental health treatment.[10] We know of no prior studies that compare mental health care disparities across specific areas of the United States.

In health care disparities measurement, racial/ethnic differences can be grouped into racial/ethnic differences that are considered to be "fair" or "just" and differences considered to be "unfair" or "unjust."[11] The Institute of Medicine (IOM) definition of health care disparities provides a guide, defining a health care disparity as all differences except those due to clinical need and preferences.[12] Methods of measuring health care disparities concordant with this definition should adjust for racial/ethnic differences due to clinical appropriateness and need and patient preferences, but not differences due to system-level characteristics and provider discrimination.[3,11,13] Propensity score- and rank-based methods have been developed to implement this definition in non-linear and linear regression models.[e.g.,3,5,11,13,14]

Small-area estimation techniques have been developed to identify statistics of areas (i.e., Census blocks, Census tracts, MSAs) where only very small samples are available. These methods have been used to compare areas on health outcomes[15,16] and health services (e.g., comparing hospitals on quality measures[17,18]). In this paper, we used one method of small area estimation, an empirical Bayes shrinkage (EBS) estimator based on a random-effects model that has been shown to have advantages over other small area estimation methods[19] and to be more conservative than fixed effects modeling. We compared results to a standard fixed effect regression modeling approach to identifying area-level mental health care disparities. We build upon previous work identifying variation in rankings of cardiac surgeons and hospitals that finds that random-effects models were more conservative (identified fewer outliers) and more precise (smaller confidence bounds around predictions) than fixed effects modeling approaches.[20] A similar comparison of regression methods is here applied to measuring geographic variation in racial/ethnic disparities.

Previous literature on health care quality provides evidence that there will be geographic variation in racial/ethnic disparities, identifying poorer quality of care in clinical procedures for Medicare beneficiaries in geographic areas with high concentrations of racial/ethnic minorities,[21] and low standards of care among providers that predominantly treat racial/ethnic minorities.[22] However, the mental health care literature on this topic has been mixed. Horvitz-Lennon et al.[23] identified both racial/ethnic and geographic differences in the adoption of an innovative pharmacological treatment for individuals with schizophrenia and found that racial/ethnic disparities were eliminated after adjustment for geographic differences. Cook et al.[24] found significant geographic and racial/ethnic disparities in mental health care access, that racial/ethnic disparities were not eliminated after adjustment for geographic variation, and that county-level provider supply, HMO penetration, and the existence of a community mental health center were significantly associated with reductions in Black-White mental health care access disparities. Another study identified significant associations between state health care policies and health care market characteristics and racial/ethnic differences in youth mental health care utilization.[25] This study used multi-level models to identify area-level correlates of mental health care but provide no information on geographic areas showing greater racial/ethnic disparities in mental health care access. One study has identified that the South region of the U.S. (compared with the Northeast, West, and Midwest regions) has the greatest mental health care use disparities among the elderly population,[26] but the need for study of smaller areas among the general population remains.

In this paper, we combined a method concordant with the IOM definition with EBS estimation to describe a method of identifying disparate and non-disparate metropolitan statistical areas (MSAs). We merged the detailed individual-level Collaborative Psychiatric Epidemiology Surveys (CPES) data on mental health care and mental health care correlates with area-level provider and SES characteristics from the Area Health Resource File (AHRF) and the U.S. Census. We compared and ranked MSAs on level of mental health service disparities, applying EBS estimation to understanding geographic disparities in mental health services use between Blacks, Latinos, Asians, and non-Latino Whites. Using these disparity calculations, we assessed whether national racial/ethnic disparities are largely due to the fact that racial/ethnic minorities predominantly live in areas with lower mental health care service use or whether disparities persist within MSAs uniformly across the country.

Methods

Data. We used data from the 2001–2003 Collaborative Psychiatric Epidemiological Surveys (CPES). This includes the 2002–2003 National Latino and Asian-American Study (NLAAS) dataset for Latinos (response rate=75.5%) and Asians (response rate=65.6%),[27] the 2001–2002 National Comorbidity Survey Replication (NCS-R) dataset for Whites (response rate=70.9%),[28] and the 2001–2003 National Survey of American Life (NSAL) dataset for Blacks (response rate=70.9%).[29] These three surveys contained identical epidemiological items related to mental disorders and service use. The Institute for Social Research at the University of Michigan collected data for all CPES datasets via in-person household interviews or telephone. Race and Latino ethnicity were ascertained using questions from the 2000 Census. The three studies share common sampling strategy, allowing combining of the datasets as though they were a single nationally-representative study.[30] The sampling weights are inversely proportional to the selection probabilities and are used in survey analysis for population-level inferences.

County-level variables were obtained from two data sources: the 2004 Area Health Resource File (AHRF) and the 2000 U.S. Census to match the years of data collected in the CPES. They were merged with the CPES using Census County identifier codes (i.e., Federal Information Processing Standard [FIPS] codes). In our final fixed effect and multi-level models, we used information from 12,395 respondents (4,352 Whites, 3,110 Latinos, 1,444 Asians, and 4,079 Blacks). We report predicted probabilities at the MSA level. When reporting predicted probabilities, we excluded MSAs with fewer than 20 Whites or fewer than 20 individuals in one of the racial/ethnic minority groups because of the unreliability of their estimates even when using EBS estimation. Because disparities analyses required both White and minority groups to be represented, not all of the sampled MSAs were included in each of the analyses. Therefore, Black-White disparities analyses were limited to 31 MSAs, areas with Black populations that represent a total of 66% of the U.S. Black population, Latino-White disparities analyses were limited to 17 MSAs, representing 70% of the U.S. Latino population, and Asian-White disparities analyses were limited to 10 MSAs, representing 61% of the U.S. Asian population.

Measures. *Dependent variable.* The dependent variable of interest was any past year use of mental health services. Mental health service use includes any mental health visit with psychiatrists, psychologists, counselors or social workers in a mental health setting, or a mental health visit with a general practitioner, other medical doctor, nurse, occupational therapist, or other health professional for a mental health problem.

