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Pandemic Injustice: Spatial and Social Distributions of COVID-19 in the US Epicenter

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We examine the uneven social and spatial distributions of COVID-19 and their relationships with indicators of social vulnerability in the U.S. epicenter, New York City (NYC). As of July 17th, 2020, NYC, despite having only 2.5% of the U.S. population, has ∼6% of all confirmed cases, and ∼16% of all deaths, making it a key learning ground for the social dynamics of the disease. Our analysis focuses on the multiple potential social, economic, and demographic drivers of disproportionate impacts in COVID-19 cases and deaths, as well as population rates of testing. Findings show that immediate impacts of COVID-19 largely fall along lines of race and class. Indicators of poverty, race, disability, language isolation, rent burden, unemployment, lack of health insurance, and housing crowding all significantly drive spatial patterns in prevalence of COVID-19 testing, confirmed cases,

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death rates, and severity. Income in particular has a consistent negative relationship with rates of death and disease severity. The largest differences in social vulnerability indicators are also driven by populations of people of color, poverty, housing crowding, and rates of disability. Results highlight the need for targeted responses to address injustice of COVID-19 cases and deaths, importance of recovery strategies that account for differential vulnerability, and provide an analytical approach for advancing research to examine potential similar injustice of COVID-19 in other U.S. cities.

Significance Statement Communities around the world have variable success in mitigating the social impacts of COVID-19, with many urban areas being hit particularly hard. Analysis of social vulnerability to COVID-19 in the NYC, the U.S. national epicenter, shows strongly disproportionate impacts of the pandemic on low income populations and communities of color. Results highlight the class and racial inequities of the coronavirus pandemic in NYC, and the need to unpack the drivers of social vulnerability. To that aim, we provide a replicable framework for examining patterns of uneven social vulnerability to COVID-19- using publicly available data which can be readily applied in other study regions, especially within the U.S.A. This study is important to inform public and policy debate over strategies for short- and long-term responses that address the injustice of disproportionate impacts of COVID-19. Although similar studies examining social vulnerability and equity dimensions of the COVID-19 outbreak in cities across the U.S. have been conducted (Cordes and Castro 2020,Kim and Bostwick 2002,Gaynor and Wilson 2020; Wang *et al.* 2020; Choi and Unwin 2020), this study provides a more comprehensive analysis in NYC that extends previous contributions to use the highest resolution spatial units for data aggregation (ZCTAs). We also include mortality and severity rates as key indicators and provide a replicable framework that draws from the Centers for Disease Control and Prevention's Social Vulnerability indicators for communities in NYC.

Keywords: COVID-19; social justice; New York City; social vulnerability; spatial disparity; impacts.

1. Introduction: Impacts of Covid-19 in New York City and the USA

The first confirmed case of 2019 novel coronavirus (COVID-19) in the U.S. occurred on January 19, 2020 in Snohomish County, Washington. On February 25, 2020, the Centers for Disease Control and Prevention (CDC) issued their first warning to the American public about a local outbreak. A national emergency was declared on March 13, 2020, and by mid-April, the U.S. death toll had reached 20,000; the highest in the world at the time. As the coronavirus pandemic continues to spread, impacts in the United States have been highest in dense urban areas such as San Francisco, Miami, Chicago, Houston, and New York City (Rosenthal 2020; Desai 2020; Rocklöv and Sjödin 2020). New York City (NYC), Figure 1, in particular emerged as a pandemic "vanguard," with the largest number of confirmed cases and deaths in the United States (Angel *et al.* 2020). As other regions and cities across the U.S. face a new wave of COVID-19 cases, the NYC case is particularly instructive for understanding how a major city that

Figure 1. The Five Boroughs of NYC

implemented significant measures to contain the disease nevertheless experienced extreme, and highly socially uneven, incidence of COVID-19 cases, deaths, and disease severity (i.e., the fraction of deaths to positive tests).

This study provides context for NYCs outbreak and immediate social responses, and provides a replicable analytical framework for using widely available 2018 American Community Survey Data in combination with NYC Department of Health and Mental Hygiene (DOHMH) data on COVID-19 impacts (New York State Department of Health 2020a) (available through their Github repository on zip code level disease incidence) in order to examine the spatial distribution of population normalized prevalence and severity of the disease. Building on the

CDCs Social Vulnerability (SV) indicators (Flanagan *et al*. 2011), we examined their relationships with COVID-19 indicators of testing, positive cases, deaths, and severity at the zip code level in NYC. We asked: what is the social distribution of COVID-19 testing and associated indicators of confirmed positive cases, deaths, and disease severity? To answer this question, this study examined the city-wide relationships between SV indicators, tests, prevalence, deaths, and severity. Further analyses provide a robust examination of how areas with high and low disease-related impacts compare and contrast in relation to their SV indicators.

In New York State, the first confirmed case of Covid-19 was documented on March 1, 2020, with the virus found in a 39-year old female healthcare worker living in Manhattan. Within a week, the confirmed cases had risen to 44, with a major outbreak identified in the town of New Rochelle. These early confirmed incidents prompted Governor Andrew Cuomo to declare a state of emergency on March 7, 2020, with NYC to remain on mandatory "P.A.U.S.E" from March 22 until June 8, 2020 (New York State Department of Health 2020b). Current research indicates that COVID-19 was circulating in NYC through community transmission weeks before the first reported case (NYU Langone 2020). At the time of this writing [Late May 2020], there have been 225,045 confirmed cases and 22,845 deaths in NYC, and the city has begun to experience significant declines in daily disease incidence. NYC presently makes up ∼6% of national confirmed cases of, and ∼16% of deaths from COVID-19 (John Hopkins University 2020), despite only having ∼2.5% of the national population, indicating that other cities and states loosening restrictions may have yet to experience their peak infection levels and mortality (Dave *et al.* 2020).

