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A Look at Health Inequity Using the 500 Cities Dataset

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An abstract of

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Abstract

A Look at Health Inequity Using the 500 Cities Dataset

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This thesis explores how preventative health behaviors and services such as frequency of doctors' visits and insurance coverage might be associated with within-city inequality of various adverse health outcomes. Some of the value in considering these measures as exposures of interest is that they are modifiable-- which means that there is a greater opportunity for public health agency. Because cities and counties make policy decisions that have a direct impact on the availability of preventative services, being able to inform legislators about the potential consequences of their decisions is critically important to improving population health. Further, stakeholders at the grassroots level are able to engage public officials in discussions on meaningful policy change based on what the data tell us, making them more effective advocates.

To that end, in order to estimate the association between the prevalence of uninsured adults and the between-neighborhood variation in adverse health outcome, we fit crude and adjusted linear regression models where the coefficient of variation (a coarse proxy for inequity) for each adverse health event (twelve events in all) was the outcome and the exposure was prevalence of the uninsured. Similarly, to estimate the association between the prevalence of adults having been for a check-up within the last 12 months and between-neighborhood variation in each outcome, we fit similar crude and adjusted linear regression models where the exposure was the prevalence of adults having had a check-up. The adjusted models controlled for racial and poverty concentration by including the percentage of blacks and percentage of those in poverty.

We found Based on the results, it appears that neighborhood segregation by race and class plays a crucial role in how we address inequity. Although the two exposures of interest are critically important, increasing access to insurance and more frequent doctors' visits are not enough to narrow the health inequity gap alone. A big piece of health equity is driven by differential diffusion of access to resources. Because neighborhoods can act as a regulator of access to resources, segregation functions as a de facto resource limiter to marginalized populations.

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Background

Health inequity is a major problem, and a well-documented subject of an entire branch of public health inquiry with myriad research foci at the intersection of social justice and disease. (1, 2)These areas are referred to as health disparities, the measured gap indicative of inequity between the population health of two or more groups; they are differences in disease incidence, prevalence and mortality which are inherently unjust, unfair, and preventable. (3, 4)Health disparities research is aimed at addressing differences that arise from systematic differences in opportunity, exposure, resources, etc. that either prevent illness or promote wellness, which track along racial- and socioeconomic- lines.(4, 5)

Where people live significantly contributes to population health inequity; neighborhood processes and community resources are at the heart of health disparities. Historic residential concentrations of poverty and race have resulted in stark environmental differences in which certain populations live and work.(6-16) Such segregation begets further disparities by race and by class. Segregation is the linkage between these broader disparities and geography. We see examples of this when we consider phenomena such as food and medical deserts. Because some areas have less access to healthy food options and fresh produce, we see higher disease prevalence and morbidity in the populations that reside in these food deserts—neighborhoods which tend to be homogeneous both racially and economically. (6, 8, 9, 17) Similarly, a dearth of health care facilities in some communities can mean restricted access to health services. For those few health centers present in a medical desert, they are subject to very high patient loads placing a strain on services provided. For the patient, it may mean they simply never see the inside of a doctors' office. (18)

Disparities in population health are worth paying attention to because of the burden they have on society. Economically, there is a cost to health inequity; not just higher expenses for families who happen to be disadvantaged but wasted tax-payer dollars that help fund our healthcare system.(19) In 2011, LaVeist, Gaskin and Richard highlighted the economic impact of health disparities for ethnic minorities in the US population. They estimated that from 2003 – 2006 alone, the direct medical care expenditures, indirect costs and cost of premature death, attributable to ethnic health disparities is upwards of $1.24 trillion dollars. In addition to the economic burden, health inequity exacts a toll on the community morale—hardships from disease morbidity, grief associated with disease mortality. This can wear on the mental health or "spirit" of already disadvantaged populations. (20)

Acting on these disparities requires knowledge and insight into geographic inequity and being thoughtful about where there are opportunities to narrow the gap. There are two indicators of community health that represent actionable opportunities. Access to insurance coverage and regular checkups with a primary care provider are two interventions that can be applied broadly irrespective of geography. Also, because they are factors that are determined by public policy, informing the policy debate on the importance of these factors in reducing health inequity is a practical application of this inquiry. This thesis explores the association between two exposures, prevalence of uninsured individuals and prevalence of those having been to a doctor within 12 months, and the between-neighborhood variance of several adverse health events (See Table 1.)

