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Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs. ZIP code analyses

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Abstract

No national, state, or local public health monitoring data in the US currently exist regarding the unequal economic and social burden of COVID-19. To address this gap, we draw on methods of the Public Health Disparities Geocoding Project, whereby we merge county-level cumulative death counts with population counts and area-based socioeconomic measures (ABSMs: % below poverty, % crowding, and % population of color, and the Index of Concentration at the Extremes) and compute rates, rate differences, and rate ratios by category of county-level ABSMs. To illustrate the performance of the method at finer levels of geographic aggregation, we analyze data on (a) confirmed cases in Illinois ZIP codes and (b) positive test results in New York City ZIP codes with ZIP code level ABSMs. We detect stark gradients though complex gradients in COVID-19 deaths by county-level ABSMs, with dramatically increased risk of death observed among residents of the most disadvantaged counties. Monotonic socioeconomic gradients in Illinois confirmed cases and New York City positive tests by ZIP code level ABSMs were also observed. We recommend that public health departments use these straightforward cost-effective methods to report on social inequities in COVID-19 outcomes to provide an evidence base for policy and resource allocation.

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ABSTRACT

No national, state, or local public health monitoring data in the US currently exist regarding the unequal economic and social burden of COVID-19. To address this gap, we draw on methods of the Public Health Disparities Geocoding Project, whereby we merge county-level cumulative death counts with population counts and area-based socioeconomic measures (ABSMs: % below poverty, % crowding, and % population of color, and the Index of Concentration at the Extremes) and compute rates, rate differences, and rate ratios by category of county-level ABSMs. To illustrate the performance of the method at finer levels of geographic aggregation, we analyze data on (a) confirmed cases in Illinois ZIP codes and (b) positive test results in New York City ZIP codes with ZIP code level ABSMs. We detect stark gradients though complex gradients in COVID-19 deaths by county-level ABSMs, with dramatically increased risk of death observed among residents of the most disadvantaged counties. Monotonic socioeconomic gradients in Illinois confirmed cases and New York City positive tests by ZIP code level ABSMs were also observed. We recommend that public health departments use these straightforward cost-effective methods to report on social inequities in COVID-19 outcomes to provide an evidence base for policy and resource allocation.

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INTRODUCTION

As communities in the United States (US) grapple with the COVID-19 pandemic, there is an urgent need for real-time data to better understand how particular populations are affected, including who is most at risk of infection, developing serious illness, and dying [1-2]. Informed by an awareness of the critical importance of racial/ethnic, economic, and gender inequalities in shaping individuals' exposure to and ability to protect themselves from SARS-CoV-2, as well as their ability to practice physical distancing, maintain economic wellbeing, and access appropriate healthcare when sick, there have been increasing calls for improved data to provide an evidence-base for action [1-4]. Descriptive epidemiology, which is vital to informing efforts to distribute resources, develop treatments, and coordinate public policy, is hampered by the paucity of disaggregated data by important social variables like race/ethnicity and socioeconomic position in the data reported by public health departments. For example, data from the COVID-19 tracking project [5] suggests that only ~21 states currently report COVID-19 cases or deaths disaggregated by race/ethnicity, and among those that do, substantial proportions (typically ≥50%) of cases and deaths are of unknown or missing race/ethnicity. Data tables on the US Centers for Disease Control and Prevention's own webpage reporting COVID-19 cases by race/ethnicity show upwards of 65% of reported cases with missing race/ethnicity information [6]. Furthermore, to our knowledge, no states are reporting COVID-19 cases or deaths by measures of individual socioeconomic position, though US death certificates routinely collect information on decedent's education [1-2, 7].

The Public Health Disparities Geocoding Project was established to address the absence of socioeconomic data in most routinely collected public health surveillance data [8-12]. By geocoding health records and linking them to US Census-derived data on neighborhood socioeconomic variables, we have shown that these methods can be used to compute valid estimates of socioeconomic gradients in health and, moreover, that area-based socioeconomic measures (ABSMs) can be used to characterize the influence of neighborhood socioeconomic context on health above and beyond their association with individual socioeconomic position. We have applied these techniques to a wide range of health outcomes, from birth to death and including cancer and infectious diseases, and have shown that the resulting estimates of socioeconomic gradients are valid and robust. The series of papers [8-12] stemming from this project have been cited over 3500 times and have had a demonstrable impact on US public health surveillance systems and health research more generally.

To respond to the urgent need in the United States for documentation of stark social inequities in who is affected by the COVID-19 pandemic, in this paper we quantify disparities in COVID-19 death rate in the US by county level sociodemographic attributes using currently available surveillance and US Census data. To illustrate the performance of these methods at finer levels of geographic aggregation, we additionally analyze data on (a) cumulative incidence of confirmed cases in Illinois ZIP codes and (b) cumulative incidence of positive test results in New York City ZIP codes with ZIP code level ABSMs. Our intention is to illustrate how state and local health departments can easily implement these types of analyses, using freely available US Census data, and provide tabular and graphic summaries of these social inequities to contribute to discussions on policies and interventions. In the discussion, we also discuss interpretation of these social inequities given limitations of the data and make recommendations for how public health departments can readily incorporate area-based socioeconomic measures into surveillance and monitoring.

METHODS

COVID-19 Data Sources

US county death data: We obtained publicly available data on COVID-19 deaths at the county level from the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) [13] and USA Facts [14]. Both sources report time series of cumulative confirmed cases and deaths, but notably, JHU CSSE reports a single entry for all of New York City, aggregating over the five counties corresponding to the city boroughs. Because this aggregation obscures substantial differences by boroughs (for example, death rates by borough were 128.3 per 100,000 in the Bronx, 108.1 per 100,000 in Brooklyn, 119.8 per 100,000 in Queens, 65.5 per 100,000 in Manhattan, and 87.1 per 100,000 in Staten Island), we used the USA Facts county dataset, which maintains separate reporting for New York counties. Differences were observed between JHU CSSE and USA Facts death counts on April 16, 2020 for 241 out of 2,717 matched counties, with discrepancies exceeding ± 10 deaths for only 21 counties. Unmatched entries in the USA Facts datasets consisted of 421 counties with 0 deaths that did not appear in the JHU CSSE dataset, with the exception of a single death in Nantucket County, MA. Conversely, 56 unmatched entries in the JHU CSSE dataset consisted of 50 entries (298 deaths in 50 states) with "county unassigned", plus 2 entries for 152 deaths on cruise ships, and four entries for US territories (Guam, Northern Mariana Islands, Puerto Rico, and US Virgin Islands, 64 deaths). Our analytic sample consisted of 30,318 COVID-19 deaths reported in 3,144 US counties (excluding territories) as of April 16, 2020. We additionally present analyses of US COVID-19 cases as of April 16, 2020 by county characteristics in the Supplemental Appendix.

Illinois data on confirmed cases at the zip code level: We obtained ZIP code tabulation area (ZCTA) level data on confirmed cases in Illinois from the lookup tool developed by the Illinois Department of Public Health and the Chicago Reporter [15]. ZCTAs are US Census defined geographic units that correspond to areas roughly covered by US Postal Service (USPS) ZIP codes [16]. While there is not always a one-to-one correspondence between ZCTAs and USPS ZIP codes, the US Census ZCTAs provide a basis for linking sociodemographic and economic variables from the US Census American Community Survey to health records geocoded at the ZIP code level. As noted by the Illinois data source, infections among incarcerated populations are not fully represented in these data, including Cook County Jail (60608) and Stateville Correctional Center (60403), and possibly other ZIP codes. Illinois also reported data suppression for ZIP codes with <6 confirmed cases. Our analytic sample thus consisted of 24,675 confirmed cases reported in 372 Illinois ZCTAs as of April 16, 2020.

New York City data on positive tests at the zip code level: We obtained ZCTA-level data on positive tests in New York City from the New York City Department of Health and Mental Hygiene's COVID-19 GitHub repository [17]. Our analytic sample consisted of 125,422 positive tests reported in New York City 177 ZCTAs as of April 16, 2020.

Population denominator and area attributes data

We extracted county and ZCTA level population counts and sociodemographic attributes from the American Community Survey (ACS) 2014-2018 five-year estimates [18] using the tidycensus package in R [19]. ABSMs included: % of persons below poverty, % household crowding, and % population of color (defined as the proportion of population who are *not* White

Non-Hispanic), and a measure of racialized economic segregation, using the Index of Concentration at the Extremes [20]. This measure captures the extent to which the population in a given area is concentrated at either extreme of a social metric and ranges from -1 (everyone in the worst category) to 1 (everyone in the best category). For our analyses, we set the extremes for this ICE as: (a) high-income White population, versus (b) low-income Black population [20]. For analysis purposes, we defined categories of ABSMs using *a priori* cutpoints for % below poverty (0-4.9%, 5-9.9%, 10-14.9%, 15-19.9%, and 20-100%) and quintile cutpoints based on the distribution of county-level attributes in the US (county-level death analysis) or the distribution of ZCTA attributes within Illinois and New York City (ZCTA level analyses of confirmed cases and positive tests, respectively). Definitions, source variables from the ACS, and categorical cutpoints are presented in Table 1.

Statistical Methods

Drawing on the methods of the Public Health Disparities Geocoding Project [10], we merged cumulative counts of confirmed cases, positive tests, and deaths at the reported level of geography with population denominators and ABSMs. We then aggregated over areas within defined categories as described above. Since no data source currently reports disaggregated data by age and county or ZCTA, we computed crude outcome rates per 100,000 by ABSM categories rather than age-standardized rates. To quantify absolute and relative disparities, we computed rate differences and rate ratios setting the reference category to the socially most advantaged groups. We note that we use the term “death rate” in the county-level analysis to refer to cumulative deaths per 100,000 population (technically a cumulative incidence proportion); this quantity is distinct from the case fatality rate or infection fatality rate. Similarly, the rate of positive tests in the NYC ZCTA analysis is computed as the number of positive tests per 100,000 population (a cumulative incidence proportion) rather than positive tests as a proportion of all tests.

RESULTS

County level COVID-19 death in the US

As shown in Figures 1a-1d and Table 2, the highest COVID-19 death rates were consistently observed among those living in the most disadvantaged versus most advantaged counties in relation to: % poverty (19.3 per 100,000 vs. 9.9 per 100,000); the Index of Concentration at the Extremes for racialized economic segregation (15.0 per 100,000 vs. 13.8 per 100,000); % crowding (16.8 per 100,000 vs. 4.9 per 100,000); and % population of color (17.1 per 100,000 vs. 2.9 per 100,000). The gradient is particularly stark for % population of color, whereby populations living in counties where 61-100% of the population is of color experienced a COVID-19 death rate 6-fold greater than those living in counties where 0-17.2% of the population is of color. However, socioeconomic gradients were not always monotonic, most notably for the Index of Concentration at the Extremes, for which residents of counties in the most advantaged quintile experienced a COVID-19 death rate (13.8 per 100,000) only slightly lower than residents of counties in the lowest quintile. In contrast, residents of counties in the middle quintile of the Index of Concentration of the Extremes experienced the lowest COVID-19 death rates (3.9 per 100,000).

ZCTA level confirmed COVID-19 cases in Illinois

As shown in Figures 2a-d and Table 3, we observed consistent and monotonic socioeconomic gradients in cumulative incidence of COVID-19 diagnoses for all ABSMs using finer resolution

ZCTA-level data in Illinois. The highest rates of COVID-19 confirmed cases were observed among the most disadvantaged compared to most advantaged categories of % poverty (367.7 per 100,000 vs. 155.3 per 100,000), Index of Concentration at the Extremes (438.3 per 100,000 vs. 155.4 per 100,000), % crowding (314.4 per 100,000 vs. 173.0 per 100,000), and % population of color (447.0 per 100,000 vs. 127.8 per 100,000). The steepest gradient was observed by quintiles of % population of color, with residents of ZCTAs in the highest quintile experiencing a rate 3.5 times that of residents in the lowest quintile.

ZCTA level positive COVID-19 tests in New York City

Similarly strong socioeconomic gradients were observed with finer resolution ZCTA-level data in New York City in relation to the rate of positive tests. These unequal patterns persist even in the context of New York City's substantially greater rates of infection. The population rate of positive COVID-19 tests was highest among residents in the most disadvantaged vs. most advantaged categories of the Index of Concentration at the Extremes (1603.6 per 100,000 vs. 1067.5 per 100,000), % crowding (1699.0 per 100,000 vs. 1219.4 per 100,000), and % population of color (1771.5 per 100,000 vs. 1248.6 per 100,000). Similarly, the highest rate of positive tests was observed among residents living in counties in the two most disadvantaged categories of ZCTA-level poverty (15-19.9% poverty: 1553.0 per 100,000 and 20-100% poverty: 1504.3 per 100,000, vs. 1046.7 per 100,000 in the most advantaged category, 0-4.9% poverty). These contrasts correspond to relative risks between 1.31 and 1.42.

DISCUSSION

The unequal burden of COVID-19

Linkage of available COVID-19 surveillance data to ABSMs at the county and ZIP code levels reveals a substantially unequal burden of COVID-19 outcomes experienced by people living in the most disadvantaged counties and ZCTAs by socioeconomic and sociodemographic characteristics. These strikingly inequitable patterns of disease burden, heretofore obscured by the lack of disaggregated reporting by race/ethnicity and socioeconomic position in publicly available US COVID-19 surveillance data, speak to the urgent need for improved testing, surveillance and monitoring, data transparency, and targeting of public health interventions for community protection and health care resources.

Looking across the US, people living in the most impoverished, crowded, and racially and economically polarized counties are experiencing substantially elevated rates of COVID-19 infection and death. We chose to focus our main analysis on COVID-19 death at the county level because this is the geographic level at which comprehensive data on COVID-19 for all parts of the US are being reported. We focus on death in particular because, unlike confirmed case counts, these numbers are less likely to be affected by well-documented inconsistencies in testing eligibility, procedures, and availability [21-22]. (We do, however, include a county-level analysis of COVID-19 cases in Supplemental Appendix 1). Reported deaths due to COVID-19 nonetheless may not capture the potentially large burden of mortality due to unexplained deaths among individuals who were not tested for SARS-CoV-2, who might have died at home or in nursing facilities, or who might have died of a pre-existing condition whose disease course was exacerbated by coronavirus infection [23-25]. If individuals living in disadvantaged counties were less likely to have been tested for SARS-CoV-2, to have accessed healthcare given infection, or generally less likely to have had their death recorded as COVID-19 related, we would expect that our analyses underestimated the magnitude of inequities across categories of ABSMs.

In spite of these data limitations, we saw strong associations of COVID-19 death rates with all four county-level ABSMs. These inequities are fundamentally related to the material circumstances in which people live and work. For example, individuals living in low income areas may be more likely to be classified as "essential workers" who are less able to practice physical distancing and may not have access to personal protective equipment (PPE) [1-3, 26-27]. "Essential workers" also include many healthcare professionals including nurses, home health aides, and nursing home employees whose risk of occupational exposure to SARS-CoV-2 is high and who live in working class communities [28-30]. Moreover, we noted a strong association with county % crowding, defined as the proportion of households in an area with more than one person per room (excluding bathrooms and kitchens) [31]; by this definition, a one-bedroom apartment with 1 bedroom, 1 dining room, and 1 living room would be categorized as crowded only if 4 or more persons were in the household.

Socioeconomic gradients in COVID-19 death rates by county poverty and the Index of Concentration at the Extremes exhibited more complex patterns. This likely reflects the contribution of particularly large counties with high levels of transmission. Depending on the stratum of county-level ABSM in which it falls, a county with a large number of deaths will tend to dominate the computed rate for that stratum. Table 5 shows the top 25 counties by cumulative count of deaths, along with population and ABSM estimates. These counties include all five boroughs of New York City as well as surrounding areas with high death counts in New York state, New Jersey, and Connecticut. The list also includes other large US urban areas with substantial transmission. Together, these 25 counties account for over 53% of reported COVID-19 deaths in the US. Examination of this list suggests that the higher death rates observed in the 5-9.9% category of county poverty and the most advantaged quintile of the Index of Concentration at the Extremes reflects the contribution of counties like Nassau, Suffolk, Westchester, and New York (Manhattan) Counties, NY to these strata. It is also important to note that county-level analyses gloss over important socioeconomic heterogeneity within counties, which may further contribute to the more complex socioeconomic gradients seen here. Also potentially relevant are changing class dynamics of COVID-19 infections, whereby early cases may have arisen from travelers who could afford international travel, followed by increased risk among essential workers and working class communities with crowded housing.

ZIP code level analyses

To illustrate the utility of using finer levels of geography, we additionally presented analyses of confirmed COVID-19 cases in Illinois and positive tests in New York City in the ZCTA level, the only two COVID-19 outcomes for which ZCTA-level data were available in these localities. ZCTA-level analyses revealed more consistently monotonic gradients for all ABSMs, though the magnitude of disparities comparing the top to the bottom socioeconomic categories was smaller on the relative disparity scale. Together, these results suggest that analyzing inequities in COVID-19 outcomes at finer levels of geographic aggregation is feasible and can provide important information about the unequal spread and impact of COVID-19 within counties and cities. As with the county-level death analysis, the results suggest that areas with higher rates of poverty, crowded housing, and populations of color are being disproportionately affected. Moreover, given unequal patterns of testing, if residents of these neighborhoods are not able to access testing, these results may be understanding the true magnitude of inequities in COVID-19 infection.

Recommendations for public health departments

The results we have presented reaffirm the urgency of documenting how historically disadvantaged communities are being unequally affected by the devastation of the COVID-19 pandemic. In the absence of national leadership and in the wake of chronic underfunding of public health infrastructure, state and local health departments have been left to fend for themselves in fulfilling the vital functions of public health surveillance in providing an evidence base for action and ensuring accountability [1-2]. The methods of the Public Health Disparities Geocoding Project [8-12] provide a well-validated, robust, and cost-effective methodology by which public health departments can enhance their reporting of disparities in COVID-19 outcomes.

Based on the analyses we have presented here, we recommend that state and local public health departments adopt reporting of COVID-19 outcomes minimally by ZCTA-level characteristics, which we consider preferable to county-level reporting. In our earlier work, we originally recommended routine reporting by socioeconomic characteristics of census tracts [10,16]. While we stand by that recommendation, we recognize that it may be more feasible for surveillance systems to implement ZCTA-level analyses in the short term, since ZIP code is easy to ask of individuals as they are being tested, is already recorded on death certificates, and does not require additional steps for geocoding, compared to census tracts [1]. We emphasize that reporting of disparities by ZCTA characteristics need not entail risk of individual data disclosure due to small numbers in small areas: because our methodology involves aggregating over

ZCTAs with similar socioeconomic characteristics, summary statistics are reported for aggregations of ZCTAs and typically have large enough numbers not to require data suppression [24]. Because of this, we additionally recommend that, whenever possible, public health departments report summary statistics by race/ethnicity, gender, and age within strata of ZCTA-level ABSMs in order to paint a fuller picture of the extent of inequities in COVID-19 outcomes. To assist public health departments who wish to implement these types of analyses, we direct interested readers to the Public Health Disparities Geocoding Project website at http://www.hsph.harvard.edu/thegeocodingproject/.

Statistical considerations

Aggregation over areas is analogous to how state and local health departments typically report disease rates by sex and race/ethnicity and avoids problems with statistical instability in the estimation of small area rates at the county and ZCTA levels by essentially assuming that populations within strata of ABSMs have a common disease experience. While marginalizing over disease counts and population at risk may obscure meaningful area differences important to questions of disease etiology or, in the case of COVID-19, infectious disease transmission dynamics, we maintain that cumulative incidence proportions computed for strata of ABSMs still provide an important description of what populations are impacted by COVID-19 and where disease burdens are most substantial.

The analyses we have presented here can be easily implemented by state and local health departments using existing surveillance data and an Excel spreadsheet or similar software. We argue that these simple descriptive analyses of inequities are vital to identifying the communities who are experiencing the most serious impacts of the pandemic and to holding government leaders and policy makers accountable for directing resources to those in need. Throughout, we have presented confidence limits based on traditional formulas for the variance of an incidence rate [25], which assumes that the count of events is Poisson distributed and arises from a homogenous pool of person-time. Given county variation in SARS-CoV-2 transmission dynamics (including when infected cases were seeded in these communities and how the pace of transmission has been affected by containment and mitigation strategies) as well as variation in the susceptibility of populations in these counties above and beyond what is explained by the area-based socioeconomic measures considered here, the assumption of homogeneity is likely unrealistic. More sophisticated statistical models can be employed to model area-level variation in rates, including overdispersed Poisson, negative binomial, mixed models, and zero-inflated models [26-28]. In our experience, however, estimates of socioeconomic inequities can be sensitive to the modelling approach taken, and the interpretation of summary measures of health disparities at the population level may be complicated by model assumptions. Even when there are variations in area-level rates within strata of ABSMs, estimates from the aggregated method still have relevant interpretation as the "average" health experience of persons living in areas with particular socioeconomic characteristics. While our future work will address small-area estimation and appropriate models for handling spatial heterogeneity in COVID-19 outcomes, we should not lose sight of the immediate need for timely data on economic and social inequities to inform policy and interventions.

