# Inequities in spatial accessibility to COVID-19 testing in 30 large US cities

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## ABSTRACT

Testing for SARS-CoV-2 infection has been a key strategy to mitigate and control the COVID-19 pandemic. Wide spatial and racial/ethnic disparities in COVID-19 outcomes have emerged in US cities. Previous research has highlighted the role of unequal access to testing as a potential driver of these disparities. We described inequities in spatial accessibility to COVID-19 testing locations in 30 large US cities. We used location data from Castlight Health Inc corresponding to October 2021. We created an accessibility metric at the level of the census block group (CBG) based on the number of sites per population in a 15-minute walkshed around the centroid of each CBG. We also calculated spatial accessibility using only testing sites without restrictions, i.e., no requirement for an appointment or a physician order prior to testing. We measured the association between the social vulnerability index (SVI) and spatial accessibility using a multilevel negative binomial model with random city intercepts and random SVI slopes. Among the 27,195 CBG analyzed, 53% had at least one testing site within a 15-minute walkshed, and 36% had at least one site without restrictions. On average, a 1-decile increase in the SVI was associated with a 3% (95% Confidence Interval: 2% - 4%) lower accessibility. Spatial inequities were similar across various components of the SVI and for sites with no restrictions. Despite this general pattern, several cities had inverted inequity, i.e., better accessibility in more vulnerable areas, which indicates that some cities may be on the right track when it comes to promoting equity in COVID-19 testing. Testing is a key component of the strategy to mitigate transmission of SARS-CoV-2 and efforts should be made to improve accessibility to testing, particularly as new and more contagious variants become dominant.

## 1. Introduction

The COVID-19 pandemic has highlighted long standing health inequities in the US, as low-income and racial/ethnic minorities have been disproportionately affected in terms of COVID-19 incidence and mortality (Bassett et al., 2020; Bilal et al., 2021; Bryan et al., 2021; Ogedegbe et al., 2020). These disparities have emerged because these groups are more likely to be exposed to COVID-19 due to living or working conditions (McCormack et al., 2020; Benfer et al., 2021; Harris, 2021; Niedzwiedz et al., 2020). Moreover, these groups may also be more vulnerable to severe COVID-19, in part, due to higher prevalence of chronic conditions such as type 2 diabetes, obesity, and cardiovascular

disease (Apicella et al., 2020; Mehra et al., 2020). As a result of higher rates of exposure and infections, Non-Hispanic Blacks, Hispanics, and American Indians and Alaska Natives have been hospitalized and have died at disproportionately higher rates compared to non-Hispanic whites (Price-Haywood et al., 2020; Artiga and Orgera, 2020; Martinez et al., 2020).

Testing for SARS-CoV-2 is critical to control community transmission of COVID-19. Testing of individuals who do not have symptoms but may have been exposed to the virus helps to prevent the spread of COVID-19 by identifying cases early on and informing decisions about isolation and contacts tracing (Manabe et al., 2020). In the early months of the COVID-19 pandemic, a series of missteps, including flawed COVID-19

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test kits, delayed the production and distribution of COVID-19 tests in the US. (Temple-Raston, 2021) Due to the shortage in supply, COVID-19 tests were being reserved for symptomatic patients under strict guidelines. However, mass media reported on prominent personalities who had obtained tests without exhibiting symptoms or having known contact with the virus (Megan Twohey and Stein, 2020), while also highlighting the lack of testing sites in some neighborhoods (Lubrano, 2020). These stories highlighted very early the emerging inequities in COVID-19 outcomes, including testing (Dalva-Baird et al., 2021).

In January of 2021, approximately 2 million COVID-19 tests were being performed per day in the US. (Atlantic, 2021) However, distribution of testing location across neighborhoods and variation in criteria for testing are likely to perpetuate disparities (Bilal et al., 2021). In this paper, we examine spatial inequities in COVID-19 testing sites located in 30 large US cities in October of 2021.

## 2. Conceptual framework

The concept of access to healthcare resources is multidimensional. Access can be defined in terms of spatial accessibility, affordability, acceptability, and availability (Frenk and White, 1992). Access can also be defined according to two dimensions: potential or revealed, and spatial or non-spatial (Luo and Wang, 2003; Andersen and Aday, 1978; Guagliardo, 2004). Potential accessibility refers to the possible utilization of services and revealed accessibility refers to the actual utilization of services. Spatial accessibility refers to the absence of geographical barriers and non-spatial accessibility refers to organizational, social, or historical factors that constitute barriers to access. These may include factors such as costs, excessive bureaucracy to obtain services, language barriers, and mistrust in the health care system. Low-income and minoritized racial/ethnic groups often experience a number or barriers to access health care, such as financial and transportation barriers, and mistrust in the health care system (Syed et al., 2013; Moore et al., 2013; Guadagnolo et al., 2009; Glied et al., 2020).