Area-level independent variables. Variables used in multi-level models were chosen based on prior literature: county-level rates of uninsurance residents because of the positive association of individual-level insurance status and mental health care access;[3,5,31] county-level differences in racial/ethnic composition because of its correlation with greater levels of poverty and lower levels of political empowerment,[32,33] and access to general medical services;[34] county-level differences in poverty because of its association with the experience of social disorder,[35] psychological distress,[36] and diagnosis of depression;[37] and county-level managed care penetration, provider supply, and existence of a community mental health care center because of their association with reduced mental health care access disparities.[24]

County-level Census variables included demographic variables (population, area [in square miles], and percent of the population of a particular racial/ethnic group [depended on which racial/ethnic group was being modeled]) from the 2000 U.S. Census and mental health supply-related variables (indicator of a shortage of available mental health care, indicator of the presence of a community mental health center, number of short term psychiatric hospitals, number of outpatient psychiatric hospitals, and number of psychiatrists treating patients) from the 2004 AHRF.

Individual-level covariates. Individual-level covariates were classified into clinical need and appropriateness variables (hereafter called "need" variables) and non-need predictor variables in order to implement the IOM definition of health care disparities. As discussed in prior studies implementing the IOM definition of health care disparities,[4,11,13] exclusion of differences due to clinical need and appropriateness (assessed by health status variables) from disparities reflects the normative stance that these differences are allowable or justified. That is, if racial/ethnic minority groups have objectively lower rates of mental illness, and thus receive less care, then the health care system should not be held accountable for this part of the racial/ethnic difference in treatment. Need variables were age (25–44, 45–64, 65 years and older), gender, marital status, indicators for any last year mental disorder as evaluated by the Composite International Diagnostic Interview (CIDI),[38] functional impairment related to health or mental health-related problems as measured by the World Health Organization Disability Assessment Schedule (WHO-DAS; measured on five dimensions: cognitive, movement, self-care, social, and role performance)[39] and whether the respondent had one of 11 chronic conditions (arthritis or rheumatism, ulcer, cancer, high blood pressure, diabetes, heart attack, stroke, asthma, tuberculosis, any other chronic lung disease, and HIV infection/AIDS).

Implementation of the IOM definition includes as part of the disparity those differences that are due to socioeconomic status and other individual characteristics other than clinical need, reflecting a view that differences in care provided due to SES factors such as income, education, and employment are unjustifiable, and health systems should be accountable for such differences. Non-need variables were income (less than $10,000, $10,000–$24,999, $25,000–$49,999, and $50,000 or more per year), education (categorized as less than high school education, high school graduate, any college education, and college graduate), employment status (employed vs. unemployed) and insurance status (categorized as privately insured, Medicare, Medicaid or other non-Medicare public insurance, and uninsured).

Analytic methods overview. We sought to identify MSAs that were outliers in terms of magnitude of mental health care service use disparities. We compared two methods of IOM-concordant disparity estimation: a fixed effects model predictions and empirical Bayes shrinkage estimates (described in more detail below). For both regression-based methods, we implemented the IOM definition of health care disparities with a three-step process: 1) estimated multi-level model parameters (as described below); 2) weighted each individual based on the propensity of being White (in a combined White-minority population) conditional on a vector of need covariates; and 3) generated predicted disparities in each MSA using coefficients from the model in (1) and the propensity-score weighted population characteristics in (2).

Standard fixed effect regression modeling. The fixed effect regression model estimates mental health service use, conditional upon area-level covariates, individual-level need and non-need covariates described above, an indicator of each racial/ethnic group, a separate MSA identifier for each MSA in the dataset, and the interaction between the racial/ethnic group indicator and the MSA identifier. Predicted probabilities for each MSA by racial/ethnic group were created using a recycled predictions method[40,41] (also called predictive margins[42]). After running the fixed effects model, indicators for the racial/ethnic group and MSA for which we wanted to make a prediction were "switched on" (recoded to 1) and all other race/ethnicity and MSA identifiers were "switched off" (recoded to 0). Predictions were then run using the coefficients from the original model and the mean taken across the entire population. This method is a generalization of the adjusted treatment means to nonlinear models, allowing us to compare mental health care disparities for each MSA by race/ethnicity cell, after adjusting the distribution of all other predictor variables used in the model. Standard errors for recycled predictions and predicted differences were derived using the bootstrap procedure[43,44] (set at 100 replications) and differences were considered significant if their 95% bootstrap intervals did not include zero. These predicted disparity rates were then ranked within each racial/ethnic group to determine "hot spots" of mental health care disparities. A limitation of this method is that it is very likely that a number of the coefficients will be measured with a high degree of uncertainty in areas with small sample sizes of respondents in the CPES dataset and the large number of interaction coefficients.

Empirical Bayes shrinkage (EBS) estimation. The hierarchical structure of the multilevel models allows for borrowing of information from other MSAs (including differential MSA-level information by race/ethnicity for supply characteristics, gender, age, education, and income) to aid the estimation of disparities in MSAs with small sample sizes. For the multi-level model, we combined individual CPES data with relevant county and MSA-level data from the AHRF and US Census. For each racial/ethnic group (Whites, Latinos, Asians, and Blacks), we estimated the following multilevel generalized linear model:

$$\begin{aligned} &\Pr(Y_{ijk} = 1) = \log it^{-1}(\beta_0 + \beta_1 X_i + \beta_C C_j + m_k) \\ &m_k \sim N(r_0, \sigma_m^2) \end{aligned} \tag{1}$$

where Y_{ijk} =1 if the *i*th individual living in the *j*th county, and the *k*th MSA, used mental health care in the past year and 0 otherwise, X_i, the above-mentioned vector of individual-level characteristics for the *i*th individual, and C_j, a vector of county-level characteristics for county *j*, m_k represents the MSA effect, σ_m^2 represents the variance of the MSA effect, β coefficients represent the effects of the individual and county-level covariates after accounting for MSA effects. County-level variables were chosen based on previous literature indicating a strong relationship with service use and to avoid strong collinearity. We estimated separate multilevel models for each racial/ethnic group, so implicitly all of these variables were interacted with race/ethnicity.