In NYC, both overall incidence and population prevalence of the disease show highly uneven spatial distributions with some populations, neighborhoods, and boroughs being much more severely impacted than others (Figure 1; SI Figures S1–S12). These uneven spatial patterns can be partially explained by existing work on the geography of COVID-19 identifying factors affecting disease prevalence and severity, including population density and age distributions, disease specific factors (e.g., timing of introduction), and social dimensions of the response and reporting mechanisms (CDC COVID-19 Response Team 2020a). Others have found relationships with mortality and susceptibility due to factors such as air pollution (Wu *et al.* 2020). Both media (Evelyn 2020; Kendi 2020; Mays and Newman 2020; Cruz 2020; Godoy and Wood 2020; Schwirtz and Cook 2020) and scholarly (New York City Department of Health and Mental Hygiene 2020; Perry *et al.* 2020; Dorn *et al.* 2020) work report highly uneven patterns of disease incidence, prevalence, and severity among different races, age groups, and income brackets. Here, we expand on these efforts by integrating information on the margins of error (MOE) inherent to the American Community Survey (ACS), allowing for robust testing of statistical significance of differences between the social characteristics of groups experiencing different rates of disease. In addition, other SV criteria besides race, income and age, such as rent burden, health insurance coverage rate, housing vacancy, employment, and others remain underexplored. Our study relies on the indicators proposed by the CDCs SV Index to provide a more comprehensive examination of SV indicators, which highlight consistent patterns of disproportionate COVID-19 impacts, and provide analysis important to contribute to ongoing policy discussions over appropriate responses to the pandemic and analytical approaches for examining other aspects of differential vulnerability and exposure both in NYC and other U.S. cities.

In using the indicators chosen by the CDC to assess SV in the context of emergency management, we frame the first wave of COVID-19 as an *extreme event* (McPhillips *et al.* 2018) fundamentally affecting rates of community transmission throughout the city and severely compromising city-wide resilience and communities' capacity to adapt and respond to, as well as recover from, the ongoing impacts of the pandemic. Additionally, the identification of key vulnerability indicators reveals legacies of social injustice causing some communities to be especially vulnerable to this extreme event. Exploring these patterns in depth could support improvements in ability to target planning and policy decisions to alleviate specific vulnerabilities and thus allow for a more just distribution of resources, both for the current crisis and future pandemics.

2. Materials and Methods

2.1. *Approach*

Data from the ACS 5-year estimates were gathered to develop the 15 SV indicators defined in CDCs SV Index (Centers for Disease Control and Prevention 2020), as well as three additional indicators (availability of health insurance, rent burden, and vacant housing). A Variance Inflation Factor (VIF) analysis was used to remove indicators that showed collinearity, selecting 15 out of the initial 18. SV indicators at the zip code level were joined with data on COVID-19 testing, positive cases, and deaths available at New York City Department of Health and Mental Hygiene's (2020) github data repository. A city-wide analysis was first carried out to explore the magnitude and direction of associations between the SV and the COVID-19 indicators. To incorporate the influence of the MOE attached to ACS data, zip codes were grouped into clusters of low, medium, and high incidence of each COVID-19 indicator. Clusters were then compared by testing the statistical significance of their differences.

2.2. *Data and sample*

2.2.1. ACS data

The most updated 5-year estimates of the ACS (2014–2018) were retrieved at the zip code (zip code) level. The 15 SV indicators developed were originally selected by the CDC to develop its SV Index (Flanagan *et al*. 2018). These 15 indicators are classified in four groups: socioeconomic status, housing composition and disability, minority status and language, and housing type and transportation. Three additional indicators were added to the ones defined by CDC in order to represent access to healthcare (*percent population without health insurance*), a measure of the economic stress induced by housing costs (*percent population experiencing rent burden*), and a coarse indicator of housing availability (*percent vacant housing units*).

Building the indicators required aggregating records from the ACS and calculating their percentages based on total population or household counts. For instance, the indicator *percentage of the total population above 65 years old* was developed by first combining the estimates of female and male individuals across several age brackets higher than 65. During the aggregation of records and the calculation of the percentage over the total population, we relied on the guidelines published by the United States Census Bureau (2018) on handling MOE during calculations (United States Census Bureau 2018).

This study then examined the multicollinearity of the indicators selected using the VIF test to avoid two or more indicators from being linearly related. Some guidelines have set VIF $\geq$ 5 or even higher as a cutoff point to indicate serious multicollinearity (Snee 1973; New York State Department of Health 2020c). We, therefore, considered only 15 indicators that showed VIF values $\leq$ 5 (Table 1) in our further analysis. Examples of indicators with VIF above this threshold include % households with single parents and % of households without a car.

Table 1. Values of Quantile and Geometric Interval Breaks and Differences, Numerically Defined Ranges for each Low, Medium, and High Category are Provided, as is the % Difference Between the Top of the Low Range and the Bottom of the High Grouping (% Diff)

COVID-19 Indicator	Quantile				Geometric Interval			
	Low	Med	High	% Diff	Low	Med	High	% Diff
% Pop. tested	0.00–5.18	5.18–6.72	6.72–15.08	29.7	0.00–6.17	6.17–8.92	8.92–15.08	44.6
% Pop. confirmed cases	0.00–1.57	1.57–2.52	2.52–4.41	60.5	0.00–1.80	1.80–2.61	2.61–4.41	45
% Pop. deceased	0.00–0.12	0.12–0.19	0.19–0.57	58.3	0.00–0.16	0.16–0.35	0.35–0.57	118.8
Estimated severity	0.00–6.70	6.70–9.17	9.17–21.71	36.9	0.00–7.86	7.86–13.86	13.86–21.71	76.3

2.2.2. COVID-19 data

Absolute numbers of COVID-19 laboratory tests, laboratory confirmed cases and deaths in NYC at the zip code level were obtained from the DOHMH on May 19, 2020. These data have been available for NYC since April 1, 2020, with ongoing daily updates as of the time of this paper's preparation, with a single missing day (April 2, 2020). The DOHMH case data are collected in real-time from a combination of state-level records and calls to individual hospitals. Testing totals, positive counts and deaths are assigned to zip codes based on each test subject's residence, with positive counts sourced directly from testing laboratories.

Examining testing is important because the official guidance from the DOHMH, while recommending tests for symptomatic individuals or those with known exposure to other confirmed cases, provides significant physician discretion (New York State Department of Health 2020c). Both testing and confirmed case data therefore are estimates of overall population prevalence using best available knowledge, which may be updated at a later date as new information comes to light (Science reference). In addition to the indicators gathered from the DOHMH repository (tests, positive cases, and deaths), we estimated zip code level severity, by calculating percentage of confirmed cases resulting in deaths, an important metric of disease impact in the absence of more detailed clinical information (Ruan 2020).

Data distributions were examined visually and using Shapiro–Wilks tests for normality, yielding the insight that while tests are roughly normally distributed among zip codes, confirmed cases, deaths, and estimated severity are not, displaying long tails of high-end values. All underlying data described in Sec. 2.2 can be available upon request to the authors.