Methods

The 500 Cities Project is a collaborative initiative between the Robert Wood Johnson Foundation, the Centers for Disease Control (CDC) and the CDC Foundation. It is comprised of small area estimations for the prevalence of health outcomes, risk factors, and preventative services in the 500 largest cities across the United States.(21) Crude and adjusted values, along with confidence intervals, are available at the census tract level within each city. For the purposes of my ecological analysis, census tract level estimates were aggregated at the county and then city level.

The 500 cities project was built on data collected via the Behavioral Risk Factor Surveillance System (BRFSS), a cross-sectional telephone survey that has been administered by state health departments with the help of the CDC since 1984. Its purpose was to make inference about populations at the state level. The BRFSS is re-administered to adults (aged 18 and older) annually in all 50 states of the US, Puerto Rico, the US Virgin Islands, and Guam. Questions on the core component of the survey are used by all states; contain demographic data; and focus on health risk behaviors, preventive health practice, and health care access as it pertains to chronic disease and injury. The study design involves random digit dialing and uses a disproportionate stratified sample design for the 50 states and a simple random sample design for the US territories (Guam, Puerto Rico, and the Virgin Islands). (22)

Eight of the questions used to build this dataset that explored individuals’ preventative health behavior or access to specific health prevention opportunities. Of the eight prevention measures, two stand out as prime potential exposures that are modifiable and impactful: 1) The prevalence of current lack of health insurance (18 - 64 yrs) (referred to as “Access”), 2) The prevalence of visits to the doctor for routine checkup within the past year (referred to as “Checkup”). While examining the association between those potential exposures and various adverse health outcomes (see Table 1) included in the dataset may yield an interesting and useful story about population health, it would not address health disparity per se. Rather, the census tract level data available for each of the 500 cities will allow me to compute a city-level variance. This variance could be calculated for each of the 13 outcomes and would serve as a coarse proxy measure of city-level inequity for a given outcome.

In this approach, the overall variance for each city describes how different census tracts (i.e., neighborhoods) are from one another. Where the variance is greater in one city as compared to another for a given outcome, we can view that city as having greater differences or inequity between neighborhoods.

Because the magnitude of the variance can be affected by size of the city population, the outcome measure needed to be normalized in order to properly compare differences between cities. To accomplish this, variance measure calculated for each city were transformed to a coefficient of variance (CV), which normalizes the variance measure such that all values fall between 0 and 1 (where 0 is no variance).

Because neighborhood inequity in health may be (in part) a function of how racially and socioeconomically diverse a place is, it seems reasonable to use racial composition and poverty status as a proxy for such diversity in each city. To account for this in the adjusted model, US Census Data were incorporated in the analysis. Because the unit of analysis here is city, potential confounders or effect measure modifiers would need to be factors associated with cities (rather than individuals). The percentage of individuals that identify as black as well as the percentage of individuals below the poverty line are both measures collected in the US Census. Each could be associated with the prevalence of those lacking health insurance and with the prevalence of individuals having had a checkup within the last 12 months. One would also expect that those measures are associated with inequity – which we measure as the CV of our various outcomes. Thus, both measures could help us address any issues of confounding.

In order to estimate the association between the prevalence of uninsured adults and the between-neighborhood variation in each health outcome, we fit crude and adjusted linear regression models where the coefficient of variation (inequity) for each health event was the outcome and the exposure was prevalence of the uninsured. Similarly, to estimate the association between the prevalence of adults having been for a check-up within the last 12 months and between-neighborhood variation in each outcome, we fit similar crude and adjusted linear regression models where the exposure was the prevalence of adults having had a check-up.

Results

Table 2 gives a brief overview of the two exposures and the thirteen adverse health outcomes considered in the analysis. Also shown for each is the mean city prevalence as well as the coefficient of variation. It is important to note that in this table, the coefficient of variation represents how different cities are from each other with respect to a given measure. This is different from what the coefficient of variation treated as the outcome for each adverse health event. In the later case, each city has a coefficient of variation for a given measure which represents how different neighbors are from each other.

In Tables 3 and 4, the data are dichotomized for further comparison. Each of the exposure variables were dichotomized around the median so that prevalence values greater than the median value are classified as high and those lower than the median value are classified as low. For each adverse health event, the average coefficient of variation, minimum, and maximum was calculated within each exposure group. The left side of Table 3 shows the mean coefficient of variation for all cities with a prevalence of uninsured below the median (EXP Access_Low); while the right side shows the mean coefficient of variation for cities above the median (EXP Access_High). Similarly in Table 4, the mean CV for those cities where the prevalence of doctors' visits falls below the median are found on the left (EXP Checkup-Low), and those above the median are found on the right (EXP Checkup_High). Below the adverse health events in each table, the poverty rate and percentage of individuals identifying as black are calculated for their respective groups.

