NCVHS Subcommittee on Privacy, Confidentiality and Security
Comments Received in Response to Request for Comment
Federal Register Notice 85 FR 51455

Received as of September 10, 2020

	Organization	Signatory
1.	American University and Harvard Medical School/Boston Children's Computational Health Informatics Program (CHIP) Joint Position Statement	Divya Ramjee PhD Candidate/Adjunct Professor Department of Justice, Law and Criminology School of Public Affairs/American University Dr. Maimuna Majumder Harvard Medical School Boston Children's Computational Health Informatics Program (CHIP)
2.	Future of Privacy Forum	Pollyanna Sanderson Policy Counsel
3.	Harvard T.H. Chan School of Public Health	Nancy Krieger, PhD Professor of Social Epidemiology American Cancer Society Clinical Research Professor Department of Social and Behavioral Sciences
4.	New America's Open Technology Institute	Sharon Bradford Franklin Policy Director
5.	UCLA Center for Health Policy Research	Ninez A. Ponce, MPP, PhD Director, UCLA Center for Health Policy Research
6.	Women's Institute for Independent Social Enquiry	Elizabeth Pathak, PhD President

Subcommittee on Privacy, Confidentiality, and Security
National Committee on Vital and Health Statistics (NCVHS)
U.S. Department of Health and Human Services

RE: ***Request for Public Comment on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency***

September 9, 2020

To Whom It May Concern:

We greatly appreciate the opportunity to provide public comment on the issues of privacy, confidentiality, and security for data collection and use during public health emergencies. We are particularly concerned about these considerations in regards to mobile phone apps and other digital surveillance tools to supplement contact tracing and mitigation efforts. As the COVID-19 pandemic continues, now is the time for the United States to establish a national-level contact tracing initiative, as well as lay out a federal framework for regulations that protect consumer security and privacy while achieving optimum epidemiological utility.

Please find attached our position statement that reflects our ongoing work on an interdisciplinary law review regarding regulation of a national public health surveillance framework. We look forward to the Committee's upcoming hearing and being a part of the conversation.

Thank you for your time and consideration.

Sincerely,

Divya Ramjee
Department of Justice, Law and Criminology
School of Public Affairs
American University
dr1208a@american.edu

Dr. Maimuna Majumder
Harvard Medical School
Boston Children's Computational Health Informatics Program (CHIP)
Maimuna.Majumder@childrens.harvard.edu

POSITION STATEMENT

Digital contact tracing and contact tracing apps are currently at the forefront of discussions about digital public health surveillance, i.e. the use of technological devices for monitoring and tracking, for the coronavirus disease 2019 (COVID-19) pandemic. An abundance of apps continue to be developed and enter the global market, and many of these apps promise to accurately trace coronavirus infections at scale and contain the ongoing pandemic. However, unlike traditional approaches, digital contact tracing necessitates that a considerable proportion of the general population opt-in – regardless of whether individuals are infected or at high-risk of exposure – to yield true epidemiological utility. There has not yet been sufficient consideration of trade-offs between privacy, efficiency, and scale in shaping the future of digital surveillance for emerging infectious disease threats, neither for the United States nor worldwide.

Existing apps are not developed with broad interconnectivity in mind, raising a crucial question as to how incompatibility may impact information-sharing, both across platforms and across borders, to accurately trace the spread of the disease. We propose that a regulatory framework be established that addresses components that promote epidemiological utility, including (1) reporting by healthcare providers to augment self-reporting; (2) usability across varying mobile devices and operating softwares, particularly mobile devices that are not smartphones; (3) literacy and disability compatibility requirements; and (4) adoption incentivization. Interface design in particular must account for as many user groups as possible, with special attention to education, age, ability, and socioeconomic factors. Developers involved have thus far failed to incorporate important human factors concepts (e.g., usability, adaptive technology for persons with disabilities, error prevention, interface design for varying levels of literacy, etc.) into their product designs, undermining the potential utility of such apps across disparate populations – including those that are traditionally underserved. Additionally, while contact tracing efforts are indeed important for within the U.S., there must be a realization that global air travel will continue, necessitating the importance of incorporating these concerns for epidemiological utility into app development and implementation that can function and aggregate data at a global-level.

In terms of security and privacy for users, contact tracing apps in particular should follow a model of decentralized Bluetooth-based design, realizing though that this technology is still limited by inaccuracies pertaining to the collection of proximity data but preserves user privacy to more acceptable standards than location-based (i.e., GPS) designs. Google and Apple lead the way with the Google-Apple exposure notification (GAEN) application programming interface (API) that enables expanded access to Bluetooth scanning for apps using the API and improves the ability of Apple and Android devices to detect signals from one another. Of additional importance are considerations for requirements related to protected health and medical information, as well as privacy concerns related to other types of biometric data. Furthermore, the United States needs to establish regulatory guidelines for the security and privacy of digital surveillance data, particularly for metadata related to location information that may be abused and/or used for discriminatory or targeting purposes by employers, schools, or the government

A number of members of Congress have proposed legislation to regulate digital surveillance tools, and we urge lawmakers to understand that regulation of public health surveillance technologies needs to balance concerns for epidemiological utility with security and privacy concerns. Over twenty states in the United States are currently considering, designing, or implementing contact tracing apps, but these initiatives continue to lack direction at the federal level. Ultimately, the United States will need to focus on involvement with global-level contact tracing. However, we stress that there is a dire need for the United States to concentrate on creating a national framework first, one that appropriately governs digital contact tracing – and any future public health surveillance technologies – within the country and between states.

From: Polly Sanderson
To: NCVHS Mail (CDC)
Cc: John Verdi
Subject: Comments to NCVHS on the Subcommittee Hearing on Privacy, Confidentiality, and Security
Date: Wednesday, September 9, 2020 5:25:01 PM
Attachments: OSTP FPF Comments.pdf
FPF Comments to the National Committee on Vital and Health Statistics.pdf

Good evening,

I'm reaching out to submit comments (see attached) to the National Committee on Vital and Health Statistics' Hearing of the Subcommittee on Privacy, Confidentiality, and Security on the behalf of the Future of Privacy Forum. Also attached are FPF's recent comments to the Office of Science and Technology Policy (OSTP).

Respectfully,

Polly

Pollyanna Sanderson
Policy Counsel
Future of Privacy Forum
202.688.4150 | psanderson@fpf.org | www.fpf.org

1400 Eye Street NW, Suite 450, Washington, DC 20005

FUTURE OF PRIVACY FORUM 1400 Eye Street NW, Suite 450, Washington, DC 20005 | 202-768-8950 | fpf.org

September 9, 2020

National Committee on Vital and Health Statistics
3311 Toledo Road, Room 2402
Hyattsville, MD 20782

VIA EMAIL TO: NCVHSmail@cdc.gov

RE: 85 Federal Register 51455: "National Committee on Vital and Health Statistics (NCVHS), Hearing of the Subcommittee on Privacy, Confidentiality, and Security"

Dear Members of the National Committee on Vital and Health Statistics:

Thank you for the opportunity to provide comments in advance of the September 14, 2020 Hearing of the Subcommittee on Privacy, Confidentiality, and Security. Future of Privacy Forum (FPF) is a non-profit organization based in Washington, DC, with the mission of promoting privacy leadership and scholarship, and advancing principled data practices in support of emerging technologies.[1] FPF works on a range of consumer privacy issues, including connected wearable devices, health and wellness data, mobile apps and platforms, and the role of technology in addressing the COVID-19 pandemic. Through our *Privacy and Pandemics* series, we have been exploring the challenges posed by the COVID-19 crisis to existing ethical, privacy, and data protection frameworks.

We write to provide a number of existing resources that address the following issues raised by the Committee in the Request for Public Comments, including: (1) the application of the Fair Information Practice Principles (FIPPs) and proper scope of data collection, analysis, and sharing in an emergency; (2) differences in standards at the local, state, and federal levels; and (3) technical resources on understanding location data and the current design of mobile apps.

(1) Resources on the Fair Information Practice Principles (FIPPs) and Emergencies

Throughout our recent work, FPF has encouraged organizations and other stakeholders collecting digital contact tracing data to apply the Fair information Practice Principles (FIPPs)[2] to the collection and use of data for COVID-19. This includes limiting the scope of data collection to what is necessary and proportional to public health needs; adhering to purpose limitation principles; and promoting lawfulness and transparency through the use of privacy impact assessments (PIAs).

- Privacy and Pandemics: A Thoughtful Discussion (March 27, 2020). In this discussion, we provide the consensus advice from a *Privacy and Pandemics* Virtual Workshop in which FPF convened a dozen ethicists, academics, government officials, and corporate leaders,

[1] The views herein do not necessarily reflect those of our supporters or our Advisory Board.
[2] Records, Computers, and Rights of Citizens report of the U.S. Department of Health, Education and Welfare (1973), https://www.justice.gov/opcl/docs/rec-com-rights.pdf.

as well as over 100 corporate attendees, to discuss responsible data sharing in times of crisis.

- FPF's testimony before the U.S. Senate Committee on Commerce, Science, & Transportation, Enlisting Big Data in the Fight Against Coronavirus (April 9, 2020). In this testimony, FPF explored how collection and uses of data, including personal data, to respond to a public health crisis like a pandemic can be compatible with privacy and data protection principles. We recommended that organizations collecting digital contact tracing data follow the lead of public health experts; ensure transparency and lawfulness; apply privacy enhancing technologies (PETs); employ privacy risk assessments (PIAs); and follow core purpose limitation principles.

- COVID-19 Public Work Session hosted by the Washington State Senate Committee on Environment, Energy & Technology (July 28, 2020). In FPF's recent presentation to Washington lawmakers, we recommended that policymakers and technology providers follow the lead of public health experts, and outlined key considerations and recommendations for how to design and implement digital contact tracing tools, including: purpose limitation; retention limits; privacy impact assessments; prioritization of accessibility; careful integration of external software development kits (SDKs); interoperability; and security.