2.3. *Analysis*

2.3.1. City wide

The non-parametric Spearman correlation was employed to assess the monotonic relationship between our indicators (Spearman 1906). Spearman correlation is an extension of Pearson's product-moment correlation that, unlike Pearson's correlation, does not require normally distributed data in order to examine associations between ranked observations of each indicator, computing statistical significance based on observation order (Borkowf 2002). The lack of a non-normal distribution assumption is particularly necessary here, as most SOVI and COVID-19 indicators exhibit long-tailed distributions (e.g., % Population above 65, % Population uninsured, and % Population unemployed).

2.3.2. Clustering Zip codes based on COVID-19 Indicators

Clustering techniques widely used to detect spatial clustering of high or low values include Getis-Ord Gi * (Hotspot analysis), K-means, and agglomerative clustering. In the case of NYC, complex geometries of zip codes and sharp breaks in COVID-19 indicators between adjacent neighborhoods (Choi and Velasquez 2020) preclude the use of common spatial clustering algorithms. Therefore, two clustering methods were explored based on the non-spatial distributions of COVID-19 indicators, using a standard method of quantile-based grouping in even thirds, and a geometrical interval classification algorithm, to set three clusters of COVID-19 identifying factors (low, medium, and high) (Figure 6). While quantile-based grouping creates evenly sized groups, it may mask differences in highly uneven distributions, whereas geometric interval classification algorithms attempt to maximize differences between even size classes while minimizing the sum of squares of the number of elements in each class and is useful for non-normally distributed data (Arlinghaus and Kerski 2013).

2.3.3. Analysis of SV of COVID-19 clusters

For each of the high, medium, and low groups of zip codes generated for each COVID-19 indicator, we reaggregated their population and calculated their SV indicators. This aggregation allowed for testing the significance in the difference between clusters using the MOEs provided in the ACS estimates. Significance was tested using the guidelines developed by the United States Census Bureau (2018). Including the MOEs in the analysis incorporates the various forms of error within the census estimates themselves, which is critical for testing significance of differences.

3. Results

3.1. *City wide patterns and relationships indicated by correlations*

Relationships between COVID-19 and SV indicators at the zip code level (the highest spatial resolution available) across the city were examined using Spearman ranked order correlations (Figure 2). These correlations provide a broad estimate of the relationships between SV indicators and COVID-19 testing, confirmed positive and mortality rates. Median income appears to dominate the distribution of all COVID-19 indicators, especially for positive cases and death rates (-0.53 and -0.67, respectively). The inverse correlation between income and COVID-19 cases and deaths may be related to accessibility to testing as well as the relatively low incomes of essential workers who kept working during shelter-in-place orders.

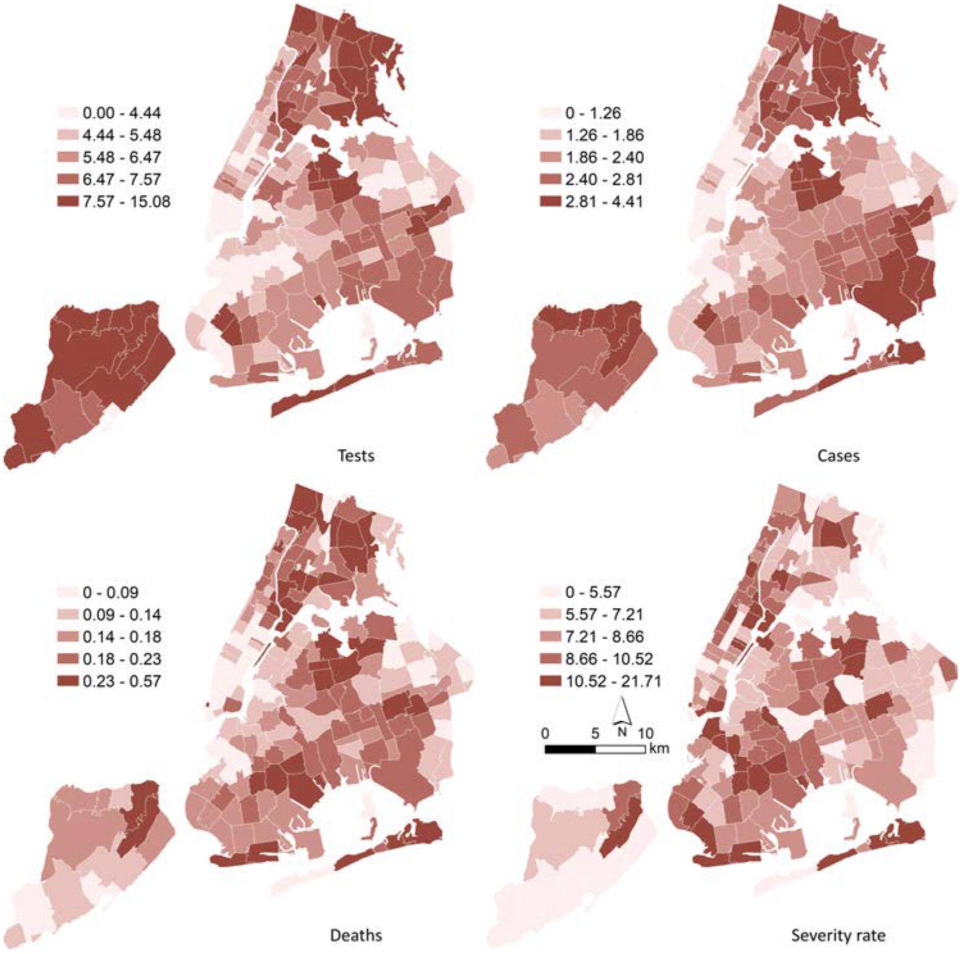

Figure 2. Spatial Variation in Primary Indicators of COVID-19 Testing and Impacts Including % Population Tested (Upper Left), % Population with Confirmed Case (Upper Right), % Population Deceased (Lower Left), and Estimated Severity (Ratio of Deaths to Positive Tests, Bottom Right)

It is also noteworthy that income impacts may actually be wider, since the ACS caps reported values at 250,000 USD.

Testing positive case rates are highly correlated with the percent of population with a disability, with the second strongest positive link with percent of rent burdened population. Percent of population without health insurance is weakly and positively correlated with testing rates (0.19), while exhibiting a stronger positive association with mortality (0.49). Zip codes with higher proportions of people of color (POC) also have strong positive correlations with increased cases (0.57) and death rates (0.53). Death rates also show relatively strong correlations across nearly all SV indicators, with notable exceptions in % multi-unit lots and % population above 65.