In this study, we examined potential accessibility, with a focus on the spatial dimension in isolation or combined with non-spatial barriers. We used two indicators of non-spatial barriers, i.e., requiring a physician order and requiring a prior appointment. Physician order requirement is a barrier to testing for people without regular access to a primary care physician (PCP). Individuals with PCP visits have declined over time, especially for individuals living in lower income areas (Ganguli et al., 2020). Requiring a prior appointment is an extra step that may discourage some from seeking a test, especially in a context of high demand for testing that may require several call attempts and/or access to internet. These types of non-spatial barriers are more likely to be experienced by disadvantaged populations (DeVoe et al., 2007).

We measured inequities in neighborhood- and city-level spatial accessibility to COVID-19 testing sites using a metric that takes into account street network data. In order to combine spatial and non-spatial components, we also calculated the same metric including only sites that required neither an appointment nor a physician order prior to testing. We conduct these analyses for each city in our sample, as the unique segregation patterns and availability of testing sites of each city are socially determined factors (Riley, 2022). As such, understanding which areas have wider or narrower inequities in testing site accessibility would provide hints as of what features of cities promote equity (Riley, 2022).

## 3. Methods

### 3.1. Study design, setting, and data sources

This is a cross-sectional descriptive study of inequities in COVID-19 testing access in 27,469 census block groups (CBG) in 30 US cities whose health departments are members of the Big Cities Health Coalition (BCHC). These cities include consolidated city-counties (e.g.,

Philadelphia), collections of counties (e.g., New York City), independent cities (e.g., Baltimore), or incorporated places, generally smaller in size than counties (e.g., Los Angeles), and represent the largest metropolitan areas in the US. Health departments in these cities have the capacity to make policy designed to address the needs of the population they serve.

We used data from Castlight Health Inc. (henceforth, Castlight), current as of October 19, 2021, containing data on 3154 testing sites in the 30 cities studies. We did not include testing sites outside of the city. This approach assumes that if someone needs to leave the city or metropolitan area to get tested somewhere else, that also indicates a barrier to access. Castlight data include location (latitude and longitude) and several characteristics of each testing site. Castlight collects data from numerous provider systems to automatically add their testing sites based on data feeds (Castlight Health, 2021). They also gather feedback from users of their website; users may note any changes in the site directory information. Any new information added by users is then verified before updating the database. Information on testing sites is updated twice a week (Castlight Health, 2021). We also obtained total population and sociodemographic data at the CBG level from the American Community Survey (2015–2019 ACS 5-year estimates), all based on 2010 census boundaries. CBG and incorporated places (cities) boundaries were obtained from the US Census (US Census, 2018). CBG is the smallest level of data aggregation used in the American Community Survey 5-year estimates. We chose this unit because it represents a more granular spatial level to characterize heterogeneity within cities. A CBG was part of a city if it overlapped at all with the extent of each city. We used street network data from ESRI Business Analyst 2018 (Redlands, CA).

### 3.2. Access metrics

To measure spatial accessibility, we used the number of testing sites per population in the CBG and surrounding areas. We constructed this metric in three steps. First, we calculated the area defined by a 15-min walking distance, a threshold commonly used in walkability studies (Gaglione et al., 2022; Hosford et al., 2022), from the population weighted centroid of each CBG (BureauUSC, 2021) (i.e., 15-min walksheds), using 2018 street network data from the Network Analyst Extension, Service Area Tool of ArcGISPro 2.8.2. Walksheds and 2010 CBG boundaries were projected in the USA Contiguous Albers Equal Area Conic USGS projection, North American Datum (NAD) 1983. Second, we redefined the walkshed such that the borders of the walkshed would coincide with the limits of the surrounding CBGs. As part of that process, CBGs that overlapped with the walkshed by less than 25% were excluded from the redefined area, whereas CBGs that had >25% of their area within the walkshed were fully included in the walkshed. This was done to facilitate the calculation of the population covered by the walkshed, which was accomplished by adding up the population of the CBGs included in the redefined area. Supplemental Fig. 1 shows an example of a walkshed area. Third, we calculated the number of sites per 1000 people in the redefined walkshed. We excluded walksheds with very small resident population (bottom 1% of distribution, or those with population smaller than 265 residents) to remove extreme outliers. To examine a combination of spatial and non-spatial barriers, we repeated steps two and three using only testing sites that required neither an appointment nor a physician order prior to testing.

As a secondary analysis, we also calculated 15-min drivesheds, or the area surrounding the CBG centroid demarcated by a 15-min driving distance. This accessibility metric does not account for variations in possession of a car across communities and is less likely to be comparable across cities with varying level of reliance on cars as a mode of transportation. We also considered the use of a metric based on public transportation. However, public transit schedules were often disrupted during parts of the pandemic and tracking all these potential disruptions was not feasible.