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Table 1: Population counts and area based socioeconomic measures, source variables, and cutpoints computed from the 2014-2018 American Community Survey 5-year estimates

Variable	**Formula: Source Variables**	**US County Cutpoints**	**ZCTA cutpoints (Illinois)**	**ZCTA cutpoints (NYC)**
Population Counts				
Total population	B01003_001E			
White Non-Hispanic Population	B01001H_001E			
Area-based socioeconomic measures				
% of persons below poverty	B17001_002E/B17001_001E	0-4.9% 5-9.9% 10-14.9% 15-19.9% 20-100%	0-4.9% 5-9.9% 10-14.9% 15-19.9% 20-100%	0-4.9% 5-9.9% 10-14.9% 15-19.9% 20-100%
Index of Concentration at the Extremes (high income white households versus low income black households)	((B19001A_014E + B19001A_015E + B19001A_016E + B19001A_017E) - (B19001B_002E + B19001B_003E + B19001B_004E + B19001B_005E))/B19001_001E,	Q1: (-0.522,0.114] Q2: (0.114,0.159] Q3: (0.159,0.205] Q4: (0.205,0.283] Q5: (0.283,0.536]	Q1: (-0.612,0.0175] Q2: (0.0175,0.171] Q3: (0.171,0.289] Q4: (0.289,0.403] Q(5: 0.403,0.721]	Q1: (-0.385,-0.102] Q2: (-0.102,0.0212] Q3: (0.0212,0.141] Q4: (0.141,0.29] Q5: (0.29,0.7]
% crowding (>1 person per room)	(B25014_005E + B25014_006E + B25014_007E + B25014_011E + B25014_012E + B25014_013E) / B25014_001E	Q1: (0,0.0147] Q2: (0.0147,0.0212] Q3: (0.0212,0.0306] Q4: (0.0306,0.0491] Q5: (0.0491,0.493]	Q1: (0,0.00975] Q2:(0.00975,0.0177] Q3:(0.0177,0.0274] Q4: (0.0274,0.0472] Q5: (0.0472,0.143]	Q1:(0.00942,0.0478] Q2: (0.0478,0.0698] Q3: (0.0698,0.0978] Q4: (0.0978,0.138] Q5: (0.138,0.297]
% population of color (not White Non-Hispanic)	B01003_001E - B01001H_001E)/ B01003_001E	Q1: (0,0.172] Q2: (0.172,0.302] Q3: (0.302,0.443] Q4: (0.443,0.61] Q5: (0.61,1]	Q1: (0.0318,0.197] Q2:c(0.197,0.315] Q3: (0.315,0.46] Q4: (0.46,0.744] Q5: (0.744,0.99]	Q1: (0.0839,0.402] Q2: (0.402,0.584] Q3: (0.584,0.826] Q4: (0.826,0.957] Q5: (0.957,0.992]

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Table 2: US COVID-19 death rate per 100,000 by county characteristics as of 4/16/2020

	Number of counties	Number of deaths	Population	Death rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	41	443	4,495,932	9.9	(8.9	,10.8)	0.0	(reference)		1.00	(reference)	
5-9.9%	558	7,877	71,157,744	11.1	(10.8	,11.3)	1.2	(0.3	,2.2)	1.12	(1.02	,1.24)
10-14.9%	1,023	8,031	108,820,591	7.4	(7.2	,7.5)	-2.5	(-3.4	,-1.5)	0.75	(0.68	,0.82)
15-19.9%	860	6,654	101,961,251	6.5	(6.4	,6.7)	-3.3	(-4.3	,-2.4)	0.66	(0.60	,0.73)
20-100%	659	7,034	36,428,205	19.3	(18.9	,19.8)	9.5	(8.4	,10.5)	1.96	(1.78	,2.16)
missing		279										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-0.522,0.114]	974	9,314	61,949,063	15.0	(14.7	,15.3)	1.3	(0.8	,1.7)	1.09	(1.06	,1.12)
(0.114,0.159]	701	4,941	64,942,197	7.6	(7.4	,7.8)	-6.2	(-6.5	,-5.8)	0.55	(0.53	,0.57)
(0.159,0.205]	696	2,564	65,113,354	3.9	(3.8	,4.1)	-9.8	(-10.2	,-9.5)	0.29	(0.27	,0.30)
(0.205,0.283]	515	4,082	64,525,801	6.3	(6.1	,6.5)	-7.4	(-7.8	,-7.1)	0.46	(0.44	,0.48)
(0.283,0.536]	255	9,138	66,333,308	13.8	(13.5	,14.1)	0.0	(reference)		1.00	(reference)	
missing		279										
% crowding (quintiles)												
(0,0.0147]	1,047	3,189	65,273,354	4.9	(4.7	,5.1)	0.0	(reference)		1.00	(reference)	
(0.0147,0.0212]	709	3,973	64,425,866	6.2	(6.0	,6.4)	1.3	(1.0	,1.5)	1.26	(1.20	,1.32)
(0.0212,0.0306]	656	6,739	63,510,499	10.6	(10.4	,10.9)	5.7	(5.4	,6.0)	2.17	(2.08	,2.27)
(0.0306,0.0491]	443	5,423	65,654,959	8.3	(8.0	,8.5)	3.4	(3.1	,3.7)	1.69	(1.62	,1.77)
(0.0491,0.493]	244	10,715	63,913,934	16.8	(16.4	,17.1)	11.9	(11.5	,12.2)	3.43	(3.30	,3.57)
missing		279										
% percent population of color												
(0,0.172]	1,635	1,862	65,219,459	2.9	(2.7	,3.0)	0.0	(reference)		1.00	(reference)	
(0.172,0.302]	549	3,981	65,166,967	6.1	(5.9	,6.3)	3.3	(3.0	,3.5)	2.14	(2.03	,2.26)
(0.302,0.443]	468	7,034	69,376,152	10.1	(9.9	,10.4)	7.3	(7.0	,7.6)	3.55	(3.37	,3.74)
(0.443,0.61]	280	6,534	60,922,155	10.7	(10.5	,11.0)	7.9	(7.6	,8.2)	3.76	(3.57	,3.96)
(0.61,1]	209	10,628	62,217,817	17.1	(16.8	,17.4)	14.2	(13.9	,14.6)	5.98	(5.70	,6.29)
missing		279										

Table 3: Illinois rate of confirmed COVID-19 cases per 100,000 population by ZCTA characteristics as of 4/16/2020

	Number of ZCTAs	Number of confirmed cases	Population	Confirmed case rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	65	2,378	1,531,569	155.3	(149.0	,161.5)	0.0	(reference)		1.00	(reference)	
5-9.9%	138	6,442	3,357,448	191.9	(187.2	,196.6)	36.6	(28.8	,44.4)	1.24	(1.18	,1.30)
10-14.9%	65	4,682	2,052,094	228.2	(221.6	,234.7)	72.9	(63.9	,81.9)	1.47	(1.40	,1.54)
15-19.9%	39	3,085	1,225,648	251.7	(242.8	,260.6)	96.4	(85.6	,107.3)	1.62	(1.54	,1.71)
20-100%	63	8,041	2,186,595	367.7	(359.7	,375.8)	212.5	(202.3	,222.7)	2.37	(2.26	,2.48)
missing		47										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-0.612,0.0175]	63	9,077	2,070,809	438.3	(429.3	,447.3)	283.0	(272.5	,293.5)	2.82	(2.71	,2.94)
(0.0175,0.171]	72	4,258	2,087,542	204.0	(197.8	,210.1)	48.6	(40.5	,56.8)	1.31	(1.25	,1.37)
(0.171,0.289]	75	4,582	2,070,229	221.3	(214.9	,227.7)	66.0	(57.6	,74.3)	1.42	(1.36	,1.49)
(0.289,0.403]	77	3,502	2,058,711	170.1	(164.5	,175.7)	14.7	(7.0	,22.5)	1.09	(1.04	,1.15)
(0.403,0.721]	82	3,196	2,057,150	155.4	(150.0	,160.7)	0.0	(reference)		1.00	(reference)	
missing		60										
% crowding (quintiles)												
(0,0.00975]	87	3,370	1,948,122	173.0	(167.1	,178.8)	0.0	(reference)		1.00	(reference)	
(0.00975,0.0177]	82	3,131	2,060,973	151.9	(146.6	,157.2)	-21.1	(-29.0	,-13.2)	0.88	(0.84	,0.92)
(0.0177,0.0274]	64	5,009	2,052,139	244.1	(237.3	,250.8)	71.1	(62.2	,80.0)	1.41	(1.35	,1.47)
(0.0274,0.0472]	68	6,386	2,101,938	303.8	(296.4	,311.3)	130.8	(121.4	,140.3)	1.76	(1.68	,1.83)
(0.0472,0.143]	54	6,450	2,051,676	314.4	(306.7	,322.0)	141.4	(131.7	,151.0)	1.82	(1.74	,1.89)
missing		329										
% percent population of color												
(0.0318,0.197]	99	2,651	2,073,667	127.8	(123.0	,132.7)	0.0	(reference)		1.00	(reference)	
(0.197,0.315]	78	2,992	2,023,605	147.9	(142.6	,153.2)	20.0	(12.8	,27.2)	1.16	(1.10	,1.22)
(0.315,0.46]	77	4,071	2,159,499	188.5	(182.7	,194.3)	60.7	(53.1	,68.2)	1.47	(1.40	,1.55)
(0.46,0.744]	60	5,731	2,038,179	281.2	(273.9	,288.5)	153.3	(144.6	,162.1)	2.20	(2.10	,2.30)
(0.744,0.99]	55	9,172	2,051,861	447.0	(437.9	,456.2)	319.2	(308.8	,329.5)	3.50	(3.35	,3.65)
missing		58										

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Table 4: New York City rate of positive COVID-19 tests per 100,000 population by ZCTA characteristics as of 4/16/2020

	Number of ZCTAs	Number of positive tests	Population	Rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	9	1,362	130,121	1046.7	(991.1	,1102.3)	0.0	(reference)		1.00	(reference)	
5-9.9%	41	20,609	1,506,286	1368.2	(1349.5	,1386.9)	321.5	(262.8	,380.1)	1.31	(1.24	,1.38)
10-14.9%	48	30,294	2,100,915	1441.9	(1425.7	,1458.2)	395.2	(337.3	,453.1)	1.38	(1.30	,1.45)
15-19.9%	27	22,359	1,439,746	1553.0	(1532.6	,1573.3)	506.3	(447.1	,565.5)	1.48	(1.40	,1.57)
20+%	52	48,982	3,256,108	1504.3	(1491.0	,1517.6)	457.6	(400.4	,514.8)	1.44	(1.36	,1.52)
missing		1,816										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-0.385,-0.102]	28	25,855	1,612,266	1603.6	(1584.1	,1623.2)	536.2	(511.1	,561.2)	1.50	(1.47	,1.53)
(-0.102,0.0212]	30	28,209	1,749,736	1612.2	(1593.4	,1631.0)	544.7	(520.3	,569.2)	1.51	(1.48	,1.54)
(0.0212,0.141]	29	26,844	1,623,732	1653.2	(1633.5	,1673.0)	585.8	(560.6	,611.0)	1.55	(1.52	,1.58)
(0.141,0.29]	39	23,751	1,692,826	1403.0	(1385.2	,1420.9)	335.6	(311.9	,359.3)	1.31	(1.29	,1.34)
(0.29,0.7]	50	17,913	1,678,089	1067.5	(1051.8	,1083.1)	0.0	(reference)		1.00	(reference)	
missing		2,850										
% crowding (quintiles)												
(0.00942,0.0478]	47	20,428	1,675,260	1219.4	(1202.7	,1236.1)	0.0	(reference)		1.00	(reference)	
(0.0478,0.0698]	37	23,808	1,688,963	1409.6	(1391.7	,1427.5)	190.2	(165.7	,214.7)	1.16	(1.13	,1.18)
(0.0698,0.0978]	38	24,507	1,679,177	1459.5	(1441.2	,1477.7)	240.1	(215.3	,264.8)	1.20	(1.17	,1.22)
(0.0978,0.138]	31	25,783	1,682,708	1532.2	(1513.5	,1550.9)	312.8	(287.8	,337.9)	1.26	(1.23	,1.28)
(0.138,0.297]	23	28,434	1,673,537	1699.0	(1679.3	,1718.8)	479.6	(453.8	,505.5)	1.39	(1.37	,1.42)
missing		2,462										
% population of color (quintiles)												
(0.0839,0.402]	43	21,166	1,695,113	1248.6	(1231.8	,1265.5)	0.0	(reference)		1.00	(reference)	
(0.402,0.584]	38	20,554	1,678,144	1224.8	(1208.1	,1241.6)	-23.8	(-47.6	,-0.1)	0.98	(0.96	,1.00)
(0.584,0.826]	38	25,541	1,708,248	1495.2	(1476.8	,1513.5)	246.5	(221.6	,271.4)	1.20	(1.18	,1.22)
(0.826,0.957]	29	27,231	1,708,722	1593.6	(1574.7	,1612.6)	345.0	(319.7	,370.3)	1.28	(1.25	,1.30)
(0.957,0.992]	28	29,042	1,639,409	1771.5	(1751.1	,1791.9)	522.8	(496.4	,549.3)	1.42	(1.39	,1.44)
missing		1,888										

Table 5: Deaths, population, crude death rate, and county-level area-based measures for counties with the largest cumulative death counts as of 4/16/2020

FIPS code	County Name	State	Deaths	Population	Crude death rate per 100,000	% below poverty	Index of Concentration at the Extremes (white/black race + income)	% crowding (>1 person per room)	% population of color
36081	Queens County	NY	37,918	2,298,513	1649.7	0.130	0.117	0.095	0.747
36047	Kings County	NY	33,521	2,600,747	1288.9	0.211	0.070	0.103	0.638
36059	Nassau County	NY	27,772	1,356,564	2047.2	0.057	0.412	0.026	0.392
36005	Bronx County	NY	25,932	1,437,872	1803.5	0.291	-0.065	0.123	0.907
36103	Suffolk County	NY	24,182	1,487,901	1625.2	0.071	0.416	0.026	0.319
36119	Westchester County	NY	21,828	968,815	2253.1	0.092	0.336	0.041	0.460
17031	Cook County	IL	18,087	5,223,719	346.2	0.151	0.138	0.034	0.575
36061	New York County	NY	17,091	1,632,480	1046.9	0.166	0.289	0.058	0.531
26163	Wayne County	MI	13,002	1,761,382	738.2	0.231	-0.022	0.022	0.504
34003	Bergen County	NJ	11,409	929,999	1226.8	0.070	0.356	0.024	0.427
6037	Los Angeles County	CA	10,854	10,098,052	107.5	0.160	0.168	0.114	0.737
34017	Hudson County	NJ	9,165	668,631	1370.7	0.163	0.175	0.075	0.711
34013	Essex County	NJ	9,084	793,555	1144.7	0.164	0.072	0.042	0.692
36087	Rockland County	NY	8,752	323,686	2703.9	0.143	0.337	0.066	0.367
36085	Richmond County	NY	8,684	474,101	1831.7	0.128	0.293	0.043	0.383
12086	Miami-Dade County	FL	8,326	2,715,516	306.6	0.180	0.127	0.063	0.866
34039	Union County	NJ	7,904	553,066	1429.1	0.098	0.227	0.045	0.597
42101	Philadelphia County	PA	7,684	1,575,522	487.7	0.249	-0.040	0.026	0.654
34031	Passaic County	NJ	7,317	504,041	1451.7	0.167	0.220	0.071	0.582
25017	Middlesex County	MA	7,206	1,595,192	451.7	0.079	0.400	0.019	0.275
34023	Middlesex County	NJ	6,994	826,698	846.0	0.085	0.238	0.042	0.562
25025	Suffolk County	MA	6,820	791,766	861.4	0.193	0.192	0.036	0.550
9001	Fairfield County	CT	6,816	944,348	721.8	0.088	0.379	0.027	0.376
36071	Orange County	NY	5,888	378,227	1556.7	0.118	0.289	0.037	0.351
22071	Orleans Parish	LA	5,847	389,648	1500.6	0.246	-0.134	0.015	0.694

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Supplemental Appendix Table A.1: US COVID-19 cases per 100,000 by county characteristics as of 4/16/2020

	Number of counties	Number of deaths	Population	Death rate per 100,000	(95% CI)	Rate difference per 100,000	(95% CI)	Rate ratio	(95% CI)
% poverty (categories)									
0-4.9%	41	9,236	4,495,932	205.4	(201.2 ,209.6)	0.0	(reference)	1.00	(reference)
5-9.9%	558	200,112	71,157,744	281.2	(280.0 ,282.5)	75.8	(71.4 ,80.2)	1.37	(1.34 ,1.40)
10-14.9%	1023	177,196	108,820,591	162.8	(162.1 ,163.6)	-42.6	(-46.9 ,-38.3)	0.79	(0.78 ,0.81)
15-19.9%	860	161,502	101,961,251	158.4	(157.6 ,159.2)	-47.0	(-51.3 ,-42.8)	0.77	(0.76 ,0.79)
20-100%	659	112,604	36,428,205	309.1	(307.3 ,310.9)	103.7	(99.1 ,108.2)	1.50	(1.47 ,1.54)
missing		31							
Index of Concentration at the Extremes (high income white households versus low income black households)									
(-0.522,0.114]	974	160,588	61,949,063	259.2	(258.0 ,260.5)	-82.8	(-84.7 ,-80.9)	0.76	(0.75 ,0.76)
(0.114,0.159]	701	103,896	64,942,197	160.0	(159.0 ,161.0)	-182.1	(-183.8 ,-180.4)	0.47	(0.46 ,0.47)
(0.159,0.205]	696	70,626	65,113,354	108.5	(107.7 ,109.3)	-233.6	(-235.2 ,-232.0)	0.32	(0.31 ,0.32)
(0.205,0.283]	515	98,635	64,525,801	152.9	(151.9 ,153.8)	-189.2	(-190.9 ,-187.5)	0.45	(0.44 ,0.45)
(0.283,0.536]	255	226,905	66,333,308	342.1	(340.7 ,343.5)	0.0	(reference)	1.00	(reference)
missing		31							
% crowding (quintiles)									
(0,0.0147]	1047	75,149	65,273,354	115.1	(114.3 ,116.0)	0.0	(reference)	1.00	(reference)
(0.0147,0.0212]	709	95,224	64,425,866	147.8	(146.9 ,148.7)	32.7	(31.4 ,33.9)	1.28	(1.27 ,1.30)
(0.0212,0.0306]	656	160,008	63,510,499	251.9	(250.7 ,253.2)	136.8	(135.3 ,138.3)	2.19	(2.17 ,2.21)
(0.0306,0.0491]	443	142,573	65,654,959	217.2	(216.0 ,218.3)	102.0	(100.6 ,103.4)	1.89	(1.87 ,1.90)
(0.0491,0.493]	244	187,660	63,913,934	293.6	(292.3 ,294.9)	178.5	(176.9 ,180.0)	2.55	(2.53 ,2.57)
missing		67							
% percent population of color									
(0,0.172]	1635	44,958	65,219,459	68.9	(68.3 ,69.6)	0.0	(reference)	1.00	(reference)
(0.172,0.302]	549	95,876	65,166,967	147.1	(146.2 ,148.1)	78.2	(77.1 ,79.3)	2.13	(2.11 ,2.16)
(0.302,0.443]	468	177,223	69,376,152	255.5	(254.3 ,256.6)	186.5	(185.2 ,187.9)	3.71	(3.67 ,3.74)
(0.443,0.61]	280	155,758	60,922,155	255.7	(254.4 ,256.9)	186.7	(185.3 ,188.2)	3.71	(3.67 ,3.75)
(0.61,1]	209	186,845	62,217,817	300.3	(298.9 ,301.7)	231.4	(229.9 ,232.9)	4.36	(4.31 ,4.40)
missing		21							

Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020.
https://tinyurl.com/y7v72446

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by county % below poverty (categories) (as of 4.16.2020)