In step 2, we adjusted the racial/ethnic minority distributions of need variables (age, gender, marital status, number of chronic conditions, WHO-DAS measures of disability, and indicators for any last year mental health) to be the same as Whites using a propensity score-based method.[13] This method estimates the probability of "being White" regressed on mental health status covariates within each MSA (in a combined White-minority population) and converts predicted probabilities into weights so that minority populations have marginal distributions of need variables that are adjusted to look like Whites in the same MSA. In MSAs with small sample sizes, we removed the eleven indicators of chronic conditions from the logistic regression models to avoid collinearity and over-fitting. Because we have only included need variables in the propensity score equation, conditional on the propensity score, the distributions of observed need covariates are the same for minorities and Whites[45] whereas differences in non-need variables were not altered other than to the extent that they were associated with need variables. Similar to Cook et al.,[4] we used the propensity score to weight minority individuals by their probability to be White ($\hat{e}(H_i)$), and White individuals by their probability to be minority ($1- \hat{e}(H_i)$), both in weighted regressions conditional on need covariates.

In step 3, we calculated disparity predictions for MSAs using the sum of the products of the coefficients from the original model (including random numbers to account for random effects parameters) and the adjusted covariate values and transformed the result using the inverse logit function. We ranked the MSAs by their estimated disparity, with rank 1 having the highest estimated disparity. Using a bootstrap procedure,[43] we repeated the entire procedure described above 100 times, each time taking a random sample with replacement from those individuals in our CPES sample while preserving racial/ethnic sample sizes within each MSA. For each bootstrap sample we re-fit propensity score models to recalculate propensity score weights and re-fit model 1. We derived standard errors and confidence intervals from the 100 bootstrap iterations and produced sets of rankings. Rankings from the two methods (rankings from fixed effect regression-based predictions and shrinkage estimation predictions) were compared for consistency. We assume that the EBS estimation will identify greater numbers of disparity outliers because the additional use of information in shrinkage estimation is expected to reduce the variability of the estimates.

Geographic or racial/ethnic disparities? Are national disparities due to disparate care by location or race/ethnicity? Using estimates from the EBS estimation allows us to identify geographic patterns in service disparities across the United States. We placed predicted White mental health care use on the x-axis and predicted minority mental health care use on the y-axis, plotting each MSA while shading the MSA point according to the racial/ethnic minority population size within the MSA (the greater minority percentage the greater the shading). If disparities are driven solely by location where minorities live, and there are no disparities within MSAs, then all points would lie on the 45-degree line. If national disparities are caused entirely by the fact that racial/ethnic minorities live in areas of low mental health care service use, then the heavily shaded areas (with large racial/ethnic minority populations) will lie further towards the origin along the 45 degree line whereas the areas with fewer racial/ethnic minorities will be higher up the 45 degree line.

Results

Disparities in mental health care use by MSA in each racial/ethnic group. Tables 1a, 1b, and 1c present the White rate of mental health care use by MSA followed by predicted Black-White, Latino-White and Asian-White disparities, using two different methods (predicted disparities from a fixed effects regression model, and empirical Bayes estimates). The tables are ordered based on the rank of the MSA using the empirical Bayes estimation method. These tables show the magnitudes of disparities using the different methods and how consistent the methods are in ranking the MSAs on service disparities. As one would expect, the model-based estimates were less variable and the range of estimates across MSAs was narrower than the unadjusted estimates. In most but not all cases, the empirical Bayes shrinkage estimates had smaller standard errors than the standard fixed effects regression approach. Significant disparities found in unadjusted estimates were, in nearly all cases, found to be significant disparities using the other two methods. In terms of Black-White disparities (Table 1a), Richmond, VA was consistently found to be the MSA with the highest level of disparities regardless of method used. Columbus, GA was also found to be consistently high ranking across different methods, being the MSA that ranked as having the 3rd highest service disparities using the empirical Bayes method and 2nd highest using the fixed effect model prediction. Regarding Latino-White disparities (Table 1b), Houston, Texas, Fresno, California and Los Angeles, California were ranked as having the highest disparities in our sample using the empirical Bayes method. Asian-White disparities analyses found that Fresno, California, Riverside, California and Houston, Texas were the highest ranked “hot spots” in our sample (Table 1c).

“**Hot spots” of disparities**. To assess “hot spots” of disparities most accurately, we plotted disparity estimates and confidence intervals in relation to the average disparity for all of the MSAs under analysis (the sum of the MSA disparity averages divided

Table 1a.

BLACK-WHITE MENTAL HEALTH CARE USE DISPARITIES BY MSA[a]