### 3.3. Social vulnerability

To measure social vulnerability, we used the CDC's social vulnerability index (SVI), defined in terms of the characteristics of a community that affects their capacity to anticipate or recover from a disaster (Flanagan et al., 2018). The SVI has been used to characterize variations across several COVID-19-related predictors and outcomes, and allows researchers to examine variation between and within jurisdictions (Barry et al., 2021; Hughes et al., 2021; De Ramos et al., 2022). The SVI has also been used to allocate resources such as COVID19 vaccines to communities in high need (Schmidt et al., 2021). We chose to use the SVI because it represents a composite measure census variables that captures disadvantage at a granular geographic level. The 15 variables included in the calculation of the SVI are grouped into four domains: socioeconomic status, household composition and disability, minority status and language, and housing type and transportation (**Supplemental Table 1**). We adapted the original CDC calculation of the SVI, done at the census tract level, to obtain a measure at the CBG level, using the 2015–2019 ACS 5-year estimates. Two out the 15 SVI variables (persons in group quarters and civilian noninstitutionalized population with a disability) were not available at the CBG level; for these two variables, we assigned the census tract level values to their respective block group before calculating the SVI. To calculate the SVI, CBGs were ranked according to each of the variables in descending order – except for per capita income, which was ranked in ascending order – as per Flanagan et al. (2018) The ranking of the CBG was done separately within each city. After ranking the CBG, we calculated the percentile ranking for each variable using the formula:

$$Percentile = (Rank - 1)/(N - 1)$$

where *Rank* is the position of the CBG, and *N* is the total number of CBGs in each city. Following the calculation of the percentile ranking, we calculated domain specific and overall SVI summary measures. The domain specific SVI was calculated as the sum of the percentile ranks for each variable comprising the domain. The overall SVI was calculated as the sum of the percentile ranks of the four domains.

### 3.4. Analysis

We conducted the analysis in five steps. First, we calculated descriptive statistics characterizing CBGs with and without sites, and the percent of CBGs with at least one testing site within the walkshed. We also constructed maps for each city showing the CBGs for which the 15-min walkshed overlapped with at least one testing site location (Supplemental Figs. 2–6). Second, we calculated inequities in spatial accessibility using the 90/10 ratio, i.e., ratio between CBGs at or above the 90th percentile (high vulnerability) and CBGs at or below the 10th percentile (low vulnerability) of the SVI. For this, we created the two groups, high and low vulnerability) and then calculated the ratio of site per population between the two groups. We also conducted a secondary analysis where we used a different cut-off (75/25).

Third, we used multilevel negative binomial models to estimate the strength of the association between SVI and spatial accessibility. We chose negative binomial models because they allowed us to model the outcomes as counts of sites within each CBG's walkshed/drived and include an offset for total population in the walkshed/drived. In each model, we included the SVI or its four domains as independent variables, all in separate models. These models also included a random intercept for city and a random slope for the SVI or SVI domains. Exponentiated coefficients resulting from this model represent the association between a 1-decile difference in the SVI and the relative difference in the number of sites per population. Since these models include a random slope for the independent variable, the main results represent the association between the SVI and accessibility metrics for the median city. We also present the Best Linear Unbiased Prediction (BLUP) of random effects

(Supplemental Figs. 7 and 8 for walkshed and drivshed, respectively), representing the city-specific random slopes. Fourth, we repeated the modeling steps using only the testing sites that did not require an appointment nor a physician order prior to testing.

Last, we explored for the presence of spatial autocorrelation on testing site accessibility conditional on the SVI using Global Moran's I. For this, we followed an approach similar to Bilal et al. (2021), by fitting a negative binomial model separately for each city, extracting the Pearson residuals from this model, and then calculating Global Moran's I. Neighbors were calculated using queen-type weights. We found evidence of significant spatial autocorrelation in 18 of the 30 cities (see Supplemental Table 2). To address this in the modeling stage, we followed Bilal et al. (2021) and fitted a negative binomial Besag–York–Mollié conditional autoregressive model using integrated nested Laplace approximations (INLA), a method that approximates Bayesian inference. We fitted this model separately for each city and repeated the analysis for both analysis (unrestricted and restricted to sites with no barriers). The INLA model failed to converge for 3 and 9 cities in the unrestricted and restricted analyses, respectively. Therefore, we present these results as a sensitivity analysis that compares the results from the INLA models to the main analysis to ensure that residual spatial autocorrelation is not driving our inferences.

Analyses were conducted in R version 4.0.2 using the glmmTMB and INLA packages.

## 4. Results

Among the 27,195 census block groups (CBG) included in the analysis, 53% had at least one testing site within a 15-min walkshed, and 36% had at least one site that required neither a physician order nor an appointment (no restriction sites). The median population size and the SVI were similar across CBGs with and without testing sites. CBGs without testing sites had a larger median area compared to those with testing sites. (Table 1). The proportion of CBGs with at least one testing site varied considerably across cities, from 22% in Minneapolis to 87% in New York City, while the proportion of CBGs with at least one testing site with no restrictions varied from 3% in Detroit to 77% in New York City (Table 2). Among all cities, the median value for sites per population was 0.03 sites per 1000 people, with large variation within cities (Fig. 1).