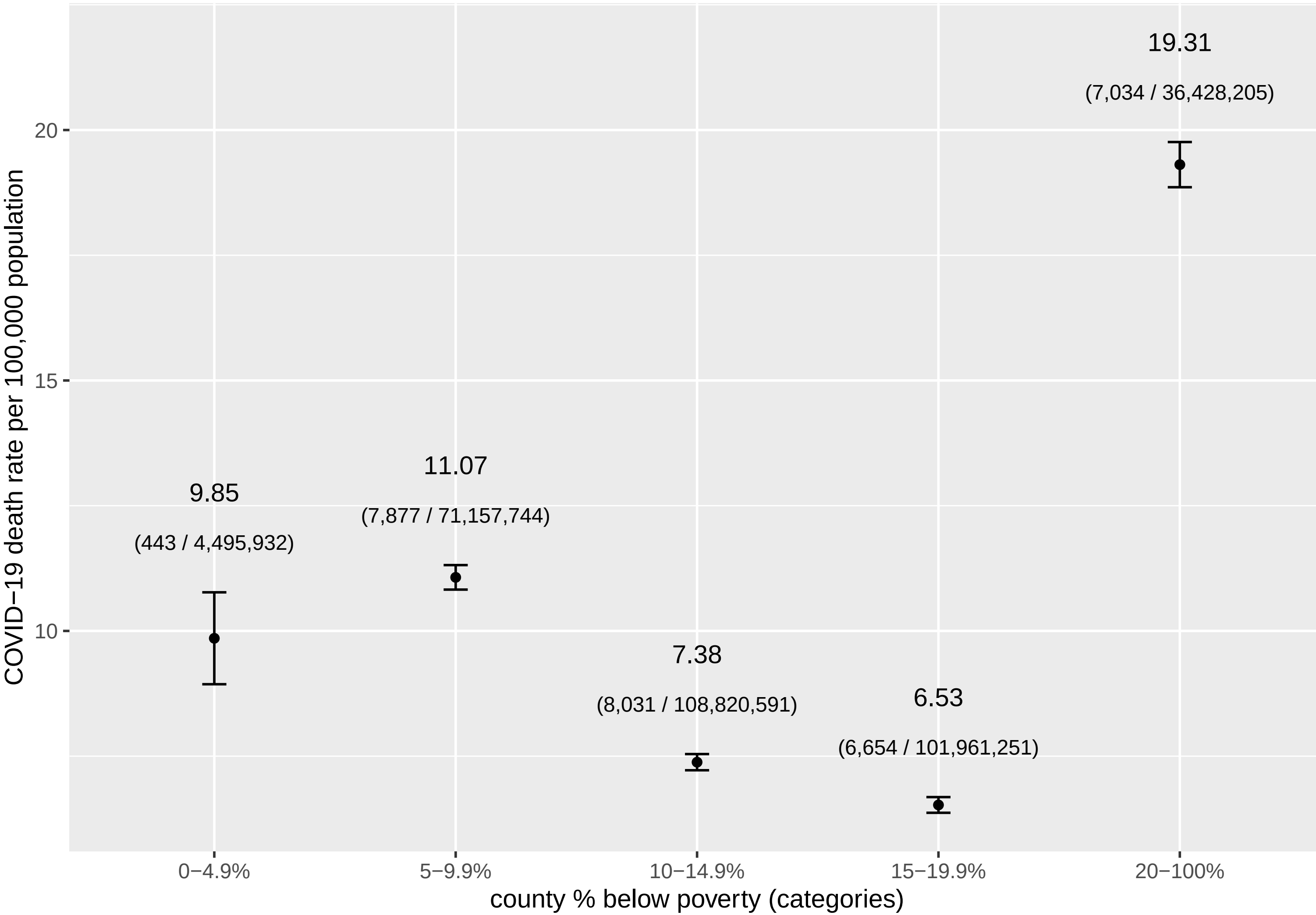

Figure 1b: US COVID−19 deaths per 100,000 population
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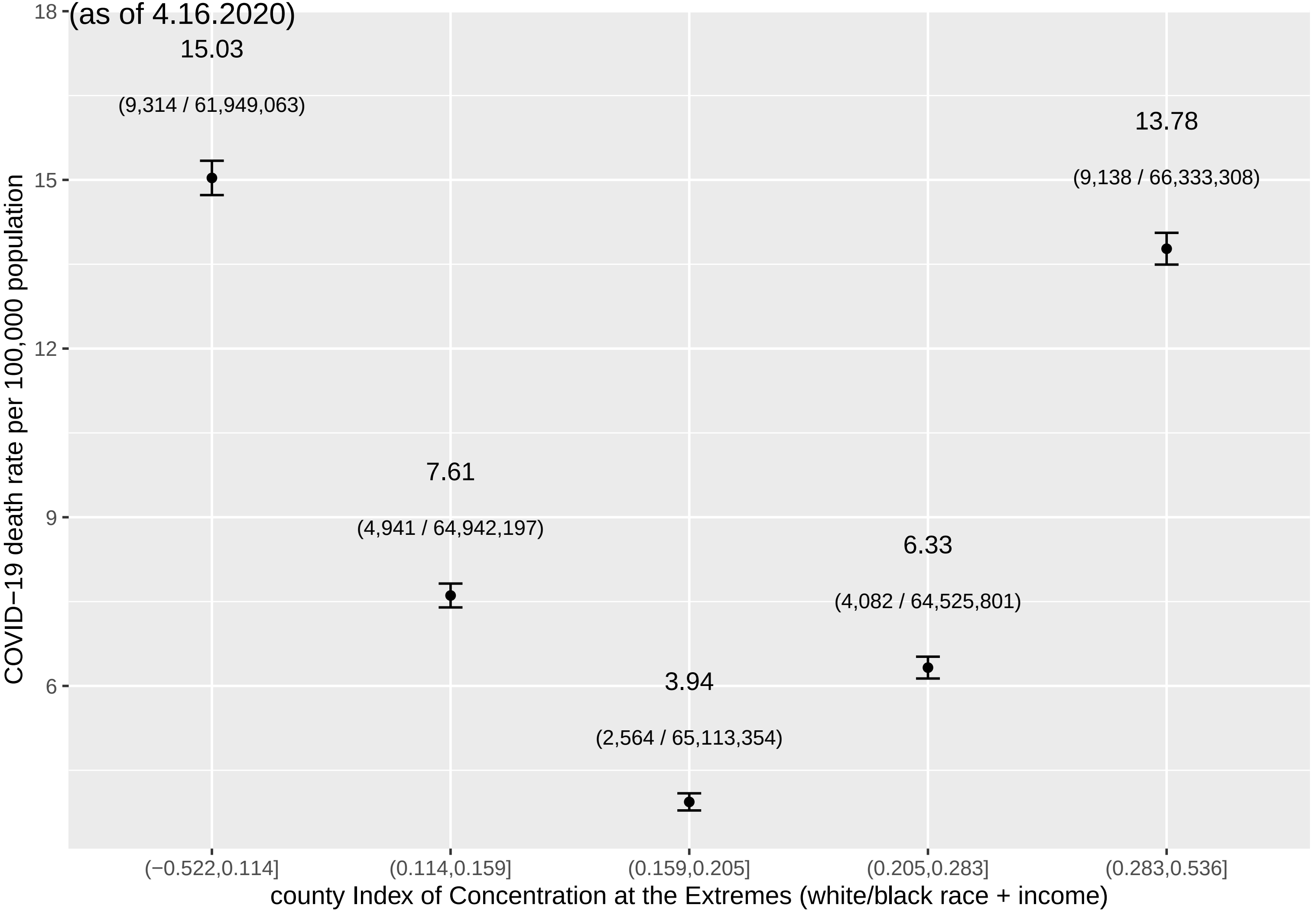

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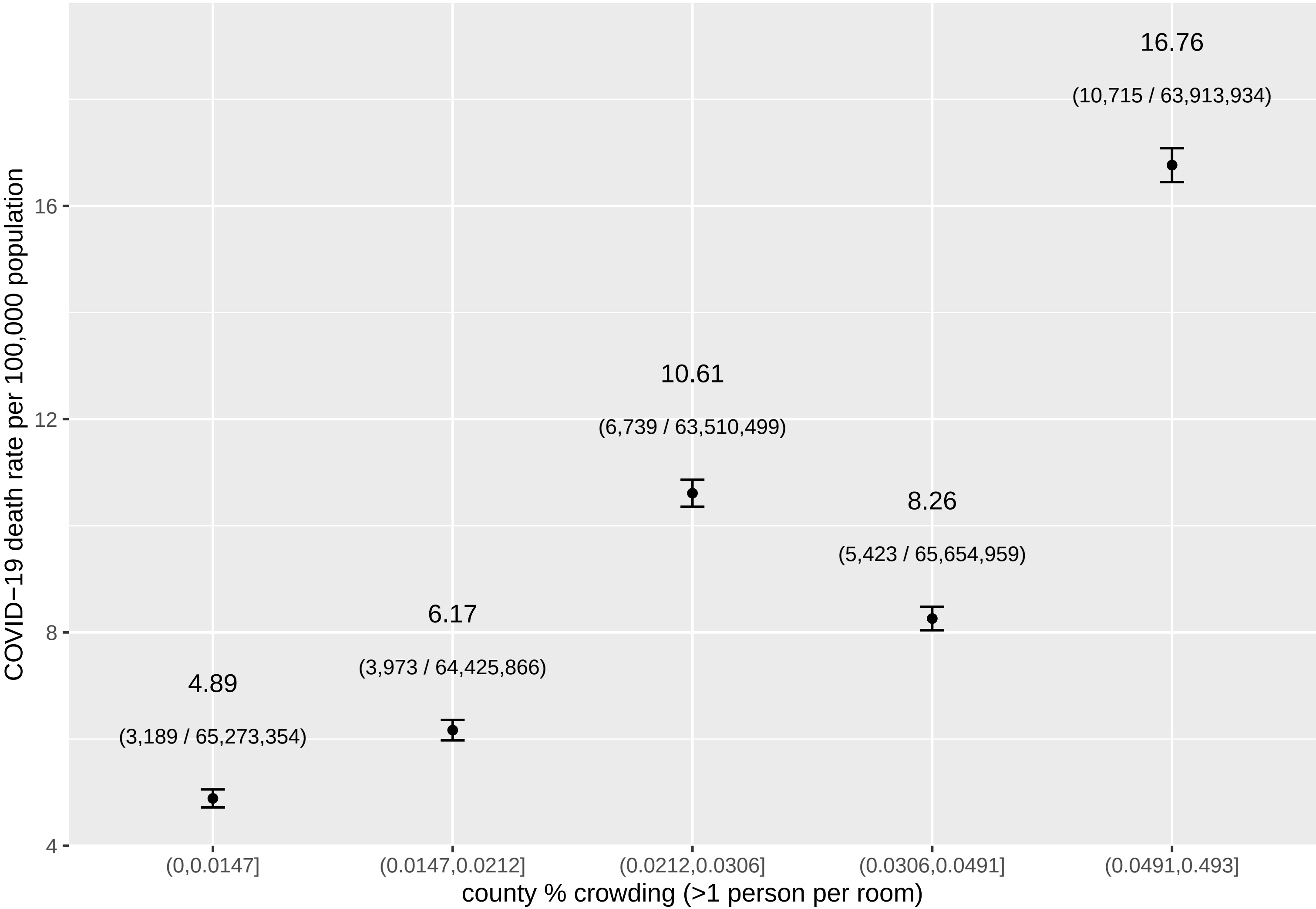

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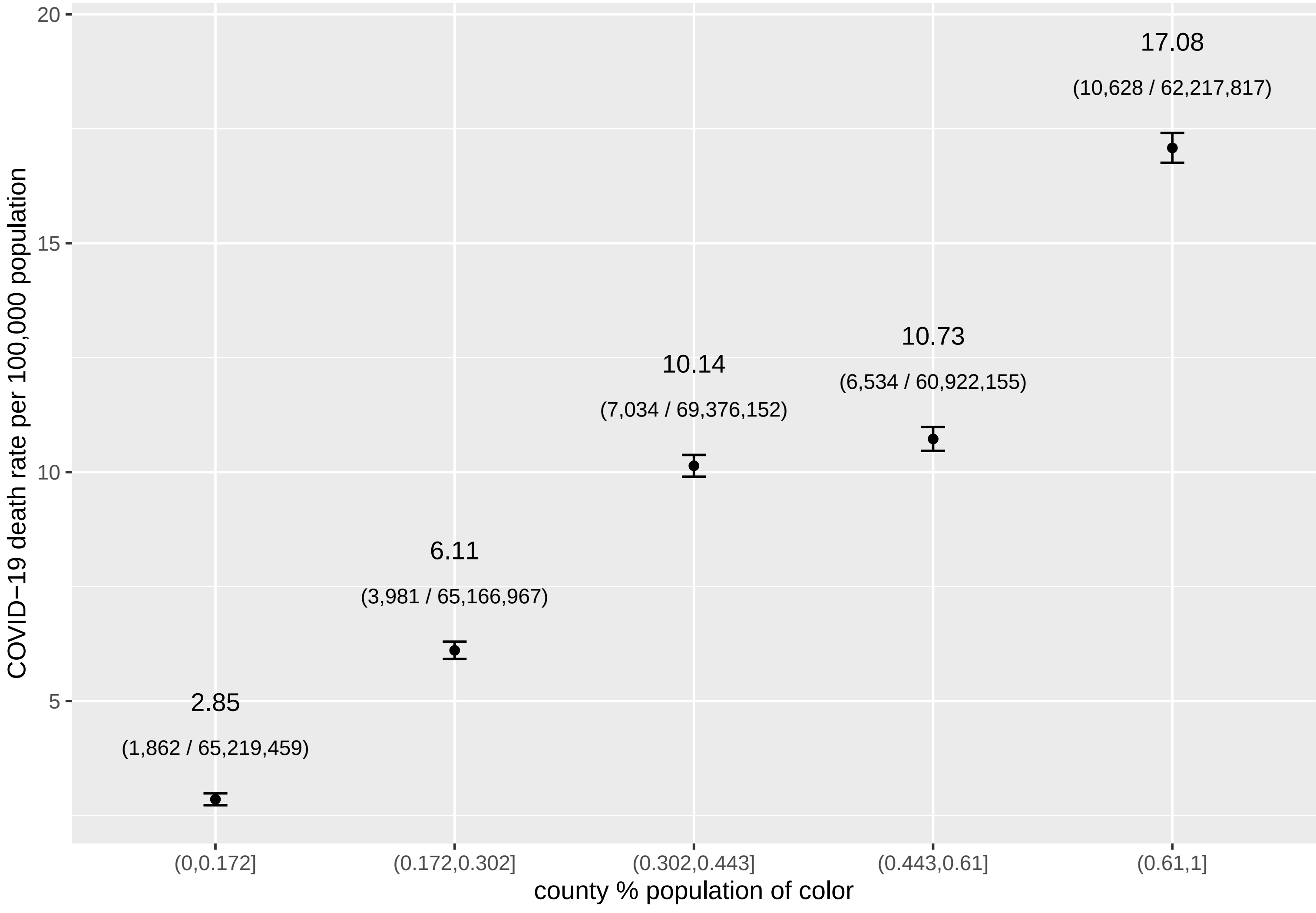

Figure 2a: Illinois COVID−19 confirmed cases per 100,000 population
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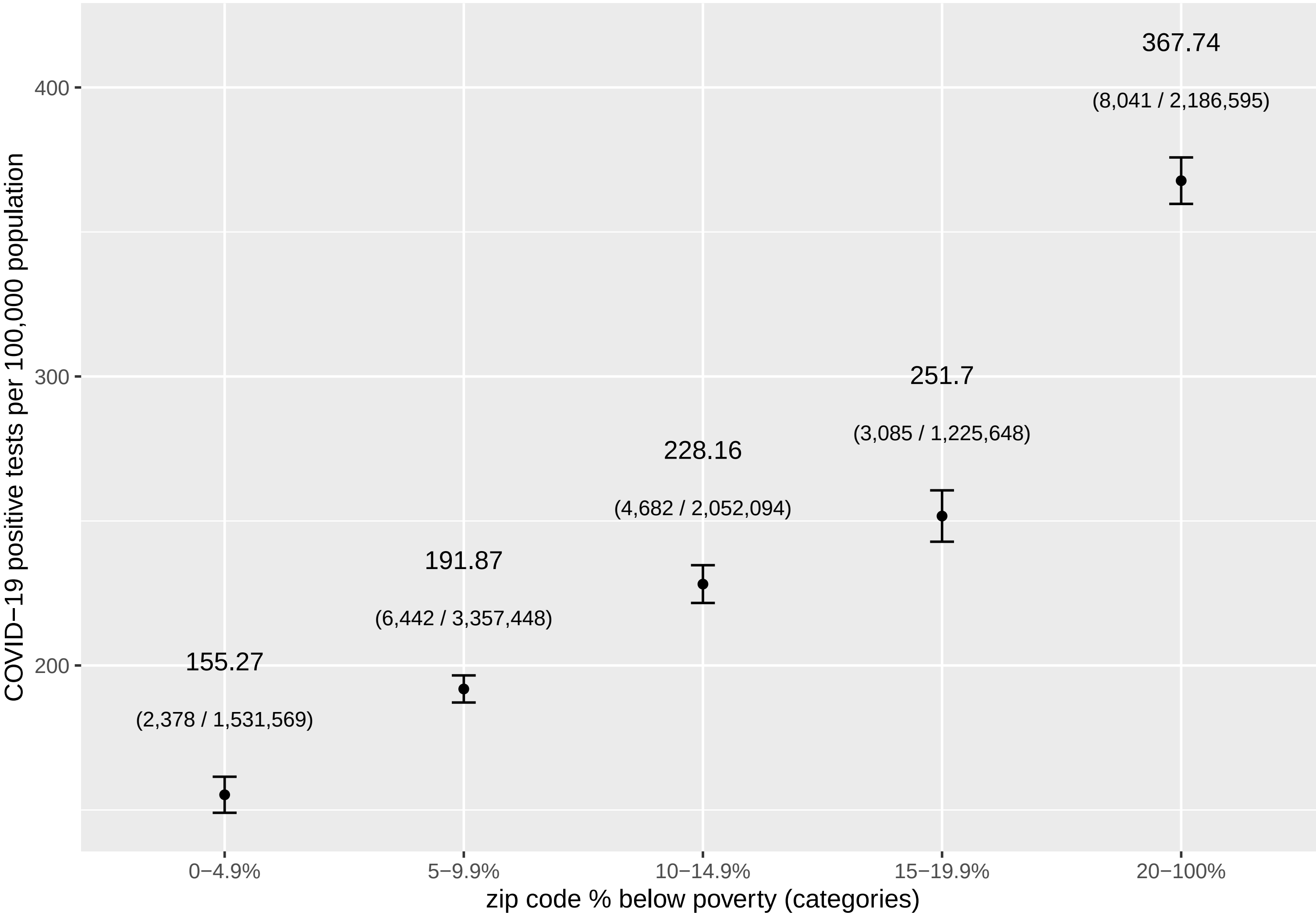

Figure 2b: Illinois COVID−19 confirmed cases per 100,000 population by ZIP code Index of Concentration at the Extremes (white/black race + income) (as of 4.16.2020)

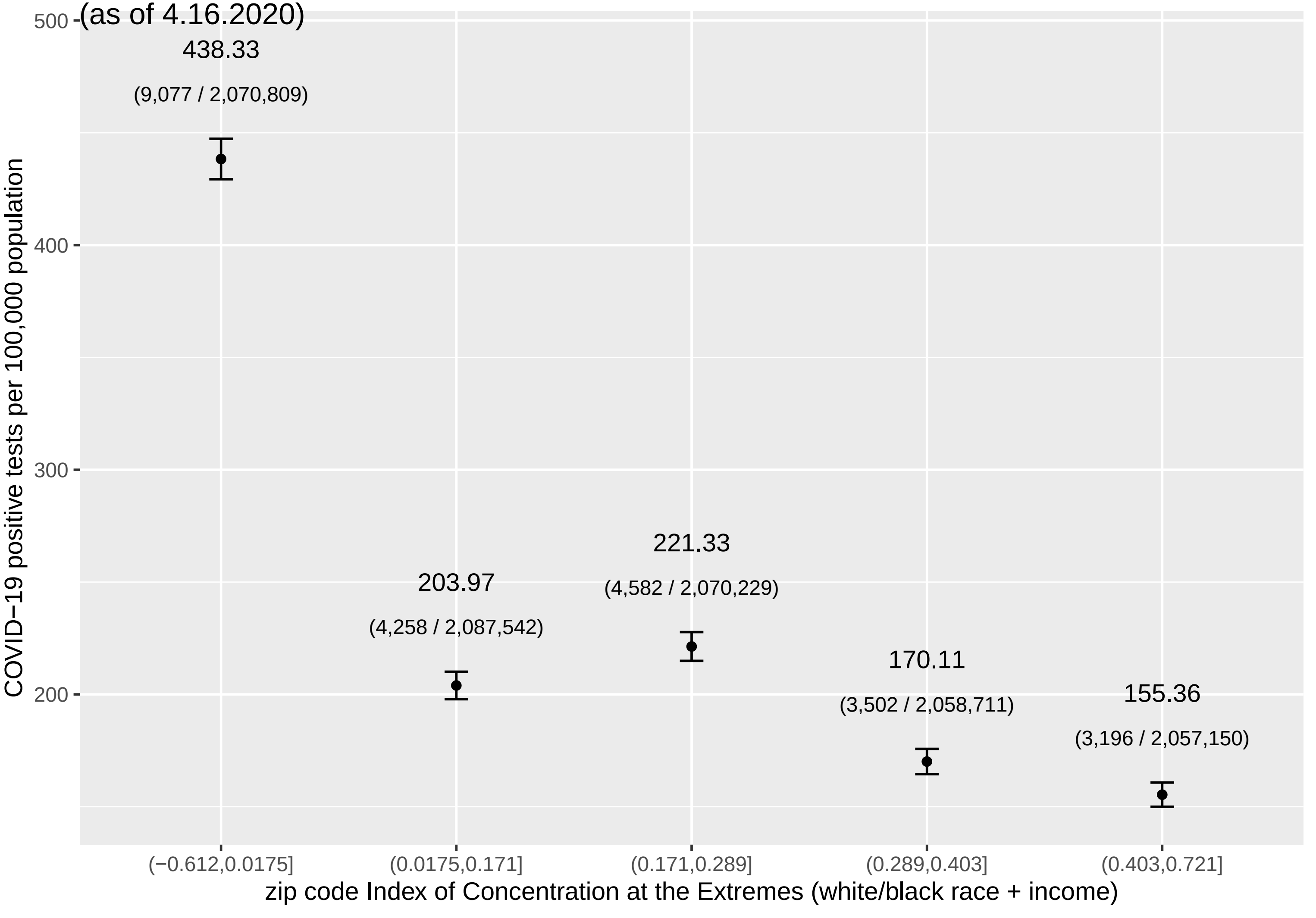

Figure 2c: Illinois COVID−19 confirmed cases per 100,000 population by ZIP code % crowding (>1 person per room) (as of 4.16.2020)