- FPF and BrightHive's Digital Contact Tracing: A Playbook for Responsible Data Use (August 14, 2020). In this Playbook, we encourage organizations collecting digital contact tracing data to commit to limiting the scope of data collection according to the needs of public health experts. Decisions about which data, analytic, and technological models to pursue should be based on medical and public health partners' needs, their estimates of efficacy, and grounded in the best available evidence. We encourage stakeholders to limit the sharing of data to established partners who have demonstrated experience with responsible data sharing; and to be guided by the principles of necessity and proportionality.

(2) Resources on Differing Standards at State, Federal, Local Levels

In response to the ongoing public health emergency, organizations must comply with a wide range of existing regulations and standards, including Europe's General Data Protection Regulation (GDPR). In the United States, several federal proposals have been proposed, including the COVID-19 Exposure Notification Act. State legislatures have also been involved in emerging regulatory efforts to promote public trust and public participation by addressing concerns over the impact of digital contact tracing on privacy and civil liberties. Commercial entities using the Apple-Google Exposure Notification API must also comply with the privacy rules in the Terms of Service for those platforms.

The following FPF resources explore these topics:

- EU DPAs Issue Green and Red Lights for Processing Health Data During the COVID-19 Epidemic (March 10, 2020) – exploring how various European Data Protection Authorities issued public interest guidance on the limits of collecting, sharing and using personal data relating to health in these exceptional circumstances under the General Data Protection Regulation (GDPR).
- Newly Released COVID-19 Privacy Bills Would Regulate Pandemic-Related Data (May 15, 2020) — analyzing the Public Health Emergency Privacy Act (introduced by leading House and Senate Democrats) and the COVID–19 Consumer Data Protection Act of 2020 (introduced by leading Republicans), including its scope of covered data and entities; legal requirements; and a few key differences from its Republican counterpart.
- Bipartisan Privacy Bill Would Govern Exposure Notification Services (June 2, 2020) — analyzing the Exposure Notification Privacy Act, introduced by Senators Cantwell (D-WA), Cassidy (R-LA), and Klobuchar (D-MN), which would create legal limits for automated exposure notification services.
- Apple & Google Update Terms for COVID-19 Apps (May 27, 2020) — analyzing the privacy and security requirements of the Apple Google Exposure Notification API, designed for decentralized Bluetooth-based digital exposure notification apps. In September, Apple and Google also launched "Exposure Notification Express", making exposure notification functionality available at the operating system level.

(3) Additional Technical Resources

The following additional technical resources may provide helpful insights on the role of location data and the current design of mobile apps:

- FPF Charts the Role of Mobile Apps in Pandemic Response (April 3, 2020) — providing early analysis of the various objectives and methods of early digital contact tracing apps and software development kits.
- Infographic: Understanding the World of Location Data (May 22, 2020) — demonstrating how mobile devices interpret signals from their surroundings, including GPS satellites, cell towers, Wi-Fi networks, and Bluetooth, to generate precise location measurements.
- Thermal Imaging as Pandemic Exit Strategy: Limitations, Use Cases and Privacy Implications (June 3, 2020) — surveying the leading technologies, products, and use cases for thermal imaging, reviewing the technical limitations of thermal scanning as described in scientific literature, discussing the concerns articulated by privacy and civil rights advocates, and providing an in-depth overview of regulatory guidance on thermal imaging from the US, Europe, and Singapore.
- FPF's comments to the Office of Science and Technology Policy's (OSTP) (attached) advised that all federally funded research projects adopt a strong, risk-conscious, approach to privacy protections. We recommend that OSTP adopt a nuanced approach to requirements for fidelity to consent that acknowledges the limitations to consent and reinvigorates the use of consent documents to outline which research purposes conform to participants expectations. We recommend projects include language that outlines the potential privacy risks for reuse of the data, including results from a well-designed open

data risk-benefit assessment, and will clarify boundaries to privacy respecting reuse of the data.

Sincerely,

John Verdi
Vice-President of Policy
Future of Privacy Forum

Stacey Gray
Senior Counsel
Future of Privacy Forum

Pollyanna Sanderson
Policy Counsel
Future of Privacy Forum

Comments from
THE FUTURE OF PRIVACY FORUM

to EXECUTIVE OFFICE OF THE PRESIDENT
Office of Science and Technology Policy

Document Number: 2020-00689
Draft Desirable Characteristics of Repositories for Managing and Sharing Data Resulting from Federally Funded Research

Email Subject: RFC Response: Desirable Repository Characteristics
Submitted to:
Lisa Nichols
Open Science
℅ Sean C. Bonyun
Chief of Staff, Office of Science and Technology Policy
Email: OpenScience@ostp.eop.gov

Dr. Sara R. Jordan, Policy Counsel, Artificial Intelligence
THE FUTURE OF PRIVACY FORUM [1,2]
1400 I St. NW Ste. 450
Washington, DC 20005
www.fpf.org

Scientific Disciplines of Submitting Organization: Law, Public Policy, Machine Learning

Dear Mr. Bonyun,
On January 17, 2020, the Executive Office of the President, Office of Science and Technology Policy (hereinafter OSTP) published a Notice for public comments on the characteristics desired for data repositories storing data from federally funded research projects. We thank the OSTP for the opportunity to submit comments to the Draft Desirable Characteristics of Repositories for Managing and Sharing Data Resulting from Federally Funded Research.

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[1] The Future of Privacy Forum (FPF) is a nonprofit organization that serves as a catalyst for privacy leadership and scholarship, advancing principled data practices in support of emerging technologies.

[2] The views herein do not necessarily reflect those of our supporters or our Advisory Board.

FPF are broadly supportive of the draft guidelines. We believe that the requirement for data built through federally funded projects to be made indefinitely available as described in Part I clearly preserves stewardship of public resources and ensures thoughtful data management and data security from acquisition to archiving to de-accession.

We wish to offer suggestions to modify components of Part II, Additional Considerations for Repositories Storing Human Data (even if de-identified) to ensure effective data sharing between organizations, whether public or private. Our comments are intended to encourage the OSTP to adopt a strong, risk-conscious, approach to privacy protections in the context of sharing personal data gathered through Federally funded research projects. Our concern is that stipulations listed in Part II may limit data sharing across organizations due to incompatibilities in privacy law frameworks, due to enthusiastic but misguided efforts to subject all human data to "HIPAA" data requirements, and due to insufficiently articulated enforcement mechanisms that will may limit robust pathways to realization of these desiderate. We outline our recommendations in line with each of the components to Part II on which we comment.

Part II.A: Fidelity to Consent

Consent may be an appropriate mechanism for protecting the privacy and data rights of research participants in many cases, but not in all cases. Guidance from the European Data Protection Board (EDPB) reminds that consent may be less appropriate when there is an imbalance of power between data subjects and researchers.[3] FPF encourages OSTP to adopt a nuanced approach to requirements for fidelity to consent that acknowledge the limitations to consent and reinvigorates the use of consent documents to outline which research purposes conform to participants expectations.

Recent discussions by EU states[4] and by the EU Data Protection Supervisor[5] itself suggest that EU member states will permit sharing of de-identified research data under the guide of "broad consent". "Broad consent" permits researchers to use data for almost any form of clinical research when the data was originally given for the purpose of clinical research. Likewise, the 2018 Revisions to the Common Rule, "broad consent for secondary use may be obtained when standard informed consent is obtained for the original or initial primary research when investigators are interacting or intervening with subjects, for example, for a clinical trial".[6] Broad consent requirements give investigators the latitude to request that subjects consider future

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[3] Article 29 Working Party (2018). Guidelines on Consent under Regulation 2016/679. https://ec.europa.eu/newsroom/article29/document.cfm?action=display&doc_id=51030

[4] Federal Ministry of Justice and Consumer Protection. (2020). Opinion of the Data Ethics Commission. Federal Government of Germany. January 22, 2020. https://www.bmjv.de/SharedDocs/Downloads/DE/Themen/Fokusthemen/Gutachten_DEK_EN_lang.html;jsessionid=088D6FC6594FF0130AEC723D7A82FEC1.2_cid334?nn=11678512

[5] European Data Protection Supervisor (EDPS). (2020). A Preliminary Opinion on Data Protection and Scientific Research. January 6, 2020. https://edps.europa.eu/sites/edp/files/publication/20-01-06_opinion_research_en.pdf

[6] Office for Human Research Protections. (2018). Revised Common Rule Q&As. July 30, 2018. https://www.hhs.gov/ohrp/education-and-outreach/revised-common-rule/revised-common-rule-q-and-a/index.html#broad-consent-in-the-revised-common-rule

unknown uses of their data and give consent to those unknown future uses, within the restrictions that they must set out for the period of time the data may be stored, maintained, or used. Under these terms, investigators do not need to re-approach subjects to notify them if clinically relevant research results emerge from secondary use under broad consent.
The requirement that data managed and shared under these guidelines are faithful to the original consent statement is contradictory to present thinking whether in the US or its major research competitors in the EU.

Part II.B: Restricted Use Compliant
The restricted use compliance requirement outlines that a data repository will enforce submitters' data use restrictions. Two concerns arise regarding this requirement: 1) requirements for data repositories to reconfirm and "evergreen" data submitters' preferences for data use restrictions and 2) repositories' required responses to change data as the individuals who submitted data change their individual requirements for data use. Particularly as legislation evolves which allows consumers to restrict secondary uses of their data, including removing their information from databases, repositories may become liable for checking to ensure that individuals' data uses restrictions are reflected in the data use restrictions sent by data holders to repositories.