Table 3 shows large inequities in accessibility within cities, with lower spatial accessibility in areas of higher social vulnerability. The number of sites per population was 30% lower in CBGs at or above the 90th percentile of the SVI (highest vulnerability), compared to CBGs at or below the 10th percentile of the SVI (lowest vulnerability). Inequities were similar among all components of the SVI except housing and transportation, for which inequity was inverted, i.e., the number of sites per population was 50% higher in CBGs with the highest (vs. lowest) vulnerability. When comparing all testing sites with testing sites with no restrictions, inequities were generally similar in magnitude and direction. Results were similar when using the 75th/25th percentile cut-off

**Table 1**

Characteristics of the census block groups with and without sites.

|  | CBGs without sites within a 15-min walkshed | CBGs with at least one site within a 15-min walkshed | CBGs with least one site (w/o restrictions) within a 15-min walkshed |
| --- | --- | --- | --- |
| N (%) | 12,838 (46.7%) | 14,631 (53.3%) | 9870 (35.9%) |
| Population | 1277 [889–1832] | 1244 [904–1695] | 1271 [927–1704] |
| SVI | 0.51 [0.26–0.75] | 0.51 [0.25–0.76] | 0.53 [0.26–0.77] |
| Area (square Km) | 0.42 [0.23–0.84] | 0.15 [0.07–0.33] | 0.12 [0.05–0.29] |

Footnote: SVI=Social Vulnerability Index, CBG=Census Block Group; all values are Medians [IQR].

**Table 2**
Spatial accessibility to COVID-19 testing in 30 large US cities.

| City | Number of CBG | Population (in 100,000) | CBGs with at least one testing site within a 15-min walkshed | CBGs with at least one site with no restriction within a 15-min walkshed |
|---|---|---|---|---|
| | | | % (n) | % (n) |
| Austin | 496 | 9.6 | 34.5 (171) | 22.2 (110) |
| Baltimore | 625 | 6.0 | 34.9 (218) | 17 (106) |
| Boston | 543 | 6.8 | 52.1 (283) | 16.6 (90) |
| Charlotte | 454 | 8.7 | 23.1 (105) | 14.1 (64) |
| Chicago | 2149 | 27.0 | 69.7 (1498) | 61 (1311) |
| Cleveland | 443 | 3.8 | 43.1 (191) | 12.6 (56) |
| Columbus | 610 | 8.7 | 27.2 (166) | 13.1 (80) |
| Dallas | 903 | 13.0 | 45.2 (408) | 28 (253) |
| Denver | 480 | 7.1 | 45.6 (219) | 25.6 (123) |
| Detroit | 792 | 6.6 | 23.7 (188) | 3.4 (27) |
| Fort Worth | 505 | 8.6 | 31.3 (158) | 16.8 (85) |
| Houston | 1307 | 23.0 | 40.7 (532) | 26.6 (348) |
| Indianapolis | 574 | 8.6 | 22.8 (131) | 9.8 (56) |
| Kansas City | 421 | 4.9 | 26.6 (112) | 14 (59) |
| Las Vegas | 443 | 6.3 | 36.1 (160) | 24.6 (109) |
| Long Beach | 326 | 4.7 | 48.2 (157) | 26.7 (87) |
| Los Angeles | 2490 | 40.0 | 43.5 (1084) | 25.1 (624) |
| Miami | 296 | 4.5 | 69.9 (207) | 55.7 (165) |
| Minneapolis | 378 | 4.2 | 22.2 (84) | 11.4 (43) |
| New York City | 6173 | 84.0 | 87.9 (5425) | 77.7 (4799) |
| Oakland | 330 | 4.2 | 67 (221) | 52.1 (172) |
| Philadelphia | 1319 | 16.0 | 73.6 (971) | 8 (106) |
| Phoenix | 955 | 16.0 | 35.2 (336) | 25.1 (240) |
| Portland | 435 | 6.4 | 36.6 (159) | 19.1 (83) |
| San Antonio | 876 | 15.0 | 32 (280) | 21.3 (187) |
| San Diego | 827 | 14.0 | 23.8 (197) | 8.9 (73) |
| San Francisco | 575 | 8.7 | 56.3 (324) | 14.3 (82) |
| San Jose | 544 | 10.0 | 25.2 (137) | 19.9 (108) |
| Seattle | 477 | 7.2 | 32.1 (153) | 10.3 (49) |
| Washington | 449 | 6.9 | 54.6 (245) | 25.6 (115) |
| Total | 27,195 | 390.8 | 53.4 (14,520) | 36.1 (9810) |

**Footnotes**: Population refers to total city population in 2015–2019 (5-year American Community Survey). CBG=Census Block Group. CBGs with no restrictions were those that required neither an appointment nor a physician order prior to testing. Median Site per 1000 people is the median value per city for the metric calculated as the number of sites divided by the population covered in each walkshed. Testing site data is current as of October 19th, 2021

(Supplemental Table 3).

Fig. 2 shows the 90/10 ratios for all cities. When including all testing sites, 17 out of 30 cities had lower accessibility in high-vulnerability (top 10% of the SVI) CBGs, compared to low-vulnerability (bottom 10% of the SVI) CBGs. However, 13 cities had higher accessibility in low-vulnerability (vs. high-vulnerability) CBGs. When considering only testing sites with no restrictions, the pattern of inequity changed in several cities. In three cities, Washington D.C., Boston, and Philadelphia, inequity was inverted, meaning that when considering only testing sites with no restrictions these cities had higher accessibility in CBGs with high vulnerability. In two cities, Austin and San Jose, inequity was smaller when considering only testing sites with no restrictions (vs. all testing sites). In two cities, San Francisco and Minneapolis, accessibility changed from higher in high (vs. low) vulnerability CBGs to higher low (vs. high) vulnerability CBGs when considering only testing sites with no restrictions.