As shown in Table 5, the unadjusted model with prevalence of uninsured as the exposure showed a significant association with between-neighborhood variation in Asthma, COPD, Diabetes, Kidney Disease, Mental Health, Physical Health, Stroke, and Teeth Lost. The adjusted model with prevalence of uninsured as the exposure showed a significant association with between-neighborhood variation in High Blood Pressure, High Cholesterol, and Physical Health.

Shown in Table 6, the unadjusted model with prevalence of adults having been for a check-up as the exposure showed a significant association with between-neighborhood variation in High Blood Pressure, Cancer, Asthma, COPD, Diabetes, Kidney Disease, Mental Health, Physical Health, and Stroke. The adjusted model with prevalence of adults having been for a check-up as the exposure showed a significant association with between-neighborhood variation in Arthritis, High Blood Pressure, Cancer, CHD, High Cholesterol, and Teeth Lost.

Upon further inspection, the several patterns emerge in Tables 5 and 6 of the results. Where the Prevalence of Uninsured (Access) is the exposure, statistically significant associations found in the crude model disappear when controlling for racial and poverty concentration. Associations that were not significant with the crude model became significant when adjusting for racial and poverty concentration. Physical Health was the exception with significant associations in both the crude and adjusted models. Nevertheless, the association between uninsured and physical health is attenuated in the adjusted model. Where our exposure was the prevalence of individuals having a checkup within the last 12 months, the direction of the association with High Blood Pressure flipped after controlling for racial and poverty concentration. In Table 6 we see a negative association with neighborhood variation in cancer. This association gets a little stronger and much more significant in the adjusted model. Also, in Table 6, both CHD and High Cholesterol went from a p-value of almost 1 in the crude model to very significant in the adjusted model ($p=0.008$ and $p=0.0257$ respectively). The strongest pattern consistent throughout the results, is the attenuation of the association between each of the exposures and outcomes. In each exposure/outcome condition, the model parameter estimates are attenuated when adjusting for racial and poverty concentration.

Discussion

The purpose of this inquiry was to explore health inequity and identify candidates for interventions that would help close the gap. These avenues needed to allow for agency at the grassroots level via impacting policy or supporting non-profit initiatives around that goal. My hypothesis was that an increase in the prevalence of regular doctors' checkups or a decrease in the prevalence of uninsured would be associated with reduced between-neighborhood variation in adverse health outcomes.

The overarching theme in my results is that for each model, adjusting racial and poverty concentration attenuates the strength of the association found in the crude model, irrespective of the exposure or health outcome. We know that one of the reasons for inequity is due to spatial concentration by poverty and race (i.e., segregation is a major contributor to health inequity).(6, 8, 9) Thus, we expect that in moving from the crude to the adjusted models, some of the differences that we observe between neighborhoods appear to be absorbed by these proxies for residential segregation. We could infer from this that percent Black and percent Poverty are not confounders, but intermediates that help explain health inequity.

A big piece of health equity is driven by differential diffusion of access to resources. (23, 24) If there is something that makes a difference and it is only available to some people, any increase in that resource would also increase inequity rather than decrease it. If reducing the prevalence of uninsured only happens in certain neighborhoods (where the population is more privileged) we would expect to see an increase in disparity. Only if everyone has access to that resource would it help to mitigate inequity.

Based on the results, it appears that neighborhood segregation by race and class plays a crucial role in how we address inequity. Although the two exposures of interest are critically important, increasing access to insurance and more frequent doctors' visits are not enough to narrow the health inequity gap alone. Because neighborhoods can act as a regulator of access to resources, segregation functions as a de facto resource limiter to marginalized populations.

These insights are important to public health because it provides evidence that the solution to reducing health inequity is going to require careful though about how we ensure equitable distribution of resources such that we mitigate the historical systems that helped to create these disparities in the first place. A future direction along this line of inquiry would be to consider the variance of uninsured prevalence and checkups as the exposures of interest. This might help paint a clearer picture about whether inequity in those two measures explain inequity in the prevalence of adverse health events. Additionally, we might also explore other indices of segregation to see whether their integration in the analysis yields results consistent with what was found here.