Part II.C: Privacy
FPF recommends that the OSTP include a strong statement for the protection of research subjects' data privacy throughout the research data lifecycle. We recommend adoption of a nuanced and targeted approach to privacy protection which recognizes the different risks to participants that arise from storing and sharing research data in the many forms that research data takes. We advise OSTP to consider including stronger language that outlines best practices for de-identification of data for research uses and recommend OSTP to consult our materials developed on this topic.[7] However, HIPAA requirements are both too narrow and too broad to be applied wholesale to research data. A nuanced assessment of the risks based on data types is needed to protect participants privacy and facilitate data sharing.
We are concerned that the language associated with privacy conflates privacy with security in ways that could lead to aggressive management of all forms of repository data through application of the HIPAA privacy and security rule.[8] While cybersecurity and privacy are intertwined, as the NIST Privacy Framework 1.0[9] outlines, security rules for human subjects data as outlined in HIPAA are not appropriate for all forms of individually identifiable data as described in this Notice. Our partners in research institutions report that secondary uses of data are stymied by broad application of HIPAA requirements for safeguarding of data, including HIPAA level security protocols. One of our concerns is that this section could be read to re-interpret the role

[7] Finch, K. (2016). A Visual Guide to Practical Data De-Identification. https://fpf.org/2016/04/25/a-visual-guide-to-practical-data-de-identification/

[8] Department of Health and Human Services, Health Information Privacy. (2013). Summary of the HIPAA Security Rule. July 26, 2013. https://www.hhs.gov/hipaa/for-professionals/security/laws-regulations/index.html

[9] National Institutes of Standards and Technology. (2020). NIST Privacy Framework, Version 1.0: A Tool for Improving Privacy Through Enterprise Risk Management. January 16. 2020. https://www.nist.gov/system/files/documents/2020/01/16/NIST%20Privacy%20Framework_V1.0.pdf

of research data repositories as "business associates" under the HIPAA security rule would amplify a risk-averse approach to data sharing and collaboration.[10] Although "organization that acts merely as a conduit for protected health information" is not considered to be subject to a Business Associate Contract under the HIPAA Security rule, there is latitude for reinterpretation of this given other obligations listed for data repositories in this notice. Particularly if data sharing repositories are required to ensure continuous updating of data providers' sharing preferences, there is an argument to be made that these repositories will perform "data aggregation" or "data analysis" functions in order to carry out their normal business activities.

For organizations that encourage data sharing as part of their repository function or through their work with repositories, imposition of HIPAA Security Rule requirements would be onerous, whether *de jure* through specification as such here or *de facto* through adoption of a common risk averse posture. We recommend that the OSTP work with organizations like FPF to carefully craft the language around privacy protections, whether data is de-identified or not, in repositories storing human data.

Part II.E: Download Control

We applaud the inclusion of language here to describe control and audit mechanisms for download of datasets that contain data on human subjects. We encourage stronger language to be included that addresses the automated downloading ("scraping") of datasets from repositories. In particular, we encourage OSTP to include language that encourages software developers, such as the Python Software Foundation, to include dependencies in their scraping and analytics packages that notify users when their scraping violates repository terms of service or that notify repositories that their data is being scraped. We support use of data in development of automated processes and machine learning research, but encourage a more robust set of controls that incorporate software companies as part of the organizations responsible for download control.

In addition, and in conjunction with our remarks for Part II.H. we encourage the OSTP to pursue design of enforcement actions against organizations who create "shadow repositories" for unrestricted uses of research data.

Part II.F: Clear Use Guidance

To effectively facilitate use of data in repositories, a clear-language approach, with robust verbal and symbolic descriptions of restrictions and use permissions, should be incorporated into final requirements for use guidance. The Future of Privacy Forum has developed infographics that describe data on a spectrum of fully identified to fully anonymized on which we have received excellent user feedback regarding interpretability and explicability.[11] We encourage adoption of

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[10] "A "business associate" is a person or entity that performs certain functions or activities that involve the use or disclosure of protected health information on behalf of, or provides services to, a covered entity. Business associate functions and activities include: claims processing or administration; data analysis, processing or administration; utilization review; quality assurance; billing; benefit management; practice management; and repricing. Business associate services are: legal; actuarial; accounting; consulting; data aggregation; management; administrative; accreditation; and financial. See the definition of "business associate" at 45 CFR 160.103." (Emphasis added).

[11] Finch, K. (2016). A Visual Guide to Practical Data De-Identification. https://fpf.org/2016/04/25/a-visual-guide-to-practical-data-de-identification/

our model as one mechanism for description of datasets and terms of their use. Including language that outlines the potential privacy risks for reuse of the data, including results from a well-designed open data risk-benefit assessment, will clarify boundaries to privacy respecting reuse of the data.[12]

Part II.H: Violations

With respect to security of the repository itself, we applaud adaptation of the NIST Cybersecurity Framework[13] and NIST Privacy Frameworks for all repositories storing any form of human subject's data acquired through federally funded research projects, whether funding is direct or "flow through". We encourage the OSTP to include strong language and a robust organization architecture for enforcement of violations of the terms of fair use for data repositories. In particular, we encourage the OSTP to collaborate with analytics software companies to develop dependencies in their packages that monitor and report uses of data from repositories.

Part II.I: Request for Review

The Future of Privacy Forum welcomes the opportunity to work with the OSTP to develop policies and procedures necessary to implement an oversight group that can be responsible for reviewing data use requests on behalf of repositories storing human subjects data from federally funded research projects. We have received a grant for the express purpose to design an ethical review process for data sharing between corporations and research organizations.[14] We have committed to development of an ethical data sharing review board that broadly meets the mandate described in this Notice for comment. While it is not our intent to develop a data repository, we will provide a framework for review that is compatible with the research ethics and research integrity infrastructure that already governs federally funded research projects[15] and will serve as an independent body to provide review of data sharing arrangements made between for-profit and not-for-profit, non-profit, academic, and other organizations when those data sharing arrangements are made for the specific purpose of research. Our expertise in corporate

[12] Finch, K. (2018). FPF Publishes Model Open Data Benefit-Risk Analysis. https://fpf.org/2018/01/30/fpf-publishes-model-open-data-benefit-risk-analysis/

[13] National Institute for Standards and Technology. (2018). Cybersecurity Framework Version 1.1. https://www.nist.gov/cyberframework/framework

[14] Leong, B. (2019). FPF Receives Grant to Design Ethical Review Process for Research Access to Corporate Data. https://fpf.org/2019/10/15/fpf-receives-grant-to-design-ethical-review-process-for-research-access-to-corporate-data/

[15] Jordan, S.R. (2019). Designing an AI Research Review Committee. https://fpf.org/wp-content/uploads/2019/10/DesigningAIResearchReviewCommittee.pdf

data sharing practices[16],[17], privacy risks for machine learning systems[18] and embedding data protection principles for machine learning[19] puts our organization in an ideal place to serve as a reliable partner for oversight of data use requests.

Conclusion

We commend the Office of Science and Technology Policy for their engagement with stakeholders on crafting these draft characteristics for data repositories. We welcome additional engagement with OSTP as these draft desirable characteristics are developed into more robust guidelines.

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[16] Harris, L. & Sharma, C. (2017). Understanding Corporate Data Sharing Decisions: Practices, Challenges, and Opportunities for Sharing Corporate Data with Researchers. https://fpf.org/2017/11/14/understanding-corporate-data-sharing-decisions-practices-challenges-and-opportunities-for-sharing-corporate-data-with-researchers/

[17] FPF Staff. (2019). Ethical and Privacy Protective Academic Research and Corporate Data. https://fpf.org/2019/06/07/fpf-companies-academics-developing-best-practices-on-data-sharing/

[18] Stalla-Bourdillon, S., Leong, B., Hall, P., & Burt, A. (2019). WARNING SIGNS: The future of privacy and security in an age of machine learning. https://fpf.org/2019/09/20/warning-signs-identifying-privacy-and-security-risks-to-machine-learning-systems/

[19] Stalla-Bourdillon, S., Rossi, A., & Zanfir-Fortuna, G. (2019). Data Protection by Process: How to Operationalize Data Protection by Design for Machine Learning. https://fpf.org/2019/12/19/new-white-paper-provides-guidance-on-embedding-data-protection-principles-in-machine-learning/

From:	Krieger, Nancy
To:	NCVHS Mail (CDC)
Cc:	Krieger, Nancy
Subject:	Comments & relevant publications for: "Request for Public Comment on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency"
Date:	Saturday, September 5, 2020 6:15:35 PM
Attachments:	20_Bassett-Chen-Krieger_COVID-19_plus_age_working-paper_0612_Vol-19_No-3_with-cover.pdf 20_chen+krieger_RevealingUnequalBurden_HCPDSWorkingPaper_04212020-1.pdf 20_chin et al_us county characteristics relevan to COVID-19 equitable response_BMJ open.pdf 20_chotiner_NK interview_The Coronavirus and the Interwoven Threads of Inequality and Health_The New Yorker_0414.pdf 20_cowger et al_covid-19+critique of CDC_jama open network.pdf 20_jtc_pdw_nk_COVID19_MA-excess-mortality_text_tables_figures_final_0509_with-cover-1.pdf 20_Krieger et al_COVID-19 Resources The Public Health Disparities Geocoding Project Monograph_0905.pdf 20_krieger et al_excess mortality in women + men in MA during COVID-19_lancet_may 27_PIIS0140673620312344.pdf 20_Krieger et al_The Fierce Urgency Of Now Closing Glaring Gaps In US Surveillance Data On COVID_Health Affairs.pdf 20_krieger_COVID-19, Data, and Health Justice_Commonwealth Fund.pdf 20_krieger_ENOUGH_ajph essay_advance access_AJPH.2020.305886_0820.pdf 20_Public Health Awakened and The Spirit of 1848 COVID-19 Resources - Google Sheet_0905.pdf

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September 5, 2020

To: NCVHS (NCVHSmail@cdc.gov)

I am sending you brief comments and numerous publications relevant to your ""Request for Public Comment on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency," to be held on September 14, 2020 (https://ncvhs.hhs.gov/wp-content/uploads/2020/08/NCVHS-September-2020-PCS-Subcommittee-Hearing-Public-Comment-Questions-as-of-Aug-26.pdf). The specific questions I am responding to are:

"a) What is the proper scope of data collection, analysis, and sharing in an emergency?"