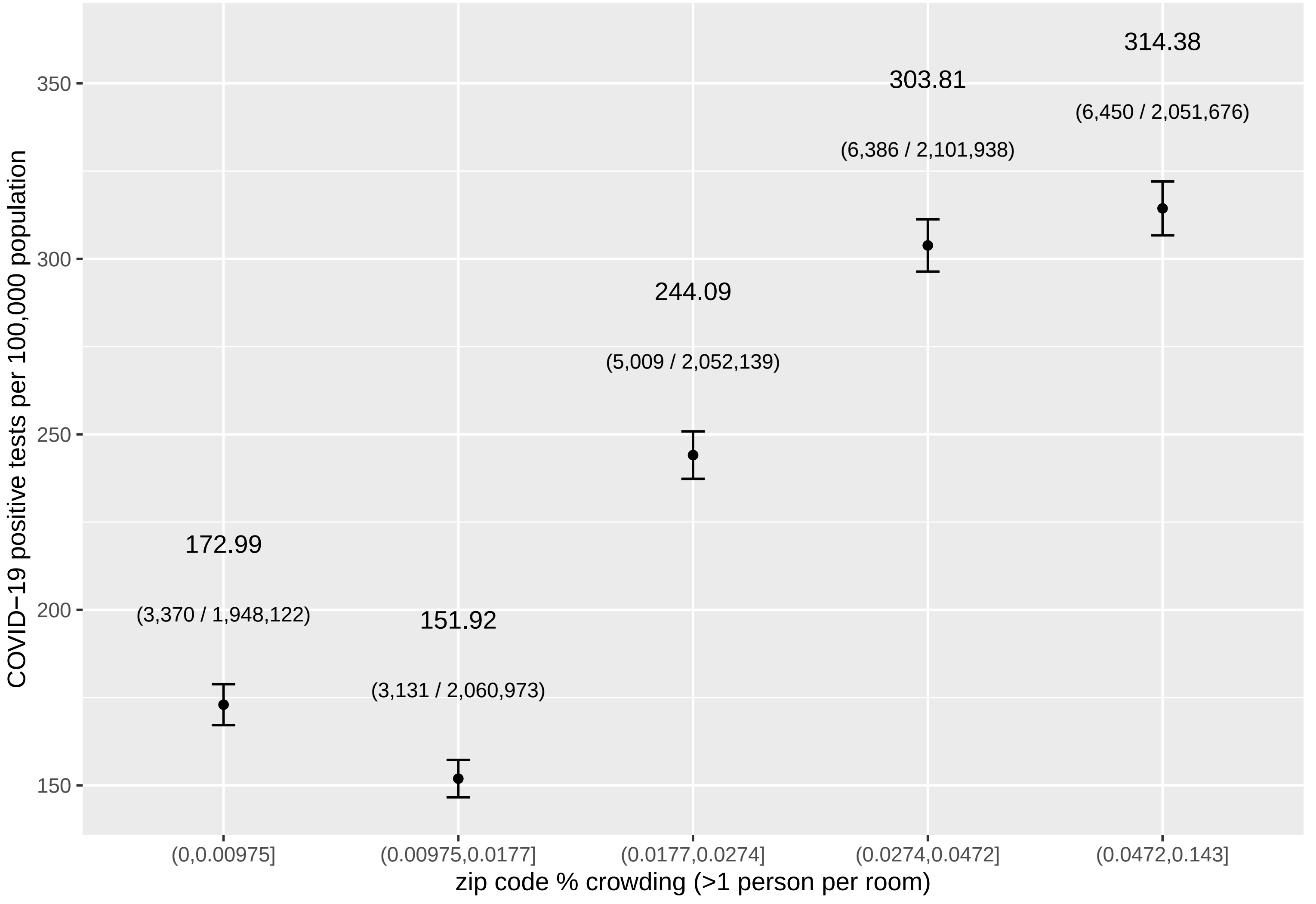

Figure 2d: Illinois COVID−19 confirmed cases per 100,000 population by ZIP code % population of color (as of 4.16.2020)

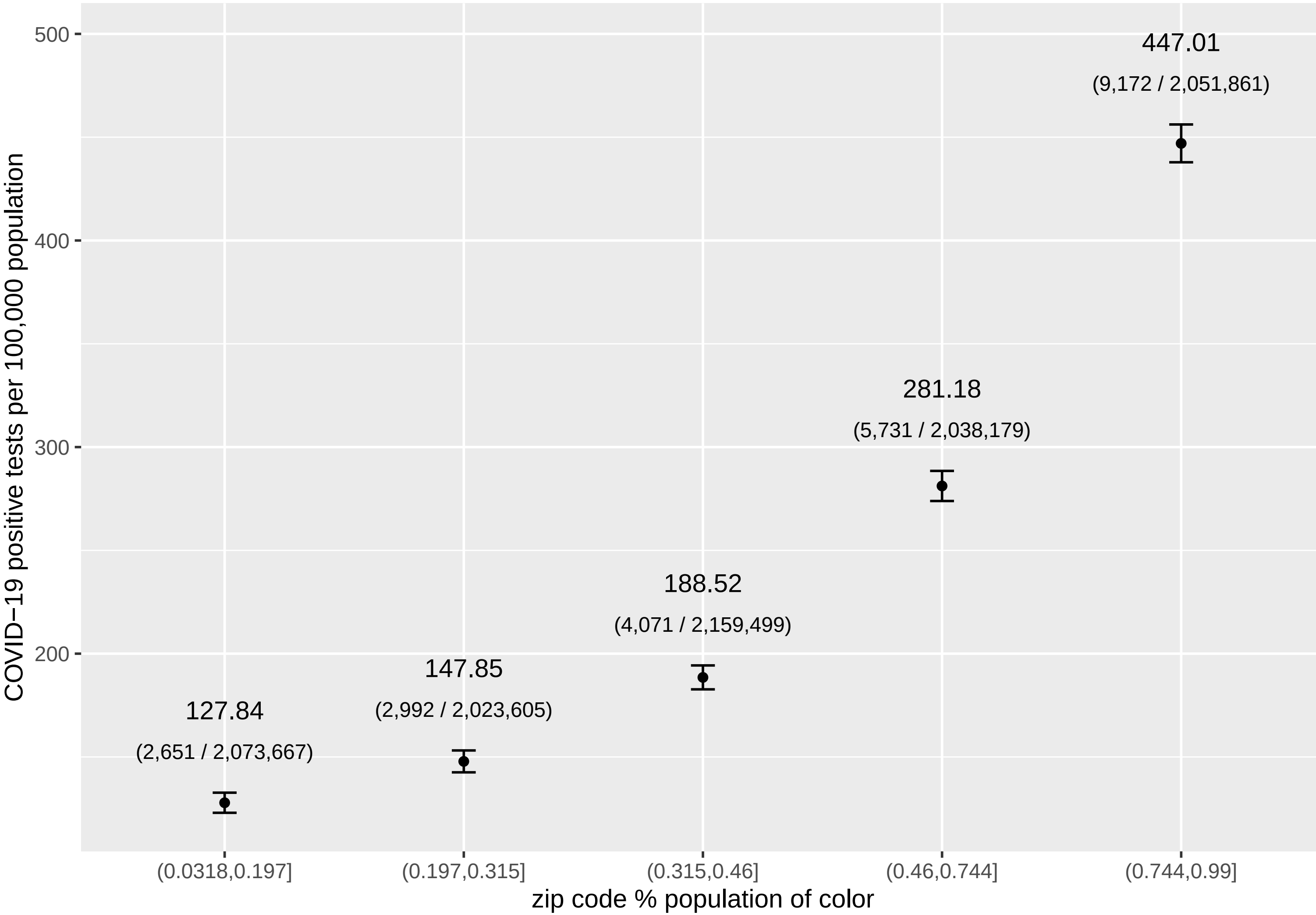

Figure 3a: NYC COVID−19 positive tests per 100,000 population
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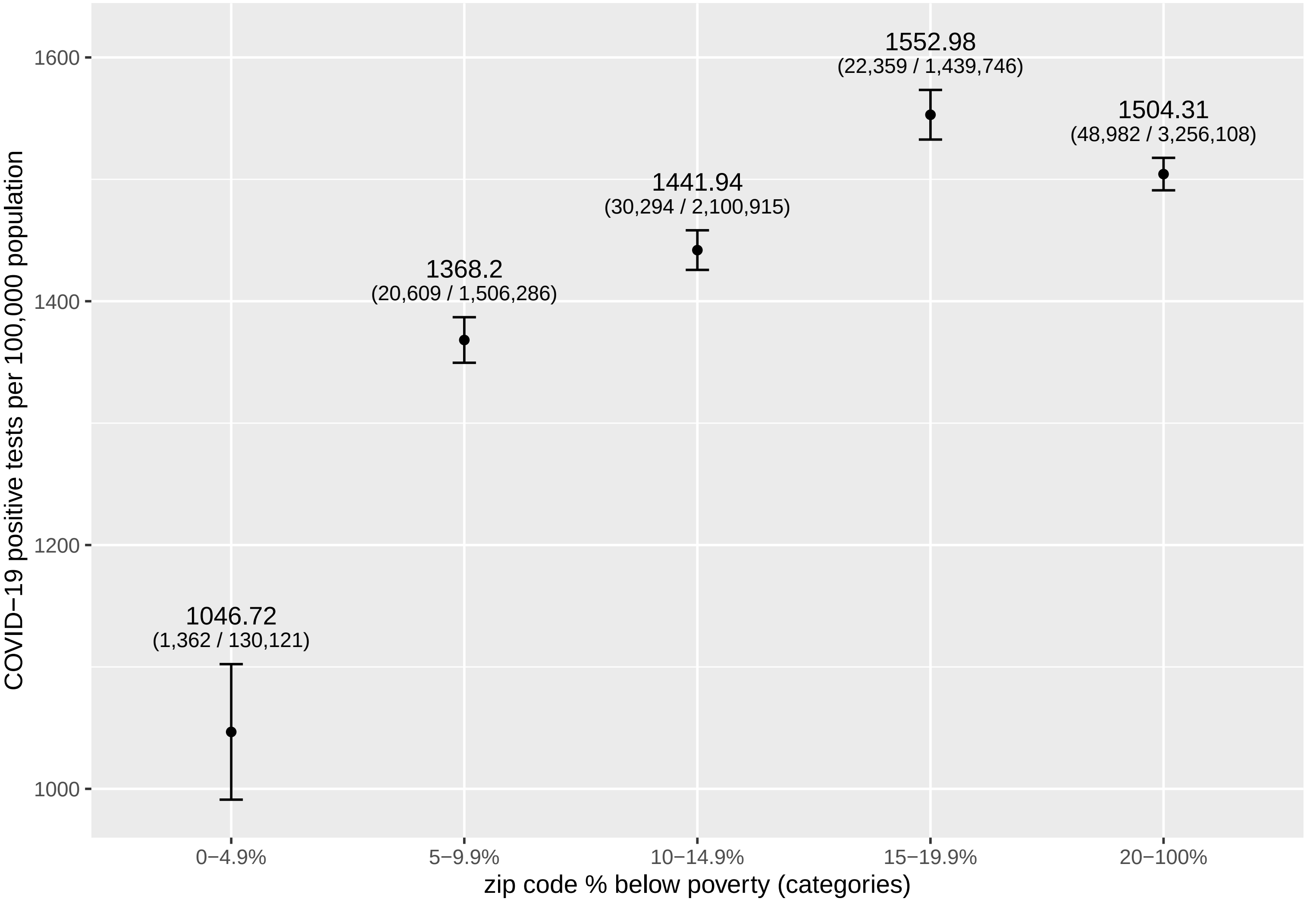

Figure 3b: NYC COVID−19 positive tests per 100,000 population
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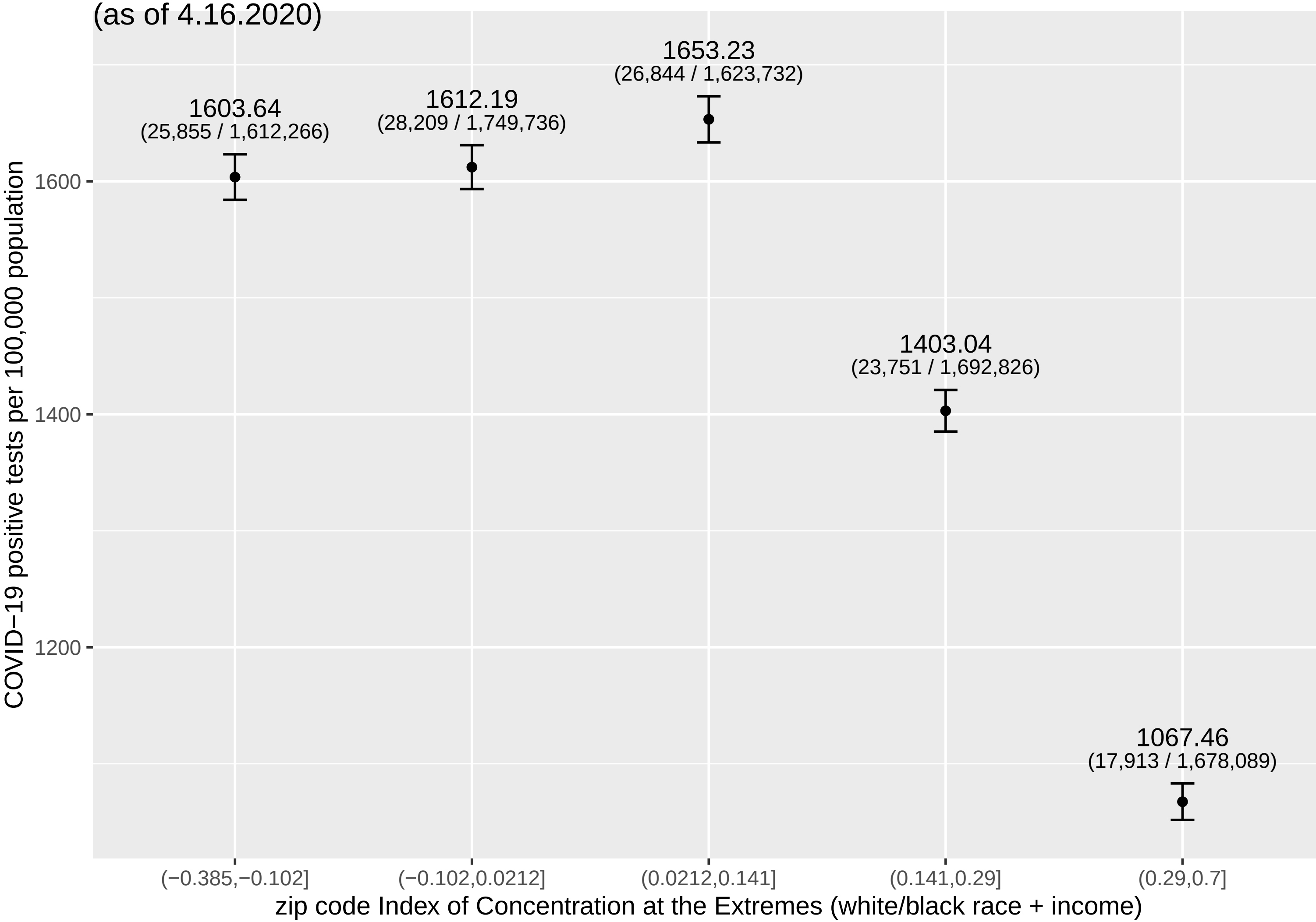

Figure 3c: NYC COVID−19 positive tests per 100,000 population
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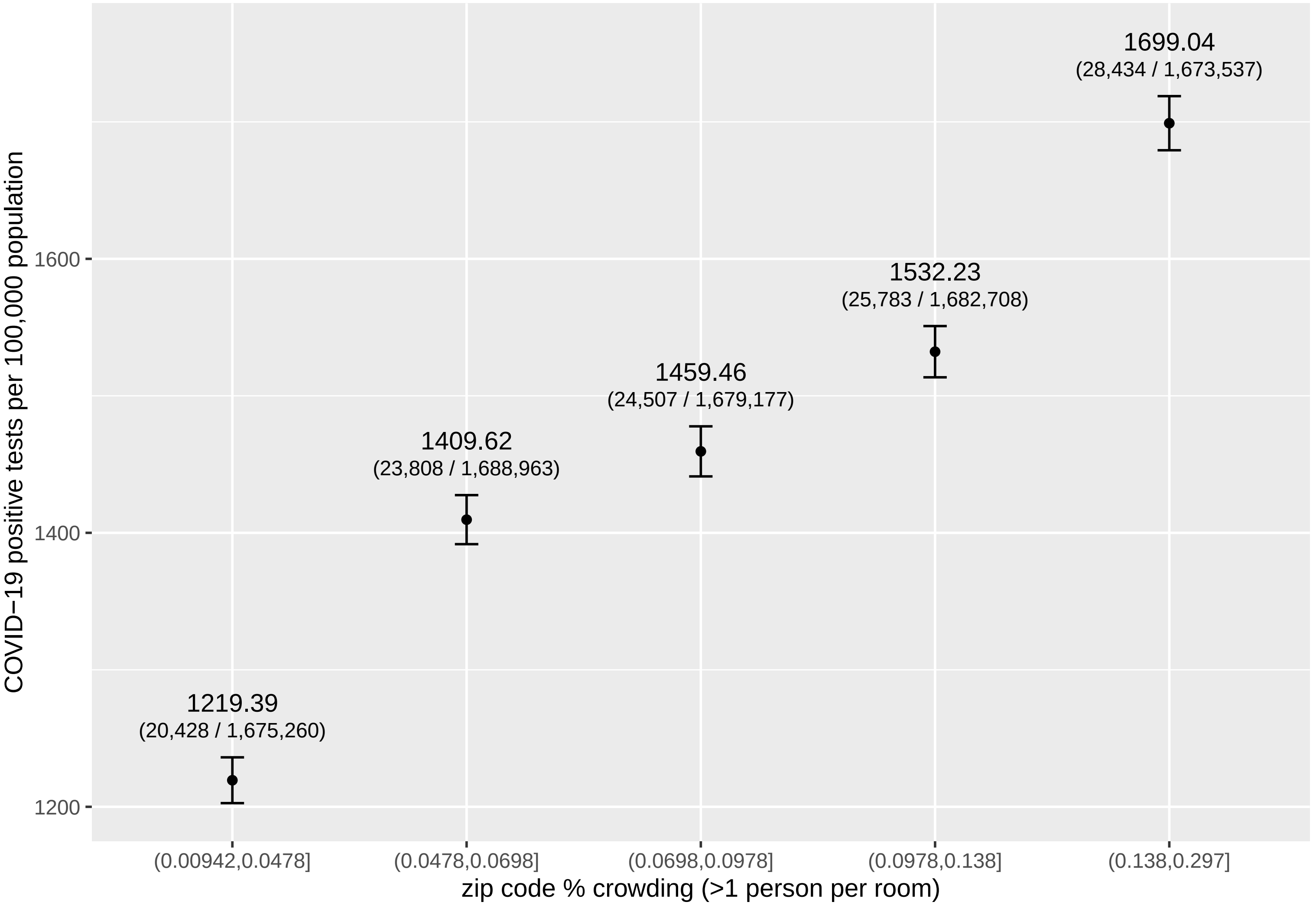

Figure 3d: NYC COVID−19 positive tests per 100,000 population
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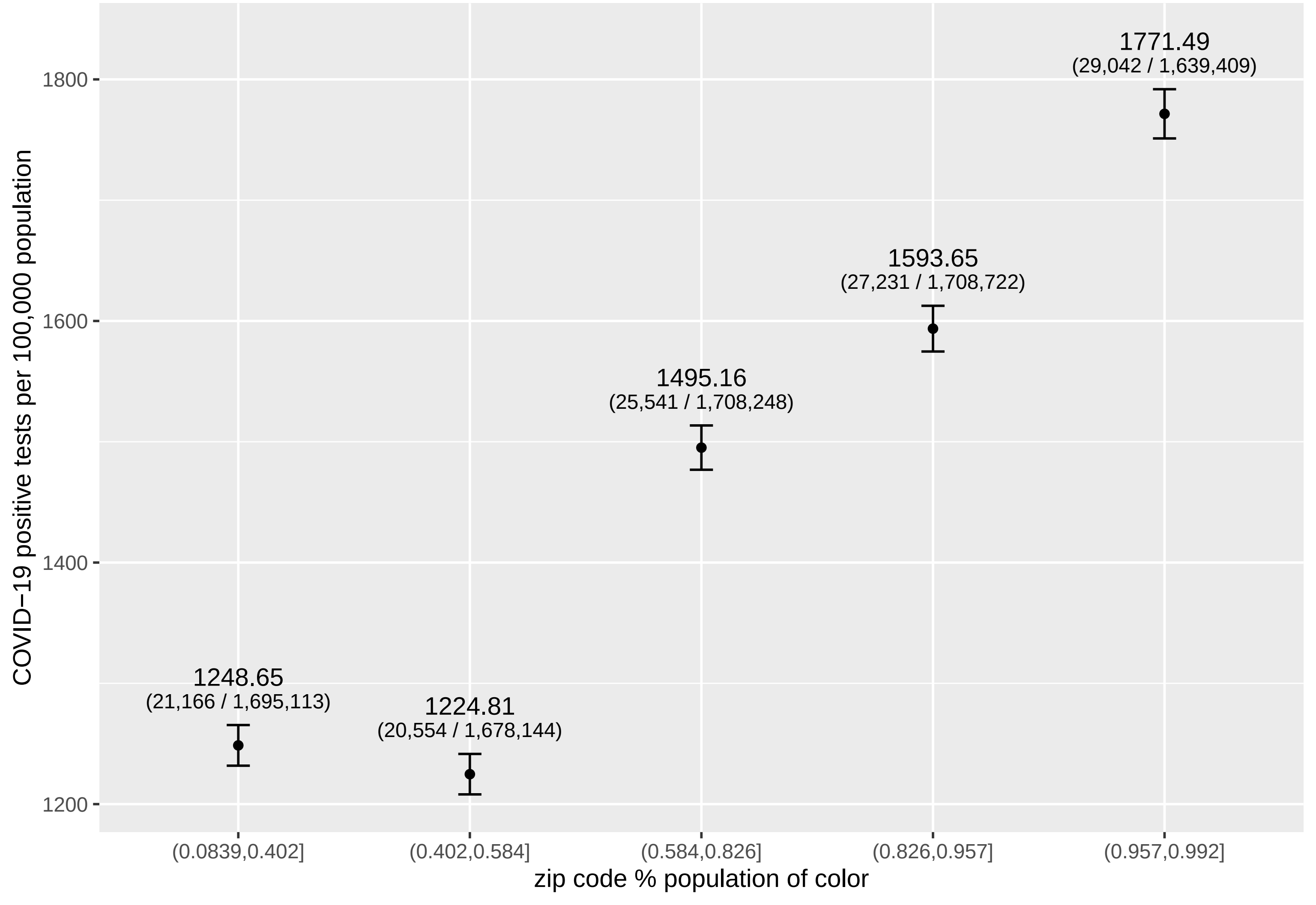