Whites n	Blacks n	MSA	White Rate	White SE	Fixed Effect Model Disparity	Fixed Effect Model SE	Fixed Effect Model Rank	Shrinkage Estimator Disparity	Shrinkage Estimator SE	Shrinkage Estimator Rank
144	124	Richmond, VA	24.9%	(4.0%)	**11.8%**	(1.8%)	1	**10.7%**	(1.8%)	1
45	121	Houston-Baytown-Sugar Land, TX	16.1%	(0.1%)	**8.2%**	(2.8%)	10	**10.6%**	(3.0%)	2
80	98	Columbus, GA-AL	20.4%	(5.1%)	**9.7%**	(2.1%)	3	**10.6%**	(1.5%)	3
84	54	San Francisco-Oakland-Fremont, CA	14.1%	(4.1%)	7.6%	(4.6%)	13	**9.5%**	(2.9%)	4
50	271	Atlanta-Sandy Springs-Marietta, GA	12.6%	(3.7%)	**5.2%**	(1.5%)	24	**9.3%**	(1.8%)	5
159	33	Knoxville, TN	18.2%	(3.1%)	**9.3%**	(4.6%)	5	**9.2%**	(2.1%)	6
82	186	Washington-Arlington-Alexandria, DC-VA-MD-W	13.8%	(5.0%)	**4.6%**	(2.3%)	25	**8.9%**	(1.5%)	7
91	103	Birmingham-Hoover, AL	17.4%	(4.2%)	**8.4%**	(2.7%)	8	**8.7%**	(1.8%)	8
156	226	Chicago-Naperville-Joliet, IL-IN-WI	14.8%	(0.4%)	**7.1%**	(2.3%)	14	**8.6%**	(1.4%)	9
93	56	Dayton, OH	10.4%	(3.1%)	4.2%	(5.0%)	26	**8.6%**	(2.1%)	10
97	83	Jacksonville, FL	9.7%	(3.0%)	3.8%	(3.8%)	28	**8.0%**	(1.6%)	11
242	1,108	New York-Newark-Edison, NY-NJ-PA	13.8%	(2.3%)	**5.2%**	(1.2%)	23	**7.8%**	(0.8%)	12
77	27	New Haven-Milford, CT	20.4%	(4.9%)	**9.4%**	(2.3%)	4	**7.6%**	(2.7%)	13
62	74	Dallas-Fort Worth-Arlington, TX	19.5%	(0.1%)	**8.2%**	(3.3%)	9	**7.5%**	(1.9%)	14
141	122	Philadelphia-Camden-Wilmington, PA-NJ-DE-M	18.5%	(4.2%)	**6.8%**	(2.7%)	17	**7.2%**	(1.6%)	15
86	69	Seattle-Tacoma-Bellevue, WA	19.0%	(2.2%)	8.3%	(4.5%)	8	**7.0%**	(2.3%)	16
94	24	Buffalo-Cheektowaga-Tonawanda, NY	15.3%	(4.1%)	7.0%	(4.1%)	16	6.0%	(3.7%)	17
198	90	Los Angeles-Long Beach-Santa Ana, CA	14.9%	(2.7%)	5.8%	(3.0%)	20	**5.5%**	(1.7%)	18
130	84	Grand Rapids-Wyoming, MI	15.3%	(3.3%)	5.4%	(3.8%)	22	**5.3%**	(2.0%)	19
113	27	Lakeland-Winter Haven, FL	10.6%	(3.0%)	3.7%	(5.6%)	29	4.5%	(2.9%)	20
49	80	Baltimore-Towson, MD	8.8%	(3.8%)	1.8%	(3.3%)	31	**4.3%**	(1.9%)	21
103	63	Milwaukee-Waukesha-West Allis, WI	19.9%	(4.1%)	**8.0%**	(3.4%)	12	3.8%	(2.7%)	22
113	24	Kansas City, MO-KS	15.5%	(3.6%)	**6.2%**		18	3.8%	(3.0%)	23
114	77	Boston-Cambridge-Quincy, MA-NH	14.3%	(3.6%)	6.0%	(3.6%)	19	3.5%	(2.4%)	24
94	45	Pittsburgh, PA	12.8%	(4.4%)	4.0%	(4.9%)	27	2.8%	(2.5%)	25
114	128	Detroit-Warren-Livonia, MI	4.6%	(1.1%)	0.4%	(2.8%)	33	2.4%	(1.7%)	26
122	32	Waco, TX	15.2%	(3.5%)	5.4%	(4.8%)	21	1.6%	(3.0%)	27
106	44	Riverside-San Bernardino-Ontario, CA	16.1%	(3.8%)	7.0%	(6.1%)	15	1.2%	(3.0%)	28
142	68	Atlantic City, NJ	11.3%	(2.8%)	2.8%	(3.7%)	30	−0.3%	(1.9%)	29
101	23	Phoenix-Mesa-Scottsdale, AZ	18.1%	(3.8%)	8.7%	(5.5%)	5	−2.2%	(4.1%)	30
82	30	Minneapolis-St. Paul-Bloomington, MN-WI	19.0%	(0.9%)	8.1%	(6.4%)	11	−2.5%	(3.0%)	31

[a]Predicted values and standard errors take into account sampling weights and stratification used to make CPES representative of U.S. population.
Notes: Disparity estimates in bold are significant.

Table 1b.

LATINO-WHITE MENTAL HEALTH CARE USE DISPARITIES BY MSA[a]

Whites	Latinos		White		Fixed Effect Model			Shrinkage Estimator		
n	n	MSA	Rate	SE	Disparity	SE	Rank	Disparity	SE	Rank
45	72	Houston-Baytown-Sugar Land, TX	16.1%	(0.1%)	**7.2%**	(2.6%)	8	**9.5%**	(3.6%)	1
68	280	Fresno, CA	18.1%	(4.9%)	**10.8%**	(1.2%)	2	**9.4%**	(2.1%)	2
198	310	Los Angeles-Long Beach-Santa Ana, CA	14.9%	(2.7%)	**6.5%**	(1.6%)	9	**8.4%**	(1.9%)	3
156	114	Chicago-Naperville-Joliet, IL-IN-WI	14.8%	(0.4%)	**5.1%**	(2.5%)	11	**8.0%**	(1.9%)	4
62	49	Dallas-Fort Worth-Arlington, TX	19.5%	(0.1%)	**11.5%**	(3.3%)	1	**8.0%**	(1.8%)	5
111	62	Denver-Aurora, CO	16.7%	(3.7%)	**8.9%**	(3.1%)	5	**7.9%**	(1.9%)	6
82	35	Washington-Arlington-Alexandria, DC-VA-MD-W	13.8%	(5.0%)	4.9%	(3.8%)	12	**7.7%**	(2.2%)	7
101	105	Phoenix-Mesa-Scottsdale, AZ	18.1%	(3.8%)	**9.0%**	(2.2%)	3	**6.7%**	(1.7%)	8
106	177	Riverside-San Bernardino-Ontario, CA	16.1%	(3.8%)	**7.4%**	(1.6%)	7	**4.8%**	(2.2%)	9
242	614	New York-Newark-Edison, NY-NJ-PA	13.8%	(2.3%)	**5.5%**	(1.1%)	10	3.3%	(2.8%)	10
114	73	Boston-Cambridge-Quincy, MA-NH	14.3%	(3.6%)	–1.2%	(3.4%)	16	3.1%	(3.6%)	11
77	31	New Haven-Milford, CT	20.4%	(4.9%)	8.7%	(5.1%)	6	2.3%	(3.1%)	12
141	29	Philadelphia-Camden-Wilmington, PA-NJ-DE-M	18.5%	(4.2%)	**–15.5%**	(7.3%)	17	1.6%	(2.4%)	13
142	38	Atlantic City, NJ	11.3%	(2.8%)	4.9%	(3.0%)	13	1.2%	(3.8%)	14
86	34	Seattle-Tacoma-Bellevue, WA	19.0%	(2.2%)	**8.9%**	(4.1%)	4	0.1%	(2.4%)	15
122	46	Waco, TX	15.2%	(3.5%)	3.9%	(4.8%)	14	0.001%	(3.3%)	16
111	26	Saginaw-Saginaw Township North, MI	7.8%	(2.9%)	2.6%	(3.5%)	15	-1.6%	(3.6%)	17