"i) When is aggregate data more appropriate?"

"j) Is case-level data without identifiers an adequate compromise?"

I focus on one specific aspect of data needs, specifically the data required to ensure an equitable response to and during a public health emergency. This focus is in accord with the recently released *Healthy People 2030 Framework*, released by the US Department of Health and Human Services on August 18, 2020 (https://www.healthypeople.gov/2020/About-Healthy-People/Development-Healthy-People-2030/Framework). As enunciated in the *Healthy People 2030 Framework's* "Foundational Principles" health equity is a core concern:

-- "Health and well-being of all people and communities are essential to a thriving, equitable society."
-- "Achieving health and well-being requires eliminating health disparities, achieving health equity, and attaining health literacy."

The *Healthy People 2030 Framework's* "Overarching Goals" likewise state:

-- "Eliminate health disparities, achieve health equity, and attain health literacy to improve the health and well-being of all."

The *Healthy People 2030 Framework's* "Plan of Action" translates this, operationally, as entailing:

-- "Provide data that is accurate, timely, accessible, and can drive targeted actions to address regions and populations with poor health or at high risk for poor health in the future."

It is in this spirit that I offer the following recommendations – and I provide a list of publications of mine I am submitting with this comment that provide the conceptual underpinnings and empirical foundations of these comments.

RECOMMENDATIONS

1) In a public health emergency, ensure that timely (and ideally real-time) accurate data are available, at the federal, state, and local level, to ascertain the extent to which the emergency intersects with and potentially compounds existing societal and health inequities affecting both individuals and communities, especially in relation to: race/ethnicity, socioeconomic position, sex/gender, disability, nativity, and sexual orientation and gender identity. Reliance on data for the total population is inadequate.

Additionally, , geographic areas included must encompass all relevant American Indian and tribal geographies and also Island Areas of the United States, and not just solely those areas which fit within the spine of US Census geographies (e.g., state, county, county subdivision, place (or part), census tract (or part), block group (or part), block) or created out of these elements (e.g., core-based statistical areas); see: https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_10

2) To the extent possible, the data required to gauge the extent of and monitor health inequities should be collected on individuals AND also the community characteristics of where they reside, and these two levels of data should be linked for purposes of public health monitoring and analysis. Examples of relevant community level characteristics include, at the census tract or block group level: racial/ethnic composition, income and poverty level, extent of residential segregation – including racial segregation, economic segregation, and racialized economic segregation; data on other characteristics relevant to the specifics of the type of emergency may be warranted – e.g., extent of household crowding, availability of public transportation, distance to health care facilities, etc.). If individual records cannot be geocoded to the census tract or block group level, they minimally should include a person's residential address and ZIP Code, so that ZIP Code characteristics can be assessed. Reliance on county level characteristics is too crude.

3) It is essential to provide data on the population health burden and inequities in relation to not only COUNTS of individuals affected, but also RATES (i.e., data on the outcome per population per unit time), and to document the magnitude of health inequities in relation to both rate ratios and rate differences. Moreover, both age-standardized and age-specific rate data are essential, since the magnitude of health inequities may vary by age group, in ways relevant for addressing public health prevention and mitigation of the emergency.

4) To the extent health inequities can be quickly assessed through data linkages across existing data sets (e.g., linking testing, hospitalization, or mortality records to census-derived community indicators), or via expanding questions on ongoing federal, state, and local surveys (such as the National Health Interview Survey, or the Behavioral Risk Factor Surveillance System), this should be prioritized.

A related option is to ensure relevant health questions are included in any rapid surveys conducted by non-health agencies. A timely and important model is provided by the US Census Bureau Household Pulse Survey during the COVID-19 pandemic, which included not only core demographic and income data, but also health-relevant data regarding depression, anxiety, access to and use of health care services, food insecurity, and housing insecurity. The US census published data from this survey on a WEEKLY basis, with these data representative "for the nation, each of the fifty states, plus Washington, D.C., and the fifteen largest metropolitan areas"; see:

-- https://www.census.gov/data/experimental-data-products/household-pulse-survey.html
-- https://www.census.gov/programs-surveys/household-pulse-survey.html

Sincerely,

Nancy Krieger, PhD
Professor of Social Epidemiology
American Cancer Society Clinical Research Professor
Department of Social and Behavioral Sciences
Harvard T.H. Chan School of Public Health
677 Huntington Avenue
Boston, MA 02115
office: 617-432-1571
email: nkrieger@hsph.harvard.edu

LIST OF SUPPORTING REFERENCES

COVID-19: Empirical Papers – N. Krieger

-- Note: in addition to providing the published peer-reviewed papers, I am providing the Working Papers (which inform the published papers, including those in press, which are still under embargo) to demonstrate the kinds of scientific work on health inequities that can be performed rapidly in a public health emergency

- Krieger N, Waterman PD, Chen JT. COVID-19 and overall mortality inequities in the surge in death rates by ZIP Code characteristics: Massachusetts, January 1 to May 19, 2020. *Am J Public Health* (in press; accepted August 3, 2020); see attached the Working Paper version, posted on May 9, 2020:
    - Chen JT, Waterman P Krieger N. COVID-19 and the unequal surge in mortality rates in

Massachusetts, by city/town and ZIP Code measures of poverty, household crowding, race/ethnicity, and racialized economic segregation. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 2. May 9, 2020. https://tinyurl.com/y7qzot3l

- Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county vs ZIP code analyses. *J Public Health Management Policy* (in press); see attached the Working Paper version, posted on April 21, 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. https://tinyurl.com/ya44we2r
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    - Chin T, Kahn R, Li R, Chen JT, Krieger N, Buckee CO, Balsari S, Kiang SV. U.S. county-level factors relevant to COVID-19 burden and response. *MedRxiv*, posted April 11, 2020. doi: https://doi.org/10.1101/2020.04.08.20058248
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- Bassett MT, Chen JT, Krieger N. The Unequal Toll of COVID-19 Mortality by Age in the United States: Quantifying Racial/Ethnic Disparities. *Harvard Center for Population and Development Studies Working Paper Series*, Volume 19, Number 3. June 15, 2020. https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1266/2020/06/20_Bassett-Chen-Krieger_COVID-19_plus_age_working-paper_0612_Vol-19_No-3_with-cover.pdf [note: a resubmission of this paper is under review and we anticipate it will be accepted in the very near future]
- Cowger TL, Davis BA, Etkins OS, Makofane K, Lawrence JA, Bassett MT, Krieger N. Comparison of weighted and unweighted population data to assess inequities in Coronavirus Disease 2019 by race/ethnicity reported by the US Centers for Disease Control and Prevention. *JAMA Network Open.* 2020;3(7):e2016933. https://doi.org/10.1001/jamanetworkopen.2020.16933

COVID-19: conceptual, regarding health inequities and needed data – N. Krieger

- Krieger N. COVID-19, Data, and Health Justice. *The Commonwealth Fund*, April 16, 2020. https://www.commonwealthfund.org/blog/2020/covid-19-data-and-health-justice
- Krieger N, Gonsalves G, Bassett MT, Hanage W, Krumholz HM. The fierce urgency of now: closing glaring gaps in US surveillance data on COVID-19. *Health Affairs Blog*, April 14, 2020. https://www.healthaffairs.org/do/10.1377/hblog20200414.238084/full/
- Krieger N. ENOUGH: COVID-19, structural racism, police brutality, plutocracy, climate change

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- Chotiner I. The interwoven threads of inequality and health. The coronavirus crisis is revealing the inequities inherent in public health due to societal factors, Nancy Krieger, a professor of social epidemiology, says (Interview with Nancy Krieger). *The New Yorker*, April 14, 2020. https://www.newyorker.com/news/q-and-a/the-coronavirus-and-the-interwoven-threads-of-inequality-and-health

COVID-19: resources regarding data to monitor health inequities and guide equity-oriented interventions

- Public Health Disparities Geocoding Project's Using the Methods of the Public Health Disparities Geocoding Project to Monitor COVID-19 Inequities and Guide Action for Health Justice
- Spirit of 1848 Caucus and Public Health Awakened's COVID-19 & Health Justice Resource Page

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Nancy Krieger, PhD
Professor of Social Epidemiology
American Cancer Society Clinical Research Professor
Department of Social and Behavioral Sciences
Harvard T.H. Chan School of Public Health
677 Huntington Avenue, Kresge 717
Boston, MA 02115
office: 617-432-1571
fax: 617-432-3123
email: nkrieger@hsph.harvard.edu
web page: http://www.hsph.harvard.edu/faculty/nancy-krieger/
pronouns: she/her/hers

For appointments, please contact Amanda Harris, Executive Assistant;
email: aharris@hsph.harvard.edu ; phone: 617-432-3915.

HARVARD CENTER FOR POPULATION AND DEVELOPMENT STUDIES

Working Paper Series

The unequal toll of COVID-19 mortality by age in the United States: Quantifying racial/ethnic disparities

MT Bassett, MD, MPH[1,2], Jarvis T. Chen, ScD[1], Nancy Krieger, PhD[1]

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Affiliations

1. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health
2. Francois-Xavier Bagnoud Center for Health and Human Rights, Harvard University

Corresponding Author

Dr. Mary Bassett
Address: FXB Center for Health and Human Rights, Room 704, 651 Huntington Avenue, Boston, MA 02115
Email: mailto:mbassett@hsph.harvard.edu
Tel: +1(917) 282-1567 (during COVID-19)

Author contributions: MTB initiated the study and led framing of the study and drafting the manuscript; NK and JTC conceptualized the study design and contributed to drafting the manuscript; JTC led and conducted the data analysis; all authors contributed to interpreting the results and all approved the final version of the submitted manuscript.