Figure A.1a: US COVID−19 cases per 100,000 population
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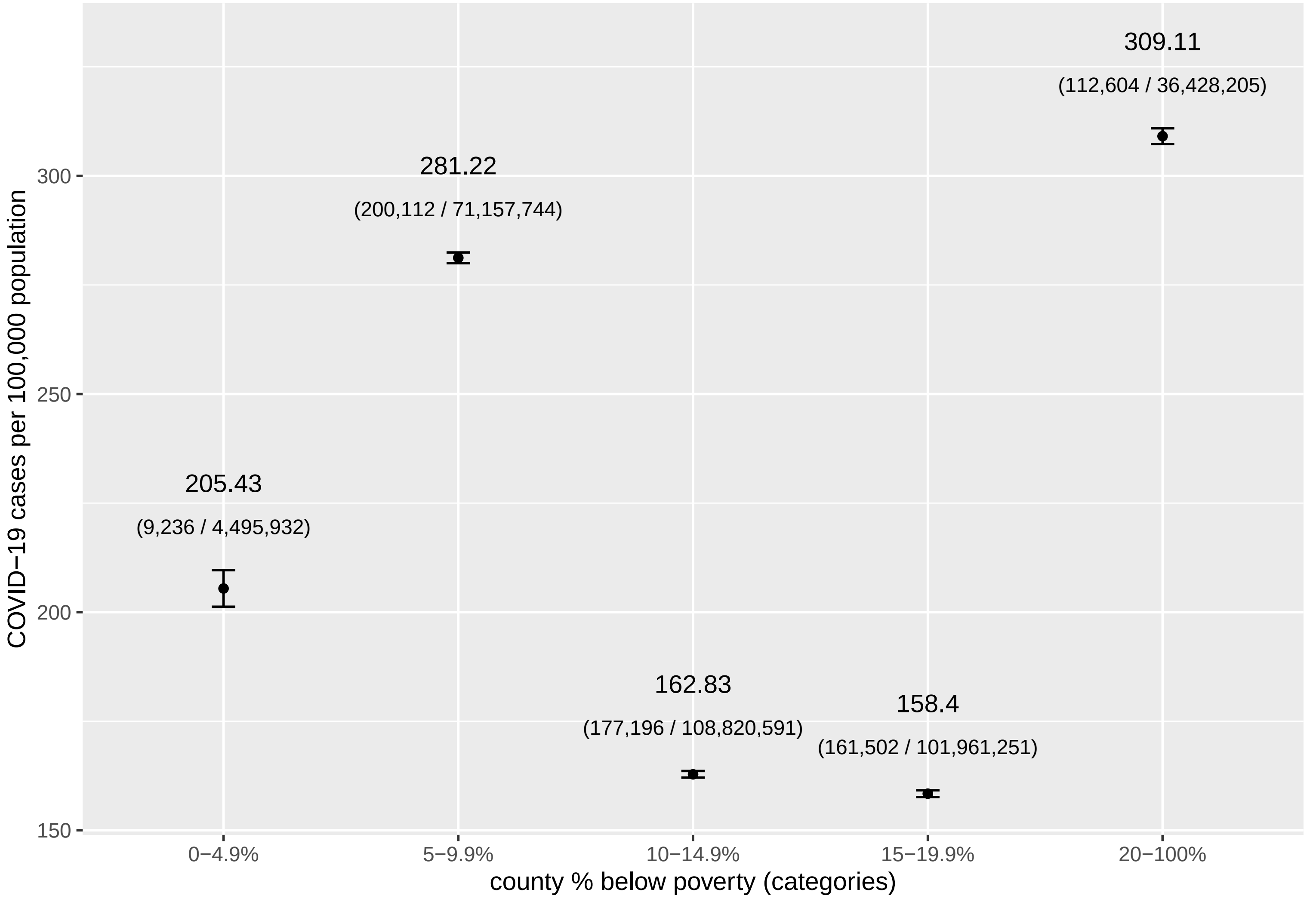

Figure A.1b: US COVID−19 cases per 100,000 population
by county Index of Concentration at the Extremes (white/black race + income)
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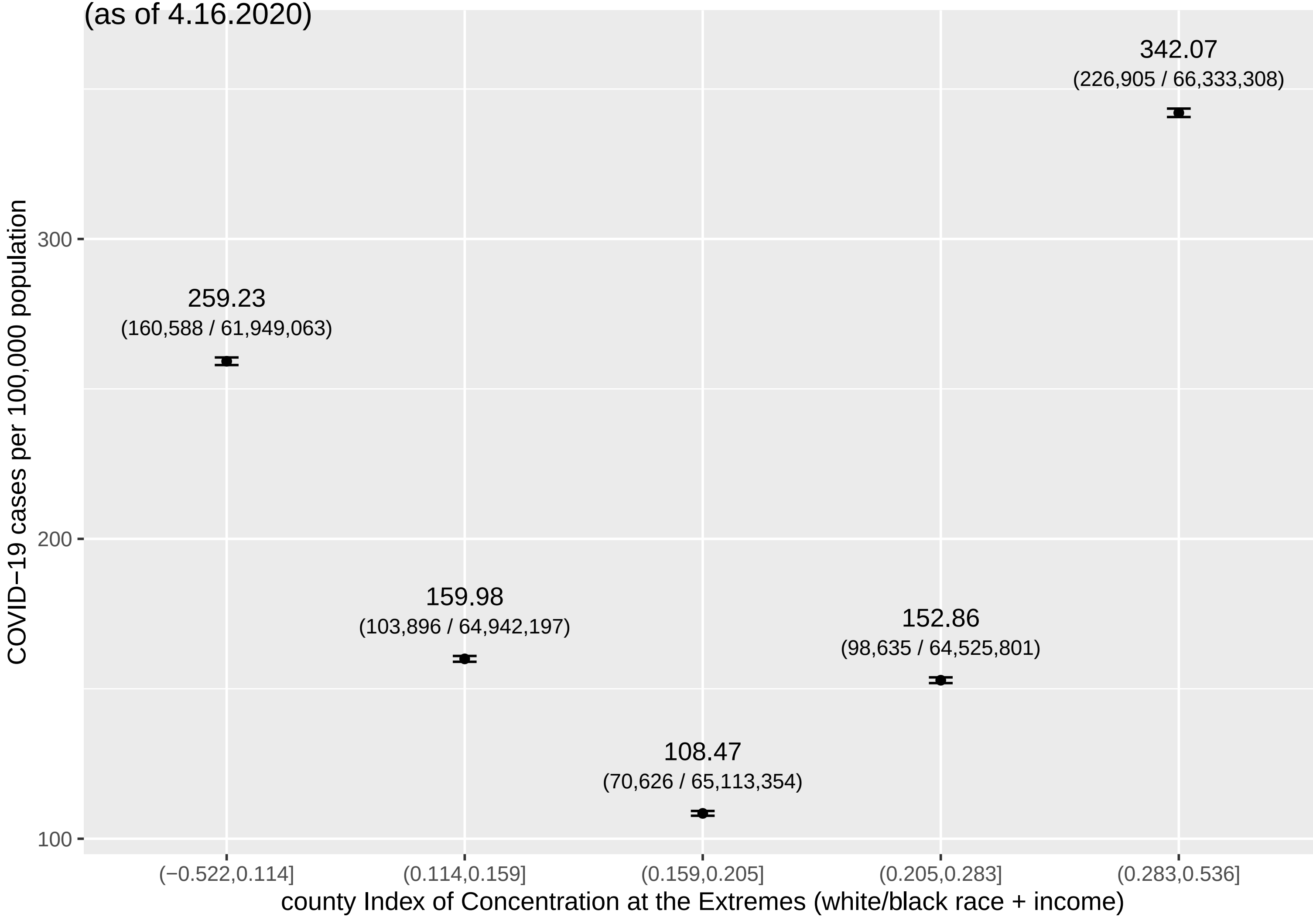


Figure A.1c: US COVID−19 cases per 100,000 population by county % crowding (>1 person per room) (as of 4.16.2020)

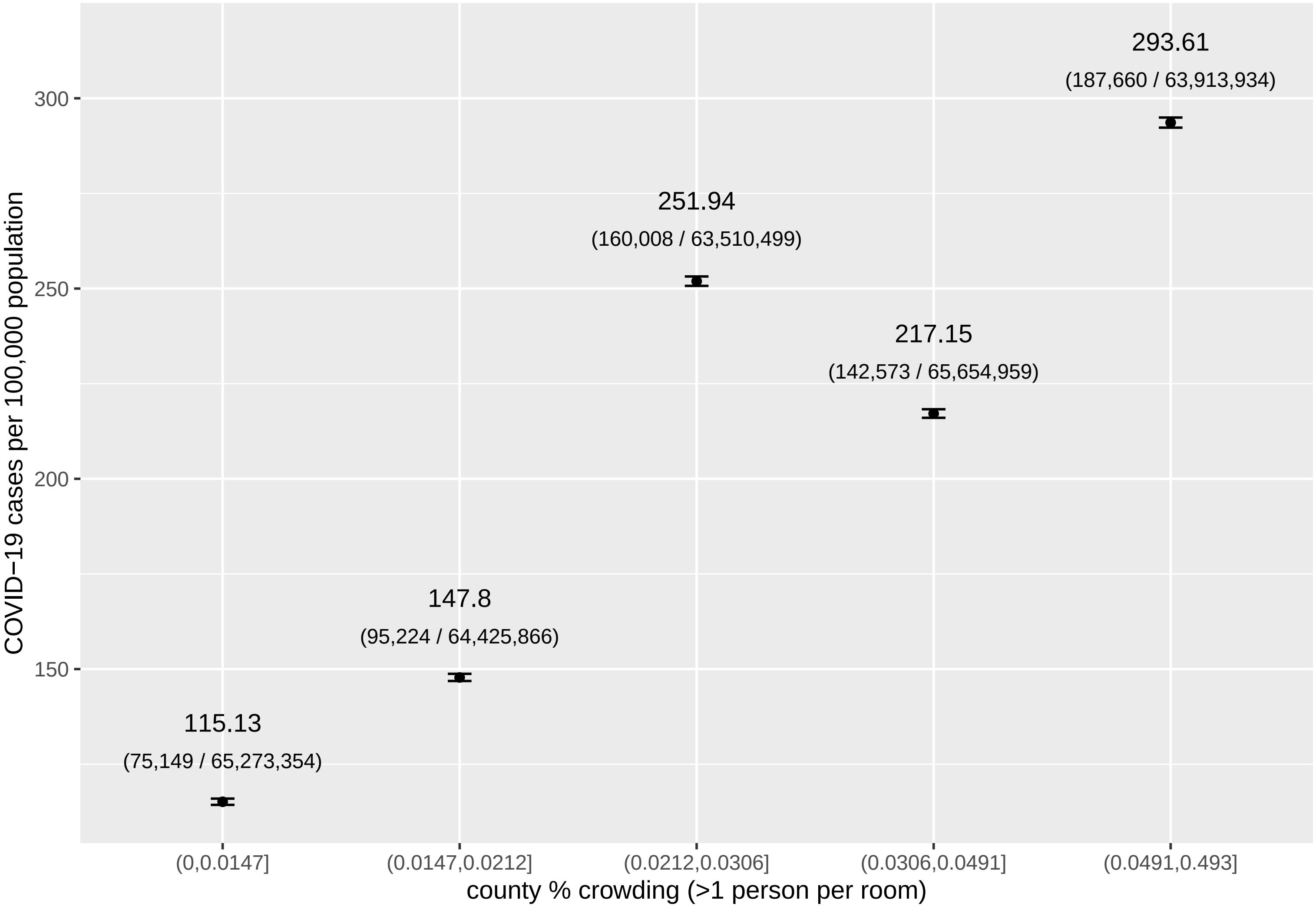
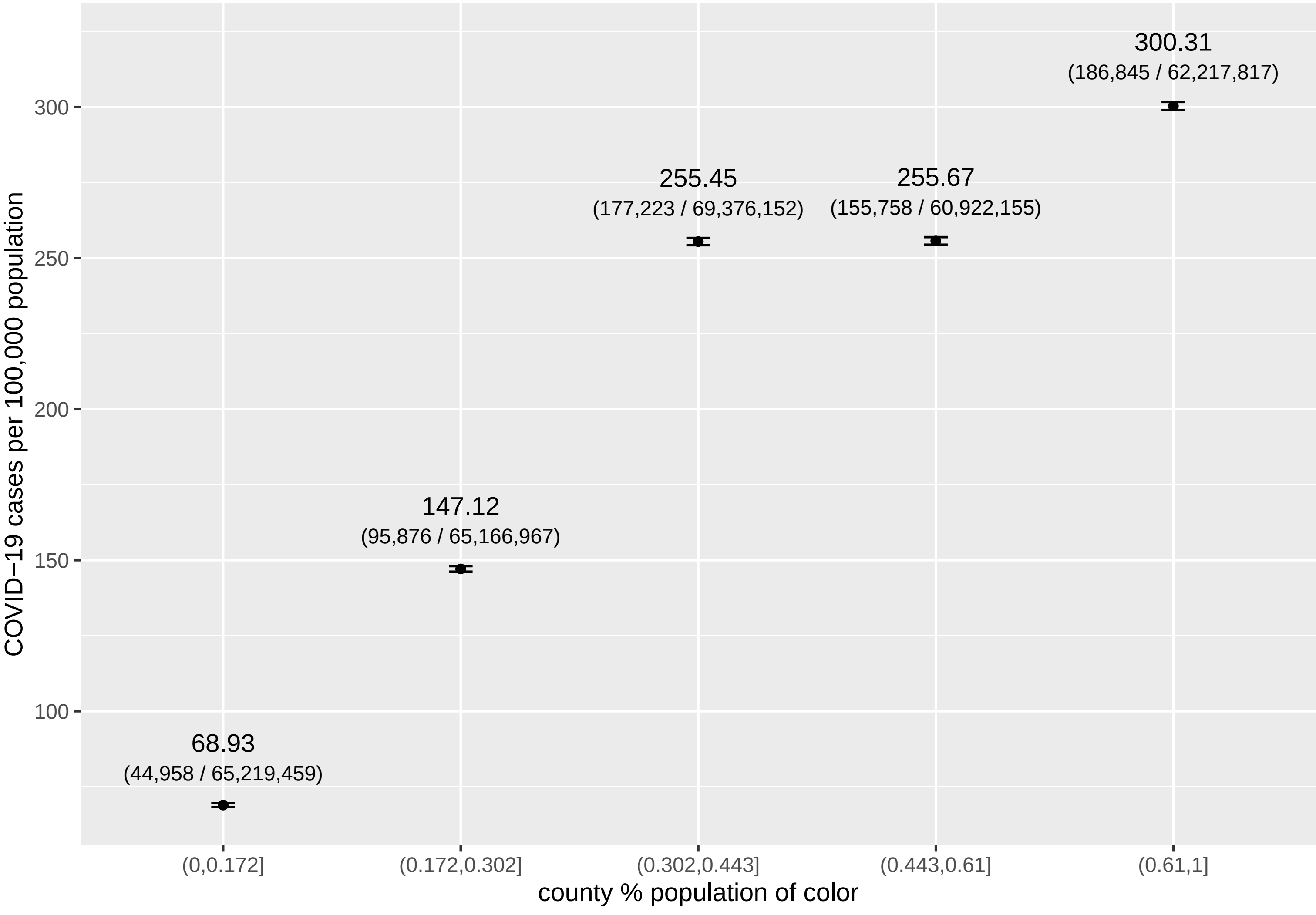


Figure A.1d: US COVID−19 cases per 100,000 population
by county % population of color (as of 4.16.2020)



Addendum: May 28, 2020

This document contains updates to the analyses we present in our working paper,

Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020.

Background

In our original working paper, we presented analyses of disparities in COVID-19 deaths by United States (US) county social metrics, confirmed COVID-19 cases in Illinois by ZIP code social metrics, and positive tests in New York City by ZIP code social metrics as of April 16, 2020.

In this addendum, we update our analyses as of May 5, 2020. We also note refinements and minor corrections we made to our analytic methodology, and interpret the data in the context of the ongoing COVID-19 pandemic.

Methods

Population denominator sources

In our original analyses, we used population estimates for counties and ZIP code tabulation areas (ZCTAs) from the 2014-2018 American Community Survey (ACS) five-year estimates [1]. The ACS is still the most viable source for ZCTA level population estimates, but for the county analysis, we have switched to using the population estimates made available by

USA Facts in conjunction with their county COVID-19 data [2]. These estimates are based on the US Census county-level projections for 2018.

Calculation of age-standardized rates

In our previous analyses, we presented crude “rates” for mortality, confirmed cases, and positive tests per 100,000 by dividing counts by the relevant population estimates. As we considered replicating our analyses for other dates, we realized that this quantity is technically a cumulative incidence proportion and that its magnitude would be sensitive to the amount of person time under observation. That is, even if underlying rates were constant, the cumulative incidence would be larger at a later date because more cases are accrued over a longer period of observation. This type of quantity is being reported in the popular press as a “per capita” rate.

In these updated analyses we present “true” incidence rates by dividing observed counts by *person-time* under observations, which we express as events per 100,000 person-years. To compute person-time, we calculate the number of days since January 22, 2020 (the start of the USA Facts COVID-19 death data), and divide this quantity by 365.25 to re-express the denominator on the scale of person-years.

An advantage of this approach is that it readily permits comparison of the magnitude of COVID-19 mortality rates to published mortality rates for other causes of death. We have revised our analysis of COVID-19 outcomes as of April 16, 2020 to present this type of rate, which also allows comparison across time. We note that this does not change the magnitude of the incidence rate ratio results since it merely involves multiplying the denominators by a constant.

Temporal Comparison

Comparing analyses of US COVID-19 deaths by county social metrics over time is particularly sensitive to which counties had substantial transmission To provide further context to the comparisons we make between April 16, 2020 and May 5, 2020, for US COVID-19 deaths by county social metrics, we also conducted sensitivity analyses restricting to (a) counties with ≥50 confirmed COVID-19 cases as of April 16 and (b) counties with <50 confirmed cases as of April 16 and ≥50 confirmed cases as of May 5.

Quintile cutpoints

Our latest analysis also corrects a small error in the handling of values for the lowest quintiles of social metrics where some zero values were not included in the lowest quintile.

Availability of R code and ACS-derived county and ZCTA variables

We have also made ACS-derived county and ZCTA level variables and R code for replicating our analyses available on the COVID-19 Resources page of our Public Health Disparities Geocoding Project website [3].

Results

County level COVID-19 death in the US

As of April 16, 2020, the highest COVID-19 death rates per 100 000 person-years were consistently observed among those living in the most disadvantaged versus most advantaged counties in relation to: % poverty (91.3 vs. 41.4); ICE (69.2 vs. 59.8), % crowding (80.2 vs. 20.9), and % population of color (80.2 vs. 12.2) (see Table S.1 and Figure S.1). These contrasts correspond to mortality rate ratios of 2.21 (95% CI 2.01, 2.43), 1.16 (95% CI 1.13, 1.19), 3.83 (95% CI 3.69, 3.99), and 6.57 (95% CI 6.26, 6.90).