[a]Predicted values and standard errors take into account sampling weights and stratification used to make CPES representative of U.S. population.
Notes: Disparity estimates in bold are significant.

Table 1c.

ASIAN-WHITE MENTAL HEALTH CARE USE DISPARITIES BY MSA[a]

Whites	Asians		White		Fixed Effect Model			Shrinkage Estimator		
n	n	MSA	Rate	SE	Disparity	SE	Rank	Disparity	SE	Rank
68	25	Fresno, CA	18.1%	(4.9%)	5.0%	(6.1%)	8	**13.1%**	(2.5%)	1
106	155	Riverside-San Bernardino-Ontario, CA	16.1%	(3.8%)	**10.0%**	(2.3%)	3	**12.8%**	(1.8%)	2
45	21	Houston-Baytown-Sugar Land, TX	16.1%	(0.1%)	**10.8%**	(3.6%)	2	**12.0%**	(3.2%)	3
156	77	Chicago-Naperville-Joliet, IL-IN-WI	14.8%	(0.4%)	5.7%	(3.4%)	7	**9.9%**	(1.7%)	4
198	588	Los Angeles-Long Beach-Santa Ana, CA	14.9%	(2.7%)	**9.2%**	(1.2%)	4	**9.3%**	(1.2%)	5
86	269	Seattle-Tacoma-Bellevue, WA	19.0%	(2.2%)	**13.0%**	(1.3%)	1	**8.9%**	(1.8%)	6
119	58	St. Louis, MO-IL	14.1%	(3.4%)	**8.5%**	(2.8%)	5	**8.5%**	(1.5%)	7
114	25	Boston-Cambridge-Quincy, MA-NH	14.3%	(3.6%)	–6.7%	(8.0%)	10	6.9%	(4.6%)	8
242	111	New York-Newark-Edison, NY-NJ-PA	13.8%	(2.3%)	**6.8%**	(2.5%)	6	**6.8%**	(1.1%)	9
142	22	Atlantic City, NJ	11.3%	(2.8%)	–2.1%	(7.4%)	9	2.6%	(1.5%)	10

[a]Predicted values and standard errors take into account sampling weights and stratification used to make CPES representative of U.S. population.
Notes: Disparity estimates in bold are significant.

by the number of MSAs) (Figure 1). For Latino-White disparities, Fresno, California was found to be significantly greater than the average disparity across the MSAs under analysis and Saginaw, Michigan and Seattle, Washington were found to be significantly lower than the average disparity. For Asian-White disparities, while numerous MSAs were found to be significantly different from zero (no disparities), no MSAs were found to be different from the mean disparity across MSAs. For Black-White disparities, Richmond, Virginia and Columbus, Georgia were the only two MSAs with significantly greater service disparities than the mean service disparity across all MSAs. Minneapolis, Minnesota and Atlantic City, New Jersey were two MSAs that have significantly lower disparities than the mean disparity across all MSAs.

Predictors of mental health care use—Results derived from multilevel model covariates. Significant area-level and individual-level predictors of mental health care use were similar for most but not all racial/ethnic groups (see Table 2). Ethnic density (defined as the percent of the population in a given MSA belonging to one or more racial/ethnic minority groups) was a significant negative area-level predictor of mental health care for all three racial/ethnic minority groups. At the individual level, having any mental health disorder and more severe scores on social, role, and cognitive functioning were significant positive predictors of access to mental health care for all racial/ethnic groups. Younger age, female gender, having Medicaid or Medicare or other public insurance (compared with private insurance), and having any chronic condition were significant positive predictors for all racial/ethnic groups except for Asians. Being single (compared with married) was a significant positive predictor of any mental health care for all racial/ethnic groups except for Blacks. Other significant positive predictors for Whites were having less than a high school degree and being employed. An additional significant predictor for Blacks was being of age 25–64 (compared with 18–24), having graduated from college, and having less than $10,000 in annual income.

In this multi-level model, assessing the standard deviation of the randomly distributed intercepts identified the amount of variance among the MSAs, adjusting for all individual- and county-level characteristics. Using Likelihood Ratio tests to compare the random intercepts model to a logistic regression without a multi-level structure, we identified that there was insignificant variance between MSAs among Whites and Asians, and borderline significant variance between MSAs among Latinos and Blacks ($p<.13$ and $p<.06$, respectively), after controlling for individual- and county-level variables.