Table 4 shows the results from the negative binomial models. The models using walksheds indicate that a 1-decile higher SVI was associated with a 3% (95% CI 2%–4%) lower accessibility. We observed similar associations for all SVI components except housing and transportation, which had an inverted inequity. Models including only testing sites with no restrictions showed similar results. Models using drive-sheds indicate a similar overall pattern, but inequalities were generally smaller. But Fig. 3 shows that the relationship between spatial accessibility to testing sites and the SVI varied considerably across cities; cities in the Northeast and South had a more consistent pattern of lower accessibility for CBGs with higher vulnerability, and cities in the Midwest and West had more heterogeneity in the association with a number of cities presenting inverted disparities (higher accessibility in high-vulnerability areas) (Fig. 3). Sensitivity analysis using a spatially explicit model showed that results were robust to residual spatial autocorrelation (Supplemental Fig. 9).

Supplemental Figs. 7 and 8 show city-specific random slopes or best linear unbiased prediction. The fixed effect of the SVI (see Table 4) is negative, indicating lower accessibility with higher social vulnerability. Therefore, a negative random slope indicates an even stronger inequity, while a positive random slope indicates a weaker or inverted inequity. The relationship between the two slopes, i.e., from all sites vs. no restriction sites, is shown in Supplemental Fig. 10.

## 5. Discussion

In this analysis examining inequities in spatial accessibility to COVID-19 testing sites in 30 large US cities, we found five key results. First, there is wide heterogeneity in accessibility to testing across cities with almost half of all CBGs lacking at least one testing site within a 15-min walk. Second, there is also wide heterogeneity in spatial accessibility within cities, with areas of higher social vulnerability generally having lower spatial access to testing. On average, areas at or above the 90th percentile of the social vulnerability index had 30% lower rate of sites per population in the 15-min walkshed, compared to areas at or below the 10th percentile of vulnerability. Third, these differences varied by city, with several cities having inverted disparities (i.e., high-vulnerability areas had higher access to testing). Fourth, accessibility was lower when including only sites with no restrictions (i.e., physician orders and appointments), but inequities were similar to those found for the totality of sites. However, some cities had a more equitable distribution of sites when considering only sites with no restriction. Fifth and last, when examining different components of the SVI, inequities were similar except for the housing and transportation component.

Inequities in accessibility to COVID-19 testing have been reported since the beginning of the pandemic with studies showing that testing resources were primarily allocated to more affluent communities (Dalva-Baird et al., 2021; Dryden-Peterson et al., 2021; Servick, 2020; Asabor et al., 2022). Consistent with this pattern, other studies have also shown inequities in utilization of tests across different geographies within states and cities (Bilal et al., 2021; Dryden-Peterson et al., 2021; Seto et al., 2020; Lieberman-Cribbin et al., 2020). Socioeconomically disadvantaged counties and communities of color have higher need for and lower accessibility to testing, as indicated by high COVID-19 positivity ratios in these communities (Bilal et al., 2021; Dryden-Peterson et al., 2021; Lieberman-Cribbin et al., 2020; Rader et al., 2020). Our study shows that even a year after initial descriptions of these inequities, and after much improvement in overall availability of tests across the country, inequities in accessibility to COVID-19 testing in some of the largest US cities persist. Our results also show that non-spatial barriers are persistent, with a majority of CBGs in most cities having some type of restrictions to testing (i.e., need for an appointment before testing or a physician order).

Despite this general pattern of inequity, several cities had inverted inequities (i.e., better accessibility in more vulnerable areas), particularly when considering the distribution of sites with no restrictions to testing. The Best Unbiased Prediction (BLUP) shows that city-specific random slopes varied considerably. For example, in Houston and Dallas, the random slopes were negative, indicating that, in these cities, higher vulnerability was more strongly associated with lower access, as compared to the average city. The pattern of distribution of sites can be visually examined in the map (Supplemental Fig. 3), which shows that the suburbs located east of Houston, where poor communities and
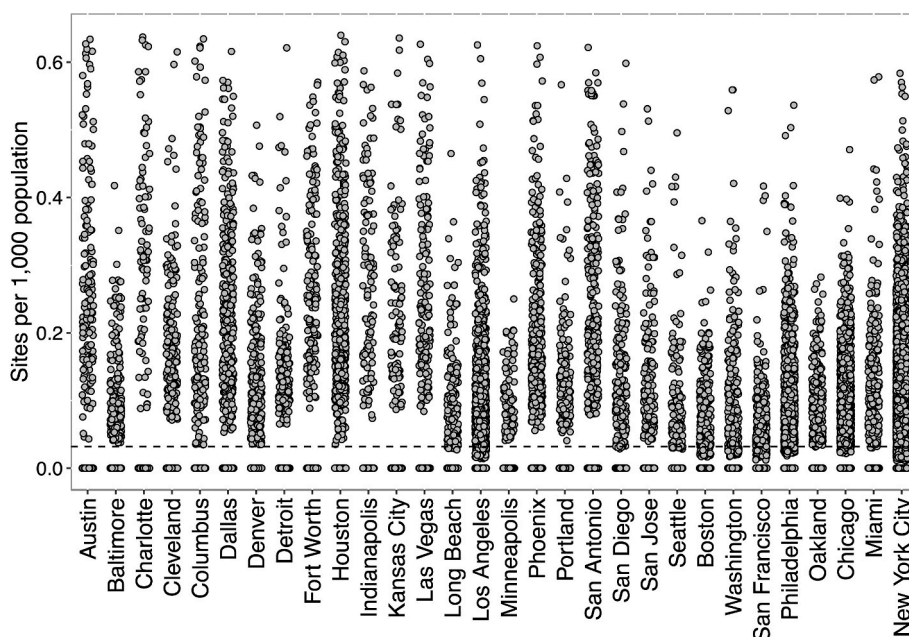
**Fig. 1.** Sites per population in the block group 15-min walkshed by city **Footnotes**: Dashed line represents the median value for all cities. This plot excludes outliers, i.e., top 1% of the CBGs with values ranging from 0.65 to 5 sites per 1000 people. Cities are ordered from lowest to highest median value of site per 1000 population.