As of May 5, 2020, rates per 100,000 were dramatically higher (Table S.4 and Figure S.4), and the disparity between rates among the most disadvantaged and most advantaged counties was: % poverty (143.2 vs. 83.3); ICE (113.0 vs. 108.8); % crowding (124.4 vs. 48.2); and % population of color (127.7 vs. 25.9). Because the magnitude of rates by May ≥5, 2020 was much larger than in April, the absolute rate differences were correspondingly larger. Meanwhile, the mortality rate ratios for the most disadvantaged category vs. the most advantaged category were somewhat attenuated: for % poverty IRR=1.72 (95% CI 1.61, 1.83); for the Index of Concentration at the Extremes IRR=1.04 (95% CI 1.02, 1.06); for % crowding 2.58 (95% CI 2.52, 2.65); and for % population of color IRR=4.94 (95% CI 4.78, 5.09). Socioeconomic gradients were not always monotonic, most notably for ICE, for which residents of counties in the most advantaged quintile experienced a death rate only slightly lower than residents of counties in the most disadvantaged quintile. In contrast, residents of counties in the middle quintile of ICE experienced the lowest COVID-19 death rates (16.7 per 100,000 on April 16 and 37.1 per 100,000 on May 5).

In sensitivity analyses restricting to (a) counties with ≥50 confirmed COVID-19 cases as of April 16, and (b) counties with <50 confirmed cases as of April 16 and ≥50 confirmed cases as of May 5 (Table S.7) we see that the additional contribution of deaths and population at risk from counties with <50 confirmed cases as of April 16 and ≥50 confirmed cases as of May 5 is small relative to counties with ≥50 confirmed cases in both time periods. In the counties with ≥50 confirmed cases in both time periods, mortality rates increase across all categories of social metrics, but they increase more rapidly in the least disadvantaged categories, which results in attenuated social gradients on May 5 compared with April 16.

ZCTA level confirmed COVID-19 cases in Illinois

As shown in Table S.2 and Figure S.2, we observed consistent and monotonic socioeconomic gradients in cumulative incidence of COVID-19 diagnoses for all ABSMs using finer resolution ZCTA-level data in Illinois. As of April 16, the highest rates of COVID-19 confirmed cases per 100,000 person-years were observed among the most disadvantaged compared to most advantaged categories of % poverty (1291.5 vs. 545.3), ICE (1,535.0 vs. 545.6), % crowding (1104.1 vs. 614.7), and % population of color (1,569.9 vs. 449.4). These correspond to incidence rate ratios of 2.37 (2.26, 2.48), 2.81 (95% CI 2.70, 2.93), 1.8- (95% CI 1.72, 1.87), and 3.49 (95% CI 3.35, 3.65).

As of May 5, overall rates were dramatically higher (Table S.5 and Figure S.5), and disparities persisted by poverty (2,817.5 vs. 1,093.3), ICE (3,453.6 vs. 1,084.0), % crowding (3,454.2 vs. 1,084.0), and % population of color (4,027.5 vs. 782.4). Relative disparities were also higher than in April, with IRRs comparing the most advantaged to disadvantaged categories observed for % poverty of IRR=2.58 (95% CI 2.50, 2.66); for ICE IRR=3.19 (95% CI 3.10, 3.27); for % crowding IRR=3.07 (95% CI 2.99, 3.15); and for % population of color IRR=5.15 (95% CI 5.00, 5.30).

ZCTA level positive COVID-19 tests in New York City

Strong socioeconomic gradients were also observed with finer resolution ZCTA-level data in New York City in relation to the rate of positive tests (Table S.3 and Figure S.3). These unequal patterns persist even in the context of New York City's substantially greater rates of infection overall. The rate of positive COVID-19 tests per 100,000 person-years was highest among residents in the most disadvantaged vs. most advantaged categories of ICE (5,591.8 vs. 3,749.0), % crowding (5,967.0 vs. 4,331.3), and % population of color (6,221.5 vs. 4,391.0), while for poverty, the highest rates were seen in the 15-19.9% category (5,454.1) and the 20-100% category (5,283.2) vs. the 0-4.9% category (3,676.1). These disparities correspond to incidence rate ratios for ICE of 1.49 (95% CI 1.46, 1.62), for % crowding 1.38 (95% CI 1.35, 1.40), and for % population of color 1.42 (95% CI 1.39, 1.44).

As of May 5, the population rate of positive COVID-19 tests per 100 000 person-years was highest among residents in the most disadvantaged vs. most advantaged categories of % crowding (8,441.5 vs. 5,616.4), and % population of color (8,919.2 vs. 5,645.0) (Table S.6 and Figure S.6). Similarly, the highest rate of positive tests was observed among residents living in counties in the two most disadvantaged categories of ZCTA-level poverty (15-19.9% poverty: 7,651.7 and 20-100% poverty: 7,411.7 vs. 4,561.4 in the most advantaged category, 0-4.9% poverty). By quintiles of the ICE, the highest rates were observed in the most disadvantaged quintile and the third quintile (8,024.6 and 8,026.0 vs. 4,771.1). These correspond to incidence rate ratios of approximately 1.6 for for the categories of % poverty, ICE, and % population of color with the highest rates compared with the lowest rates, and for % crowding, IRR=1.50 (95% CI 1.48, 1.53), indicating that disparities increased between April and May.

Discussion

We continue to find stark disparities in who is diagnosed with and who is dying from COVID-19, with residents of the most disadvantaged counties and ZIP codes showing markedly elevated rates. Using the metric of rates per 100,000 person years, which is more robust to differences in length of observation period than cumulative incidence “per capita”, rates of positive tests in New York City, confirmed cases in Illinois, and deaths across the US have nevertheless substantially increased, reflecting the exponential spread of coronavirus in US communities.

When looking at changes in disparities over time, we note that disparities in death rates by county social metrics have somewhat attenuated between April 16 and May 5. Our sensitivity analyses confirm that the overall attenuation between the most disadvantaged and advantaged categories represents faster increases in the mortality rates for more affluent counties compared with more disadvantaged counties. In the US county analysis, there was a large pool of counties that, as of April 16, and not registered many deaths. As the epidemic spread and some of these more affluent counties begin to register deaths, this served to dampen some of the disparity comparing the most disadvantaged and advantaged categories of county social metrics. However, this slight diminution of the relative risk in no way undercuts two key points: (a) even with higher baseline rates, the rate ratio across categories of county-level social metrics is large, and (b) the magnitude of the observed rate differences is both large and increasing over time, pointing to the profound burden on communities with the least economic and racial/ethnic privilege.

Notably, disparities using finer grained ZIP code level metrics in Illinois and New York City increased between April 16 and May 5. This suggests that in these areas, populations living in disadvantaged ZIP codes continued to experience a disproportionate burden of COVID-19 risk and that increases in the more disadvantaged areas outstripped increases in more affluent ZIP codes.

In interpreting these data, it is important to keep in mind the limitations of COVID-19 data. Data on the population rate of positive tests and confirmed cases is sensitive to where testing is being conducted [4]. Though deaths are less sensitive to inconsistencies of testing, jurisdictions may nevertheless vary in how deaths are reported and whether numbers are for confirmed COVID-19 deaths, presumed COVID-19 deaths, or both [5, 6]. Moreover, the county and ZIP code level data we used were not available disaggregated by race/ethnicity or age. This precludes age-adjusted analyses, and so we were only able to analyze crude rates. Reliance on comparison of crude rates is hampered by two potential issues: (a) likely differences in age structure across the different social strata, and (b) the possibility of different age-specific risks across social strata. If worst-off areas had younger populations, on average, compared to better-off areas, but all social groups had the same age-specific rates, then estimates of social gradients based on the crude rates would underestimate the true social gradient. If, in addition, the age-specific risks were greater among worse-off groups (due to differences in exposure, given occupational structures, and also differences in severity, due to differentials in pre-existing premature morbidity, then the crude estimate would more severely underestimate the actual social gradient. Moreover, the absence of race/ethnicity in the data also make it impossible to characterize racial/ethnic disparities in COVID-19 outcomes.

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Table S.1: US COVID-19 death rate per 100 000 person-years, rate differences, and rate ratios by county characteristics as of April 16, 2020 (3 142 counties, 31,437 deaths, 328,239,523 population)

	Number of counties	Number of deaths	Population*	Death rate per 100 000 person-years	(95% CI)	Rate difference per 100 000 person-years	(95% CI)	Rate ratio	(95% CI)
% poverty (categories)									
0-4.9%	41	449	4,661,334	41.4	(37.6 ,45.2)	0.0	(reference)	1.00	(reference)
5-9.9%	558	7,904	72,698,937	46.7	(45.7 ,47.7)	5.3	(1.4 ,9.3)	1.13	(1.03 ,1.24)
10-14.9%	1 023	8,463	111,359,813	32.7	(32.0 ,33.4)	-8.7	(-12.6 ,-4.8)	0.79	(0.72 ,0.87)
15-19.9%	860	6,898	103,142,585	28.7	(28.1 ,29.4)	-12.7	(-16.5 ,-8.8)	0.69	(0.63 ,0.76)
20-100%	659	7,723	36,337,933	91.3	(89.3 ,93.4)	49.9	(45.6 ,54.3)	2.21	(2.01 ,2.43)
Index of Concentration at the Extremes (high income white households versus low income black households)									
(-0.522,0.114]	974	10,015	62,191,173	69.2	(67.8 ,70.6)	9.4	(7.6 ,11.3)	1.16	(1.13 ,1.19)
(0.114,0.159]	701	5,337	65,858,776	34.8	(33.9 ,35.8)	-24.9	(-26.5 ,-23.4)	0.58	(0.56 ,0.60)
(0.159,0.205]	696	2,565	66,166,730	16.7	(16.0 ,17.3)	-43.1	(-44.5 ,-41.7)	0.28	(0.27 ,0.29)
(0.205,0.283]	515	4,093	66,201,038	26.6	(25.8 ,27.4)	-33.2	(-34.6 ,-31.7)	0.44	(0.43 ,0.46)
(0.283,0.536]	255	9,427	67,782,885	59.8	(58.6 ,61.0)	0.0	(reference)	1.00	(reference)
% crowding (quintiles)									
(0,0.0147]	1 089	3,213	65,973,004	20.9	(20.2 ,21.7)	0.0	(reference)	1.00	(reference)
(0.0147,0.0212]	709	3,989	65,506,176	26.2	(25.4 ,27.0)	5.2	(4.2 ,6.3)	1.25	(1.19 ,1.31)
(0.0212,0.0306]	656	6,751	64,811,652	44.8	(43.7 ,45.8)	23.8	(22.5 ,25.1)	2.14	(2.05 ,2.23)
(0.0306,0.0491]	443	5,462	67,551,767	34.7	(33.8 ,35.7)	13.8	(12.6 ,15.0)	1.66	(1.59 ,1.73)
(0.0491,0.493]	244	12,022	64,388,610	80.2	(78.8 ,81.7)	59.3	(57.7 ,60.9)	3.83	(3.69 ,3.99)
% percent population of color									
(0,0.172]	1 636	1,872	65,899,452	12.2	(11.7 ,12.8)	0.0	(reference)	1.00	(reference)
(0.172,0.302]	549	3,995	66,645,498	25.8	(25.0 ,26.6)	13.6	(12.6 ,14.5)	2.11	(2.00 ,2.23)
(0.302,0.443]	468	7,091	71,036,761	42.9	(41.9 ,43.9)	30.7	(29.5 ,31.8)	3.51	(3.34 ,3.70)
(0.443,0.61]	280	6,766	61,880,053	47.0	(45.9 ,48.1)	34.8	(33.5 ,36.0)	3.85	(3.66 ,4.05)
(0.61,1]	209	11,713	62,777,759	80.2	(78.7 ,81.6)	68.0	(66.4 ,69.5)	6.57	(6.26 ,6.90)

* Population totals can vary due to counties with missing area-based socioeconomic measures.

Table S.2: Illinois rate of confirmed COVID-19 cases per 100 000 person-years, rate differences, and rate ratios by ZCTA characteristics as of April 16, 2020 (461 ZIP codes, 24,675 cases, 10,353,354 population)

	Number of ZCTAs	Number of confirmed cases	Population*	Confirmed case rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	72	2,378	1,531,569	545.3	(523.4	,567.2)	0.0	(reference)		1.00	(reference)	
5-9.9%	159	6,442	3,357,448	673.9	(657.4	,690.3)	128.6	(101.2	,156.0)	1.24	(1.18	,1.30)
10-14.9%	90	4,682	2,052,094	801.3	(778.3	,824.2)	256.0	(224.3	,287.7)	1.47	(1.40	,1.54)
15-19.9%	60	3,085	1,225,648	884.0	(852.8	,915.2)	338.7	(300.6	,376.8)	1.62	(1.54	,1.71)
20-100%	80	8,041	2,186,595	1291.5	(1263.3	,1319.7)	746.2	(710.5	,782.0)	2.37	(2.26	,2.48)
missing ZCTA		47										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-1,0.0375]	73	9,090	2,079,722	1535.0	(1503.5	,1566.6)	989.4	(952.6	,1026.2)	2.81	(2.70	,2.93)
(0.0375,0.166]	95	4,258	2,087,542	716.4	(694.8	,737.9)	170.7	(142.1	,199.4)	1.31	(1.25	,1.37)
(0.166,0.27]	101	4,582	2,070,229	777.3	(754.8	,799.8)	231.7	(202.3	,261.1)	1.42	(1.36	,1.49)
(0.27,0.396]	100	3,502	2,058,711	597.4	(577.6	,617.2)	51.8	(24.4	,79.2)	1.09	(1.04	,1.15)
(0.396,0.721]	91	3,196	2,057,150	545.6	(526.7	,564.5)	0.0	(reference)		1.00	(reference)	
missing ZCTA		47										
% crowding (quintiles)												
(0,0.00971]	133	3,652	2,086,628	614.7	(594.7	,634.6)	0.0	(reference)		1.00	(reference)	
(0.00971,0.017]	99	3,131	2,060,973	533.5	(514.9	,552.2)	-81.1	(-108.5	,-53.8)	0.87	(0.83	,0.91)
(0.017,0.0264]	84	5,009	2,052,139	857.2	(833.5	,881.0)	242.6	(211.6	,273.6)	1.39	(1.34	,1.46)
(0.0264,0.0446]	81	6,386	2,101,938	1067.0	(1040.8	,1093.2)	452.3	(419.4	,485.2)	1.74	(1.67	,1.81)
(0.0446,0.143]	64	6,450	2,051,676	1104.1	(1077.2	,1131.0)	489.4	(455.9	,522.9)	1.80	(1.72	,1.87)
missing ZCTA		47										
% percent population of color												
(0.00685,0.18]	146	2,662	2,080,210	449.4	(432.4	,466.5)	0.0	(reference)		1.00	(reference)	
(0.18,0.286]	89	2,992	2,023,605	519.3	(500.7	,537.9)	69.8	(44.6	,95.1)	1.16	(1.10	,1.22)
(0.286,0.445]	94	4,071	2,159,499	662.1	(641.7	,682.4)	212.6	(186.1	,239.2)	1.47	(1.40	,1.55)
(0.445,0.718]	71	5,731	2,038,179	987.5	(962.0	,1013.1)	538.1	(507.3	,568.8)	2.20	(2.10	,2.30)
(0.718,0.99]	61	9,172	2,051,861	1569.9	(1537.8	,1602.0)	1120.5	(1084.1	,1156.9)	3.49	(3.35	,3.65)
missing ZCTA		47										

Table S.3: New York City rate of positive COVID-19 tests per 100 000 person-years, rate differences, and rate ratios by ZCTA characteristics as of April 16, 2020 (177 ZCTAs, 125,422 positive tests, 8 433 176 population)

	Number of ZCTAs	Number of positive tests	Population*	Rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	9	1,362	130,121	3676.1	(3480.9	,3871.3)	0.0	(reference)		1.00	(reference)	
5-9.9%	41	20,609	1,506,286	4805.1	(4739.5	,4870.7)	1129.0	(923.1	,1335.0)	1.31	(1.24	,1.38)
10-14.9%	48	30,294	2,100,915	5064.1	(5007.1	,5121.2)	1388.0	(1184.6	,1591.4)	1.38	(1.30	,1.45)
15-19.9%	27	22,359	1,439,746	5454.1	(5382.6	,5525.6)	1778.0	(1570.1	,1985.9)	1.48	(1.40	,1.57)
20+%	52	48,982	3,256,108	5283.2	(5236.4	,5330.0)	1607.1	(1406.3	,1807.8)	1.44	(1.36	,1.52)
missing ZCTA		1,816										
Index of Concentration at the Extremes (high income white households versus low income black households)												
[-0.385,-0.102]	29	26,889	1,688,793	5591.8	(5525.0	,5658.7)	1842.9	(1756.4	,1929.4)	1.49	(1.46	,1.52)
(-0.102,0.0212]	30	28,209	1,749,736	5662.0	(5596.0	,5728.1)	1913.1	(1827.2	,1999.0)	1.51	(1.48	,1.54)
(0.0212,0.141]	29	26,844	1,623,732	5806.2	(5736.7	,5875.6)	2057.2	(1968.7	,2145.8)	1.55	(1.52	,1.58)
(0.141,0.29]	39	23,751	1,692,826	4927.5	(4864.8	,4990.2)	1178.5	(1095.2	,1261.9)	1.31	(1.29	,1.34)
(0.29,0.7]	50	17,913	1,678,089	3749.0	(3694.1	,3803.9)	0.0	(reference)		1.00	(reference)	
missing ZCTA		1,816										
% crowding (quintiles)												
[0.00942,0.0478]	48	21,074	1,708,791	4331.3	(4272.8	,4389.7)	0.0	(reference)		1.00	(reference)	
(0.0478,0.0698]	37	23,808	1,688,963	4950.6	(4887.7	,5013.5)	619.4	(533.5	,705.2)	1.14	(1.12	,1.16)
(0.0698,0.0978]	38	24,507	1,679,177	5125.7	(5061.5	,5189.8)	794.4	(707.6	,881.2)	1.18	(1.16	,1.21)
(0.0978,0.138]	31	25,783	1,682,708	5381.2	(5315.5	,5446.9)	1050.0	(962.0	,1137.9)	1.24	(1.22	,1.27)
(0.138,0.297]	23	28,434	1,673,537	5967.0	(5897.7	,6036.4)	1635.8	(1545.1	,1726.5)	1.38	(1.35	,1.40)
missing ZCTA		1,816										
% population of color (quintiles)												
[0.0839,0.402]	44	21,238	1,698,653	4391.0	(4332.0	,4450.1)	0.0	(reference)		1.00	(reference)	
(0.402,0.584]	38	20,554	1,678,144	4301.5	(4242.7	,4360.3)	-89.5	(-172.8	,-6.1)	0.98	(0.96	,1.00)
(0.584,0.826]	38	25,541	1,708,248	5251.0	(5186.6	,5315.4)	860.0	(772.6	,947.4)	1.20	(1.17	,1.22)
(0.826,0.957]	29	27,231	1,708,722	5596.9	(5530.4	,5663.4)	1205.9	(1117.0	,1294.8)	1.27	(1.25	,1.30)
(0.957,0.992]	28	29,042	1,639,409	6221.5	(6150.0	,6293.1)	1830.5	(1737.7	,1923.3)	1.42	(1.39	,1.44)
missing ZCTA		1,816										

Table S.4: US COVID-19 death rate per 100 000 person-years, rate differences, and rate ratios by county characteristics as of May 5, 2020 (3,142 counties, 68,656 deaths, 322,903,030 population)

	Number of counties	Number of deaths	Population*	Death rate per 100 000 person-years	(95% CI)		Rate difference per 100 000 person-years	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	41	1 067	4 495 932	83.3	78.3	88.4	0.0	(reference)		1.00	(reference)	
5-9.9%	558	17 855	71 157 744	88.1	86.8	89.4	4.8	- 0.4	9.9	1.06	0.99	1.12
10-14.9%	1 023	18 895	108 820 591	61.0	60.1	61.9	- 22.4	- 27.4	- 17.3	0.73	0.69	0.78
15-19.9%	860	15 990	101 961 251	55.1	54.2	55.9	- 28.3	- 33.3	- 23.2	0.66	0.62	0.70
20-100%	659	14 849	36 428 205	143.2	140.9	145.5	59.8	54.3	65.3	1.72	1.61	1.83
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-0.522,0.114]	974	19 939	61 949 063	113.0	111.5	114.6	4.2	2.1	6.4	1.04	1.02	1.06
(0.114,0.159]	701	10 991	64 942 197	59.4	58.3	60.5	- 49.4	- 51.2	- 47.5	0.55	0.53	0.56
(0.159,0.205]	696	6 879	65 113 354	37.1	36.2	38.0	- 71.7	- 73.4	- 70.0	0.34	0.33	0.35
(0.205,0.283]	515	10 297	64 525 801	56.0	55.0	57.1	- 52.8	- 54.6	- 50.9	0.52	0.50	0.53
(0.283,0.536]	255	20 550	66 333 308	108.8	107.3	110.3	0.0	(reference)		1.00	(reference)	
% crowding (quintiles)												
(0,0.0147]	1 089	8 953	65 273 354	48.2	47.2	49.2	0.0	(reference)		1.00	(reference)	
(0.0147,0.0212]	709	10 331	64 425 866	56.3	55.2	57.4	8.1	6.7	9.6	1.17	1.14	1.20
(0.0212,0.0306]	656	14 499	63 510 499	80.2	78.9	81.5	32.0	30.4	33.6	1.66	1.62	1.71
(0.0306,0.0491]	443	12 242	65 654 959	65.5	64.3	66.6	17.3	15.8	18.8	1.36	1.32	1.40
(0.0491,0.493]	244	22 630	63 913 934	124.4	122.7	126.0	76.2	74.3	78.1	2.58	2.52	2.65
% percent population of color												
(0,0.172]	1 636	4 804	65 219 939	25.9	25.1	26.6	0.0	(reference)		1.00	(reference)	
(0.172,0.302]	549	10 570	65 166 967	57.0	55.9	58.1	31.1	29.8	32.4	2.20	2.13	2.28
(0.302,0.443]	468	15 687	69 376 152	79.4	78.2	80.7	53.5	52.1	55.0	3.07	2.97	3.17
(0.443,0.61]	280	14 974	60 922 155	86.3	84.9	87.7	60.5	58.9	62.0	3.34	3.23	3.45
(0.61,1]	209	22 621	62 217 817	127.7	126.0	129.4	101.8	100.0	103.6	4.94	4.78	5.09

* Population totals can vary due to counties with missing area-based socioeconomic measures.