Relationship between geographic and racial/ethnic disparities in mental health care access. Figure 2 displays the relationship between minority mental health care use and White mental health care use (represented by the slope of the dots and the distance of the dots from the 45 degree line) and the relationship between percentage of racial/ethnic minority within MSA and magnitude of disparities (MSAs with a greater percentage of racial/ethnic minorities have dots that are more darkly shaded). If national disparities were solely due to minorities living more in cities that tend to use mental health care less, all dots would fall on the line and darker shaded dots representing MSAs with large racial/ethnic minority populations would be located towards the bottom left. However, this was not the case. In general, darker shaded dots are located near the bottom of the chart, indicating that minorities were more likely to live in cities with low utilization of mental health care, but most dots fall below the line, indicating

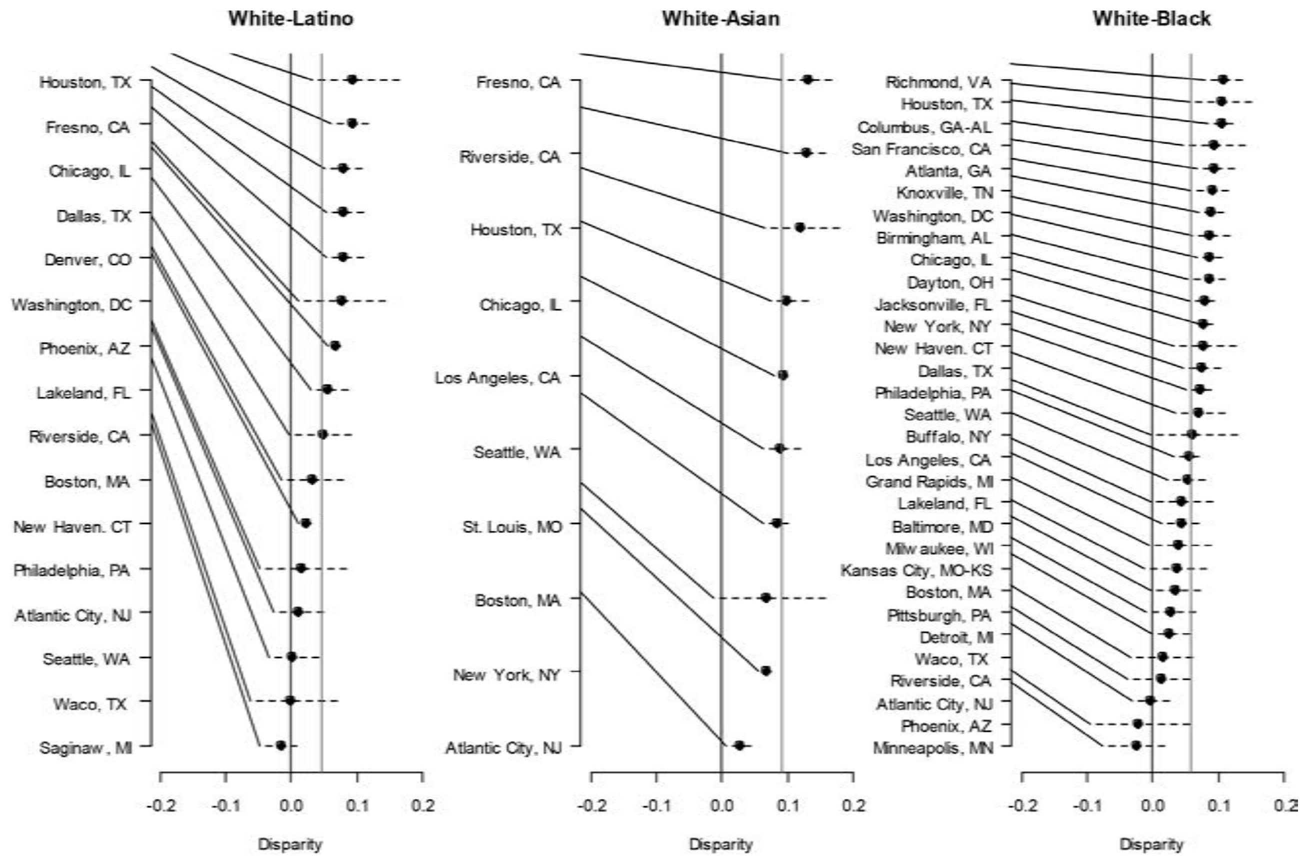

Figure 1.[abc] Plot of disparity in rates of mental health care access and 95% confidence intervals by metropolitan statistical area (MSA).

[a]Disparities are calculated as the predicted White rate minus the predicted rate of each racial/ethnic minority group. Higher numbers signify greater disparity.

[b]The Black vertical line signifies zero disparity. Points to the right of the Black line indicate the existence of a racial/ethnic disparity.

[c]The red vertical line signifies the mean disparity across all MSAs. Points to the right of the red line indicate that the MSA has a level of disparity greater than the average MSA.

Table 2.

HIERARCHICAL REGRESSION MODEL (RANDOM INTERCEPTS) OF MENTAL HEALTH SERVICES USE REGRESSED ON NEED, NON-NEED, AND COUNTY-LEVEL VARIABLES (N=12985)[a]