**Table 3**

Median ratio (IQR) of spatial accessibility to COVID-19 testing sites between CBGs at or above the 90th and at or below the 10th percentile of SVI, and its components among 30 cities.

| | All testing sites | | Only testing sites without restrictions | |
|---|---|---|---|---|
| | Median | IQR (25th-75th) | Median | IQR (25th-75th) |
| SVI – overall | 0.7 | 0.4–1.4 | 0.7 | 0.5–1.7 |
| SVI – socioeconomic status | 0.7 | 0.5–1.0 | 0.7 | 0.4–1.0 |
| SVI – household composition and disability | 0.7 | 0.5–1.0 | 0.9 | 0.6–1.2 |
| SVI – minority status and language | 0.6 | 0.4–1.2 | 0.5 | 0.3–1.4 |
| SVI – housing type and transportation | 1.5 | 1.0–2.2 | 1.2 | 0.6–1.7 |

**Footnote**: Inequities were measured by the 90/10 ratio between the top and bottom deciles of the SVI, overall and by SVI components. IQR=Interquartile range.

communities of color are located, have only a small number of testing sites. In Dallas, we also see an overlap between neighborhoods that have been historically disadvantaged by segregationist policies (Gándara and Orfield, 2021) and areas with fewer testing sites (Supplemental Fig. 3). Conversely, cities like Seattle, had a positive random slope, meaning that the association between vulnerability and accessibility was weaker or inverted. However, inequity findings should be interpreted in conjunction with overall metrics of accessibility. For example, in Minneapolis, areas of high vulnerability also had higher accessibility, compared to areas of low vulnerability, but the city had few testing sites (Supplemental Fig. 4), even though the existing sites were more often located near areas of high vulnerability. We have interactive maps available in the "COVID-19 inequities in cities dashboard" (Bilal et al., 2022a) (https://www.covid-inequities.info/).

Inequity in spatial accessibility was larger when measured via the walkshed (vs. the driveshed) metric. This is somewhat expected as drivesheds cover larger geographic areas potentially resulting in less heterogeneity in accessibility. However, city-specific random slopes show large differences, with many cities showing a stronger association

between SVI and accessibility compared to the average city.

Our finding indicates that some cities may be on the right track when it comes to promoting equity in COVID-19 testing. Further examination of the actions taken by these cities' health department may point to policies that have the potential to promote equity in testing. Positive results can be shared and replicated/adapted by other jurisdictions with policy-making capacity. In addition, further examination of variation public health and healthcare infrastructure in these cities can provide insights into the drivers of disparities within and across cities (Riley, 2022) as well as potential solutions to mitigate disparities related to COVID-related public health interventions, such as testing and vaccination, for which large disparities have also been reported (Bilal et al., 2022b). Lastly, further research is needed to assess whether higher accessibility and fewer restrictions were translated into smaller inequities in utilization.

We found generally consistent results for the social vulnerability index, overall and by components, except for the housing and transportation component. The social vulnerability index has been used to characterize variations across several COVID-19 related predictors and outcomes. Higher social vulnerability was associated with accessibility to healthcare resources in the context of COVID-19 (Kang et al., 2020), higher risk of becoming a COVID-19 hotspot (Dasgupta et al., 2020), and higher COVID-19 case fatality (Nayak et al., 2020). Inconsistent results for the housing and transportation component may be related to the indicators included in this component; in particular, indicators like percentage of mobile homes and households without vehicles may be less useful to measure social vulnerability in large cities. A previous study examining the association between the housing and transportation indicator and COVID-19 outcomes found inexistent or narrower disparities in this domain compared to the other SVI domains (Bilal et al., 2021).