Table S.5: Illinois rate of confirmed COVID-19 cases per 100 000 person-years, rate differences, and rate ratios by ZCTA characteristics as of May 5, 2020 (461 ZCTAs, 63,901 confirmed cases, 11,383,197 population)

	Number of ZCTAs	Number of confirmed cases	Population*	Confirmed case rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	72	4 912	1 577 939	1 093.3	1 062.7	1 123.8	0.0	(reference)		1.00	reference)	
5-9.9%	159	15 584	3 556 778	1 538.8	1 514.6	1 562.9	445.5	406.6	484.5	1.41	1.36	1.45
10-14.9%	90	13 235	2 309 648	2 012.5	1 978.2	2 046.8	919.2	873.3	965.2	1.84	1.78	1.90
15-19.9%	60	10 085	1 458 799	2 427.9	2 380.5	2 475.3	1 334.7	1 278.3	1 391.1	2.22	2.15	2.30
20-100%	80	19 896	2 480 033	2 817.5	2 778.4	2 856.7	1 724.2	1 674.6	1 773.9	2.58	2.50	2.66
missing ZCTA		189										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-1,0.0375]	73	22 090	2 245 980	3 454.2	3 408.6	3 499.7	2 370.2	2 318.1	2 422.3	3.19	3.10	3.27
(0.0375,0.166]	95	12 447	2 304 293	1 897.1	1 863.7	1 930.4	813.0	771.2	854.9	1.75	1.70	1.80
(0.166,0.27]	101	13 182	2 276 391	2 033.7	1 999.0	2 068.4	949.7	906.7	992.7	1.88	1.82	1.93
(0.27,0.396]	100	8 919	2 263 673	1 383.8	1 355.0	1 412.5	299.7	261.5	338.0	1.28	1.24	1.32
(0.396,0.721]	91	7 051	2 284 383	1 084.0	1 058.7	1 109.3	0.0	(reference)		1.00	(reference)	
missing ZCTA		212										
% crowding (quintiles)												
(0,0.00971]	133	7 584	2 296 157	1 160.0	1 133.9	1 186.1	0.0	(reference)		1.00	(reference)	
(0.00971,0.017]	99	5 900	2 221 492	932.7	908.9	956.5	- 227.2	- 262.6	- 191.9	0.80	0.78	0.83
(0.017,0.0264]	84	10 763	2 307 613	1 638.1	1 607.1	1 669.0	478.1	437.6	518.6	1.41	1.37	1.45
(0.0264,0.0446]	81	16 319	2 272 821	2 521.7	2 483.0	2 560.3	1 361.7	1 315.0	1 408.3	2.17	2.12	2.23
(0.0446,0.143]	64	23 146	2 285 114	3 557.3	3 511.5	3 603.2	2 397.3	2 344.6	2 450.1	3.07	2.99	3.15
missing ZCTA		189										
% percent population of color												
(0.00685,0.18]	146	5 104	2 290 991	782.4	761.0	803.9	0.0	(reference)		1.00	(reference)	
(0.18,0.286]	89	6 636	2 268 672	1 027.3	1 002.6	1 052.0	244.9	212.1	277.6	1.31	1.27	1.36
(0.286,0.445]	94	9 652	2 291 717	1 479.2	1 449.6	1 508.7	696.7	660.2	733.2	1.89	1.83	1.96
(0.445,0.718]	71	16 598	2 288 835	2 546.8	2 508.1	2 585.6	1 764.4	1 720.1	1 808.7	3.26	3.15	3.36
(0.718,0.99]	61	25 722	2 242 982	4 027.5	3 978.3	4 076.7	3 245.1	3 191.4	3 298.8	5.15	5.00	5.30
missing ZCTA		189										

Table S.6: New York City rate of positive COVID-19 tests per 100 000 person-years, rate differences, and rate ratios by ZCTA characteristics as of May 5, 2020 (177 ZCTAs, 171 615 positive tests, 8 433 176 population)

	Number of ZCTAs	Number of positive tests	Population*	Rate per 100,000	(95% CI)		Rate difference per 100,000	(95% CI)		Rate ratio	(95% CI)	
% poverty (categories)												
0-4.9%	9	1 690	130 121	4 561.4	4 343.9	4 778.9	0.0	(reference)		1.00	(reference)	
5-9.9%	41	26 941	1 506 286	6 281.5	6 206.5	6 356.5	1 720.1	1 490.1	1 950.2	1.38	1.31	1.45
10-14.9%	48	41 280	2 100 915	6 900.6	6 834.1	6 967.2	2 339.2	2 111.8	2 566.7	1.51	1.44	1.59
15-19.9%	27	31 368	1 439 746	7 651.7	7 567.0	7 736.4	3 090.3	2 856.9	3 323.7	1.68	1.60	1.76
20+%	52	68 716	3 256 108	7 411.7	7 356.3	7 467.1	2 850.3	2 625.9	3 074.7	1.62	1.55	1.71
missing ZCTA		1 620										
Index of Concentration at the Extremes (high income white households versus low income black households)												
(-0.385,-0.102]	29	38 587	1 688 793	8 024.6	7 944.5	8 104.6	3 253.5	3 152.2	3 354.7	1.68	1.65	1.71
(-0.102,0.0212]	30	39 324	1 749 736	7 893.0	7 815.0	7 971.0	3 121.9	3 022.3	3 221.5	1.65	1.63	1.68
(0.0212,0.141]	29	37 107	1 623 732	8 026.0	7 944.3	8 107.6	3 254.9	3 152.4	3 357.4	1.68	1.65	1.71
(0.141,0.29]	39	32 180	1 692 826	6 676.2	6 603.3	6 749.2	1 905.1	1 809.4	2 000.8	1.40	1.38	1.42
(0.29,0.7]	50	22 797	1 678 089	4 771.1	4 709.2	4 833.0	0.0	(reference)		1.00	(reference)	
missing ZCTA		1 620										
% crowding (quintiles)												
(0.00942,0.0478]	48	27 327	1 708 791	5 616.4	5 549.8	5 683.0	0.0	(reference)		1.00	(reference)	
(0.0478,0.0698]	37	32 369	1 688 963	6 730.8	6 657.5	6 804.1	1 114.4	1 015.3	1 213.4	1.20	1.18	1.22
(0.0698,0.0978]	38	34 018	1 679 177	7 114.9	7 039.3	7 190.5	1 498.5	1 397.7	1 599.2	1.27	1.25	1.29
(0.0978,0.138]	31	36 056	1 682 708	7 525.3	7 447.7	7 603.0	1 908.9	1 806.6	2 011.2	1.34	1.32	1.36
(0.138,0.297]	23	40 225	1 673 537	8 441.5	8 359.0	8 524.0	2 825.0	2 719.0	2 931.1	1.50	1.48	1.53
missing ZCTA		1 620										
% population of color (quintiles)												
(0.0839,0.402]	44	27 303	1 698 653	5 645.0	5 578.0	5 711.9	0.0	(reference)		1.00	(reference)	
(0.402,0.584]	38	27 575	1 678 144	5 770.9	5 702.8	5 839.0	125.9	30.4	221.4	1.02	1.01	1.04
(0.584,0.826]	38	35 079	1 708 248	7 212.0	7 136.5	7 287.4	1 567.0	1 466.1	1 667.9	1.28	1.26	1.30
(0.826,0.957]	29	38 403	1 708 722	7 893.2	7 814.2	7 972.1	2 248.2	2 144.7	2 351.7	1.40	1.38	1.42
(0.957,0.992]	28	41 635	1 639 409	8 919.2	8 833.6	9 004.9	3 274.3	3 165.5	3 383.0	1.58	1.56	1.60

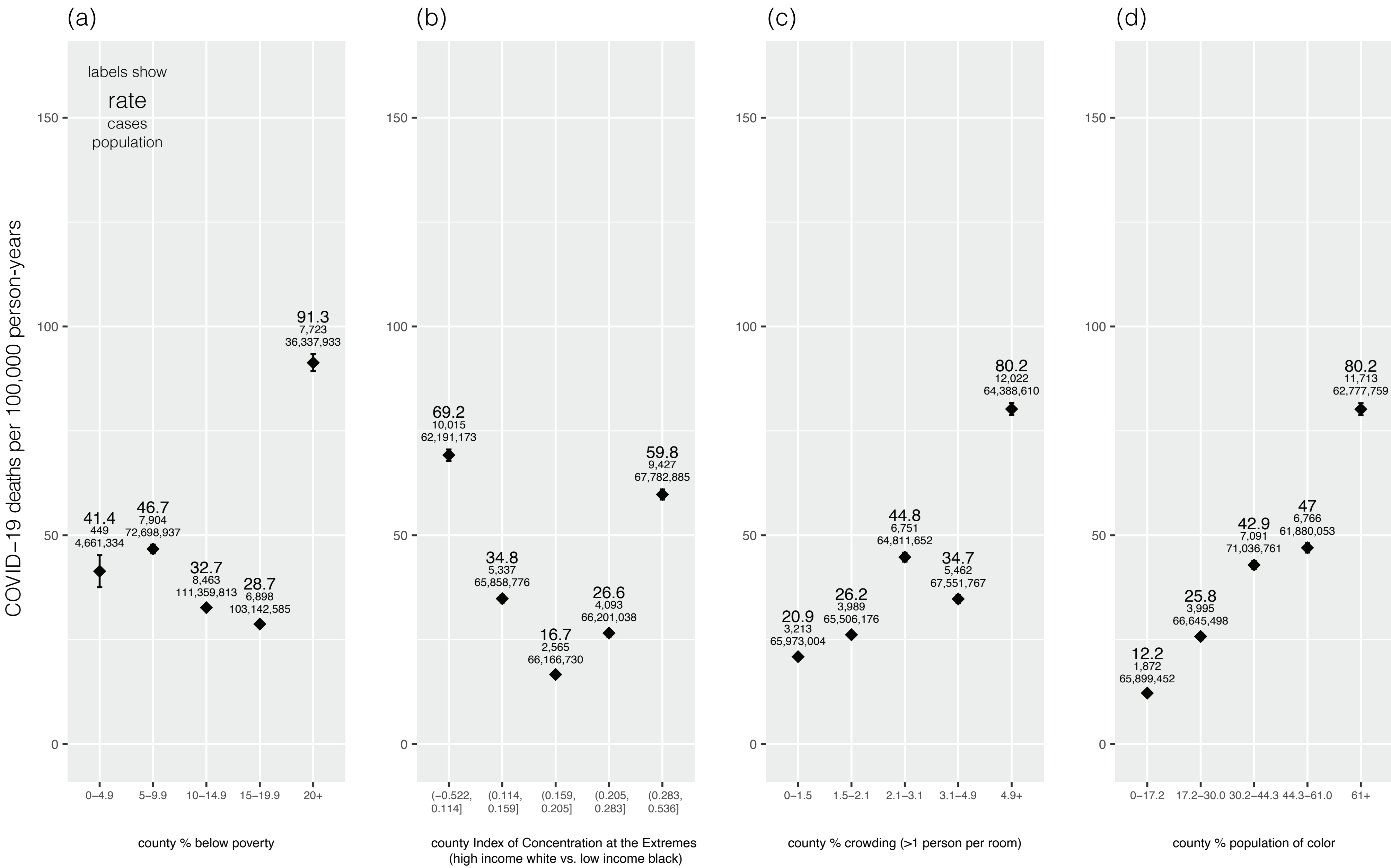
Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020. Addendum: May 28, 2020.

Table S.7: US COVID-19 death rates, rate differences, and rate ratios by county social metrics on April 16, 2020 and May 5, 2020, stratified by counties with >=50 cases as of April 16, 2020 and counties with <50 cases as of April 16 but >=50 cases as of May 5, 2020

		16-Apr-20											5-May-20										
	ABSM	Deaths	Population	Rate	(95% CI)		IRD	(95% CI)		IRR	(95% CI)		Deaths	Population	Rate	(95% CI)		IRD	(95% CI)		IRR	(95% CI)	
counties with >=50 cases as of April 16, 2020	% poverty																						
	0-4.9%	445	4,118,402	46.4	42.1	50.7	0.0	(reference)		1.00	(reference)		1,050	4,118,402	89.5	84.1	95.0	0.0	(reference)		1.00	(reference)	
	5-9.9%	7,812	63,277,389	53.0	51.9	54.2	6.6	2.1	11.1	1.14	1.04	1.26	17,644	63,277,389	97.9	96.5	99.4	8.4	2.8	14.0	1.09	1.03	1.16
	10-14.9%	8,218	88,473,231	39.9	39.1	40.8	-6.5	-10.9	-2.1	0.86	0.78	0.95	18,189	88,473,231	72.2	71.2	73.3	-17.3	-22.9	-11.8	0.81	0.76	0.86
	15-19.9%	6,643	80,755,273	35.3	34.5	36.2	-11.1	-15.5	-6.7	0.76	0.69	0.84	15,436	80,755,273	67.1	66.1	68.2	-22.4	-27.9	-16.9	0.75	0.70	0.80
	20-100%	7,541	23,195,580	139.7	136.5	142.9	93.3	87.9	98.6	3.01	2.73	3.31	14,245	23,195,580	215.7	212.1	219.2	126.1	119.7	132.6	2.41	2.26	2.56
	% crowding																						
	[0,0.0147]	2,983	45,478,318	28.2	27.2	29.2	0.0	(reference)		1.00	(reference)		8,314	45,478,318	64.2	62.8	65.6	0.0	(reference)		1.00	(reference)	
	(0.0147,0.0212]	3,789	47,979,024	33.9	32.9	35.0	5.7	4.3	7.2	1.20	1.15	1.26	9,824	47,979,024	71.9	70.5	73.3	7.7	5.7	9.7	1.12	1.09	1.15
	(0.0212,0.0306]	6,575	48,971,309	57.7	56.3	59.1	29.5	27.8	31.2	2.05	1.96	2.14	14,056	48,971,309	100.8	99.1	102.5	36.6	34.4	38.8	1.57	1.53	1.61
	(0.0306,0.0491]	5,341	58,104,538	39.5	38.4	40.6	11.3	9.8	12.8	1.40	1.34	1.47	11,930	58,104,538	72.1	70.8	73.4	7.9	6.0	9.8	1.12	1.09	1.16
	(0.0491,0.493]	11,971	59,286,686	86.8	85.2	88.3	58.6	56.7	60.4	3.08	2.96	3.20	22,440	59,286,686	132.9	131.2	134.7	68.7	66.5	70.9	2.07	2.02	2.12
	Index of Concentration at the Extremes (white high income vs. black low income)																						
	[-0.522,0.114]	9,753	44,925,359	93.3	91.4	95.1	29.9	27.6	32.1	1.47	1.43	1.51	19,137	44,925,359	149.6	147.5	151.7	36.3	33.6	38.9	1.32	1.29	1.35
	(0.114,0.159]	5,173	48,263,585	46.1	44.8	47.3	-17.4	-19.2	-15.6	0.73	0.70	0.75	10,463	48,263,585	76.1	74.7	77.6	-37.2	-39.3	-35.1	0.67	0.66	0.69
	(0.159,0.205]	2,389	49,471,762	20.8	19.9	21.6	-42.7	-44.2	-41.1	0.33	0.31	0.34	6,459	49,471,762	45.9	44.7	47.0	-67.5	-69.4	-65.6	0.40	0.39	0.42
	(0.205,0.283]	3,955	53,551,070	31.7	30.7	32.7	-31.7	-33.3	-30.1	0.50	0.48	0.52	9,979	53,551,070	65.4	64.2	66.7	-47.9	-49.9	-45.9	0.58	0.56	0.59
	(0.283,0.536]	9,389	63,608,099	63.4	62.1	64.7	0.0	(reference)		1.00	(reference)		20,526	63,608,099	113.3	111.8	114.9	0.0	(reference)		1.00	(reference)	
	% population of color																						
	[0,0.172]	1,465	26,556,436	23.7	22.5	24.9	0.0	(reference)		1.00	(reference)		3,789	26,556,436	50.1	48.5	51.7	0.0	(reference)		1.00	(reference)	
	(0.172,0.302]	3,847	52,822,609	31.3	30.3	32.3	7.6	6.0	9.2	1.32	1.24	1.40	10,228	52,822,609	68.0	66.7	69.3	17.9	15.8	20.0	1.36	1.31	1.41
	(0.302,0.443]	6,983	63,369,394	47.4	46.2	48.5	23.6	22.0	25.3	2.00	1.89	2.11	15,366	63,369,394	85.2	83.8	86.5	35.1	33.0	37.1	1.70	1.64	1.76
	(0.443,0.61]	6,696	57,701,817	49.9	48.7	51.1	26.2	24.5	27.9	2.10	1.99	2.23	14,811	57,701,817	90.1	88.7	91.6	40.0	37.9	42.2	1.80	1.74	1.86
	(0.61,1]	11,668	59,369,619	84.5	82.9	86.0	60.7	58.8	62.7	3.56	3.37	3.76	22,370	59,369,619	132.3	130.6	134.1	82.2	79.9	84.6	2.64	2.55	2.73

		16-Apr-20												5-May-20											
	ABSM	Deaths	Population	Rate	(95% CI)		IRD	(95% CI)		IRR	(95% CI)		Deaths	Population	Rate	(95% CI)		IRD	(95% CI)		IRR	(95% CI)	
counties with <50 cases as of April 16, 2020 and >=50 cases as of May 5, 2020	% poverty																						
	0-4.9%	1	138,377	3.1	-3.0	9.2	0.0	(reference)		1.00	(reference)		1	138,377	2.5	-2.4	7.5	0.0	(reference)		1.00	(reference)	
	5-9.9%	41	3,125,406	5.6	3.9	7.4	2.5	-3.8	8.9	1.82	0.25	13.20	122	3,125,406	13.7	11.3	16.1	11.2	5.6	16.7	5.40	0.75	38.66
	10-14.9%	105	7,446,916	6.1	4.9	7.2	3.0	-3.2	9.1	1.95	0.27	13.98	343	7,446,916	16.2	14.5	17.9	13.6	8.4	18.9	6.37	0.90	45.38
	15-19.9%	108	7,619,297	6.1	4.9	7.2	3.0	-3.2	9.2	1.96	0.27	14.05	328	7,619,297	15.1	13.5	16.8	12.6	7.3	17.8	5.96	0.84	42.42
	20-100%	81	4,083,938	8.5	6.7	10.4	5.4	-0.9	11.8	2.74	0.38	19.72	356	4,083,938	30.6	27.4	33.8	28.1	22.2	34.0	12.06	1.69	85.87
	% crowding																						
	[0,0.0147]	85	5,205,506	7.0	5.5	8.5	0.0	(reference)		1.00	(reference)		357	5,205,506	24.1	21.6	26.6	0.0	(reference)		1.00	(reference)	
	(0.0147,0.0212]	97	6,536,594	6.4	5.1	7.6	-0.6	-2.6	1.3	0.91	0.68	1.22	281	6,536,594	15.1	13.3	16.9	-9.0	-12.0	-5.9	0.63	0.54	0.73
	(0.0212,0.0306]	76	5,649,502	5.8	4.5	7.1	-1.2	-3.2	0.7	0.82	0.60	1.12	249	5,649,502	15.5	13.6	17.4	-8.6	-11.8	-5.5	0.64	0.55	0.76
	(0.0306,0.0491]	53	2,953,848	7.7	5.6	9.8	0.7	-1.9	3.2	1.10	0.78	1.55	198	2,953,848	23.5	20.3	26.8	-0.5	-4.7	3.6	0.98	0.82	1.16
	(0.0491,0.493]	25	2,068,484	5.2	3.2	7.2	-1.8	-4.3	0.7	0.74	0.47	1.16	65	2,068,484	11.0	8.4	13.7	-13.0	-16.7	-9.4	0.46	0.35	0.60
	Index of Concentration at the Extremes (white high income vs. black low income)																						
	[-0.522,0.114]	111	5,439,858	8.8	7.1	10.4	3.3	0.6	6.1	1.62	1.03	2.53	446	5,439,858	28.8	26.1	31.5	18.6	14.7	22.4	2.82	2.12	3.75
	(0.114,0.159]	68	5,067,232	5.8	4.4	7.1	0.3	-2.3	2.9	1.06	0.66	1.71	244	5,067,232	16.9	14.8	19.0	6.7	3.2	10.2	1.66	1.23	2.23
	(0.159,0.205]	72	4,979,777	6.2	4.8	7.6	0.8	-1.9	3.4	1.15	0.72	1.83	220	4,979,777	15.5	13.5	17.6	5.3	1.9	8.7	1.52	1.13	2.05
	(0.205,0.283]	62	5,105,347	5.2	3.9	6.5	-0.2	-2.8	2.4	0.96	0.60	1.55	187	5,105,347	12.9	11.0	14.7	2.6	-0.7	6.0	1.26	0.93	1.71
	(0.283,0.536]	23	1,821,720	5.4	3.2	7.6	0.0	(reference)		1.00	(reference)		53	1,821,720	10.2	7.5	13.0	0.0	(reference)		1.00	(reference)	
	% population of color																						
	[0,0.172]	164	10,324,630	6.8	5.8	7.9	0.0	(reference)		1.00	(reference)		559	10,324,630	19.0	17.4	20.6	0.0	(reference)		1.00	(reference)	
	(0.172,0.302]	69	5,541,701	5.4	4.1	6.6	-1.5	-3.1	0.2	0.78	0.59	1.04	182	5,541,701	11.5	9.9	13.2	-7.5	-9.8	-5.2	0.61	0.51	0.72
	(0.302,0.443]	46	3,048,253	6.5	4.6	8.4	-0.3	-2.5	1.8	0.95	0.69	1.32	195	3,048,253	22.5	19.3	25.6	3.5	-0.1	7.0	1.18	1.00	1.39
	(0.443,0.61]	36	1,722,083	9.0	6.0	11.9	2.2	-1.0	5.3	1.32	0.92	1.89	134	1,722,083	27.3	22.7	32.0	8.3	3.4	13.2	1.44	1.19	1.74
	(0.61,1]	21	1,777,267	5.1	2.9	7.2	-1.7	-4.2	0.7	0.74	0.47	1.17	80	1,777,267	15.8	12.3	19.3	-3.2	-7.0	0.6	0.83	0.66	1.05

Figure S.1: US COVID–19 deaths per 100,000 person-years by county area-based social metrics as of April 16, 2020



Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020. Addendum: May 28, 2020.

