

# Supplementary material for “Reparations for Black American descendants of persons enslaved in the U.S. and their potential impact on SARS-CoV-2 transmission”

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## 1. Theoretical model

Structural racism affects systems of housing, education, employment, earnings, benefits, credit, media, healthcare, and criminal justice (Bailey et al., 2017), but here we focus only on employment (in frontline work) and housing (overcrowding), as they affect exposure to SARS-CoV-2 (two other factors, commuting (McLaren, 2020; Kissler et al., 2020), and incarceration (Simpson and Butler, 2020; Montoya-Barthelemy et al., 2020) are also significant drivers of exposure that have major racial disparities; but we did not investigate these). In addition to the direct effect caused by greater exposure to SARS-CoV-2, there are numerous causal pathways by which racism leads to lower overall physical and mental health.

We do not engage in original modeling to show the relationship of COVID-19 cases or deaths to race, by itself or in combination with frontline work or overcrowded housing. This is because, at the available resolution of publicly-available data, only ecological regression models are possible, and these have already been explored in the literature (Millett et al., 2020; Adhikari et al., 2020; Cowger et al., 2020; Cordes and Castro, 2020;

Karaca-Mandic et al., 2020; McLaren, 2020; Lieberman-Cribbin et al., 2020; Gold et al., 2020; Wu et al., 2020). These have also been validated by individual-level models by those with access to such data (Yehia et al., 2020; Renelus et al., 2020). Consequently, we focus our contribution on exploring the larger structural issues and imagining alternatives (Kelley, 2002; Hartman, 2008; da Silva, 2014, 2015; Mignolo, 2015).

## 2. Pathways of a reparations intervention

We take as our specific proposed reparations plan (Darity and Mullen, 2020) one that eliminates of the Black-white wealth differential at the national level now approaching an average of \$850,000 (Bhutta et al., 2020). We assume that reparations would directly affect occupation and housing, thereby decreasing two major sources of inequality affecting differential exposure rates.

For occupation, our assumption is justified by evidence that certain people in frontline jobs work there only in order to survive. In fact, risky (health-endangering) jobs are often poorly compensated (Morgan et al., 2013), which makes economic sense only under labor market segregation (Carrieri et al., 2011; Cozzi, 2012)—that certain people (i.e., Black and brown people) are locked out of large portions of the labor market and are forced to take risky jobs.

Reparations that allow people to not need frontline jobs would both spread the risk of these jobs across the population, and could also lead to overall higher wages and better working conditions in frontline work—if people are not forced to take such work out of desperation, especially during a pandemic (Gershon et al., 2010), then wages and benefits would reflect the risk of these jobs. Anecdotaly, this is what has happened in the Stockton, California basic income experiment (Emison, 2020).

For housing, our assumption is similarly justified by previous findings. Some analysis has used a casino opening on the Eastern

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Cherokee reservation as a natural experiment for looking at the impact of unconditional cash transfers, as a portion of the profits generated from was distributed on a per capita basis to all adult tribal members. In terms of housing, there was an increase (only for those residing outside the reservation) of households moving to census tracts with higher median household incomes (Akee et al., 2015). Even if cash transfers do not lead to moving, spending a smaller proportion of income on housing (Morrell and Kiersz, 2014) allows spending on necessities and dealing with unexpected shocks.

There is also evidence for the benefits of unconditional cash transfers on health outcomes, particularly for the children of transfer recipients (Akee et al., 2013).

Referencing Malcolm X's famous distinction between pulling the knife out and healing the wound left by the knife, we do not imagine that reparations would solve every problem. Ending anti-Black police violence and ending mass incarceration— aspects of pulling the knife out rather than healing the wound (compensating for the harm as reparations does)—are essential but cannot be accomplished exclusively by reparations. However, more wealth does provide greater political agency to influence both sets of policies and greater resources to obtain quality legal counsel in dealing with both of these types of harms.

### 3. Black populations and ancestry in Louisiana

Black American descendants of persons enslaved in the U.S. have a specific *legal* claim to reparations from the United States government, based on the undelivered promise of “40 acres and a mule” (Darity and Mullen, 2020). Black descendants of persons enslaved elsewhere from the trans-Atlantic slave trade, such as in Brazil, Jamaica, Haiti, and elsewhere in the West Indies and Latin America, have claims against other bodies—namely, the governments of the U.K., France, Portugal, Spain, and other European powers. And, while we are not focusing on other claims, we do note that all Black Americans, both those

descended from persons enslaved in the U.S. and/or who suffered under segregation and those who are recent immigrants to the U.S., arguably have a separate *moral* claim to reparations for the effects of ongoing systemic racism. For example, while Black immigrants initially have better health outcomes than Black American descendants of persons enslaved in the U.S., the longer they spend in the U.S., the more their health outcomes deteriorate to the same level (Doamekpor and Dinwiddie, 2015). However, as this is a consequence of systems of injustice built around and focused on the descendants of persons enslaved in the U.S., we prioritize this latter group. Other groups, including indigenous peoples, non-Black people of color, and the victims of U.S. imperialism and colonialism both domestically and abroad also have moral claims (and, for indigenous peoples, legal as well, on the basis of treaties the U.S. has failed to honor; Taylor et al., 2019) to reparations from the U.S., but we do not consider these here.

Thus, we are taking as our hypothetical intervention a version of reparations based on the *legal* claims of Black American descendants of persons enslaved in the U.S. This means that Black Americans not descended from persons enslaved in the U.S. (i.e., not descended from enslaved persons, or descended from persons enslaved elsewhere), as well as other marginalized groups who are also *morally* deserving of reparations, would not receive them on *this* basis.

Louisiana is, unlike other places in the U.S., distinct in having relatively small populations both of Black immigrants and of non-Black people of color. We use the ACS Public Use Microdata Sample (2018 5-year estimates) to show this. Since there is no Census category for being the descendant of persons enslaved in the U.S., we rely on looking at estimated numbers of people who are classified as “Black alone or in combination with one or more other races” and cross-reference it with a “Detailed Ancestry” variable, looking at ancestry outside of the United States (Table 1). While it is possible that some Black American descendants of persons enslaved in the U.S. might report West

	Black American	African	West Indies	Latin American	Other	Total
<b>Citizen</b>	1,225,627 (79.32%)	3,432 (0.22%)	4,378 (0.28%)	7,744 (0.50%)	303,910 (19.67%)	1,545,091 (100%)
<b>Non-Citizen</b>	733 (8.63%)	1,148 (13.51%)	2,066 (24.31%)	2,058 (24.22%)	2,492 (29.33%)	8,497 (100%)
<b>Total</b>	1,226,360 (78.94%)	4,580 (0.29%)	6,444 (0.41%)	9,802 (0.63%)	306,402 (19.72%)	1,553,588 (100%)

**Table 1:** For the population of those classified as “Black alone or in combination with one or more other races,” a cross-tabulation, with row percentages, of citizenship status with ACS variable ANC1P, “Recoded Detailed Ancestry - first entry” (American Community Survey, 2020). “Black American” is our combination of codes 900–904. “African” is our combination of codes 508–599, “West Indies” is our combination of codes 300–370, “Latin American” is our combination of codes 210–295, and “Other” is everything else. Note that code 907, Creole, was only 0.38% of Black citizen and 0% of Black non-citizens; code 937, Cajun, was only 0.03% of Black citizens and 0% of Black non-citizens; and other potentially relevant codes (927, Appalachian; 939, American; 940, United States; and 983, Texas) were only 1.87% of Black citizens and 0% of Black non-citizens. Consequently, we include these under “Other.” Also, there are an estimated 18,089 Black citizens who have something other than one of the “Black American” codes for the “Recoded Detailed Ancestry - second entry” variable (ANC2P), an additional 1.17% of the Black population.