Abstract

Importance: Excess COVID-19 mortality has been described among Non-Hispanic Blacks (NHB), Hispanics and Non-Hispanic American Indians/Alaska Natives (NHAIAN), compared to non-Hispanic Whites (NHW), but not in relation to age at death. Recent release of national COVID-19 deaths by racial/ethnic group now permit analysis of age-specific mortality rates.

Objective: To examine variation in age-specific mortality rates by racial/ethnicity and calculate its impact using Years of Potential Life Lost (YPLL).

Design: This is a descriptive study using the most recently publicly available data on COVID-19 deaths, with population data drawn from the US Census

Setting: United States

Participants: All persons for whom there were reported deaths, COVID-19 deaths and reported racial/ethnicity February 1, 2020-May 20, 2020

Results: Age-standardized rate ratios relative to NHW were 3.6 (95% CI 3.5, 3.7) for NHB, 2.6 95% CI 2.4, 2.7) for Hispanics, 1.2 (0.8, 1.6) for NHAIAN, and 1.7 (1.6, 1.9) for NHAPI. By contrast, NHB rate ratios relative to NHW were as high as 7.3 (95% CI 5.6, 9.5) for 25-34 year old, 9.0 (95% CI 7.6, 10.8) for 35-44 year old, and 6.9 (95% CI 6.3, 7.6) for 45-54 year old. Even at older ages, NHB rate ratios were between 1.9 and 5.7. Similarly, rate ratios for Hispanics vs. NHW were 5.5 (95% CI 4.2, 7.2), 7.9 (95% CI 6.7, 9.3), and 5.8 (95% CI 5.3, 6.3) for corresponding age strata, with remaining rate ratios ranging from 1.4 to 4.1. Rate ratios for NHAIAN were similarly high, ranging from 1.4 to 8.2 over ages 25-75, and only dipping below 1.0 for age 75-84 and 85+. Among NHAPI, rate ratios ranged from 2.2 to 2.4 for ages 25-75 and were 1.6 and 1.2 for age 75-84 and 85+ respectively. As a consequence, more years of potential life lost were experienced by African Americans and Latinos than whites, although the white population is 3-4 fold larger.

Conclusion/Relevance: This analysis makes clear the importance of examining age-specific mortality rates and underscore how age standardization can obscure extreme variations within age strata. Data that permit age-specific analyses should be routinely publicly available.

Title: The Unequal Toll of COVID-19 Mortality by age in the United States: Quantifying Racial/Ethnic Disparities

Authors: MT Bassett, MD, MPH (1,2), Jarvis T. Chen, ScD (1), Nancy Krieger, PhD (1)

Affiliations:

(1) Department of Social and Behavioral Sciences, Harvard T.H. Chan A School of Public Health.
(2) Francois-Xavier Bagnoud Center for Health and Human Rights at Harvard University

Corresponding Author:
Dr. Mary Bassett
Address: FXB Center for Health and Human Rights, Room 704, 651 Huntington Avenue, Boston, MA 02115.
Email: mbassett@hsph.harvard.edu
Tel: +1(917) 282-1567 (during COVID-19)

Author contributions: MTB initiated the study and led framing of the study and drafting the manuscript; NK and JTC conceptualized the study design and contributed to drafting the manuscript; JTC led and conducted the data analysis; all authors contributed to interpreting the results and all approved the final version of the submitted manuscript.

Key Points

Question: How do COVID-19 mortality rates vary by age across US racial/ethnic groups?

Findings: In all age strata, COVID-19 mortality rates were higher for racial/ethnic minorities compared to whites, with extremely high rate ratios (5-9-fold higher) among younger adults (24-54 years) more than 3 times the age-standardized rate ratio. More years of potential life lost were experienced by African Americans and Latinos than whites, although the white population is 3-4 fold larger.

Meaning: Extreme variations in age-specific mortality are obscured by age standardization. Inspection of age-specific mortality rates is crucial to understanding the disparate impact of COVID-19 on racial/ethnic minorities.

Abstract

Importance: Excess COVID-19 mortality has been described among Non-Hispanic Blacks (NHB), Hispanics and Non-Hispanic American Indians/Alaska Natives (NHAIAN), compared to non-Hispanic Whites (NHW), but not in relation to age at death. Recent release of national COVID-19 deaths by racial/ethnic group now permit analysis of age-specific mortality rates.

Objective: To examine variation in age-specific mortality rates by racial/ethnicity and calculate its impact using Years of Potential Life Lost (YPLL).

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Results: Age-standardized rate ratios relative to NHW were 3.6 (95% CI 3.5, 3.7) for NHB, 2.6 95% CI 2.4, 2.7) for Hispanics, 1.2 (0.8, 1.6) for NHAIAN, and 1.7 (1.6, 1.9) for NHAPI. By contrast, NHB rate ratios relative to NHW were as high as 7.3 (95% CI 5.6, 9.5) for 25-34 year old, 9.0 (95% CI 7.6, 10.8) for 35-44 year old, and 6.9 (95% CI 6.3, 7.6) for 45-54 year old. Even at older ages, NHB rate ratios were between 1.9 and 5.7. Similarly, rate ratios for Hispanics vs. NHW were 5.5 (95% CI 4.2, 7.2), 7.9 (95% CI 6.7, 9.3), and 5.8 (95% CI 5.3, 6.3) for corresponding age strata, with remaining rate ratios ranging from 1.4 to 4.1. Rate ratios for NHAIAN were similarly high, ranging from 1.4 to 8.2 over ages 25-75, and only dipping below 1.0 for age 75-84 and 85+. Among NHAPI, rate ratios ranged from 2.2 to 2.4 for ages 25-75 and were 1.6 and 1.2 for age 75-84 and 85+ respectively. As a consequence,

more years of potential life lost were experienced by African Americans and Latinos than whites, although the white population is 3-4 fold larger.

Conclusion/Relevance: This analysis makes clear the importance of examining age-specific mortality rates and underscore how age standardization can obscure extreme variations within age strata. Data that permit age-specific analyses should be routinely publicly available.

Introduction

The first death due to COVID-19 in the United States was reported on February 29, 2020. In late March, media reports brought to national attention of the disproportionate number of COVID-19 cases and deaths occurring among Blacks and Latinos (1). Typically these reports compared the proportion of cases and deaths by reported racial/ethnicity to the racial/ethnic composition of the population. Milwaukee, for example, noted on March 27 that all (100%) of its eight deaths were African Americans, who comprised 38% of their population; in all of Wisconsin, only 15 deaths statewide had occurred (2). Such reports came from state and local jurisdictions. At the time, the Centers for Disease Control and Prevention (CDC) made data COVID-19 data publicly available only by age and sex, prompting many calls to release racial/ethnicity data (3). New York City produced both crude and age-adjusted COVID-19 mortality rates, permitting some insight into the impact of population age structure and age at death on racial/ethnic specific mortality rates (4). Suggesting such information could be important, marked racial/ethnic inequities in premature morbidity and mortality, including for conditions that increase risk of COVID-19 mortality (e.g., diabetes and cardiovascular disease), are well-documented (5-7).

Newly released data by the National Center for Health Statistics (NCHS) (8) make it possible for the first time to explore with national data the likelihood that Blacks, Latinos, American Indian/Alaska Natives, and Asian and Pacific Islanders, in addition to experiencing higher COVID-19 mortality rates than white Americans, are also dying at younger ages.

Methods

Mortality rates and rate ratios

We used the publicly available NCHS data on Covid19 deaths race/ethnicity, age, and state (8) instead of the data on cases and race and ethnicity by age posted by the Centers for Disease Control (CDC) (9), because the NCHS data file includes death counts from New York City (NYC), a major hotspot for COVID-19, which is excluded in the CDC webpage and also provides the data jointly (rather than separately) by “race” and “ethnicity” (Hispanic or not). Racial/ethnic groups were limited to non-Hispanic white (NHW), non-Hispanic black (NHB), non-Hispanic American Indian or Alaskan Native (NHAIAN), non-Hispanic Asian or Pacific Islander (NHAPI), and Hispanic by the availability of denominator data in CDC Wonder (10). Only 1.7% of the NCHS COVID-19 deaths had missing data on race/ethnicity.

We calculated rates for 100,000 person years by dividing deaths by the person-time from February 1 (the "Start Week" listed in the CDC data file) and May 20 (the "Data as of" field in the data file). This permits comparison of the age-specific and age-standardized rates to published mortality rates for common causes of death in previous years. We age-standardized to the Year 2000 standard million and computed age-standardized rates, rate ratios, rate differences, and their confidence intervals using standard methods (11,12).

Years of Potential Life Lost (YPLL) and Years of Potential Life Lost (YPLL) rates

To capture the population impact of premature death, we computed Years of Potential Life Lost (YPLL) by multiplying the number of deaths in each age category by the number of years from the midpoint of the age category to age 65 and summing over age. We used the cut-point of 65 because of the importance of attainment of 65 years to eligibility for a range of social benefits, including Medicare.

Because the YPLL is sensitive to the size of the population and differences in the age distribution for racial/ethnic groups, we also computed the age-standardized YPLL rate per 100,000 by computing age-specific YPLL rates and then taking a weighted sum with the weights coming from the Year 2000 standard million) (13).

Results

As of May 20, the number of COVID-19 deaths equaled 36,545 for NHW, 15,631 for NHB, 322 for NHAIAN, 3,862 for NHAPI, and 11,303 for Hispanics; the corresponding population sizes were 186.4 million, 40.6 million, 2.6 million, 19.5 million, and 57.7 million (Supplemental Table 1).