The lack of statistically significant links between % population above 65 and COVID-19 indicators in spite of increased severity, including more symptomatic cases (Omori *et al.* 2020) in older populations is notable, and suggests that socio-economic factors other than age alone drive sub-population rates of severity and death. The lack of statistically significant links may be partially explained by the positive relationship between % population above 65 and median income as well as negative correlations with % crowded units and % POC, all of which have strong links to COVID-19 indicators.

Meanwhile, indicators that are usually used nationwide as a measure of urban decay and vulnerability such as percent vacancy are associated here with higher incomes and lower COVID-19 risk. This is consistent with reports of vacant luxury apartments having much lower vacancy rates in low- and medium-income areas (Chen 2019). Overall, these measures of statistical association indicate that the distribution of COVID-19 and SV indicators are uneven, and potentially nonlinear, prompting the need for further evaluation of zip code level associations of COVID-19 indicators and aggregated SV characteristics.

3.2. *Classification of high, medium, and low COVID-19 indicators*

Two different methods were used to examine the high and low prevalence of COVID-19 across neighborhoods in NYC. Zip codes were grouped in quantiles as well as geometric classes to study how COVID-19 impacts are distributed across SV indicators. Quantile-based clustering (Figure 3) shows the broad differences between areas by grouping them into equally sized groups, whereas geometric interval clustering isolates areas with particularly high values (for results of geometric interval analyses see SI Figures S14 and S15). Due to the right skewness of the COVID-19 indicator distributions, particularly in severity and mortality rates, geometric clusters in the high end have both much higher values and fewer associated zip codes than in the quantile classification (Table 2). Notably, zip codes in the high COVID-19 response clusters in both methods have (respectively) 30–45% higher testing rates, 60–45% higher confirmed case rates, 58–119% higher mortality, and 37–76% higher estimated severity (SI Figure S13) than areas in the low category. The focus here is on quantile results in order to emphasize broad differences between zip codes experiencing divergent incidence of disease, and below on more extreme cases identified through geometric clustering.

Spatial distribution of high, medium, and low groupings varies across the different COVID-19 response variables studied. Clusters of tests, cases, and deaths

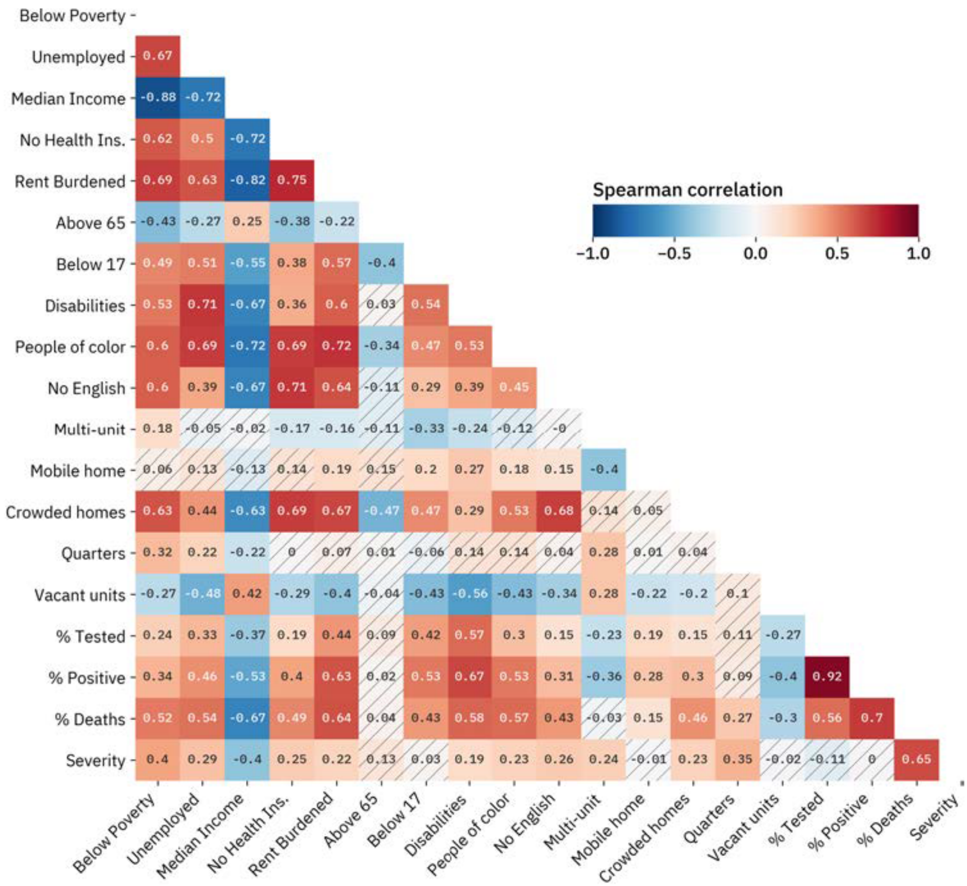

Figure 3. Spearman Correlation Between all SV and COVID-19 Indicators for NYC. Hatched Squares Mark Correlations that are not Statistically Significant ($p > 0.05$)

have a similar distribution, with zip codes in the Bronx, North Queens, North Staten Island, all consistently classified as high. Fewer zip codes in Staten Island are classified as high for deaths than for testing and positive cases, whereas Brooklyn shows the opposite trend. A similar result is observed for the distribution of severity clusters, where a group of neighboring zip codes in Brooklyn is classified as high, while some parts of the Bronx and almost all the zip codes in Staten Island are classified in the low quantile. Eleven zip codes were consistently classified as a high value cluster according to the quantile classification method for tests, cases, deaths, and severity. Of these eleven zip codes, five are in the Bronx (10,469 and 10,475 in Northeast Bronx, 10,463 in Kingsbridge — Riverdale, 10,459 in Hunts Point — Mott Haven, and 10,451 in High Bridge — Morrisania),

Table 2. Summary Statistics for the Selected SV Indicators in NYCs Zip Codes, Arranged in the Different Thematic Groups Defined by CDC with the Addition of Population Without Health Insurance, Rent Burden, and Vacant Housing Indicators