African ancestry (or even from a specific African nation), and some Black immigrants might not report a specific national origin (e.g., 733 Black non-citizens are classified under ancestry codes associated with Black Americans), these errors are likely small and balance each other out.

Only 0.55% of the Black population of Louisiana are non-citizens (i.e. visitors, expatriates, or non-naturalized immigrants), and an estimated 79.32% of the citizen Black population self-report no ancestry outside of the U.S. This group, an estimated 1,225,627 people, is 26.28% of the state population. PUMS data estimates only 201,803 non-Black people of Latinx origin (4.33% of the state population), and 119,449 people (2.56% of the state population) who are neither white alone or in combination with one or more other races, nor Black alone or in combination with one or more other races, nor from Latinx ancestry. This would be people falling under Census categories of American Indian, Alaska Native, Asian, Native Hawaiian and Pacific Islander, some other race, or some combination of the above.

Consequently, a reparations intervention targeting (only) Black American descendants of persons enslaved in the U.S. would affect the vast majority of the non-white population of Louisiana, and provide a setting in which a two-group matrix population model is appropriate.

Because other Census variables (especially related to overcrowding) are not available by ancestry, the approximately 79% overlap between Black American descendants of persons enslaved in the U.S. and the category of “Black alone or in combination with one or more other races” justifies our reliance on this latter category.

#### 4. Black/non-Black segregation

An Exposure Index is a measure of residential segregation (Iceland et al., 2002; Massey and Denton, 1988). Exposure Index  $ij$  represents the average fraction of people ‘neighboring’ a member of group  $i$  who belong to group  $j$ . Here, ‘neighboring’ means residing in the same geographic unit, so the smaller the units of aggregation, the more epidemiologically informative an Exposure Index will be. The data available from the U.S. Census, American Community Survey (ACS) 5-year estimates for 2018, is at the block group level; excluding block groups with an estimated zero population, there are 3428 block groups in Louisiana, ranging in population from 10 to 9634 (median: 1154.5). Block groups with large populations are obviously not very precise in terms of quantifying potential interpersonal exposure, but also, block groups with very small populations are generally rural or otherwise remote large areas and so also do not quantify potential interpersonal exposure. As such, the block group level is perhaps not fine-grained enough for precisely modeling likely intergroup residential transmissibility, but it is the best available proxy and gives some sense.

If  $x_{ni}$  is the count of members of group  $i$  in geographic unit  $n$ ,  $n = 1, \dots, N$ ,  $x_{nj}$  is the count of members of group  $j$  in geographic unit  $n$ , for  $i, j = 1, \dots, M$  total groups, then the Exposure Index

$P_{ij}$  is:

$$P_{ij} = \sum_{n=1}^N \left( \frac{x_{ni}}{\sum_{h=1}^N x_{hi}} \right) \left( \frac{x_{nj}}{\sum_{m=1}^M x_{nm}} \right) \quad (1)$$

I.e., it is a summation, across all geographic units, of the number of members of group  $i$  in a given geographic unit normalized by their total population across *all* geographic units, times the number of members of group  $j$  in that geographic unit normalized by the total population within that geographic unit.

With matrix algebra, we can get all Exposure Indexes simultaneously. Let  $\mathbf{X} \in \mathbb{N}^{N \times M}$  be a matrix whose  $nm$ th entry is the count of individuals of group  $m$  living in geographic unit  $n$ . Then the matrix of Exposure Indexes is calculated in R as:

```
P <- t(X)%*(X/rowSums(X))/colSums(X)
```

We used the ACS 5-year estimates for 2018 at the block group level, and specifically variable B02009, “Black or African American alone or in combination with one or more other races,” along with B01003, the total population, to get Exposure Indexes (Table 2).

	Black	White/Other
Black	62.35% (61.09%, 63.59%)	37.65% (36.41%, 38.91%)
White/Other	18.80% (18.11%, 19.52%)	81.20% (80.48%, 81.89%)

**Table 2:** Exposure Indexes for the Louisiana population, calculated by U.S. Census block groups from the ACS 5-year estimates for 2018. Empirical 95% confidence intervals, calculated via bootstrap, are given in parentheses. If there were no segregation, the matrix would be  $\begin{pmatrix} 36\% & 64\% \\ 36\% & 64\% \end{pmatrix}$ , i.e. exposure would be equal to proportion of population regardless of group.

We take the ratio of the off-diagonal terms as capturing the relative risk ratio of exposure between groups—Black people are exposed to non-Black people twice as much as the converse. However, we should not take the Exposure Indexes to overall correlate with  $\beta$ ’s, since we would want on-diagonal elements to capture something about how people of the same group are often living in the same households, leading to far greater potential exposure than what is measured by residence in the same geographic unit.

#### 5. Race-based differences in overcrowded housing

Following recent investigative journalism explorations around the importance of overcrowded housing (Chadha, 2020; Coryne, 2020) in transmitting COVID-19, we use 2018 ACS 5-year estimates, for which estimates of overcrowding, disaggregated by race, are available at the Census tract level. Specifically, we use ACS variables B25014B\_001E, the total population in housing with a “Black or African American alone householder” per Census tract, and compare it to B25014B\_003E, the population within that living in housing with “1.01 or more occupants per

room.” This quantity, also known as persons per room (PPR), being larger than 1 is a suitable measure of overcrowding (ICF Consulting, Inc. et al., 2007).

For comparison, we subtract B25014B\_001E from ACS variable B25014\_001E, the estimated total population per Census tract, to get the estimated non-Black population. For the general population (not disaggregated by race), occupants per room are given with greater detail: owner-occupied and renter-occupied, and in 5 bins for the ratio (below .50, .51-1.00, 1.01-1.50, 1.51-2.00, and above 2.01) instead of 2. To make these comparable to the level of aggregation available for the Black population, we take the following variables:

- B25014\_005E, estimated population in owner-occupied housing with 1.01 to 1.50 occupants per room;
- B25014\_006E, estimated population in owner-occupied housing with 1.51 to 2.00 occupants per room;
- B25014\_007E, estimated population in owner-occupied housing with 2.01 or more occupants per room;
- B25014\_011E, estimated population in renter-occupied housing with 1.01 to 1.50 occupants per room;
- B25014\_012E, estimated population in renter-occupied housing with 1.51 to 2.00 occupants per room;
- B25014\_013E, estimated population in renter-occupied housing with 2.01 or more occupants per room;

and add them to get an estimate of the total number of people in overcrowded housing per Census tract. From this we subtract B25014B\_003E to get an estimate of the non-Black population living in overcrowded housing per Census tract.