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Tables

Outcome Variable	Description
Arthritis	Arthritis among adults aged≥18 years
Current Asthma	Current asthma prevalence among adults aged≥18 years
High BP	High blood pressure among adults aged ≥18 years
Cancer	Cancer (excluding skin cancer) among adults aged ≥18 years
High Cholesterol	High cholesterol among adults aged ≥18 years
Chronic Kidney Disease	Chronic kidney disease among adults aged ≥18 years
COPD	Chronic obstructive pulmonary disease among adults aged ≥18 years
Coronary Heart Disease	Coronary heart disease among adults aged ≥18 years
Diabetes Diagnoses	Diagnosed diabetes among adults aged ≥18 years
Poor Mental Health	Mental health not good for ≥14 days among adults aged ≥18 years
Poor Physical Health	Physical health not good for ≥14 days among adults aged ≥18 years
Teeth Lost	All teeth lost among adults aged ≥65 years
Stroke	Stroke among adults aged ≥18 years

Table 1.

		Avg City Prevalence	Coeff. of Variation
Exposures	Lack of Health Insurance (weighted)	16.478	0.359
	Checkup with Doctor within past year (weighted)	67.535	0.046
Outcomes	Arthritis	21.977	0.192
	Current Asthma	9.260	0.095
	High BP	29.842	0.170
	Cancer	5.782	0.265
	High Cholesterol	34.521	0.112
	Chronic Kidney Disease	2.642	0.210
	COPD	6.041	0.250
	Coronary Heart Disease	5.579	0.276
	Diabetes Diagnoses	10.037	0.250
	Poor Mental Health	12.638	0.185
	Poor Physical Health	12.556	0.222
	Teeth Lost	15.228	0.341
	Stroke	2.986	0.310

Table 2.

	EXP Access_Low			EXP Access_High		
	Mean	Min	Max	Mean	Min	Max
CV_ARTHRITIS	0.185	0.064	0.439	0.199	0.061	0.517
CV_BPHIGH	0.159	0.044	0.383	0.181	0.037	0.441
CV_CANCER	0.252	0.093	0.566	0.279	0.092	0.721
CV_CASTHMA	0.081	0.014	0.197	0.108	0.031	0.219
CV_CHD	0.262	0.086	0.599	0.291	0.078	0.650
CV_COPD	0.231	0.068	0.456	0.268	0.086	0.483
CV_DIABETES	0.218	0.062	0.537	0.283	0.067	0.623
CV_HIGHCHOL	0.107	0.035	0.314	0.118	0.025	0.325
CV_KIDNEY	0.189	0.046	0.419	0.232	0.063	0.426
CV_MHLTH	0.174	0.044	0.319	0.195	0.059	0.303
CV_PHLTH	0.197	0.047	0.413	0.247	0.076	0.429
CV_STROKE	0.276	0.074	0.597	0.343	0.088	0.647
CV_TEETHLOST	0.323	0.099	0.589	0.360	0.103	0.589
POV_RATE	0.131	0.033	0.375	0.205	0.056	0.412
PRCNT_BLK	0.091	0.004	0.685	0.213	0.001	0.837

Table 3.

	EXP Checkup_Low			EXP Checkup_High		
	Mean	Min	Max	Mean	Min	Max
CV_ARTHRITIS	0.195	0.061	0.449	0.189	0.064	0.517
CV_BPHIGH	0.162	0.037	0.383	0.178	0.044	0.441
CV_CANCER	0.274	0.094	0.648	0.257	0.092	0.721
CV_CASTHMA	0.081	0.014	0.169	0.108	0.031	0.219
CV_CHD	0.276	0.078	0.599	0.277	0.086	0.650
CV_COPD	0.239	0.068	0.459	0.260	0.079	0.483
CV_DIABETES	0.229	0.062	0.543	0.272	0.085	0.623
CV_HIGHCHOL	0.112	0.025	0.325	0.113	0.037	0.316
CV_KIDNEY	0.196	0.062	0.419	0.224	0.046	0.426
CV_MHLTH	0.178	0.044	0.304	0.191	0.067	0.319
CV_PHLTH	0.211	0.047	0.396	0.234	0.076	0.429
CV_STROKE	0.286	0.088	0.616	0.334	0.074	0.647
CV_TEETHLOST	0.331	0.099	0.573	0.352	0.132	0.589
POV_RATE	0.155	0.033	0.375	0.181	0.037	0.412
PRCNT_BLK	0.071	0.001	0.425	0.233	0.006	0.837

Table 4.