		White (n=4352)			Latino (n=3110)			Asian (n=1444)			Black (n=4079)		
		Coefficient		SE	Coefficient		SE	Coefficient		SE	Coefficient		SE
Need Variables													
Last Year Any MH disorder		1.38	***	(0.10)	1.58	***	(0.14)	1.53	***	(0.31)	1.90	***	(0.14)
WHO-DAS Function Scales	Social Interaction	0.03	***	(0.01)	0.01		(0.01)	−0.08		(0.04)	0.01		(0.01)
	Out of Role in Last Month	0.01	***	(0.00)	0.01	***	(0.00)	0.01	***	(0.01)	0.01	***	(0.00)
	Mobility	−0.01		(0.00)	0.00		(0.00)	0.00		(0.01)	0.00		(0.00)
	Cognitive	0.02	***	(0.01)	0.03	***	(0.01)	0.04		(0.03)	0.00		(0.01)
Any Chronic Physical Health Condition		0.43	***	(0.10)	0.51	***	(0.15)	0.33		(0.28)	0.46	***	(0.15)
Age	25–44	0.41	***	(0.18)	0.30		(0.23)	0.80		(0.57)	0.46	***	(0.22)
(referent 18–24)	45–64	0.22		(0.19)	0.39		(0.26)	0.83		(0.62)	0.68	***	(0.25)
	65+	−0.92	***	(0.26)	−0.70		(0.40)	0.91		(0.77)	−0.50		(0.39)
Gender(referent male)	Female	0.48	***	(0.10)	0.66	***	(0.15)	−0.10		(0.25)	0.37	***	(0.15)
Non-Need Variables													
Education	High School Graduate	−0.31	***	(0.16)	−0.03		(0.16)	−0.29		(0.34)	0.33		(0.18)
(referent Less than HS Grad)	College Graduate	−0.13		(0.17)	0.44		(0.22)	−0.31		(0.37)	0.63	***	(0.23)
Employment (referent unemployed)	Employed	0.30	***	(0.12)	0.22		(0.16)	0.49		(0.29)	0.11		(0.24)
Income	10k–25k	0.07		(0.21)	0.18		(0.21)	−0.06		(0.47)	−0.22		(0.19)
(referent <10K)	25k–50k	0.05		(0.19)	0.15		(0.23)	−0.22		(0.43)	−0.41	***	(0.20)
	50k+	0.30		(0.19)	0.17		(0.24)	0.31		(0.40)	−0.36		(0.24)
Insurance Status (referent uninsured)	Private	0.29		(0.18)	0.60	***	(0.21)	−0.27		(0.37)	0.35		(0.20)
	Medicare	0.73	***	(0.29)	1.05	***	(0.23)	0.53		(0.51)	0.62	***	(0.25)
	Medicaid/Other Public	0.81	***	(0.25)	1.16	***	(0.29)	0.03		(0.51)	0.67	***	(0.25)
Marital Status	Single, Never Divorced	0.43	***	(0.12)	0.43	***	(0.18)	1.11	***	(0.36)	0.03		(0.17)
(referent married)	Separated/Divorced	0.40	***	(0.14)	0.12		(0.20)	0.07		(0.40)	0.15		(0.17)

(Continued on p. 676)

Table 2. (*continued*)

		White (n=4352)			Latino (n=3110)			Asian (n=1444)			Black (n=4079)		
		Coefficient		SE	Coefficient		SE	Coefficient		SE	Coefficient		SE
County-level variables													
Population(100,000's)		0.003		(0.003)	−0.0002		(0.004)	−0.0004		0.005	−0.001		(0.004)
Area (1000 square miles)		0.004		(0.02)	0.022		(0.03)	−0.056		(0.04)	0.021		(0.03)
Percent racial/ethnic density		0.002		(0.004)	−0.009	***	(0.00)	−0.052	***	(0.02)	−0.012	***	(0.01)
Shortage of available mental health care		0.05		(0.11)	−0.02		(0.23)	0.00		(0.39)	0.22		(0.16)
Community mental health center		−0.05		(0.10)	0.16		(0.20)	-0.02		(0.33)	−0.09		(0.15)
Number of short term psychiatric hospitals		0.12		(0.11)	0.01		(0.20)	−0.29		(0.35)	−0.24		(0.16)
Number of outpatient psychiatric hospitals		−0.07		(0.12)	−0.46		(0.29)	−0.23		(0.66)	0.36		(0.27)
Number of psychiatrists treating patients		617.51		(423.06)	561.31		(406.26)	1476.23		(931.50)	25.61		(473.46)
constant		−3.65	***	(0.48)	−4.25	***	(0.48)	−3.20	***	(0.99)	−4.56	***	(0.46)
SD(Random Intercept)	msa: variance	1.39E−08		(0.16)	0.20		(0.13)	1.28E−09		(0.14)	0.20		(0.09)
	P value	1.00			.13			1.00			.06		

[a] Coefficients and standard errors take into account sampling weights and stratification used to make CPES representative of U.S. population.
Notes: Significantly different from 0 at p<.05.

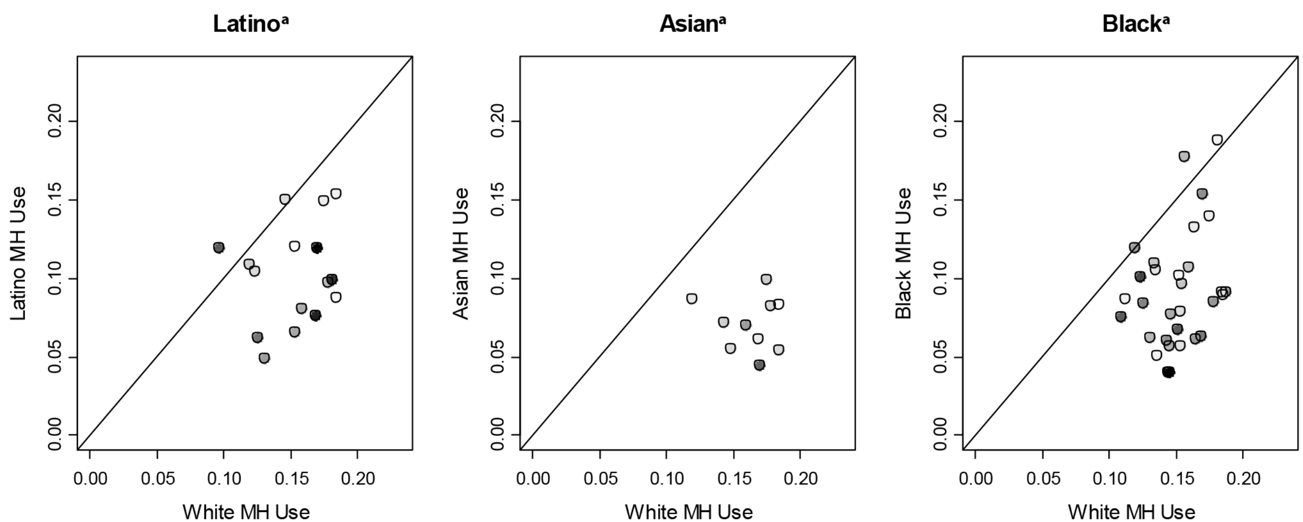

Figure 2. Relationship between white and racial/ethnic minority mental health care by MSA and racial/ethnic population size within MSA.

[a]MSAs with a greater percentage of racial/ethnic minorities have dots that are more darkly shaded. Greater distance below 45 degree line represents greater magnitude of disparities.

that there are also disparities within MSAs that are not explained by low service use in the areas where minorities live.