ACS 90% margins of error can be propagated through a normal approximation,  $\sqrt{\sum_{i=1}^k (\frac{MOE_i}{1.645})^2}$ . However, there unfortunately are not appropriate models to propagate these errors through a regression. Errors-in-variable models are inappropriate since the size of the errors are proportional to the value of the variables. While results are significant at the 0.001 level, if we were to account for the ACS sampling error, as well as if we were to account for spatial autocorrelation, would probably make standard errors larger; but it is unlikely that the

difference would be so great as to make results no longer significant at the 0.05 level.

Rather than directly modeling the quotient of the population in overcrowded housing to the total population per Census tract, as ratios can have ill-behaved distributions, we model the count of population in overcrowded housing  $y$  in a log-linear model, with the total population  $x$  as an offset (log term with a coefficient set at 1),

$$\log \mathbb{E}(y|x) = \beta_0 \mathbf{1} + \log(x) \quad (2)$$

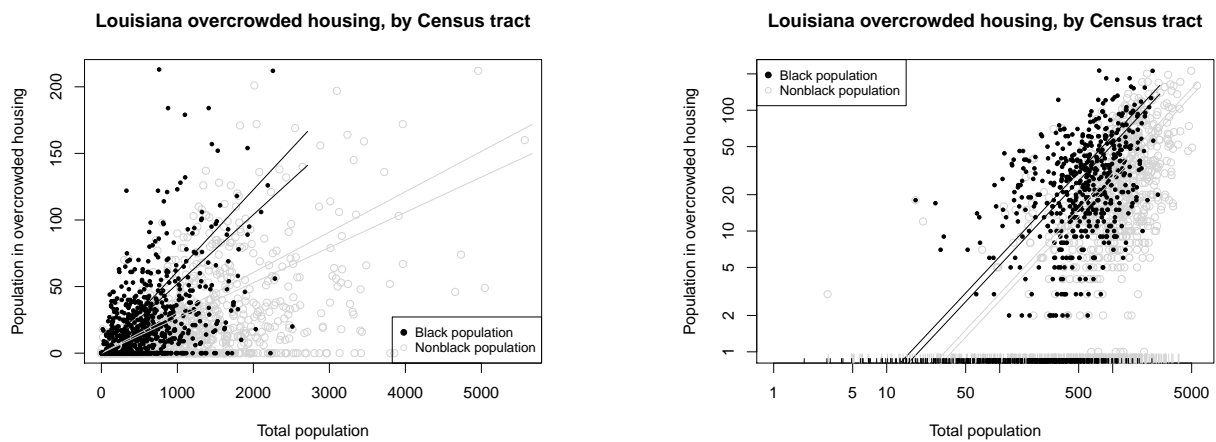
This is equivalent to  $\mathbb{E}(y|x) = e^{\beta_0 \mathbf{1} + \log x} = e^{\beta_0} \mathbf{1} e^{\log x} = e^{\beta_0} x$ , i.e. the exponential of the estimated  $\beta_0$  is a fitted ratio of the population in overcrowded housing to the total population.

As a Poisson model was overdispersed, and there were many Census tracts with no population in overcrowded housing, a zero-inflated negative binomial model (Zeileis et al., 2008) was most appropriate. This is a mixture model  $P_{ZINB}(Y|X) = P_{\text{Bernoulli}}(Y = 0)I(Y = 0) + (1 - P_{\text{Bernoulli}}(Y = 0))P_{\text{NegBin}}(Y|X)$ , where  $\text{logit } \mathbb{E}_{\text{Bernoulli}}(Y) = \alpha_0$  and  $\log \mathbb{E}_{\text{NegBin}}(Y|X) = \beta_0 + \log(X)$ .

While we could include further covariates for either the zero-inflation or negative binomial portion of the model, and may do so in future work, here we used a bivariate specification. For simplicity, we also run two separate models, one for the Black population and one for the non-Black population, rather than having indicators with interactions in one model. Results are shown in Figure 1 and detailed in Table 3. For each model, we exclude tracts from where the total population is zero.

The estimated count ratio for the Black population, 0.0565, is approximately double that of the non-Black population, 0.0283. If we average over the estimated number of zeros (the Bernoulli portion of the model) as well, the difference is slightly less dramatic but still stark, with ratios respectively of  $(1 - 0.458) \times 0.0565 = 0.0306$  and  $(1 - 0.336) \times 0.0283 = 0.0188$ , different by a factor of 1.63 instead of 2.00.

Note that although this is an ecological model (doing inference among aggregated units, rather than between individuals), we do not run into the main problem of ecological inference (Freedman et al., 2010) because we have the cell counts of the cross-tabulations per unit (the number of Black people living in overcrowded housing per Census tract, the total number of Black people per Census tract, the total



**Figure 1:** Top: linear scale, showing a 95% confidence band around the estimated ratio of population in overcrowded housing to total population for the Black and non-Black population. The ratio of the Black population is approximately double that of the non-Black population. Bottom: same plot in log scale. Since zeros cannot be plotted on log axis, rug marks are included for Census tracts with zero population in overcrowded housing.



	Black population		Non-Black population	
Count model coefficients (negative binomial with log link)	Estimate	95% CI	Estimate	95% CI
$e^{\hat{\beta}_0}$ (Ratio)	0.0565	(0.0520, 0.0614)	0.0283	(0.0264, 0.0303)
$\hat{\theta}$ (Dispersion)	1.15	(0.985, 1.35)	1.32	(1.155, 1.507)
Zero-inflation model coefficients (binomial with logit link)				
logistic( $\hat{\alpha}_0$ )	0.458	(0.424, 0.492)	0.336	(0.306, 0.368)
Observations	1,090		1,121	
Log Likelihood	-3,060.825		-3,699.218	

**Table 3:** Zero-inflated negative binomial fits for Black population and the non-Black population, per Louisiana Census tract. Census tracts with zero Black or zero non-Black populations respectively were excluded (the zero-inflation is for Census tracts with zero Black or zero non-Black populations in overcrowded housing, in Census tracts with nonzero total Black/non-Black populations).

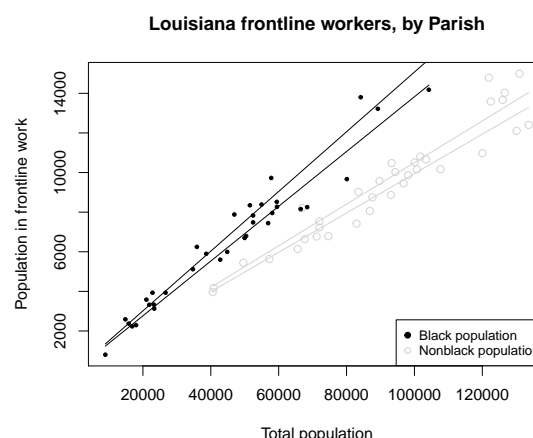
number of people living in overcrowded housing per Census tract, the total number of people per Census tract), rather than just the marginals (the number of Black people per Census tract, and the number of people living in overcrowded housing per Census tract). I.e., the target of our inference is not the cell counts of a contingency table (as it is in ecological inference), but the underlying pattern of the ratio of the Black population in overcrowded housing to non-overcrowded housing as compared to the same ratio for the non-Black population over the geographic variance in Louisiana.