Table 1 and Figure 1 show the racial/ethnic disparities in COVID-19 mortality, with Table 1 additionally providing the age-standardized comparisons. Discounting trends for ages below 25 because of instability due to small numbers, disparities were observed in every age stratum and were especially stark among young adults into midlife (25-54 years). NHB rate ratios relative to NHW were as high as 7.3 (95% CI 5.6, 9.5) for 25-34 year old, 9.0 (95% CI 7.6, 10.8) for 35-44 year old, and 6.9 (95% CI 6.3, 7.6) for 45-54 year old. Even at older ages, NHB rate ratios were between 1.9 and 5.7. Similarly, rate ratios for Hispanics vs. NHW were 5.5 (95% CI 4.2, 7.2), 7.9 (95% CI 6.7, 9.3), and 5.8 (95% CI 5.3, 6.3) for corresponding age strata, with remaining rate ratios ranging from 1.4 to 4.1. Rate ratios for NHAIAN were similarly high, ranging from 1.4 to 8.2 over ages 25-75, and only dipping below 1.0 for age 75-84 and 85+. Among NHAPI, rate ratios ranged from 2.2 to 2.4 for ages 25-75 and were 1.6 and 1.2 for age 75-84 and 85+ respectively. By contrast, the age-standardized rate ratios equaled 3.6 (95% CI 3.5, 3.7) for NHB, 2.6 95% CI 2.4, 2.7) for Hispanic, 1.2 (0.8, 1.6) for NHAIAN, and 1.7 (1.6, 1.9) for NHAPI.

Table 2 shows corresponding Years of Potential Life Lost (YPLL) for COVID-19 (with Supplemental Table 2 also showing YPPL for all-cause mortality, for comparison). For NHB, disparities in COVID-19 mortality translate to 45,777 (95% CI 32,061 to 34,832) years of potential life lost, for Hispanics, 48,204 (95% CI 46,328 to 50,080), 1,745 (95% CI 1,371 to 2,119) for NHAIAN, and 8,905 (95% CI 8,156 to 9,654) for NHAPI, compared with 33,446 (95% CI 32,061 to 34,832) for NHW. Accounting for age distribution and population size differences between racial/ethnic groups, the age-standardized YPLL rate was 6.7 (95% CI 6.7, 6.8) for NHB, 5.4 (95% CI 5.3, 5.4) for Hispanics, 4.0 (95% CI 3.9, 4.0) for NHAIAN, and 2.6 (95% CI 2.6, 2.7) for NHAPI times higher compared with NHW.

Discussion

These data demonstrate excess risk of COVID-19 death at all ages among Non-Hispanic Blacks, Hispanics, Non-Hispanic American Indian or Alaskan Natives, and Non-Hispanic Asian Pacific Islanders (NHAPI) as compared to Non-Hispanic Whites (NHW), with disparities particularly extreme at younger ages (25-54 years old). The impact of lives prematurely cut short (before attaining 65 years) can be measured in the absolute number of years of potential life lost. For both NHBs and Hispanics this loss is much larger than for NHW, despite the fact that the NHW population is respectively 4.5 and 3 -fold larger. Poor quality of AIAN mortality and population data likely means the estimated excesses are underestimates (14).

Examination of age-specific mortality rates, and not simply counts of deaths or crude comparisons of the racial/ethnic composition of COVID-19 deaths to the total population, is crucial to revealing racial/ethnic disparities. Nor are age-standardized rates sufficient because age standardization, while accounting for the different age distributions across racial/ethnic groups, notably obscured the magnitude of mortality inequities at younger ages (5-7). These COVID-19 mortality rate ratios, 7-9-fold higher for NHB, NHAIAN, and Hispanics, are extreme and reflect the devastating toll COVID-19 has taken among communities of color. Age-specific mortality rates for COVID-19 should be routinely available by race/ethnicity as well as by gender.

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Table 1: Age-specific and age-standardized rate ratios and rate differences per 100,000 person-years comparing rates of COVID-19 mortality for racial/ethnic groups compared with Non-Hispanic Whites, United States, February 1-May 20, 2020

Age group	Incidence Rate Ratio (95% CI) (reference group: Non-Hispanic White)			
	Non-Hispanic Black	Non-Hispanic American Indian or Alaska Native	Non-Hispanic Asian or Pacific Islander	Hispanic
age-standardized	3.61 (3.41, 3.81)	1.16 (0.84, 1.60)	1.74 (1.58, 1.91)	2.59 (2.43, 2.76)
Under 1 year	-*	-	-	3.96 (0.36, 43.70)
1-4 years	3.37 (0.21, 53.90)	-	-	-
5-14 years	13.82 (1.54, 123.70)	-	8.84 (0.55, 141.40)	-
15-24 years	5.43 (2.89, 10.20)	3.51 (0.47, 26.50)	1.64 (0.48, 5.60)	4.20 (2.27, 7.80)
25-34 years	7.29 (5.60, 9.50)	7.29 (3.79, 14.10)	2.42 (1.58, 3.70)	5.51 (4.24, 7.20)
35-44 years	9.04 (7.58, 10.80)	8.16 (5.20, 12.80)	2.44 (1.83, 3.30)	7.89 (6.67, 9.30)
45-54 years	6.91 (6.29, 7.60)	3.49 (2.46, 4.90)	2.79 (2.40, 3.20)	5.79 (5.28, 6.30)
55-64 years	5.68 (5.39, 6.00)	2.11 (1.65, 2.70)	2.72 (2.49, 3.00)	4.10 (3.87, 4.30)
65-74 years	5.05 (4.86, 5.30)	1.37 (1.09, 1.70)	2.22 (2.07, 2.40)	3.52 (3.36, 3.70)
75-84 years	3.61 (3.48, 3.70)	0.83 (0.64, 1.10)	1.61 (1.51, 1.70)	2.49 (2.38, 2.60)
85 years and over	1.92 (1.84, 2.00)	0.61 (0.47, 0.80)	1.22 (1.15, 1.30)	1.39 (1.33, 1.50)
	Incidence Rate Difference per 100,000 person-years (95% CI) (reference group: Non-Hispanic White)			
	Non-Hispanic Black	Non-Hispanic American Indian or Alaska Native	Non-Hispanic Asian or Pacific Islander	Hispanic
age-standardized	109.9 (145.0, 145.0)	6.9 (33.3, 33.3)	31.0 (66.3, 66.3)	67.0 (103.2, 103.2)
Under 1 year	-0.2 (-0.5, 0.2)	-0.2 (-0.5, 0.2)	-0.2 (-0.5, 0.2)	0.5 (-0.5, 1.5)
1-4 years	0.1 (-0.2, 0.4)	-0.0 (-0.1, 0.0)	-0.0 (-0.1, 0.0)	-0.0 (-0.1, 0.0)
5-14 years	0.2 (-0.0, 0.4)	-0.0 (-0.0, 0.0)	0.1 (-0.1, 0.4)	-0.0 (-0.0, 0.0)
15-24 years	1.0 (0.5, 1.5)	0.6 (-1.0, 2.1)	0.1 (-0.3, 0.6)	0.7 (0.4, 1.1)
25-34 years	6.9 (5.6, 8.2)	6.9 (1.9, 11.9)	1.6 (0.5, 2.6)	4.9 (4.0, 5.9)
35-44 years	20.8 (18.4, 23.2)	18.5 (9.5, 27.6)	3.7 (2.1, 5.4)	17.8 (16.0, 19.6)
45-54 years	57.3 (53.2, 61.4)	24.2 (12.6, 35.8)	17.4 (13.8, 21.0)	46.5 (43.2, 49.8)
55-64 years	281.6 (268.5, 294.7)	66.8 (36.1, 97.5)	103.4 (89.8, 117.0)	186.5 (175.5, 197.5)
65-74 years	372.5 (358.2, 386.8)	33.8 (5.4, 62.1)	111.9 (98.5, 125.3)	231.9 (219.2, 244.6)
75-84 years	755.3 (723.0, 787.6)	-49.4 (-110.0, 11.2)	176.8 (147.1, 206.4)	430.6 (402.6, 458.5)
85 years and over	943.0 (870.5, 1015.4)	-402.9 (-570.4, -235.5)	225.2 (148.4, 302.1)	400.3 (337.5, 463.0)

* "-" indicates rate ratio or rate difference not calculated due to zero cases in this age stratum.

Table 2: Years of potential life lost with age 65 cutoff (YPLL65) and age-standardized YPLL65 rate per 100,000 by race/ethnicity, with age-standardized YPLL65 rate ratios and rate differences per 100,000, COVID-19 related deaths in the United States, February 1-May 20, 2020

Race/ethnicity	YPLL65	Age-standardized YPLL65 rate per 100,000	Age-standardized YPLL65 rate ratio	Age-standardized YPLL65 rate difference per 100,000
Non-Hispanic White	33,446 (32,061 to 34,832)	18.9 (16.6, 21.2)	1.00 (reference)	0.0 (reference)
Non-Hispanic Black	45,777 (44,023 to 47,531)	127.6 (114.4, 140.9)	6.7 (6.7, 6.8)	108.7 (95.3, 122.2)
Non-Hispanic American Indian or Alaska Native	1,745 (1,371 to 2,119)	75.4 (30.6, 120.2)	4.0 (3.9, 4.0)	56.5 (11.6, 101.3)
Non-Hispanic Asian or Pacific Islander	8,905 (8,156 to 9,654)	50.1 (39.2, 61.0)	2.6 (2.6, 2.7)	31.2 (20.0, 42.3)
Hispanic or Latino	48,204 (46,328 to 50,080)	101.3 (91.2, 111.4)	5.4 (5.3, 5.4)	82.4 (72.0, 92.7)

SUPPLEMENTAL TABLES

Title: The Unequal Toll of COVID-19 Mortality by age in the United States: Quantifying Racial/Ethnic Disparities

Authors: MT Bassett, MD, MPH (1,2), Jarvis T. Chen, ScD (1), Nancy Krieger, PhD (1)

Supplemental Table 1: Age-specific and age-standardized deaths, population, and mortality rate per 100,000 person years for total all cause and COVID-19 mortality in the United States, February 1-May 9, 2020, along with corresponding mortality rate ratios and rate differences per 100,000 person-years