		Unadjusted Model			
Exposure	**Outcome**	**Intercept**	**P-Value**	**Parameter Estimate**	**P-Value**
Access	CV-Arthritis	0.1862	<.0001	0.0004	0.4813
Access	CV-High Blood Pressure	0.1603	<.0001	0.0006	0.2059
Access	CV-Cancer	0.2490	<.0001	0.0010	0.1226
Access	CV-Asthma	0.0700	<.0001	0.0015	<.0001
Access	CV-CHD	0.2567	<.0001	0.0012	0.0636
Access	CV-COPD	0.2136	<.0001	0.0022	<.0001
Access	CV-Diabetes	0.2000	<.0001	0.0031	<.0001
Access	CV-High Cholesterol	0.1072	<.0001	0.0003	0.3577
Access	CV-Kidney Disease	0.1745	<.0001	0.0022	<.0001
Access	CV-Mental Health	0.1648	<.0001	0.0012	0.0005
Access	CV-Physical Health	0.1717	<.0001	0.0031	<.0001
Access	CV-Stroke	0.2549	<.0001	0.0033	<.0001
Access	CV-Teeth Lost	0.3172	<.0001	0.0015	0.0293
Checkup	CV-Arthritis	0.2389	<.0001	-0.0007	0.2722
Checkup	CV-High Blood Pressure	0.0847	0.0325	0.0013	0.0311
Checkup	CV-Cancer	0.4004	<.0001	-0.0020	0.0151
Checkup	CV-Asthma	-0.0918	<.0001	0.0028	<.0001
Checkup	CV-CHD	0.2755	<.0001	0.0000	0.9860
Checkup	CV-COPD	0.1134	0.0117	0.0020	0.0024
Checkup	CV-Diabetes	-0.0315	0.5897	0.0042	<.0001
Checkup	CV-High Cholesterol	0.1143	<.0001	0.0000	0.9430
Checkup	CV-Kidney Disease	0.0160	0.6940	0.0029	<.0001
Checkup	CV-Mental Health	0.1182	<.0001	0.0010	0.0267
Checkup	CV-Physical Health	0.0770	0.0605	0.0022	0.0004
Checkup	CV-Stroke	-0.0138	0.8296	0.0048	<.0001
Checkup	CV-Teeth Lost	0.2455	<.0001	0.0014	0.0963

Table 5.

		Adjusted Model			
Exposure	Outcome	Intercept	P-Value	Parameter Estimate	P-Value
Access	CV-Arthritis	0.1716	<.0001	-0.0010	0.0873
Access	CV-High Blood Pressure	0.1371	<.0001	-0.0017	0.0010
Access	CV-Cancer	0.2261	<.0001	-0.0010	0.1947
Access	CV-Asthma	0.0529	<.0001	-0.0003	0.2295
Access	CV-CHD	0.2467	<.0001	0.0001	0.8553
Access	CV-COPD	0.2032	<.0001	0.0010	0.0931
Access	CV-Diabetes	0.1600	<.0001	-0.0010	0.1753
Access	CV-High Cholesterol	0.0921	<.0001	-0.0011	0.0042
Access	CV-Kidney Disease	0.1555	<.0001	0.0002	0.7268
Access	CV-Mental Health	0.1449	<.0001	-0.0007	0.0747
Access	CV-Physical Health	0.1545	<.0001	0.0013	0.0154
Access	CV-Stroke	0.2257	<.0001	0.0002	0.8054
Access	CV-Teeth Lost	0.3007	<.0001	-0.0003	0.6964
Checkup	CV-Arthritis	0.3155	<.0001	-0.0023	0.0035
Checkup	CV-High Blood Pressure	0.2257	<.0001	-0.0016	0.0252
Checkup	CV-Cancer	0.3962	<.0001	-0.0027	0.0080
Checkup	CV-Asthma	0.0369	0.0748	0.0002	0.4968
Checkup	CV-CHD	0.4260	<.0001	-0.0027	0.0083
Checkup	CV-COPD	0.3056	<.0001	-0.0014	0.0710
Checkup	CV-Diabetes	0.2345	0.0002	-0.0013	0.1903
Checkup	CV-High Cholesterol	0.1594	<.0001	-0.0012	0.0257
Checkup	CV-Kidney Disease	0.1790	0.0001	-0.0003	0.6313
Checkup	CV-Mental Health	0.1739	<.0001	-0.0005	0.3124
Checkup	CV-Physical Health	0.2457	<.0001	-0.0012	0.0760
Checkup	CV-Stroke	0.3081	<.0001	-0.0012	0.2559
Checkup	CV-Teeth Lost	0.4683	<.0001	-0.0026	0.0127

Table 6.