Still, the model is not as reliable as an individual-level model because it does also not escape a related ecological issue of potential aggregation bias in geographic units, known formally as the Modifiable Areal Unit Problem. For example, in the worst case it would be possible to have a geographic partition designed to “gerrymander” all Black people living in overcrowded housing into one geographic unit. That unit that would appear as an outlier on a plot, and would distort the inference of the overall ratio. But especially since Census tracts are designed independently of overcrowding, this worst case scenario is unlikely. And with the large number of Census tracts, the ecological model provides compelling evidence for a relationship that should exist at the individual level as well.

## 6. Race-based differences in frontline work

A March 2020 report from the New York City Office of the Comptroller used a combination of several values<sup>3</sup> of the ACS variable INDP variable to code for being frontline workers (Office of the New York City

Comptroller, 2020). While this excludes a few potentially relevant categories (e.g., TRN–Taxi and Limousine Service, 6190; and in many cases RET–Beer, Wine, and Liquor Stores, 4990), we use the same coding for purposes of comparability, especially as this coding has also been adopted elsewhere (Rho et al., 2020).



**Figure 2:** 95% confidence bands for the ratio of frontline workers to total population among the Black and non-Black population. The estimated ratio of population in overcrowded housing to total population is double that of the Black population as for the non-Black population.

Unfortunately, occupational data is only available from the ACS at the county level, again using PUMS, giving only 34 observations instead of over a thousand like at the Census tract level. While the results are still significant at the 0.001 level, these results are less reliable than both a model at the individual level or a model that could use a larger number of geographic units. Also, again, we do not take into account spatial autocorrelation nor do we propagate the sampling error of the ACS. Still, because results are significant at the 0.001 level,

Facilities, Except Skilled Nursing Facilities (8290); SCA–Individual and Family Services (8370); SCA–Community Food and Housing, and Community Services (8380); SCA–Child Day Care Services (8470).

<sup>3</sup> WHL–Grocery and Other Related Product Wholesalers (4470); RET–Supermarkets and Other Grocery (Except Convenience) Stores (4971); RET–Convenience Stores (4972); RET–Pharmacies and Drug Stores (5070); RET–General Merchandise Stores, Including Warehouse Clubs and Supercenters (5391); TRN–Rail Transportation (6080); TRN–Truck Transportation (6170); TRN–Bus Service and Urban Transit (6180); TRN–Postal Service (6370); TRN–Warehousing and Storage (6390); PRF–Services to Buildings and Dwellings (Except Cleaning During Construction and Immediately After Construction) (7690); MED–Offices of Physicians (7970); MED–Outpatient Care Centers (8090); MED–Home Health Care Centers (8170); MED–Other Health Care Services (8180); MED–General Medical and Surgical Hospitals, and Speciality (Except Psychiatric and Substance Abuse) Hospitals (8191); MED–Psychiatric and Substance Abuse Hospitals (8192); MED–Nursing Care Facilities (Skilled Nursing Facilities) (8270); MED–Residential Care

Count model coefficients (negative binomial with log link)	Black population		Non-Black population	
	Estimate	95% CI	Estimate	95% CI
$e^{\hat{\beta}_0}$ (Ratio)	0.1443	(0.1383, 0.1507)	0.1022	(0.0995, 0.1050)
$\hat{\theta}$ (Dispersion)	61.46	(31.57, 91.36)	155.92	(80.63, 231.21)
Observations	34		34	
$2 \times \text{Log Likelihood}$	-544.656		-543.912	

**Table 4:** Negative binomial fits for the proportion of the population in frontline work among Black populations and non-Black population, per Louisiana Parish.

taking these into account would likely not change the results so far as to no longer be significant at the 0.05 level.

Because of the coarser level of aggregation, there are no geographic units with counts of zero, meaning we do not need to make a zero-inflated model. However, the counts are overdispersed, so we still use a negative binomial model. The fits are plotted in Figure 2, and detailed in Table 4.

Here, the difference in ratios is less stark, with the percentage of the population in frontline work being 14.43% for the Black population versus 10.22% for the non-Black population. Still, proportionately far more Black people are in frontline work than non-Black people.

## 7. Back-calculating risk structure from reproduction number

In epidemiology, *structured models* that take into account varying risk groups among a general population are used to understand the number of secondary infections produced by a single infection among different groups (Keeling and Rohani, 2007).

However, the converse is seldom explored: if we know something about the number of secondary infections, it can reveal underlying risk structures in a population.

$\mathbf{G}$  is the *next-generation matrix*. Its entries can either be expressed as  $g_{i \rightarrow j}$ , the expected number of infections that an infected individual in group  $i$  causes in group  $j$ , or equivalently in terms of “Who Acquires Infection From Whom” (WAIFW),  $g_{j \leftarrow i}$ .  $g_{i \rightarrow j}$  is easily interpreted as a sort of causal effect of  $i$  on  $j$ , but collectively, the  $g_{i \rightarrow j}$ ’s make sense as the entries of a transition matrix; that is, entries  $g_{j \leftarrow i}$  makes more intuitive that multiplying  $\mathbf{G}$  by a population vector will give the population vector for the next generation. However, this is mainly a matter of notation; so long as we reverse the subscript indexes along with the arrows,  $\mathbf{G}$  functions as a transition matrix. We use forward arrows, for ease of interpreting terms visualized on the plots.

Each entry  $g_{i \rightarrow j}$  can be broken down in terms of the *transmission rate*  $\beta_{i \rightarrow j}$  of how much group  $i$  comes into transmissible contact with group  $j$ , a group’s proportion of the population  $\pi_i = n_i/N$ , and the recovery rate  $\gamma$ .  $\beta_{i \rightarrow j}$  is itself the product of the average contact rate,  $c_{i \rightarrow j}$ , and the transmissibility,  $\tau$ , although it is not necessary for our purposes to consider components of  $\beta_{i \rightarrow j}$ .

$$\mathbf{G} = \begin{bmatrix} g_{b \leftarrow b} & g_{w \leftarrow b} \\ g_{b \leftarrow w} & g_{w \leftarrow w} \end{bmatrix} = \begin{bmatrix} g_{b \rightarrow b} & g_{b \rightarrow w} \\ g_{w \rightarrow b} & g_{w \rightarrow w} \end{bmatrix} = \begin{bmatrix} \frac{\beta_{b \rightarrow b} \pi_b}{\gamma} & \frac{\beta_{b \rightarrow w} \pi_b}{\gamma} \\ \frac{\beta_{w \rightarrow b} \pi_w}{\gamma} & \frac{\beta_{w \rightarrow w} \pi_w}{\gamma} \end{bmatrix} \quad (3)$$

Note that the effect of the off-diagonals is the transpose of the effect in the Exposure Indexes: instead of a member of group  $i$  encountering

a member of group  $j$ , it is the members of group  $i$  who might infect a member of group  $j$  by having encountered them.