Racial/ethnic group	Cause of death	Age group	Deaths	Population	Rate per 100,000 person-years	Incidence Rate Ratio (95% CI)	Incidence Rate Difference per 100,000 person-years (95% CI)
Non-Hispanic White	COVID-19 mortality	age-standardized	36545	186,405,546	42.2 (40.9, 43.5)	referent group	referent group
		Under 1 year	1	1,994,440	0.2 (0.0, 0.6)		
		1-4 years	1	8,244,087	0.0 (0.0, 0.1)		
		5-14 years	1	21,483,759	0.0 (0.0, 0.1)		
		15-24 years	16	23,544,616	0.2 (0.1, 0.3)		
		25-34 years	84	25,657,465	1.1 (0.9, 1.3)		
		35-44 years	183	23,709,326	2.6 (2.2, 3.0)		
		45-54 years	760	26,232,985	9.7 (9.0, 10.4)		
		55-64 years	2,726	15,189,511	60.1 (57.9, 62.4)		
		65-74 years	6,340	23,091,706	92.0 (89.7, 94.3)		
		75-84 years	10,409	12,034,203	289.8 (284.3, 295.4)		
		85 years and over	16,024	5,223,448	1028.0 (1012.0, 1043.9)		
	All Cause mortality	age-standardized	671,316	186,405,546	833.7 (827.8, 839.7)		
		Under 1 year	1,898	1,994,440	318.9 (304.5, 333.2)		
		1-4 years	376	8,244,087	15.3 (13.7, 16.8)		
		5-14 years	651	21,483,759	10.2 (9.4, 10.9)		
		15-24 years	3,960	23,544,616	56.4 (54.6, 58.1)		
		25-34 years	9,834	25,657,465	128.4 (125.9, 131.0)		
		35-44 years	14,456	23,709,326	204.3 (201.0, 207.6)		
		45-54 years	29,137	26,232,985	372.2 (367.9, 376.5)		
		55-64 years	76,781	15,189,511	1693.8 (1681.9, 1705.8)		
		65-74 years	128,841	23,091,706	1869.7 (1859.4, 1879.9)		
		75-84 years	172,745	12,034,203	4810.1 (4787.4, 4832.8)		
		85 years and over	232,637	5,223,448	14924.0 (14863.4, 14984.6)		
Non-Hispanic Black	COVID-19 mortality	age-standardized	15631	40,613,993	152.1 (145.1, 159.0)	3.61 (3.41, 3.81)	109.9 (145.0, 145.0)
		Under 1 year	0	591,754	-	-	-0.2 (-0.5, 0.2)
		1-4 years	1	2,447,225	0.1 (0.0, 0.5)	3.37 (0.21, 53.90)	0.1 (-0.2, 0.4)
		5-14 years	4	6,217,144	0.2 (0.0, 0.4)	13.82 (1.54, 123.70)	0.2 (-0.0, 0.4)
		15-24 years	24	6,500,474	1.2 (0.7, 1.7)	5.43 (2.89, 10.20)	1.0 (0.5, 1.5)
		25-34 years	159	6,658,091	8.0 (6.8, 9.2)	7.29 (5.60, 9.50)	6.9 (5.6, 8.2)
		35-44 years	378	5,414,553	23.4 (21.0, 25.8)	9.04 (7.58, 10.80)	20.8 (18.4, 23.2)
		45-54 years	1,058	5,287,236	67.1 (63.0, 71.1)	6.91 (6.29, 7.60)	57.3 (53.2, 61.4)
		55-64 years	2,706	2,653,390	341.7 (328.9, 354.6)	5.68 (5.39, 6.00)	281.6 (268.5, 294.7)
		65-74 years	4,168	3,006,666	464.5 (450.4, 478.6)	5.05 (4.86, 5.30)	372.5 (358.2, 386.8)
		75-84 years	4,148	1,329,955	1045.1 (1013.3, 1076.9)	3.61 (3.48, 3.70)	755.3 (723.0, 787.6)
		85 years and over	2,985	507,505	1970.9 (1900.2, 2041.6)	1.92 (1.84, 2.00)	943.0 (870.5, 1015.4)
	All Cause mortality	age-standardized	117,244	40,613,993	1125.1 (1106.3, 1143.9)	1.35 (1.33, 1.37)	291.3 (1105.4, 1105.4)
		Under 1 year	1,243	591,754	703.9 (664.7, 743.0)	2.21 (2.05, 2.40)	385.0 (343.3, 426.7)
		1-4 years	229	2,447,225	31.4 (27.3, 35.4)	2.05 (1.74, 2.40)	16.1 (11.7, 20.4)
		5-14 years	274	6,217,144	14.8 (13.0, 16.5)	1.45 (1.26, 1.70)	4.6 (2.7, 6.5)
		15-24 years	1,899	6,500,474	97.9 (93.5, 102.3)	1.74 (1.64, 1.80)	41.5 (36.8, 46.3)

		25-34 years	3,721	6,658,091	187.3 (181.3, 193.3)	1.46 (1.40, 1.50)	58.8 (52.3, 65.4)
		35-44 years	5,038	5,414,553	311.8 (303.2, 320.4)	1.53 (1.48, 1.60)	107.5 (98.2, 116.7)
		45-54 years	9,634	5,287,236	610.6 (598.4, 622.8)	1.64 (1.60, 1.70)	238.4 (225.5, 251.3)
		55-64 years	21,297	2,653,390	2689.6 (2653.4, 2725.7)	1.59 (1.56, 1.60)	995.7 (957.7, 1033.8)
		65-74 years	27,161	3,006,666	3027.1 (2991.1, 3063.1)	1.62 (1.60, 1.60)	1157.4 (1120.0, 1194.8)
		75-84 years	24,792	1,329,955	6246.5 (6168.8, 6324.3)	1.30 (1.28, 1.30)	1436.4 (1355.4, 1517.4)
		85 years and over	21,956	507,505	14496.9 (14305.2, 14688.7)	0.97 (0.96, 1.00)	-427.1 (-628.2, -225.9)
Non-Hispanic American Indian or Alaska Native	COVID-19 mortality	age-standardized	322	2,592,666	49.0 (33.4, 64.7)	1.16 (0.84, 1.60)	6.9 (33.3, 33.3)
		Under 1 year	0	38,260	-	-	-0.2 (-0.5, 0.2)
		1-4 years	0	156,473	-	-	-0.0 (-0.1, 0.0)
		5-14 years	0	409,393	-	-	-0.0 (-0.0, 0.0)
		15-24 years	1	419,255	0.8 (0.0, 2.9)	3.51 (0.47, 26.50)	0.6 (-1.0, 2.1)
		25-34 years	10	418,797	8.0 (3.0, 13.0)	7.29 (3.79, 14.10)	6.9 (1.9, 11.9)
		35-44 years	21	333,378	21.1 (12.1, 30.1)	8.16 (5.20, 12.80)	18.5 (9.5, 27.6)
		45-54 years	33	326,384	33.9 (22.3, 45.4)	3.49 (2.46, 4.90)	24.2 (12.6, 35.8)
		55-64 years	66	174,263	126.9 (96.3, 157.5)	2.11 (1.65, 2.70)	66.8 (36.1, 97.5)
		65-74 years	76	202,493	125.8 (97.5, 154.0)	1.37 (1.09, 1.70)	33.8 (5.4, 62.1)
		75-84 years	61	85,020	240.4 (180.1, 300.8)	0.83 (0.64, 1.10)	-49.4 (-110.0, 11.2)
		85 years and over	54	28,950	625.0 (458.3, 791.8)	0.61 (0.47, 0.80)	-402.9 (-570.4, -235.5)
	All Cause mortality	age-standardized	5,190	2,592,666	776.3 (714.4, 838.1)	0.93 (0.86, 1.01)	-57.5 (714.1, 714.1)
		Under 1 year	47	38,260	411.6 (294.0, 529.3)	1.29 (0.97, 1.70)	92.8 (-25.8, 211.3)
		1-4 years	15	156,473	32.1 (15.9, 48.4)	2.10 (1.25, 3.50)	16.8 (0.5, 33.2)
		5-14 years	16	409,393	13.1 (6.7, 19.5)	1.29 (0.79, 2.10)	2.9 (-3.5, 9.4)
		15-24 years	113	419,255	90.3 (73.7, 107.0)	1.60 (1.33, 1.90)	34.0 (17.2, 50.7)
		25-34 years	316	418,797	252.8 (225.0, 280.7)	1.97 (1.76, 2.20)	124.4 (96.4, 152.4)
		35-44 years	395	333,378	397.0 (357.9, 436.2)	1.94 (1.76, 2.10)	192.7 (153.4, 232.0)
		45-54 years	583	326,384	598.6 (550.0, 647.1)	1.61 (1.48, 1.70)	226.4 (177.6, 275.1)
		55-64 years	972	174,263	1869.1 (1751.6, 1986.6)	1.10 (1.04, 1.20)	175.2 (57.1, 293.3)
		65-74 years	1,085	202,493	1795.5 (1688.7, 1902.3)	0.96 (0.90, 1.00)	-74.2 (-181.5, 33.2)
		75-84 years	949	85,020	3740.3 (3502.3, 3978.3)	0.78 (0.73, 0.80)	-1069.8 (-1308.8, -830.7)
		85 years and over	699	28,950	8090.8 (7491.0, 8690.6)	0.54 (0.50, 0.60)	-6833.2 (-7436.0, -6230.3)
Non-Hispanic Asian or Pacific Islander	COVID-19 mortality	age-standardized	3862	19,492466	73.2 (66.5, 79.9)	1.74 (1.58, 1.91)	31.0 (66.3, 66.3)
		Under 1 year	0	216,177	-	-	-0.2 (-0.5, 0.2)
		1-4 years	0	949,886	-	-	-0.0 (-0.1, 0.0)
		5-14 years	1	2,429,718	0.1 (0.0, 0.5)	8.84 (0.55, 141.40)	0.1 (-0.1, 0.4)
		15-24 years	3	2,692,199	0.4 (0.1, 0.9)	1.64 (0.48, 5.60)	0.1 (-0.3, 0.6)
		25-34 years	28	3,534,255	2.7 (1.7, 3.6)	2.42 (1.58, 3.70)	1.6 (0.5, 2.6)
		35-44 years	61	3,233,519	6.3 (4.7, 7.9)	2.44 (1.83, 3.30)	3.7 (2.1, 5.4)
		45-54 years	223	2,759,529	27.1 (23.5, 30.6)	2.79 (2.40, 3.20)	17.4 (13.8, 21.0)
		55-64 years	573	1,174,022	163.5 (150.2, 176.9)	2.72 (2.49, 3.00)	103.4 (89.8, 117.0)
		65-74 years	918	1,508,767	203.9 (190.7, 217.1)	2.22 (2.07, 2.40)	111.9 (98.5, 125.3)
		75-84 years	987	708,822	466.6 (437.5, 495.7)	1.61 (1.51, 1.70)	176.8 (147.1, 206.4)
		85 years and over	1,068	285,572	1253.2 (1178.0, 1328.4)	1.22 (1.15, 1.30)	225.2 (148.4, 302.1)
	All Cause mortality	age-standardized	28,184	19,492,466	531.1 (513.0, 549.2)	0.64 (0.62, 0.66)	-302.6 (512.1, 512.1)
		Under 1 year	167	216,177	258.9 (219.6, 298.1)	0.81 (0.69, 1.00)	-60.0 (-101.8, -18.2)
		1-4 years	41	949,886	14.5 (10.0, 18.9)	0.95 (0.69, 1.30)	-0.8 (-5.5, 3.9)
		5-14 years	61	2,429,718	8.4 (6.3, 10.5)	0.83 (0.64, 1.10)	-1.7 (-4.0, 0.5)
		15-24 years	227	2,692,199	28.3 (24.6, 31.9)	0.50 (0.44, 0.60)	-28.1 (-32.2, -24.0)
		25-34 years	434	3,534,255	41.1 (37.3, 45.0)	0.32 (0.29, 0.40)	-87.3 (-91.9, -82.7)
		35-44 years	736	3,233,519	76.3 (70.8, 81.8)	0.37 (0.35, 0.40)	-128.0 (-134.5, -121.6)
		45-54 years	1,575	2,759,529	191.3 (181.8, 200.7)	0.51 (0.49, 0.50)	-180.9 (-191.3, -170.6)
		55-64 years	3,257	1,174,022	929.6 (897.7, 961.5)	0.55 (0.53, 0.60)	-764.2 (-798.3, -730.1)
		65-74 years	5,223	1,508,767	1160.0 (1128.5, 1191.5)	0.62 (0.60, 0.60)	-709.6 (-742.7, -676.6)