This study has limitations. First, we have a few limitations related to the accessibility metric, including the fact that it does not account for the capacity of the testing sites. The metric only accounts for the number of sites and the population distribution, thus we cannot assess whether sites in high vulnerability areas also have higher capacity to meet the need for testing. The largest share of testing sites examined were pharmacy clinics and urgent care clinics, which are likely similar across cities in terms of capacity but testing sites can also be academic hospitals with
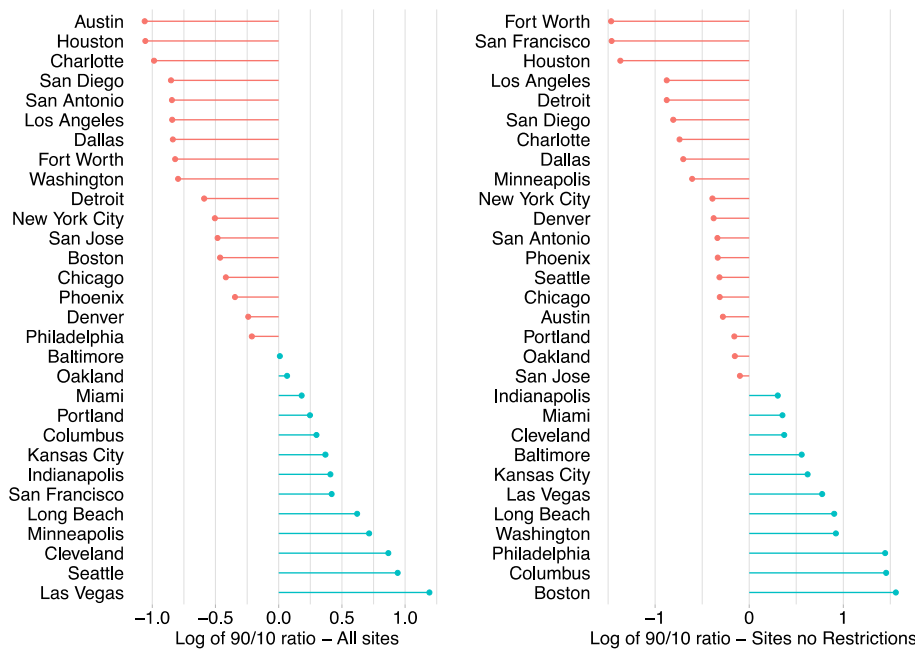
**Fig. 2.** Inequities in testing accessibility between census block groups at the top and bottom deciles of the social vulnerability index. **Footnote**: Ratios are shown on the log scale. Lines in red represent worse outcomes for most vulnerable communities (i.e., lower rates of sites per population for the top 10 percent most vulnerable CBGs compared to the 10 percent least vulnerable). Lines in green represent better outcomes for vulnerable communities. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

**Table 4**
Association of spatial accessibility and the social vulnerability index (SVI) and its components.

| | Walkshed | | | | Driveshed | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | All testing sites | | Only testing sites without restrictions | | All testing sites | | Only testing sites without restrictions | |
| | Coefficient | 95% CI | Coefficient | 95% CI | Coefficient | 95% CI | Coefficient | 95% CI |
| SVI overall | 0.97 | 0.95–0.99 | 0.98 | 0.95–1.01 | 0.98 | 0.97–0.99 | 0.98 | 0.97–0.99 |
| SVI socioeconomic status | 0.96 | 0.94–0.97 | 0.96 | 0.93–0.99 | 0.98 | 0.97–0.99 | 0.98 | 0.97–0.99 |
| SVI household composition and disability | 0.97 | 0.95–0.98 | 0.99 | 0.96–1.02 | 9.98 | 0.97–0.99 | 0.99 | 0.98–1.00 |
| SVI minority status and language | 0.95 | 0.93–0.97 | 0.96 | 0.92–0.99 | 0.98 | 0.97–0.99 | 0.98 | 0.97–1.00 |
| SVI housing type and transportation | 1.04 | 1.02–1.07 | 1.02 | 0.99–1.04 | 1.0 | 1.0–1.01 | 0.99 | 0.97–1.00 |

**Footnote**: Results are from negative binomial models including random intercept for cities and random slope for the SVI. Coefficients represent the fixed effect of SVI (median effect across all cities). Coefficients are exponentiated, representing the relative increase in sites per population per 1-decile increase in the SVI or its components.

potentially large capacity to test. Moreover, given data limitations, we were not able to include mobile test clinics, which may have focused on disadvantaged communities (Jaklevic, 2021). This may have over-estimated spatial inequities in cities that invested in pop-up sites in low-income neighborhoods. However, a recent study has found that racially segregated communities have a lower presence of COVID-19 testing sites, including mobile or pop-up sites (Asabor et al., 2022). Also, the use of street network has limitations, such as lack of detail about mid-block crossing signals or informal cut throughs that would allow for calculation of more precise routes and travel time. Regarding of the accessibility metric, we were unable to account for other types of testing strategies such as home testing. This has become especially relevant in later phases of the pandemic, as rapid at home testing has become a commonplace strategy to mitigate the transmission of SARS-CoV-2.

Second, the examination of non-spatial barriers was limited to only two indicators; we did not account for several other potential non-spatial barriers to care. In particular we were not able to measure real or perceived barriers related to costs, either direct or indirect, which are critical for economically disadvantaged and uninsured groups (Glied et al., 2020). Spatial accessibility may be high in disadvantaged communities, but if community members don't know that tests are free, test utilization may still be low, particularly in communities a high proportion of uninsured or underinsured individuals (Rader et al., 2020).