$R_0$  is the solution under equilibrium to the set of differential equations defined by an SIR model for a structured population; and, that solution turns out to be equivalent to finding the largest eigenvalue of the next-generation matrix (Keeling and Rohani, 2007). The characteristic polynomial of the next-generation matrix is  $\det(\mathbf{G} - \lambda \mathbf{I}) = \lambda^2 - \lambda \text{tr}(\mathbf{G}) + \det(\mathbf{G}) = \lambda^2 - \lambda(g_{b \rightarrow b} + g_{w \rightarrow w}) + (g_{b \rightarrow b} g_{w \rightarrow w} - g_{w \rightarrow b} g_{b \rightarrow w})$  and  $R_0$  is the larger of the two roots of this polynomial. Plugging in the coefficients to the quadratic equation and rearranging in terms of  $g_{b \rightarrow b}$ , we get

$$g_{b \rightarrow b} = \frac{g_{w \rightarrow b} g_{w \rightarrow w} + R_0 g_{w \rightarrow w} - R_0^2}{(g_{w \rightarrow w} - R_0)} \quad (4)$$

Substituting in the components of the  $g_{i \rightarrow j}$ ’s, this becomes

$$\beta_{b \rightarrow b} = \frac{\beta_{w \rightarrow b} \beta_{w \rightarrow w} \pi_w / \gamma + R_0 \beta_{w \rightarrow w} \pi_w - \gamma R_0^2}{\pi_b (\beta_{w \rightarrow w} \pi_w / \gamma - R_0)} \quad (5)$$

This formula tells us that decreasing the ratio of the within-group transmission rate of the Black population,  $\beta_{b \rightarrow b}$ , to that of the non-Black population,  $\beta_{w \rightarrow w}$ , has the potential to decrease  $R_0$  until hits an boundary at  $\beta_{w \rightarrow w} \pi_w / \gamma$ , i.e. at  $g_{w \rightarrow w}$ , at which point  $\beta_{w \rightarrow w}$  dominates and no further changes to  $\beta_{b \rightarrow b}$  can affect  $R_0$ .

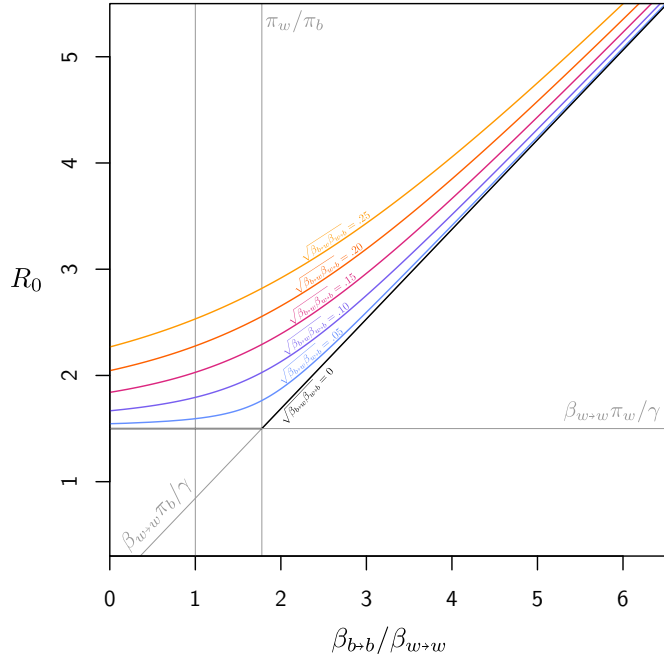
As the curve moves further away from that asymptotic value of  $R_0$ , we can understand the behavior by taking the derivative, which comes out to:

$$\frac{d\beta_{b \rightarrow b}}{dR_0} = \frac{\gamma}{\pi_b} + \frac{\beta_{w \rightarrow b} \beta_{w \rightarrow w} \pi_w / \gamma}{\pi_b (\beta_{w \rightarrow w} \pi_w / \gamma - R_0)^2} \quad (6)$$

The derivative implies that, on a plot of  $R_0$  on the  $x$ -axis and  $\beta_{b \rightarrow b}$  on the  $y$ -axis, there will be a vertical asymptote at  $\beta_{w \rightarrow w} \pi_w / \gamma$ , and as  $R_0$  increases, the curve will converge to the line  $\gamma / \pi_b$ .

Conversely, if we apply this on a plot of  $\beta_{b \rightarrow b} / \beta_{w \rightarrow w}$  on the  $x$ -axis and  $R_0$  on the  $y$ -axis (as we think of the risk structure as “causing” the basic reproduction number), as shown in Figure 3, we flip these patterns; as  $\beta_{b \rightarrow b}$  decreases and gets closer to  $\beta_{w \rightarrow w}$ ,  $R_0$  will have an asymptote at  $\beta_{w \rightarrow w} \pi_w / \gamma$ , and as  $\beta_{b \rightarrow b}$  grows, the line converges to  $\beta_{w \rightarrow w} \pi_b / \gamma$ . This corresponds to  $\beta_{w \rightarrow w} g_{b \rightarrow b}$ ; a line with slope  $\beta_{w \rightarrow w} \pi_b / \gamma$  and intercept 0.

The two off-diagonal terms (which, in the  $2 \times 2$  case, are multiplied together and so only act through their geometric mean and not individually) control how the curve moves from one regime to the other. If one or both of off-diagonal terms is zero, the line has a sharp elbow at  $\pi_w / \pi_b$ . In that case, decreasing the risk of the Black population will decrease  $R_0$  until it equals the value of  $R_0$  induced by the non-Black population, after which there is no change.



**Figure 3:** Relationship of basic reproductive ratio (y-axis) to the ratio of the Black-Black risk to the white/other-white/other risk (x-axis). The denominator of this ratio is present only to normalize the x-axis; the white/other-white/other risk is constant in this plot. See Figure 4 for a 3d plot where this risk also varies.

Increasing the diagonal elements makes the curve smooth out. But as the cross-term gets larger, it begins to dominate the slope, eventually becoming a straight line with a y-intercept of  $R_0$ . However, off-diagonal terms that are larger than diagonal terms are generally not epidemiologically realistic, so we only illustrate off-diagonal terms up to the geometric mean of the two terms being approximately equal to  $\beta_{w \rightarrow w}$ .

### 7.1. Varying $\beta_{w \rightarrow w}$

In Figure 3, we calculated  $R_0$  for varying values of  $\beta_{b \rightarrow b}$  and fixed  $\beta_{b \rightarrow b}$ , but plotted in terms of the ratio  $\beta_{b \rightarrow b} / \beta_{w \rightarrow w}$ , as the values of the ratio are easier to interpret.