Group	Indicator	Minimum	Maximum	Average	Median
Socioeconomic status	Below poverty[a]	2.05	45.36	16.33	13.70
	Unemployment[a]	0.60	15.76	6.61	6.13
	Median income	21149.00	250001.00	73901.11	66483.00
	Health insurance[a]	0.59	23.82	7.60	6.96
	Rent burden[b]	23.26	76.84	58.84	60.18
Household composition and disability	Above 65[a]	0.46	28.98	14.30	13.56
	Below 17[a]	6.35	36.23	19.93	20.18
	Disability[b]	0.00	40.01	21.69	21.49
Minority status and language	People of color[a]	8.39	99.24	63.52	63.78
	Language isolation[a]	0.08	41.91	10.75	8.25
Housing type	Multi-Unit[a]	0.39	99.68	50.58	51.19
	Mobile homes[a]	0.00	2.08	0.14	0.10
	Crowded households[a]	0.94	29.65	8.29	7.21
	Group quarters[a]	0.00	22.02	2.21	1.12
	Vacant housing[c]	1.68	46.53	9.67	7.86

Notes: All indicators represent percent of the zip code's population [a]occupied households, [b]or available housing units, and [c]except for median income in U.S.$.

three in Queens (11,691 and 11,694 in Rockaway, and 11,369 in West Queens), one in Brooklyn (11,239 in Canarsie — Flatlands), one Manhattan (10,035 in East Harlem), and one in Staten Island (10,304 in Stapleton — St. George). Excluding tests to only examine areas of negative impacts including high confirmed prevalence, deaths, and severity, four additional zip codes stand out (11,203 in East Flatbush — Flatbush, 11,236 in Canarsie — Flatlands, 11432 in Jamaica, and 11,693 in Rockaway) (Figure 4). See SI Table S1 for a zip code and neighborhood correspondence.

3.3. *Differences in underlying SV characteristics by SV dimension*

Our findings definitively show that COVID-19 disproportionately impacts communities with lower incomes and a higher proportion of POC in NYC. Zip codes in the top quantiles of testing, confirmed cases, mortality, and severity all show consistently higher SV as indicated by poverty, unemployment, disability, population under 17, language isolation, rent burden, and housing crowding (Figure 5). The largest SV differences occur in percentage of the population identifying as POC (over 80% in the top third of cases and deaths versus ~55% in the bottom

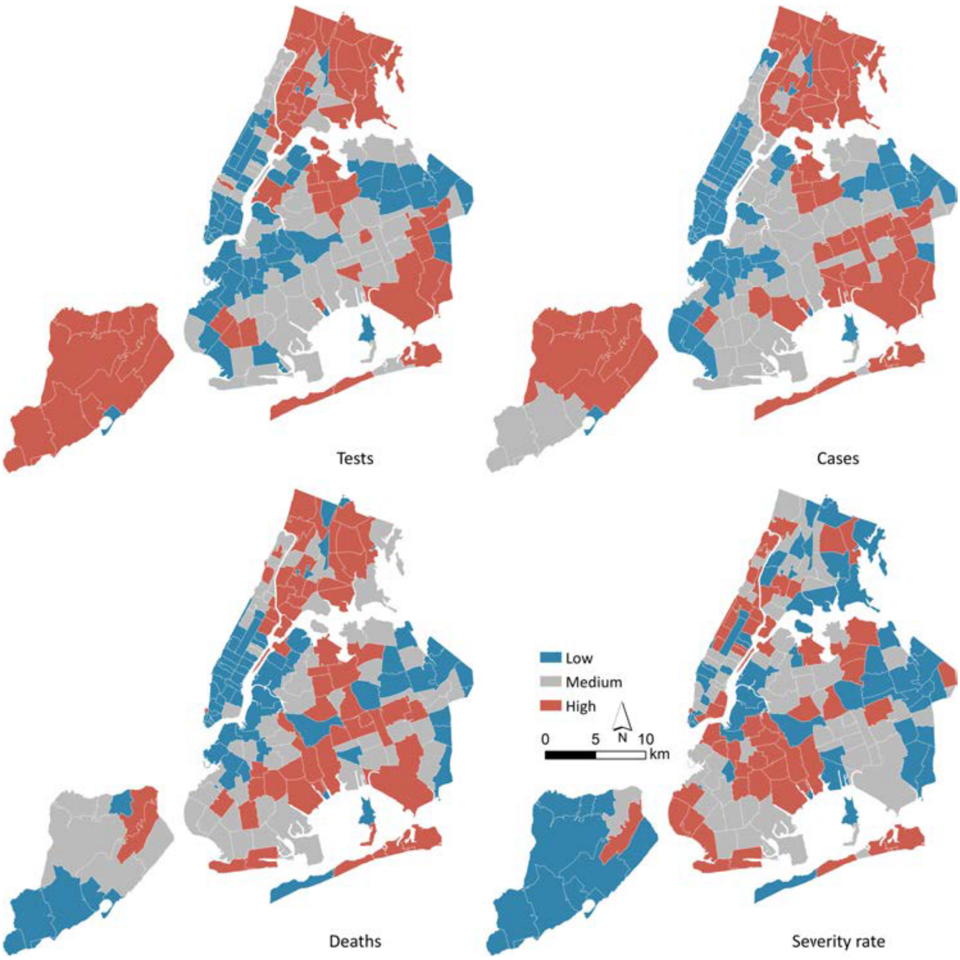

Figure 4. Spatial Distribution of High, Medium, and Low Clusters of COVID-19 Indicators (% Population Tested (upper left), % Population with Confirmed Case (Upper Right), % Population Deceased (Lower Left), and Estimated Severity (Bottom Right)) for Quantile-based Classification of High, Medium, and Low Impact Clusters

third), rent burden (over 70% in the top third of COVID-19 cases and deaths versus 55% in the bottom third), disability rates (∼27% in the top quantiles versus ∼17% in the bottom, for all indicators) and median household income (∼80,000–100,000 in the top quantiles and ∼50–60,000 in the bottom). Income shows a consistent negative significant relationship with rates of death and disease severity, although zip codes with high and medium testing rates and confirmed cases do not have statistically significant differences in median income. Other indicators also show mixed patterns. The percentage of the elderly population (over 65 years old), for