Figure S.2: Illinois COVID-19 confirmed cases per 100,000 person-years by ZIP code area-based social metrics as of April 16, 2020

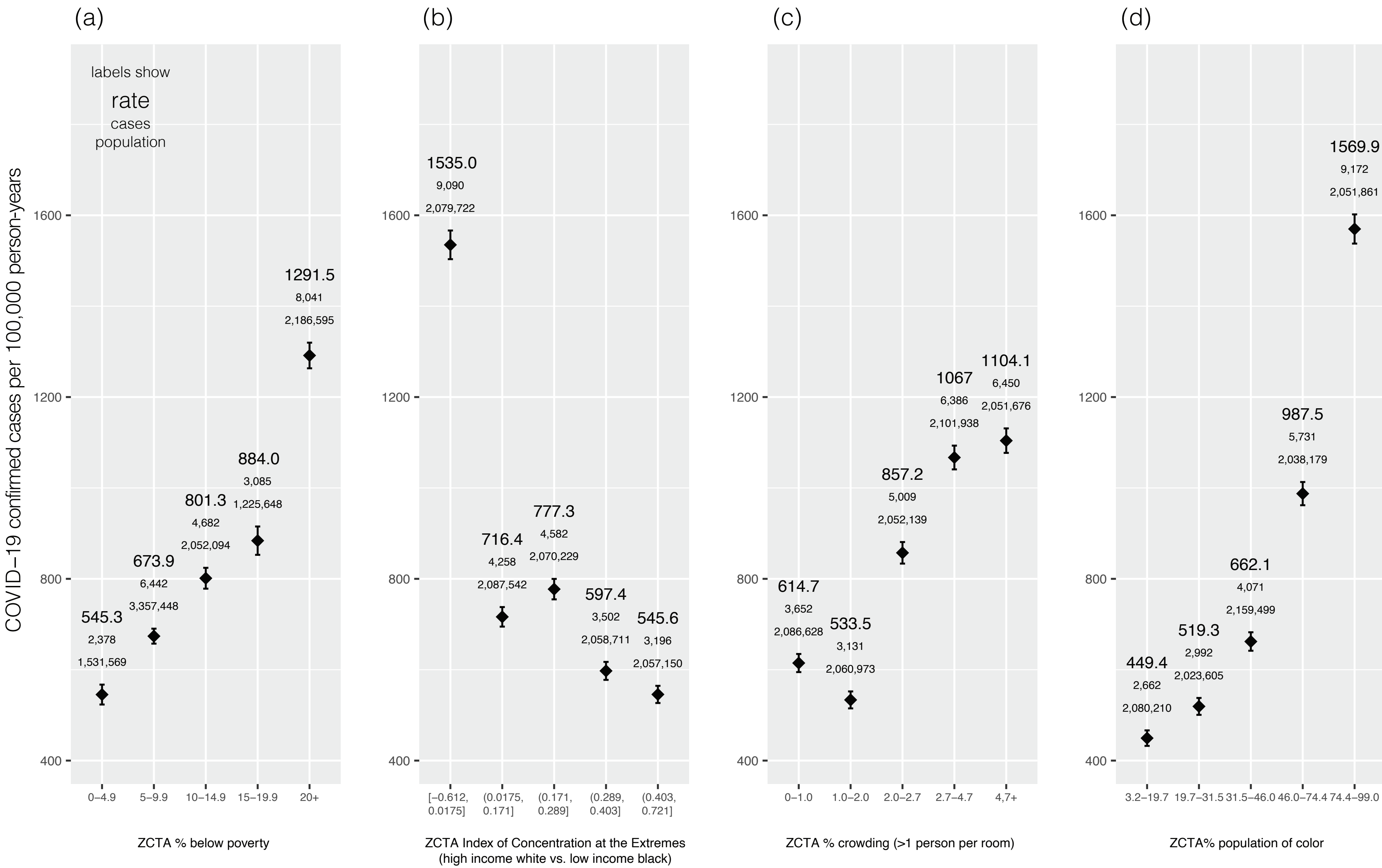


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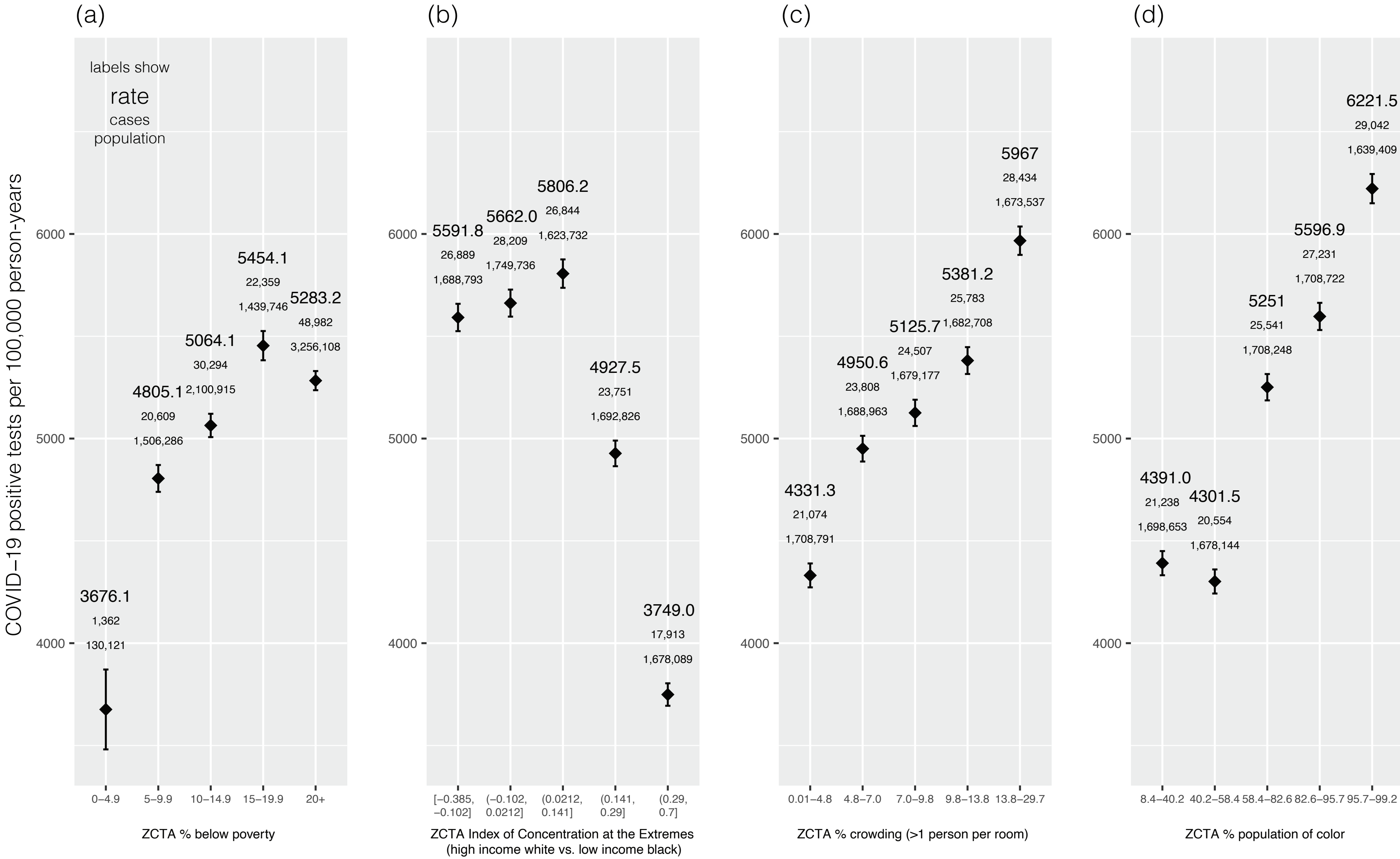
Figure S.3: NYC COVID–19 positive tests per 100,000 person-years by ZIP code area-based social metrics as of April 16, 2020



Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020. Addendum: May 28, 2020.

Figure S.4: US COVID–19 deaths per 100,000 person-years by county area-based social metrics as of May 5, 2020

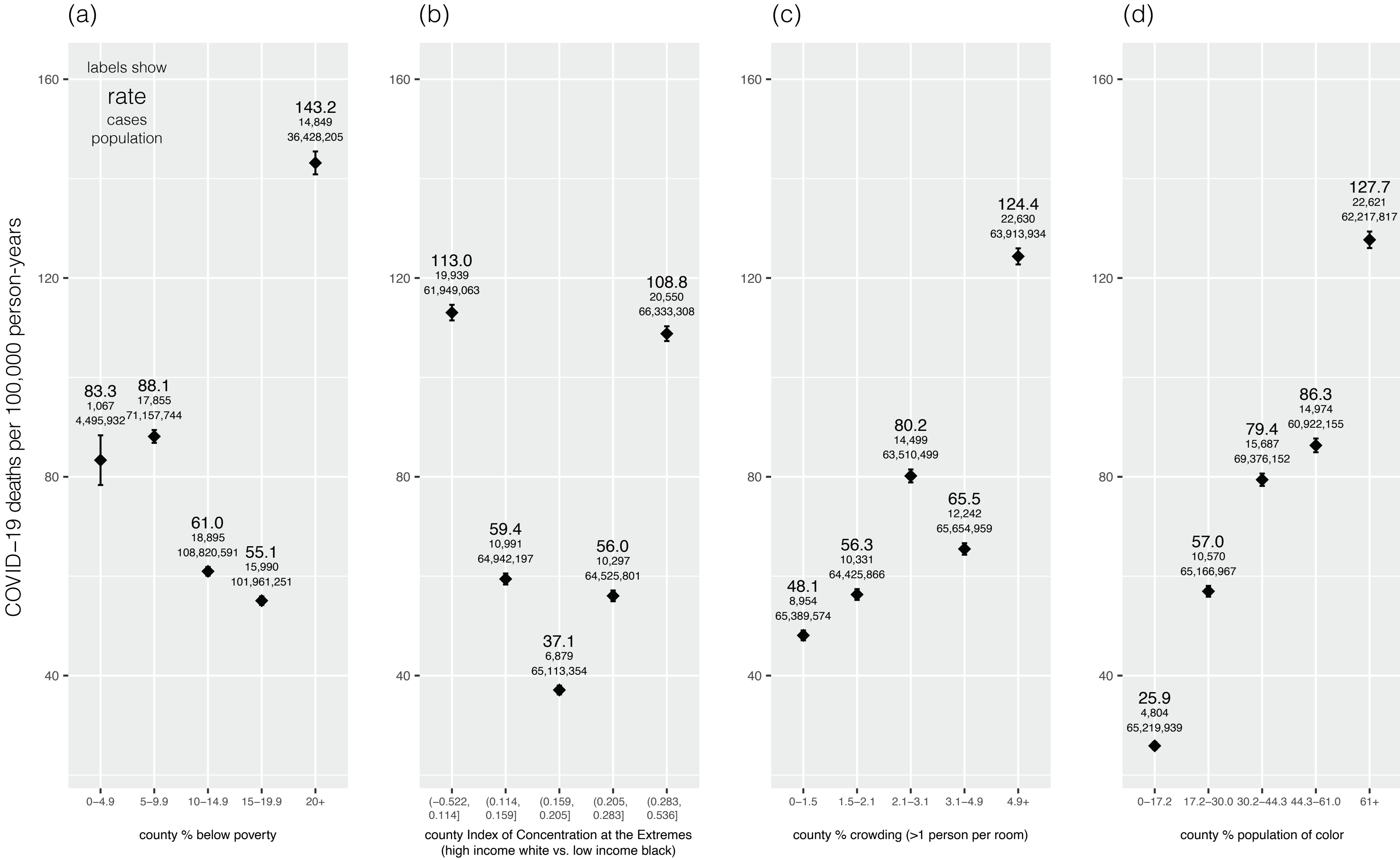


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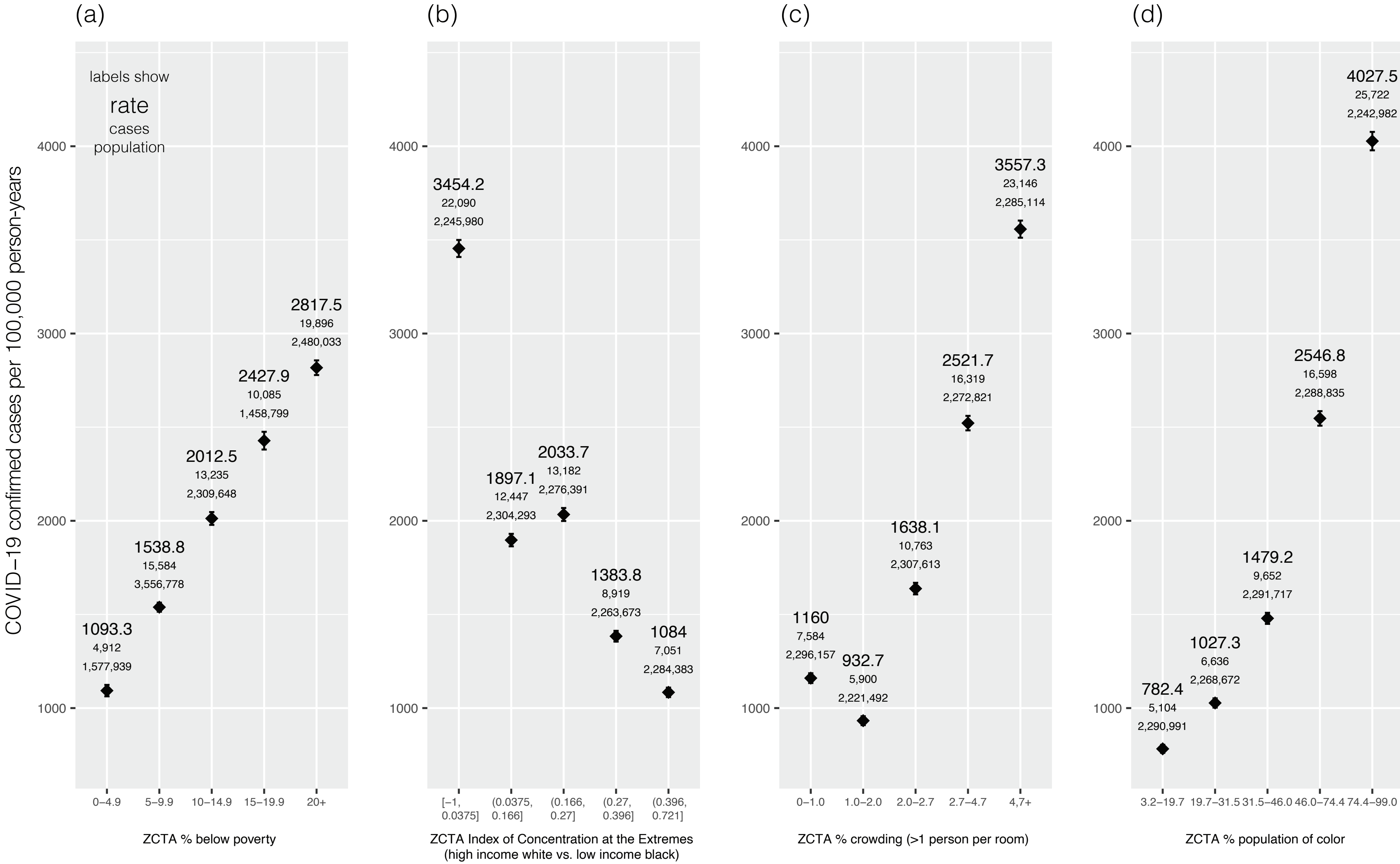
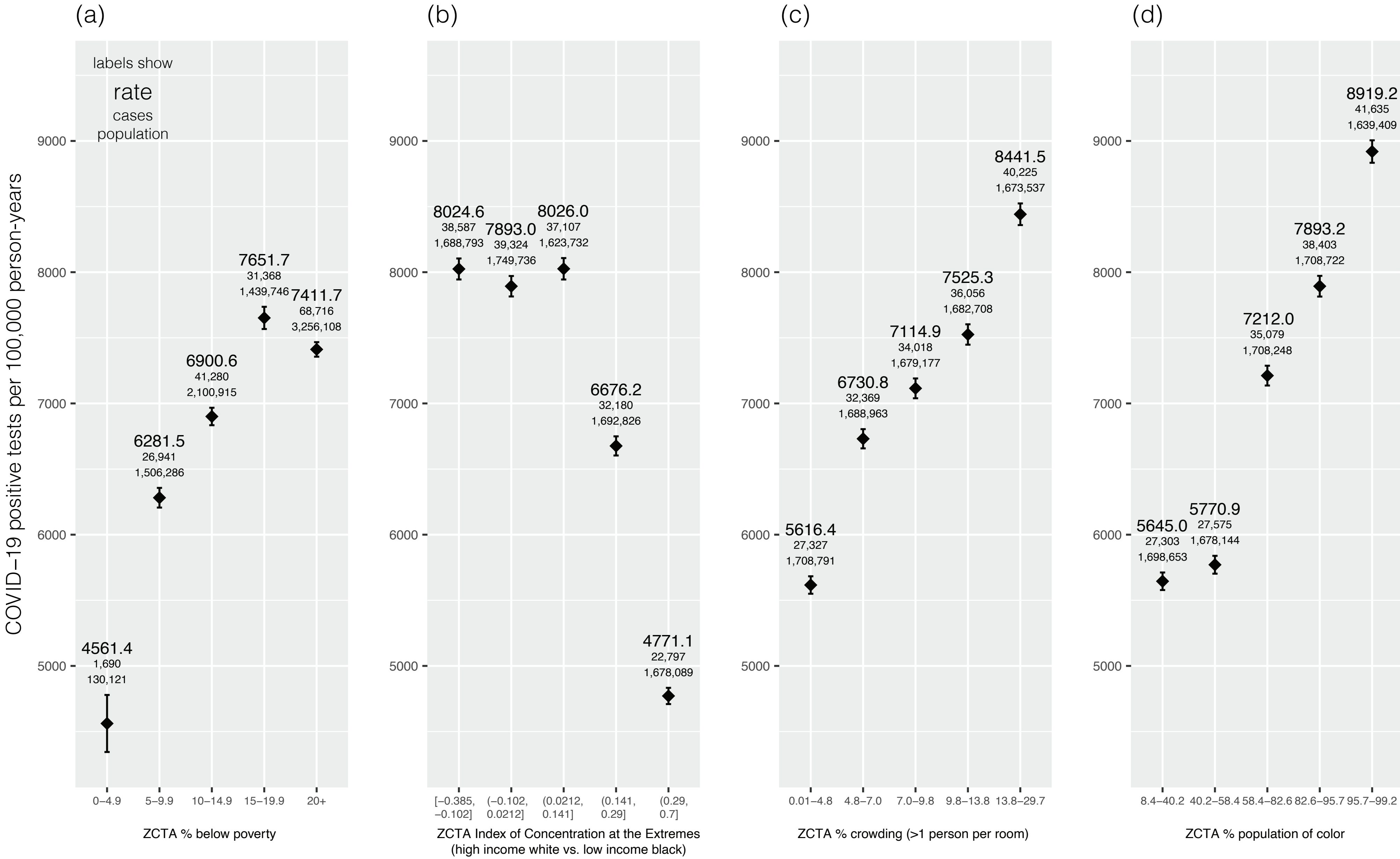
Figure S.5: Illinois COVID−19 positive tests per 100,000 person-years by ZIP code area-based social metrics as of May 5, 2020



Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020. Addendum: May 28, 2020.

Figure S.6: NYC COVID–19 positive tests per 100,000 person-years by ZIP code area-based social metrics as of May 5, 2020



Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 1. April 21, 2020. Addendum: May 28, 2020.