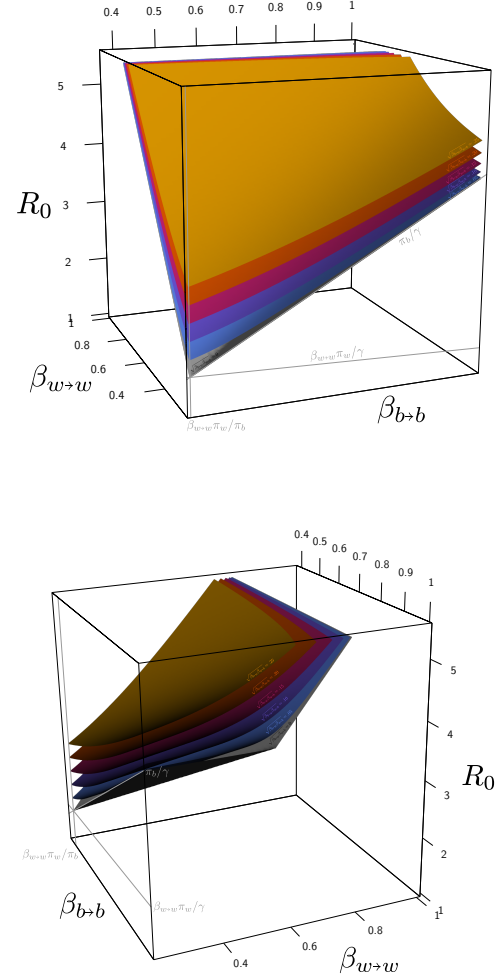
For choosing a value at which to fix  $\beta_{w \rightarrow w}$ , we chose the one that makes  $g_{w \rightarrow w} = 1.5$ , the lowest end of  $R_0$  estimates, i.e. set  $\beta_{w \rightarrow w} = 1.5 \times \gamma / \pi_w = 0.213$ .

However, we can plot  $\beta_{w \rightarrow w}$  as another axis, and see that the relative patterns captured by the horizontal line  $\beta_{w \rightarrow w} \pi_w / \gamma$ , the line with slope  $\beta_{w \rightarrow w} \pi_b / \gamma$  (on a plot with  $\beta_{b \rightarrow b}$  on the x-axis, this becomes a line with slope  $\pi_b / \gamma$ ), and the vertical lines at 1 (on a plot with  $\beta_{b \rightarrow b}$  on the x-axis, this line is at  $\beta_{w \rightarrow w}$ ), and the vertical line at  $\pi_w / \pi_b$  (on a plot with  $\beta_{b \rightarrow b}$  on the x-axis, this line is at  $\beta_{w \rightarrow w} \pi_w / \pi_b$ ). And, the larger the geometric mean of the off-diagonal elements, the “smoother” the curve is versus having a sharp elbow. This is shown in Figure 4.

### 7.2. Elasticities

The *elasticity* is the amount by which a response  $\xi$  changes with a parameter  $\theta$ , defined as  $\frac{\theta}{\xi} \frac{d\xi}{d\theta}$ .

For stage-classified population models in demography, corresponding exactly to a structured SIR model in epidemiology, the elasticity of the first eigenvalue in  $g_{i \rightarrow j}$  can be calculated from the left and right eigenvectors (Caswell, 2019). If  $\mathbf{v}$  is the right eigenvector of the leading



**Figure 4:** The relationship of  $\beta_{b \rightarrow b}$  and  $\beta_{w \rightarrow w}$  to  $R_0$  from a “front” view (top), and a “side” view (bottom) that better shows the sharp elbow for  $\sqrt{\beta_{b \rightarrow w} \beta_{w \rightarrow b}} = 0$  at different levels of  $\beta_{b \rightarrow b}$  and  $\beta_{w \rightarrow w}$ , for the same increasing values of  $\sqrt{\beta_{b \rightarrow w} \beta_{w \rightarrow b}}$ , and in the same colors, as in Figure 3 and Figure 5.

eigenvalue of  $\mathbf{G}^T$  (equivalent to the left eigenvector of the leading eigenvalue of  $\mathbf{G}$ ), and  $\mathbf{u}$  is the right eigenvector of the leading eigenvalue of  $\mathbf{G}$ , then the elasticity of the leading eigenvalue (i.e.,  $R_0$ ) with respect to its entries is:

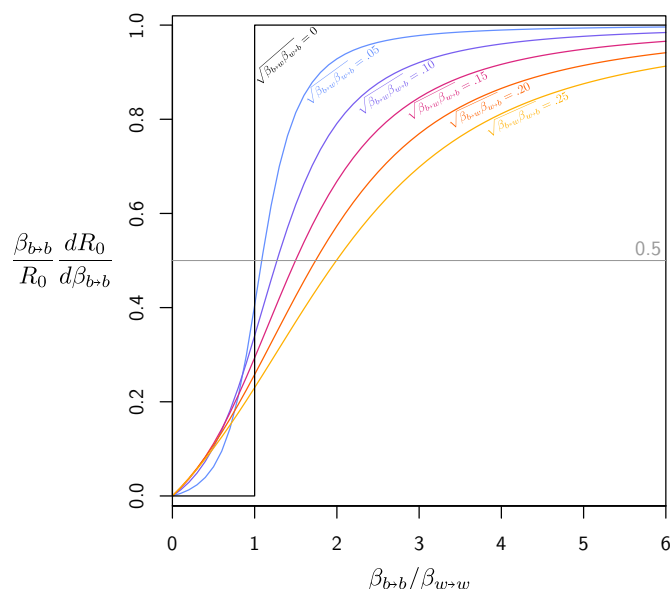
$$\frac{g_{i \rightarrow j}}{R_0} \frac{dR_0}{dg_{i \rightarrow j}} = \frac{v_i u_j}{\mathbf{v}^T \mathbf{u}} \quad (7)$$

This is easier to approach numerically, as the analytic form is unwieldy. It is also in terms of  $g_{b \rightarrow b}$  rather than  $\beta_{b \rightarrow b}$ , but the two are equal:

$$\frac{g_{b \rightarrow b}}{R_0} \frac{dR_0}{dg_{b \rightarrow b}} = \frac{\beta_{b \rightarrow b} \pi_b / \gamma}{R_0} \frac{dR_0}{d\beta_{b \rightarrow b}} \frac{d\beta_{b \rightarrow b}}{dg_{b \rightarrow b}} = \frac{\pi_b \beta_{b \rightarrow b}}{\gamma} \frac{dR_0}{d\beta_{b \rightarrow b}} \frac{\gamma}{\pi_b} = \frac{\beta_{b \rightarrow b}}{R_0} \frac{dR_0}{d\beta_{b \rightarrow b}} \quad (8)$$

Elasticities can quantify the relative impact of different interventions. At ranges where an elasticity curve with respect to some input is above 0.5, it means that at those ranges, intervening on that input is more effective than intervening on every other input combined.

Figure 5 shows, for different values of the geometric mean of the off-diagonal terms, that lowering  $\beta_{b \rightarrow b}$  would be more effective than any



**Figure 5:** Relationship of the  $\beta_{b \rightarrow b}$  risk elasticity of  $R_0$  (y-axis) to the ratio  $\beta_{b \rightarrow b} / \beta_{w \rightarrow w}$  (x-axis).

other change until  $\beta_{b \rightarrow b}$  is much closer to  $\beta_{w \rightarrow w}$ , and for small values of off-diagonal elements, until  $\beta_{b \rightarrow b}$  is nearly equal to  $\beta_{w \rightarrow w}$ .

Of course, compelling moral and historical arguments may lead us to favor taking certain interventions regardless of the sensitivity of an output to the intervention. But at least at levels of inequality in group-specific transmission rates consistent with observed epidemic patterns, this shows how interventions focusing on the most vulnerable group might also be the most effective approach for reducing overall transmission.