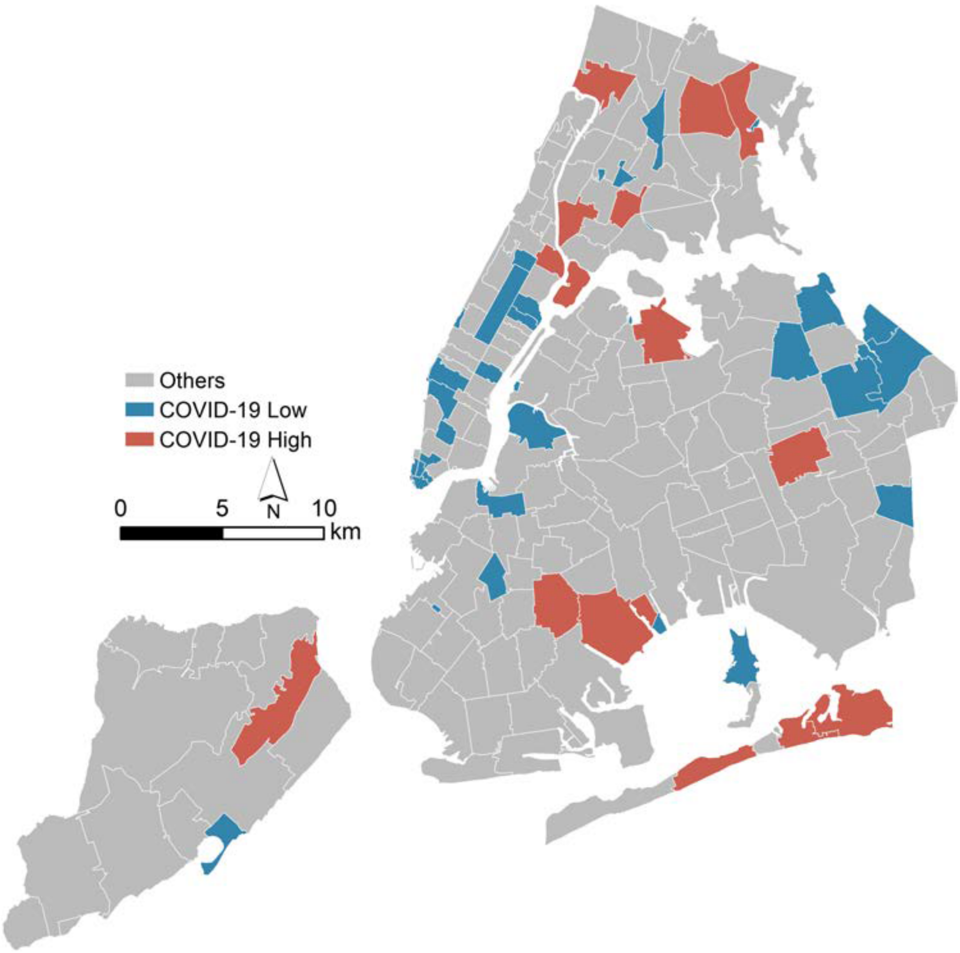

Figure 5. Zip Codes with Consistent Groupings as High and Low Impact Clusters for COVID-19 Cases, Deaths, and Estimated Severity

example, is consistently lower in the top quantiles of tests, cases and deaths, while it is higher in the top quantiles of severity. This is likely related to the lower survival rates that have been observed among the elderly. Housing vacancy rates also showed unexpected results by being considerably higher in zip codes with low COVID-19 impacts.

A closer examination of specific zip codes illustrates the distributional injustices of COVID-19 in NYC. For example, Canarsie-Flatlands (Brooklyn) (zip code 11239) shows the highest percentage of deaths relative to its total population (0.57%). Additionally, this zip code is fourth in severity (15.67%), seventh in percentage of its total population being infected (3.66%) and eighth in percentage

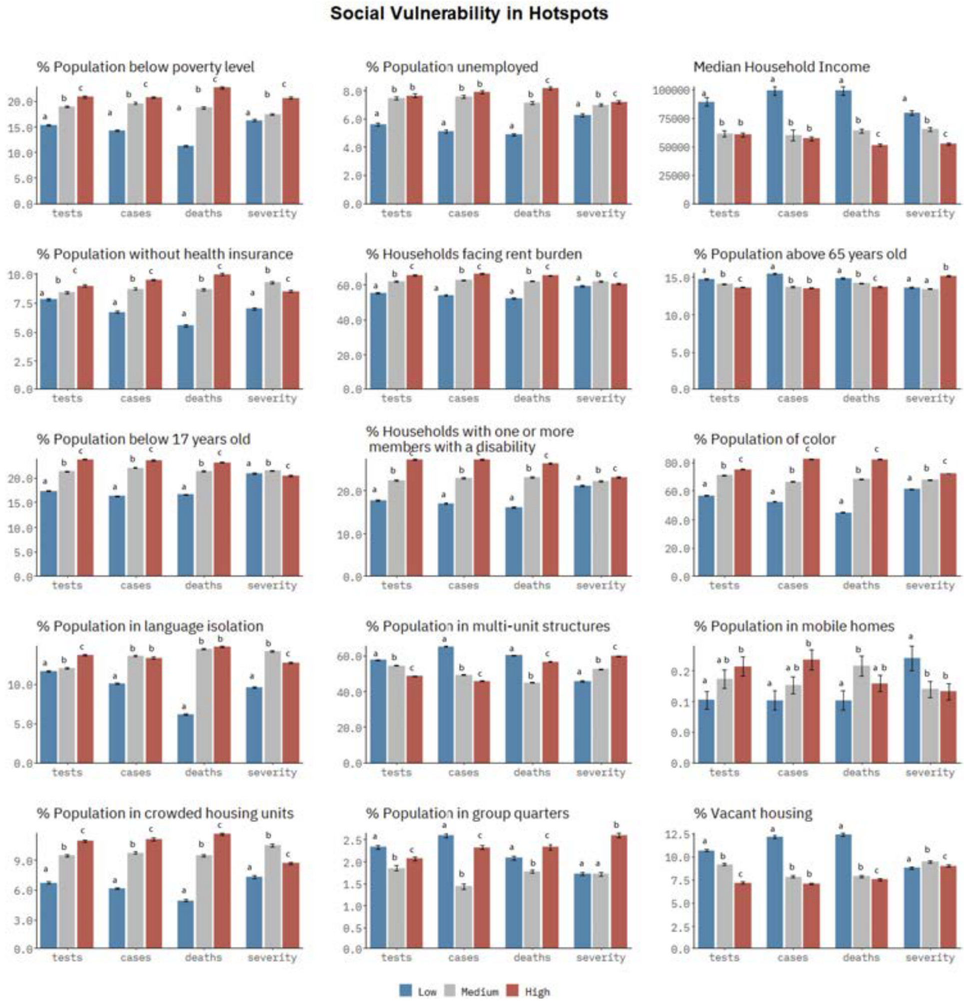

Figure 6. Comparisons of aggregated SV indicator values for quantile based grouping based on four COVID-19 indicators; percent population tested, with confirmed case, and deceased, as well as estimated severity. Bars represent standard error of aggregated ACS 5-year estimates, letters (a, b, c) indicate statistically significant differences of $p < 0.05$, with each letter corresponding to statistically distinguishable groups