Discussion

To our knowledge, this is the first study to rank MSAs on mental health care disparities and identify geographic "hot spots" of racial/ethnic disparities. Our findings demonstrate the applicability of combining methods from the health care disparities and geographic variation literature to identify the geographic contribution to racial/ethnic disparities in mental health service use. Empirical Bayes estimation serves to reduce variation and provides more precise disparity estimates in nearly all MSAs with small samples compared with a standard fixed effects regression approach. The geographic variation of mental health service disparities provides evidence that focused efforts to ameliorate disparities should be undertaken in such MSAs as Fresno (California), Houston (Texas), Richmond (Virginia), Columbus (Georgia), and San Francisco (California). Many of these MSAs are in states (Texas, Virginia, Georgia) that have decided not to expand Medicaid eligibility under the Affordable Care Act (ACA). Given that prior studies have identified insurance coverage as a key mechanism underlying health care disparities,[31,46] and assuming that these area-level disparities have persisted since CPES data collection, there is a concern that disparities in these areas may be exacerbated as ACA implementation progresses. At the least, the data provide a starting point to explore what system-level factors may be linked to poor performance of these MSAs as indicated by service disparities.

A contribution to the literature is that we identify that overall racial/ethnic mental health care disparities are due to both geographic disparities (that arise because there is poorer access to care in areas where racial/ethnic minorities predominantly live) and racial/ethnic disparities within geographic areas. For all three racial/ethnic minority groups, mental health care disparities existed within MSAs, after controlling for between-MSA variation and individual- and county-level characteristics within MSA. These results provide contrary evidence to studies in other areas of quality of medical care that suggest racial/ethnic disparities may be "explained away" by regional variation.[47,48] This could be explained by differences in the outcome variables assessed; our study focused on mental health care disparities, whereas previous studies mainly evaluated general health care disparities. It might be that geographic contexts are part of the explanatory variables that limit access to mental health services but other factors such as cumulative disadvantage in terms of patient health literacy, greater language needs, differential referral practices to specialty care, and other non-contextual factors still play a role in this types of disparities.[49] Consistent with past findings,[33] graphical analyses of the patterns of disparities across the United States show that rates of minority mental health care use tend to be lower in MSAs with large racial/ethnic minority populations and significant racial/ethnic density coefficients for minorities support these patterns. However, in nearly all MSAs, racial/ethnic minority rates of mental health care use fell below White rates. This implies that efforts to understand and address mental health care disparities cannot exclusively target geographic disparities but also should consider the root causes of these racial/ethnic disparities.

We have attempted to be extremely cautious in our ranking of MSAs in terms of racial/ethnic disparities in mental health care, recognizing the limitations of our data. Using our most conservative method (i.e., empirical Bayes estimates displayed in Figure 1), we found two MSAs (Columbus, Georgia and Richmond, Virginia) to be greater than average for Black-White disparities. We identified area-level characteristics that were unique to these two MSAs using AHRF data, finding both to be less likely to have a community mental health center and have fewer outpatient psychiatric hospitals than the nation as a whole (data available upon request). We also found Fresno, California to be greater than average for Latino-White disparities. None of the White or Latino respondents in Fresno, California lived in a county with a community mental health center compared with approximately 60% nationwide, a fact that underscores the likely importance of community mental health centers in reducing disparities.[24] Latino rates of having less than a high school education were higher in Fresno, California than for Latinos overall in the U.S. (56% vs. 46%, respectively) whereas Whites in Fresno, California had similar rates of having less than a high school education compared with Whites in the U.S. (13% and 14%, respectively).

Some methodological limitations should also be noted. First, despite the use of empirical Bayes shrinkage estimation methods designed for areas with small sample size, we were unable to confidently pinpoint the rank of all MSAs available in the data in terms of magnitude of mental health care disparities. Using plots that show confidence intervals of these estimates is an alternative that helps to qualitatively identify MSAs that are likely to be "hot spots" of mental health care use disparities. Still, future datasets that collect larger samples in local areas are needed both in the MSAs where the variability was too high to determine rank definitively and in the MSAs that were excluded because of having fewer than 20 respondents in one of the racial/ethnic groups (e.g., MSAs such as Miami, Florida and Denver, Colorado for Black-White comparisons). Second, because CPES data were collected in 2003, inferring results to disparities in present day MSAs should be done with caution. Unfortunately, since that time, no nationally representative survey has been fielded that yields equivalent structured diagnostic information and mental health service use data for a sufficient sample of racial/ethnic minorities. Third, MSAs represent numerous mental health care systems,[47] making it difficult to pinpoint responsible health care systems within urban areas that perform poorly on the mental health care disparity measure used in this study. Fourth, due to inadequate sample sizes, we were unable to examine racial/ethnic mental health care disparities in non-urban centers, an important omission given that rural residents are less likely to receive mental health treatment.[50,51] Future research should further examine the combination of rural/urban and racial/ethnic disparities in mental health care.

Identifying geographic areas with consistently wide disparities in mental health care is important for public policy. We recommend that institutions and government agencies in hot spot areas of mental health care disparities work together to address the key mechanisms underlying these disparities. Understanding factors that contribute to low disparities (in our study, we found Saginaw, Michigan and Seattle, Washington to have lower than average Latino-White disparities, and Minneapolis, Minnesota, and Atlantic City, New Jersey to have lower than average Black-White disparities) may provide strategies that can be exported to other areas of the country. Mapping where disparities are high and low can help government agencies identify geographic areas that need system-level interventions and focus on why some areas are high and others are low for certain racial/ethnic groups. Studies focusing on geographic-level analysis can be helpful in and of itself by identifying where disparities are significant, and can also provide preliminary information for analyses assessing the underlying reasons why disparities differ by geographic location.[52–54]

This research was supported by R01 HS021486—(PI Cook) from the Agency for Healthcare Research and Quality, P60 MD02261 from the National Institute for Minority Health and Health Disparities (PI Alegría) and K01 AG045342 from the National Institute of Aging (PI Kim)

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