## References

- Adhikari, S., Pantaleo, N.P., Feldman, J.M., Ogedegbe, O., Thorpe, L., Troxel, A.B., 2020. Assessment of community-level disparities in coronavirus disease 2019 (COVID-19) infections and deaths in large US metropolitan areas. *JAMA Netw. Open* 3, e2016938. doi: [10.1001/jamanetworkopen.2020.16938](https://doi.org/10.1001/jamanetworkopen.2020.16938).
- Akee, R., Simeonova, E., Copeland, W., Angold, A., Costello, E.J., 2013. Young adult obesity and household income: Effects of unconditional cash transfers. *Am. Econ. J. Appl. Econ.* 5, 1–28. doi: [10.1257/app.5.2.1](https://doi.org/10.1257/app.5.2.1).
- Akee, R., Simeonova, E., Costello, E.J., Copeland, W., 2015. How does household income affect child personality traits and behaviors? NBER Work. Pap. Ser. 21562. doi: [10.3386/w21562](https://doi.org/10.3386/w21562).
- American Community Survey, 2020. 2014–2018 ACS PUMS data dictionary. United States Census Bureau, Washington, D.C. [https://www2.census.gov/programs-surveys/acs/tech\\_docs/pums/data\\_dict/PUMS\\_Data\\_Dictionary\\_2014-2018.txt](https://www2.census.gov/programs-surveys/acs/tech_docs/pums/data_dict/PUMS_Data_Dictionary_2014-2018.txt).
- Bailey, Z.D., Krieger, N., Agénor, M., Graves, J., Linos, N., Bassett, M.T., 2017. Structural racism and health inequities in the USA: Evidence and interventions. *Lancet* 389, 1453–1463. doi: [10.1016/S0140-6736\(17\)30569-X](https://doi.org/10.1016/S0140-6736(17)30569-X).
- Bhutta, N., Chang, A.C., Dettling, L.J., Hsu, J.W., 2020. Disparities in wealth by race and ethnicity in the 2019 Survey of Consumer Finances. FEDS Notes. Board of Governors of the Federal Reserve System, Washington, D.C. doi: [10.17016/2380-7172.2797](https://doi.org/10.17016/2380-7172.2797).
- Carrieri, V., Di Porto, E., Elia, L., 2011. Risky jobs and wage differentials: An indirect test for segregation. Working paper 144. University of Rome La Sapienza, Department of Public Economics. Rome. [https://web.uniroma1.it/dip\\_ecodir/sites/default/files/wpapers/wp144.pdf](https://web.uniroma1.it/dip_ecodir/sites/default/files/wpapers/wp144.pdf).
- Caswell, H., 2019. Sensitivity analysis: Matrix methods in demography and ecology. Springer, Cham. doi: [10.1007/978-3-030-10534-1](https://doi.org/10.1007/978-3-030-10534-1).
- Chadha, J., 2020. New York City's most crowded neighborhoods are often hardest hit by coronavirus. Politico New York, 11 April. <https://www.politico.com/states/new-york/albany/story/2020/04/11/new-york-citys-most-crowded-neighborhoods-are-often-hardest-hit-by-coronavirus-127>.
- Cordes, J., Castro, M.C., 2020. Spatial analysis of COVID-19 clusters and contextual factors in New York City. *Spat. Spatiotemporal Epidemiol.* 34, 100355. doi: <https://doi.org/10.1016/j.sste.2020.100355>.
- Coryne, H., 2020. In Chicago, urban density may not be to blame for the spread of the Coronavirus. ProPublica Illinois, 30 April. <https://www.propublica.org/article/in-chicago-urban-density-may-not-be-to-blame-for-the-spread-of-the-coronavirus>.
- Cowger, T.L., Davis, B.A., Etkins, O.S., Makofane, K., Lawrence, J.A., Bassett, M.T., Krieger, N., 2020. Comparison of weighted and unweighted population data to assess inequities in coronavirus disease 2019 deaths by race/ethnicity reported by the US Centers for Disease Control and Prevention. *JAMA Netw. Open* 3, e2016933. doi: [10.1001/jamanetworkopen.2020.16933](https://doi.org/10.1001/jamanetworkopen.2020.16933).
- Cozzi, M., 2012. Risk aversion heterogeneity, risky jobs and wealth inequality. Working paper 1286. Department of Economics, Queen's University, Kingston, Ontario. [https://ageconsearch.umn.edu/record/274550/files/qed\\_wp\\_1286.pdf](https://ageconsearch.umn.edu/record/274550/files/qed_wp_1286.pdf).
- Darity, Jr., W.A., Mullen, A.K., 2020. From here to equality: Reparations for Black Americans in the Twenty-First Century. UNC Press, Chapel Hill. <https://muse.jhu.edu/book/73567>.
- Doamekpor, L.A., Dinwiddie, G.Y., 2015. Allostatic load in foreign-born and US-born Blacks: Evidence from the 2001–2010 National Health and Nutrition Examination Survey. *Am. J. Public Health* 105, 591–597. doi: [10.2105/AJPH.2014.302285](https://doi.org/10.2105/AJPH.2014.302285).
- Emison, L.F., 2020. The promising results of a citywide basic-income experiment. New Yorker, 15 July. <https://www.newyorker.com/news/news-desk/the-promising-results-of-a-citywide-basic-income-experiment>.
- Freedman, D.A., Klein, S.P., Ostland, Michael Roberts, M.R., 2010. On “solutions” to the ecological inference problem, in: Collier, D., Sekhon, J.S., Stark, P.B. (Eds.), *Statistical models and causal inference: A dialogue with the social sciences*. Cambridge University Press, Cambridge, pp. 83–96. doi: [10.1017/CBO9780511815874.007](https://doi.org/10.1017/CBO9780511815874.007).
- Gershon, R.R.M., Magda, L.A., Qureshi, K.A., Riley, H.E.M., Scanlon, E., Carney, M.T., Richards, R.J., Sherman, M.F., 2010. Factors associated with the ability and willingness of essential workers to report to duty during a pandemic. *J. Occup. Environ. Med.* 52, 995–1003. doi: [10.1097/JOM.0b013e3181f43872](https://doi.org/10.1097/JOM.0b013e3181f43872).
- Gold, J.A.W., Rossen, L.M., Ahmad, F.B., Sutton, P., Li, Z., Salvatore, P.P., Coyle, J.P., DeCuir, J., Baack, B.N., Durant, T.M., Dominguez, K.L., Henley, S.J., Annor, F.B., Fuld, J., Dee, D.L., Bhattachar, A., Jackson, B.R., 2020. Race, ethnicity, and age trends in persons who died from COVID-19 – United States, May–August 2020. *MMWR Morb. Mortal. Wkly. Rep.* 69, 1517–1521. doi: [10.15585/mmwr.mm6942e1](https://doi.org/10.15585/mmwr.mm6942e1).
- Hartman, S., 2008. Venus in two acts. *Small Axe* 12, 1–14. <https://muse.jhu.edu/article/241115>.
- Iceland, J., Weinberg, D.H., Steinmetz, E., 2002. Racial and ethnic residential segregation in the United States: 1980–2000. U.S. Government Printing Office, Washington, D.C. <https://www.census.gov/prod/2002pubs/censr-3.pdf>.
- ICF Consulting, Inc., Blake, K.S., Kellerson, R.L., Simic, A., Econometrica, Inc., 2007. Measuring overcrowding in housing. U.S. Department of Housing and Urban Development, Office of Policy Development and Research. [https://www.huduser.gov/portal/publications/polleg/overcrowding\\_hsg.html](https://www.huduser.gov/portal/publications/polleg/overcrowding_hsg.html).
- Karaca-Mandic, P., Georgiou, A., Sen, S., 2020. Assessment of COVID-19 hospitalizations by race/ethnicity in 12 states. *JAMA Intern. Med.* doi: [10.1001/jamainternmed.2020.3857](https://doi.org/10.1001/jamainternmed.2020.3857).
- Keeling, M.J., Rohani, P., 2007. Modeling infectious diseases in humans and animals. Princeton University Press, Princeton. doi: [10.2307/j.ctvc4m4gk0](https://doi.org/10.2307/j.ctvc4m4gk0).
- Kelley, R.D.G., 2002. ‘A day of reckoning’: Dreams of reparations, in: *Freedom dreams: The Black radical imagination*. Beacon Press, pp. 110–134. doi: [10.1215/9780822389811-012](https://doi.org/10.1215/9780822389811-012).
- Kissler, S.M., Kishore, N., Prabhu, M., Goffman, D., Beilin, Y., Landau, R., Gyamfi-Bannerman, C., Bateman, B.T., Snyder, J., Razavi, A.S., Katz, D.,