of the population tested (9.67%). In this zip code, median annual household income is only \$27,104, 81.2% identifies as POC, and 71.3% of the population is rent burdened. Additionally, 39.4% of the households have at least one person with a disability, and 28.4% of the population lives below the federal poverty line. Hunts Point — Mott Haven (zip code 10459), provides another case in point, with 7.26% of the population (at the time of analysis) tested for COVID-19, 2.95%

confirmed, 0.31% deceased, with resultant estimated severity of 10.53%. Besides a high percentage of POC (98.4%), this zip code has a median income of $27,687. A majority (68.8%) of the population is experiencing rent burden, and 27.9% of its households have one or more people with a disability. Finally, 34% of the population lives below the poverty line, and 18.2% may be experiencing language isolation (For a visualization of the variation per SV indicator across gradients of COVID-19 variables, see SI Figures S12–S19. COVID-19 and SV data may be directly consulted in the supplementary dataset S1 provided).

Grouping zip codes by COVID-19 response indicators using a geometric approach, as opposed to quantiles, reveals important differences for certain indicators, especially death rates and severity. In severity clusters, rates of language isolation range between ∼13–25%, while in the quantiles the values ranged between ∼9–14%. The percentage of people above 65 years old also shows a large increase between the high severity geometric and quantile groups, jumping from ∼15% to ∼20%. Finally, we also observe this change in the percentage of the population living in multi-unit structures, which jumps from ∼60% to ∼78%. These differences are a reflection of the long tailed distributions of most of the COVID-19 response indicators, a hallmark of social unevenness. Since in the geometric approach low and medium clusters contain a larger sample, median income is closer to the city-wide median and hence returns a lower value than in the quantile approach.

4. Discussion

4.1. *Direct impacts of COVID-19 are highly unequal*

Overall, the uneven patterns of COVID-19 highlight the role of SV to the disease in driving health impacts. Vulnerability in the context of a respiratory disease like COVID-19 affects susceptibility, recovery, and exposure, making it a key, if often hidden factor in many epidemiological models of transmission (Michaud *et al.* 2020). SV impacts may also help explain coronavirus disease occurrence at the county level across the U.S. (Chin *et al.* 2020). Many scholars have employed the concept of SV more generally to explain how socioeconomic status, poor access to healthcare, labor inequalities, household overcrowding, racism, and other factors increase the likelihood of adverse outcomes from disease, natural hazards, and inadequate medical care (Cutter *et al.* 2003; Cutter 2020; Link 2008; Drago and Miller 2020; Leclere *et al.* 1994). SV is also employed by the CDC as a key indicator of why certain subsets of the population are more likely to be impacted by disasters, including pandemics, as well as face higher risks of more adverse outcomes (Flanagan *et al.* 2011; CDC COVID-19 Response Team 2020b; DeCaprio *et al*. 2020).

Strikingly, the indicator for elderly populations (percentage of the population older than 65 years old) shows no significant links to any of the COVID-19 variables at the city-scale in spite of documented physiological susceptibility to the virus (Liu *et al.* 2020). However, zip codes with high severity such as those in the Bronx neighborhoods (zip codes within the neighborhoods of Kingsbridge — Riverdale, Hunts Point — Mott Haven and Higbridge — Morrisania) as well as in Jackson Heights in West Queens and the Rockaways area in Southeastern Queens all have significantly higher proportions of elderly than low severity areas (SI Figure S20). The age disparity is widened in areas with the highest severity, as shown in the geometric interval clustering, which may reflect the higher risks reported in elder care facilities (Applegate and Ouslander 2020), as well as the need to examine age-based vulnerability in relation to other risk factors.

The severity hotspot of Kingsbridge — Riverdale, is located in the southern part of Riverdale and shows a higher percentage of POC (68.3%) and population living in poverty (16.6%) than the northern part of the neighborhood (which presents 41.4% and 8.6%, respectively). The Kingsbridge — Riverdale neighborhoods are located along the Hudson River in some of the northernmost points of NYC, and characterized by a relatively low population density, historic homes, and proximity to Van Cortlandt Park and the City of Yonkers. In Hunts Point — Mott Haven, the zip code identified as a severity hotspot has an estimated percentage of POC of 98.4%, and 34.0% of its population live in poverty. It is the zip code within Hunts Point with the highest percentage of people above 65 years old (10.0% versus 7.5% in the zip code with the lowest percentage). Hunts Point is home to several large food distribution centers including Hunts Point Fish Market and Produce Market, resulting in a large volume of traffic and a history of air quality issues that make the neighborhood the third-highest in terms of asthma hospitalization rates among children ages 5 to 14 (New York City Department of Health and Mental Hygiene 2018). The severity hotspots located within Highbridge — Morrisania are home to a high POC percentage (∼98%) and poverty (∼36%). The neighborhoods of Highbridge and Morrisania are located in the southwestern Bronx along the Harlem River, characterized by dense multi-unit buildings. These neighborhoods have some of the highest poverty rates in the City as well as poor health outcomes, including a 34% adult obesity rate. In West Queens, the severity hotspot for identified zip codes has 91.9% of its population as POC, and 15.2% living in poverty. This area is identifiable as the Jackson Heights area located below LaGuardia International Airport and home to some of the most diverse South Asian communities in the U.S. In the Rockaway Peninsula, located in southern

Queens, the zip codes identified as severity hotspots show varying % of POC (between 27% and 90.2%), and poverty (between 9.4% and 24.5%). Located along the Atlantic coastline, the Rockaway Peninsula includes neighborhoods such as Edgemere, Bayswater, Seaside, Rockaway Park, Breezy Point, and the Far Rockaways. These neighborhoods, primarily coastal communities of single family and multi-unit homes, have historically suffered damage from weather events like Hurricane Sandy in 2012. See SI Table S1 for a zip code and neighborhood correspondence.