Further analyses are necessary to assess the effect of these real and perceived barriers on COVID-19 testing utilization.

Lastly, accessibility is just one of the components of access and many factors may have a role in testing utilization (Frenk and White, 1992). Improving testing capacity in vulnerable communities should be coupled with strong community engagement (Lash et al., 2020; Clark et al., 2021) and strengthening of the public health infrastructure (Romero et al., 2020; Fields et al., 2021) to support contact tracing and isolation. Moreover, an understanding of whether these spatial accessibility patterns follow racial and economic segregation patterns (Asabor et al., 2022; Torrats-Espinosa, 2021), may also help unpack the consequences of structural racism on the allocation of healthcare resources (Bailey et al., 2017). A more in-depth examination of the efforts in various cities is necessary to understand the observed heterogeneity in inequity and potentially identify successful equity-based strategies.

## 6. Conclusion

We examined inequity in spatial accessibility to COVID-19 testing in 30 of the largest US cities. We found that spatial accessibility to testing vary widely across cities, and that in general accessibility is worse in more vulnerable areas. Despite this general pattern of inequity, several cities had inverted inequity (i.e., better accessibility in more vulnerable areas). This finding indicates that these cities may be on the right track
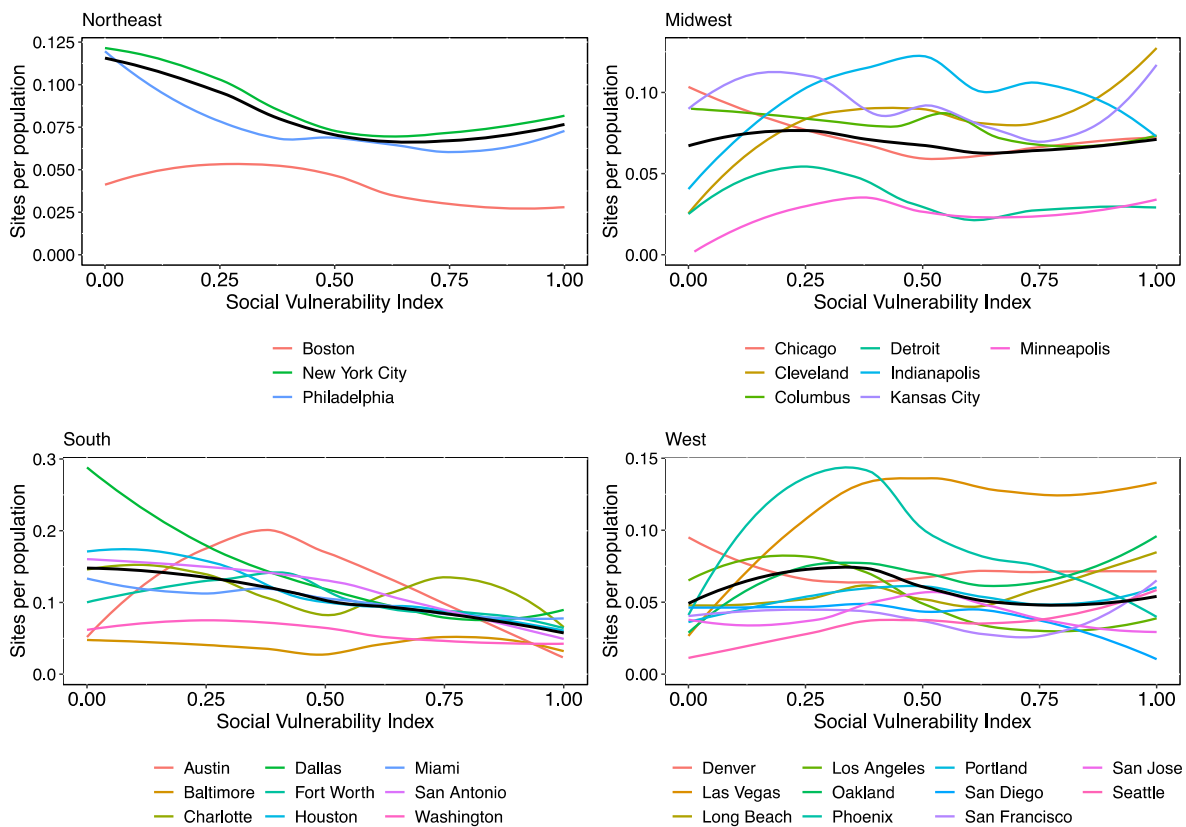
**Fig. 3.** Relationship between sites per 1000 population and social vulnerability in 30 US cities, by census region. **Footnote:** Shown are loess smoothers of spatial accessibility of testing sites on the social vulnerability index. Solid black line represents the loess smoother for the cities in the region.

when it comes to promoting equity in COVID-19 testing. Efforts should be made to improve accessibility to testing in cities, as testing is a key component of the strategy to mitigate the transmission of SARS-CoV-2, particularly as new and more transmissible variants become dominant.

## Data availability

Data on testing sites can be requested from Castlight Health Inc. Other data used in this study are available at https://www.covid-inequities.info.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115307.

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