- Gal, J., Bianco, A., Stone, J., Larremore, D., Buckee, C.O., Grad, Y.H., 2020. Reductions in commuting mobility correlate with geographic differences in SARS-CoV-2 prevalence in New York City. *Nat. Commun.* 11. doi: [10.1038/s41467-020-18271-5](https://doi.org/10.1038/s41467-020-18271-5).
- Lieberman-Cribbin, W., Tuminello, S., Flores, R.M., Taioli, E., 2020. Disparities in COVID-19 testing and positivity in New York City. *Am. J. Prev. Med.* 59, 326–332. doi: [10.1016/j.amepre.2020.06.005](https://doi.org/10.1016/j.amepre.2020.06.005).
- Massey, D.S., Denton, N.A., 1988. The dimensions of residential segregation. *Soc. Forces* 67, 281–315. <https://www.jstor.org/stable/2579183>.
- McLaren, J., 2020. Racial disparity in COVID-19 deaths: Seeking economic roots with Census data. NBER Work. Pap. Ser. 27407. doi: [10.3386/w27407](https://doi.org/10.3386/w27407).
- Mignolo, W.D., 2015. Sylvia Wynter: What does it mean to be human?, in: McKittrick, K. (Ed.), *Sylvia Wynter: On being human as praxis*. Duke University Press, Durham, pp. 106–123. doi: [10.1215/9780822375852-004](https://doi.org/10.1215/9780822375852-004).
- Millett, G.A., Jones, A.T., Benkeser, D., Baral, S., Mercer, L., Beyrer, C., Honermann, B., Lankiewicz, E., Mena, L., Crowley, J.S., Sherwood, J., Sullivan, P.S., 2020. Assessing differential impacts of COVID-19 on Black communities. *Ann. Epidemiol.* 47, 37–44. doi: [10.1016/j.annepidem.2020.05.003](https://doi.org/10.1016/j.annepidem.2020.05.003).
- Montoya-Barthelemy, A.G., Lee, C.D., Cundiff, D.R., Smith, E.B., 2020. COVID-19 and the correctional environment: The American prison as a focal point for public health. *Am. J. Prev. Med.* 58, 888–891. doi: [10.1016/j.amepre.2020.04.001](https://doi.org/10.1016/j.amepre.2020.04.001).
- Morgan, J.C., Dill, J., Kalleberg, A.L., 2013. The quality of healthcare jobs: Can intrinsic rewards compensate for low extrinsic rewards? *Work Employ. Soc.* 27, 802–822. doi: [10.1177/0950017012474707](https://doi.org/10.1177/0950017012474707).
- Morrell, A., Kiersz, A., 2014. Seeing how the highest and lowest-earners spend their money will make you think differently about ‘rich’ vs ‘poor’. *Bus. Insider*, 4 December. <https://www.businessinsider.com/how-high-income-and-low-income-americans-spend-their-money-2017-3>.
- Office of the New York City Comptroller, 2020. New York City’s frontline workers. <https://comptroller.nyc.gov/reports/new-york-citys-frontline-workers/>.
- Renelus, B.D., Khoury, N.C., Chandrasekaran, K., Bekele, E., Briggs, W.M., Ivanov, A., Mohanty, S.R., Jamorabo, D.S., 2020. Racial disparities in COVID-19 hospitalization and in-hospital mortality at the height of the New York City pandemic. *J. Racial. Ethn. Health Disparities*. doi: [10.1007/s40615-020-00872-x](https://doi.org/10.1007/s40615-020-00872-x).
- Rho, H.J., Brown, H., Fremstad, S., 2020. A basic demographic profile of workers in frontline industries. Center for Economic and Policy Research, Washington, D.C. <https://cepr.net/a-basic-demographic-profile-of-workers-in-frontline-industries/>.
- da Silva, D.F., 2014. Toward a Black Feminist Poethics: The quest(ion) of Blackness toward the end of the world. *Black Scholar* 44, 81–97. doi: [10.5816/blackscholar.44.2.0081](https://doi.org/10.5816/blackscholar.44.2.0081).
- da Silva, D.F., 2015. Before *man*: Sylvia Wynter’s rewriting of the modern episteme, in: McKittrick, K. (Ed.), *Sylvia Wynter: On being human as praxis*. Duke University Press, Durham, pp. 90–105. doi: [10.1215/9780822375852-003](https://doi.org/10.1215/9780822375852-003).
- Simpson, P.L., Butler, T.G., 2020. Covid-19, prison crowding, and release policies. *BMJ* 369. doi: [10.1136/bmj.m1551](https://doi.org/10.1136/bmj.m1551).
- Taylor, R., Risling Baldy, C., Fletcher, M., Diver, K., George-Warren, D., Houska, T., Medicine Crow, L., 2019. 6 Native leaders on what it would look like if the US kept its promises. *Vox*, 23 September. <https://www.vox.com/first-person/2019/9/23/20872713/native-american-indian-treaties>.
- Wu, X., Nethery, R.C., Sabath, B.M., Braun, D., Dominici, F., 2020. Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. *Sci. Adv.* 6, eabd4049. doi: [10.1126/sciadv.abd4049](https://doi.org/10.1126/sciadv.abd4049).
- Yehia, B.R., Winegar, A., Fogel, R., Fakih, M., Ottenbacher, A., Jesser, C., Bufalino, A., Huang, R.H., Cacchione, J., 2020. Association of race with mortality among patients hospitalized with coronavirus disease 2019 (COVID-19) at 92 US hospitals. *JAMA Netw. Open* 3, e2018039. doi: [10.1001/jamanetworkopen.2020.18039](https://doi.org/10.1001/jamanetworkopen.2020.18039).
- Zeileis, A., Kleiber, C., Jackman, S., 2008. Regression models for count data in R. *J. Stat. Softw.* 27. doi: [10.18637/jss.v027.i08](https://doi.org/10.18637/jss.v027.i08).