The largest majority of the zip codes identified as "high" across several COVID-19 indicators in the Bronx are home to some of the poorest congressional districts in the country, and with some of the highest rates of asthma, cardiovascular disease, mental illness, and other chronic health conditions, all risk factors for COVID-19 (NYC Health and Hospitals Corporation 2019). Similar to the Bronx, areas in Queens including the Rockaways and Jackson Heights are home to some of the most diverse communities in the country. However, 18% of residents in the Rockaways and 25% in Jackson Heights are living in poverty according to the City's 2018 Community Health Assessment. Epidemiological studies highlight the effects of environmental health factors that range from poor air quality, access to quality food and green spaces as playing a key role in determining health impacts (Warman *et al.* 2009; New York City Department of Health and Mental Hygiene 2018). The Citizens' Committee for Children of New York for instance, found higher rates of asthma among youth in the Bronx, as well significant rates of heart disease, low birth rate, cancer and metabolic diseases (Citizens' Committee for Children of New York 2013). Environmental justice organizations such as WE ACT, an organization based in Harlem (Northern Manhattan) founded in 1988 to advocate against environmental racism, point to the location of waste transfer stations, bus depots, hazardus waste facilities and large volumes of truck traffic as an environmental justice concern (WE ACT for Environmental Justice, 2017), an example of historical and current structural racism, and may be driving increased SV to COVID-19 in low income and neighborhoods predominantly home to POC (Calcagno 2013).

Our analysis highlights the class and racial inequities of the coronavirus pandemic in NYC, which have significant disproportionate impacts on communities of color and economically precarious communities. The results of our clustering technique and hotspot analysis point to key dimensions of disproportionate impacts, and in particular to racial and ethnic marginalization generally and especially for extreme cases such as language isolation. The inequality of impacts is reflected not just at the zip code level but also the demographics of COVID-19 deaths. For example, Black and Hispanic/Latinos account for 64% of all deaths, while accounting for about half of the total population of NYC (Kendi 2020).

In NYC, issues of poverty, race-based inequity and access to healthcare are pronounced for POC including Latino/a, African American, Black, and low-income communities (Calcagno 2013; Parrot 2019) and have been well described for vulnerability to heat waves, flooding or other extremes (Anguelovski *et al*. 2016). In relation to a pandemic, O'Sullivan and Bourgoin (2010) identify a social gradient of risk related to SV increasing exposure probability linked to living conditions rather than lifestyle choices. This phenomenon can be clearly seen in NYC subway ridership in the early days of the outbreak (SI Figure S21). Consistently, subway ridership in zip codes with lower median income and higher proportions of people below poverty and without health insurance was higher, with ridership reductions ranging from 65% reduction in low income areas to nearly 10‘0% in the wealthiest neighborhoods.

4.2. *Additional considerations*

Although the majority of the CDCs SV indicators were considered throughout our analysis, other aspects of vulnerability may also need to be considered to further improve understanding of prevalence, distribution, and severity of COVID-19 in U.S. cities. For example, factors such as differences in life expectancy (Lamantia 2019), family structure, wealth, and ability to vacate may help explain COVID-19 impacts. Additionally, relationships between labor and housing precarity (Urban Systems Lab 2020), for instance, may require further study, as well as environmental conditions that may impact health outcomes such as poor indoor and outdoor air quality, inadequate access to food, population density, and intergenerational cohabitation rates, or uneven access to greenspace (important for social distancing and mental and physical health).

The varied responses to the COVID-19 crisis are also a critical component to consider. In New York State and around the region, there was little consistency in shelter-in-place and social distancing policies at the federal, state and local level. This variability in responses may have played a critical role in health and economic impacts, especially for those most vulnerable. Furthermore, labor force characteristics may also have contributed to COVID-19 vulnerability. For example, according to the U.S. Bureau of Labor Statistics (2018), people identifying as Black and Hispanic are more likely to be employed in services occupations (healthcare support, food preparation and serving, building cleaning, and personal care) and in production, transportation, and material moving occupations, than self-identified Whites or Asians. Thus, POC are more likely to be employed in essential service industries with increased risk of exposure to COVID-19.

Daily updates of available COVID-19 data imply potential lags in reporting of the tests, positive cases and deaths that happened the previous days due to delays in the testing and reporting processes. Moreover, the CDC's framework for assessing SV may not be comprehensive in some respects, especially for urban areas. Additionally, we found high correlation between some SV indicators, including high VIF values for some of CDCs indicators used, which were subsequently removed from analysis. It is not surprising that many SV indicators are strongly correlated with one another, given that vulnerability is often compounding and intersectional. Sadly, it has been understood for quite some time that persistent racism has extreme impacts on health and well-being of POC in America, through intersecting factors affecting economic opportunities, uneven patterns of policing, access to quality housing, health insurance, and likelihood of experiencing poverty, along with other stress factors (Rothstein 2017; Harrell 2000). Such intersections of different kinds of vulnerability highlight that SV does not occur in a vacuum, rather it is produced in particular contexts by entrenched modes of decision-making and broader patterns of urban governance (O'Brien *et al.* 2007). Paying attention to the social forces producing vulnerability, rather than simply taking indicators at face value, is important in order to avoid framings of resilience that obscure, rather than illuminate the underlying social drivers requiring resilience to hazards with uneven social distributions (Kaika 2017).

5. Conclusion

The disproportionate impacts of the first wave of the Covid-19 pandemic in NYC serve as a warning and a lesson for other cities weighing their own responses to the ongoing crisis. As the pandemic continues to evolve, other U.S. cities urgently require targeted responses to protect their most vulnerable communities and prevent widespread community transmission. It is clear that underlying health disparities resulting from persistent environmental and social injustice calls for their consideration in responses seeking to contain the virus, as well as economic and social support for disproportionately impacted communities. Results of this study help make visible how decades of uneven investment in cities, disparities in access to education, affordable food, housing, and healthcare, and disproportionate economic impacts among other factors (Parrott and Moe 2020), which lead to SV, are also strongly related to disproportionate impacts of COVID-19, especially on low-income and POC populations. These social, economic and health issues are intimately linked to community resilience and reflect a long history of racism and equity issues that have laid the groundwork for a lack of preparedness across city, state and Federal scales (Wallace and Wallace 1997). As cities come to terms with the full extent of the coronavirus crisis, it will be important to undertake a deeper examination of how structural injustices and systemic racism have impacted, and may continue to impact, key decision making, emergency planning and response, and further drive increased (or decreased) SV to impacts of COVID-19.

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