		75-84 years	6,848	708,822	3237.4 (3160.7, 3314.0)	0.67 (0.66, 0.70)	-1572.7 (-1652.7, -1492.8)
		85 years and over	9,615	285,572	11282.3 (11056.8, 11507.8)	0.76 (0.74, 0.80)	-3641.7 (-3875.2, -3408.2)
Hispanic or Latino	COVID-19 mortality	age-standardized	11303	57,731,112	109.2 (103.3, 115.1)	2.59 (2.43, 2.76)	67.0 (103.2, 103.2)
		Under 1 year	2	1,007,577	0.7 (0.1, 1.9)	3.96 (0.36, 43.70)	0.5 (-0.5, 1.5)
		1-4 years	0	4,164,396	-	-	-0.0 (-0.1, 0.0)
		5-14 years	0	10,535,155	-	-	-0.0 (-0.0, 0.0)
		15-24 years	28	9,814,256	1.0 (0.6, 1.3)	4.20 (2.27, 7.80)	0.7 (0.4, 1.1)
		25-34 years	170	9,429,166	6.0 (5.1, 6.9)	5.51 (4.24, 7.20)	4.9 (4.0, 5.9)
		35-44 years	523	8,587,112	20.4 (18.7, 22.2)	7.89 (6.67, 9.30)	17.8 (16.0, 19.6)
		45-54 years	1,178	7,025,565	56.2 (53.0, 59.4)	5.79 (5.28, 6.30)	46.5 (43.2, 49.8)
		55-64 years	2,024	2,749,799	246.6 (235.9, 257.4)	4.10 (3.87, 4.30)	186.5 (175.5, 197.5)
		65-74 years	2,593	2,682,684	323.9 (311.4, 336.4)	3.52 (3.36, 3.70)	231.9 (219.2, 244.6)
		75-84 years	2,658	1,236,374	720.4 (693.0, 747.8)	2.49 (2.38, 2.60)	430.6 (402.6, 458.5)
		85 years and over	2,127	499,028	1428.3 (1367.6, 1489.0)	1.39 (1.33, 1.50)	400.3 (337.5, 463.0)
	All Cause mortality	age-standardized	77,373	57,731,112	727.3 (712.2, 742.5)	0.87 (0.85, 0.89)	-106.4 (711.0, 711.0)
		Under 1 year	1,063	1,007,577	353.5 (332.3, 374.8)	1.11 (1.03, 1.20)	34.6 (9.0, 60.3)
		1-4 years	206	4,164,396	16.6 (14.3, 18.8)	1.08 (0.92, 1.30)	1.3 (-1.4, 4.0)
		5-14 years	290	10,535,155	9.2 (8.2, 10.3)	0.91 (0.79, 1.00)	-0.9 (-2.2, 0.4)
		15-24 years	1,783	9,814,256	60.9 (58.1, 63.7)	1.08 (1.02, 1.10)	4.5 (1.2, 7.8)
		25-34 years	2,851	9,429,166	101.3 (97.6, 105.0)	0.79 (0.76, 0.80)	-27.1 (-31.6, -22.6)
		35-44 years	4,051	8,587,112	158.1 (153.2, 162.9)	0.77 (0.75, 0.80)	-46.2 (-52.1, -40.3)
		45-54 years	6,752	7,025,565	322.0 (314.4, 329.7)	0.87 (0.84, 0.90)	-50.1 (-58.9, -41.4)
		55-64 years	11,597	2,749,799	1413.2 (1387.5, 1438.9)	0.83 (0.82, 0.90)	-280.6 (-309.0, -252.3)
		65-74 years	14,234	2,682,684	1778.0 (1748.7, 1807.2)	0.95 (0.93, 1.00)	-91.7 (-122.6, -60.8)
		75-84 years	16,347	1,236,374	4430.5 (4362.6, 4498.4)	0.92 (0.91, 0.90)	-379.6 (-451.2, -308.0)
		85 years and over	18,199	499,028	12220.4 (12042.9, 12398.0)	0.82 (0.81, 0.80)	-2703.6 (-2891.2, -2516.0)

Supplemental Table 2: Years of potential life lost with age 65 cutoff (YPLL65) and age-standardized YPLL65 rate per 100,000 by race/ethnicity, with age-standardized YPLL65 rate ratios and rate differences per 100,000, COVID-19 related and total deaths in the United States, February 1-May 20, 2020

Cause	Race/ethnicity	YPLL65	Age-standardized YPLL65 rate per 100,000	Age-standardized YPLL65 rate ratio	Age-standardized YPLL65 rate difference per 100,000
covid	Non-Hispanic White	33,446 (32,061 to 34,832)	18.9 (16.6, 21.2)	1.00 (reference)	0.0 (reference)
covid	Non-Hispanic Black	45,777 (44,023 to 47,531)	127.6 (114.4, 140.9)	6.7 (6.7, 6.8)	108.7 (95.3, 122.2)
covid	Non-Hispanic American Indian or Alaska Native	1,745 (1,371 to 2,119)	75.4 (30.6, 120.2)	4.0 (3.9, 4.0)	56.5 (11.6, 101.3)
covid	Non-Hispanic Asian or Pacific Islander	8,905 (8,156 to 9,654)	50.1 (39.2, 61.0)	2.6 (2.6, 2.7)	31.2 (20.0, 42.3)
covid	Hispanic or Latino	48,204 (46,328 to 50,080)	101.3 (91.2, 111.4)	5.4 (5.3, 5.4)	82.4 (72.0, 92.7)
total	Non-Hispanic White	1,886,288 (1,872,584 to 1,899,992)	1104.5 (1080.6, 1128.5)	1.00 (reference)	0.0 (reference)
total	Non-Hispanic Black	702,076 (693,066 to 711,087)	1799.0 (1736.7, 1861.2)	1.6 (1.6, 1.6)	694.4 (627.7, 761.1)
total	Non-Hispanic American Indian or Alaska Native	44,466 (42,215 to 46,718)	1786.1 (1539.3, 2032.9)	1.6 (1.6, 1.6)	681.6 (433.6, 929.5)
total	Non-Hispanic Asian or Pacific Islander	100,384 (97,032 to 103,735)	543.6 (491.7, 595.6)	0.5 (0.5, 0.5)	-560.9 (-618.2, -503.7)
total	Hispanic or Latino	537,846 (529,638 to 546,053)	960.0 (922.8, 997.1)	0.9 (0.9, 0.9)	-144.6 (-188.8, -100.3)

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

Jarvis T. Chen, ScD[1], Nancy Krieger, PhD[2]

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Affiliations

1. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

2. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

Corresponding Author

Jarvis T. Chen, ScD, Research Scientist, Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health
Email: jarvis@hsph.harvard.edu

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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Authors: Jarvis T. Chen, ScD
Nancy Krieger, PhD

Corresponding author: Jarvis T. Chen, ScD
Research Scientist
Department of Social and Behavioral Sciences
Harvard T.H. Chan School of Public Health
677 Huntington Avenue
Boston, MA 02115
Email: jarvis@hsph.harvard.edu

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]

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										

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

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

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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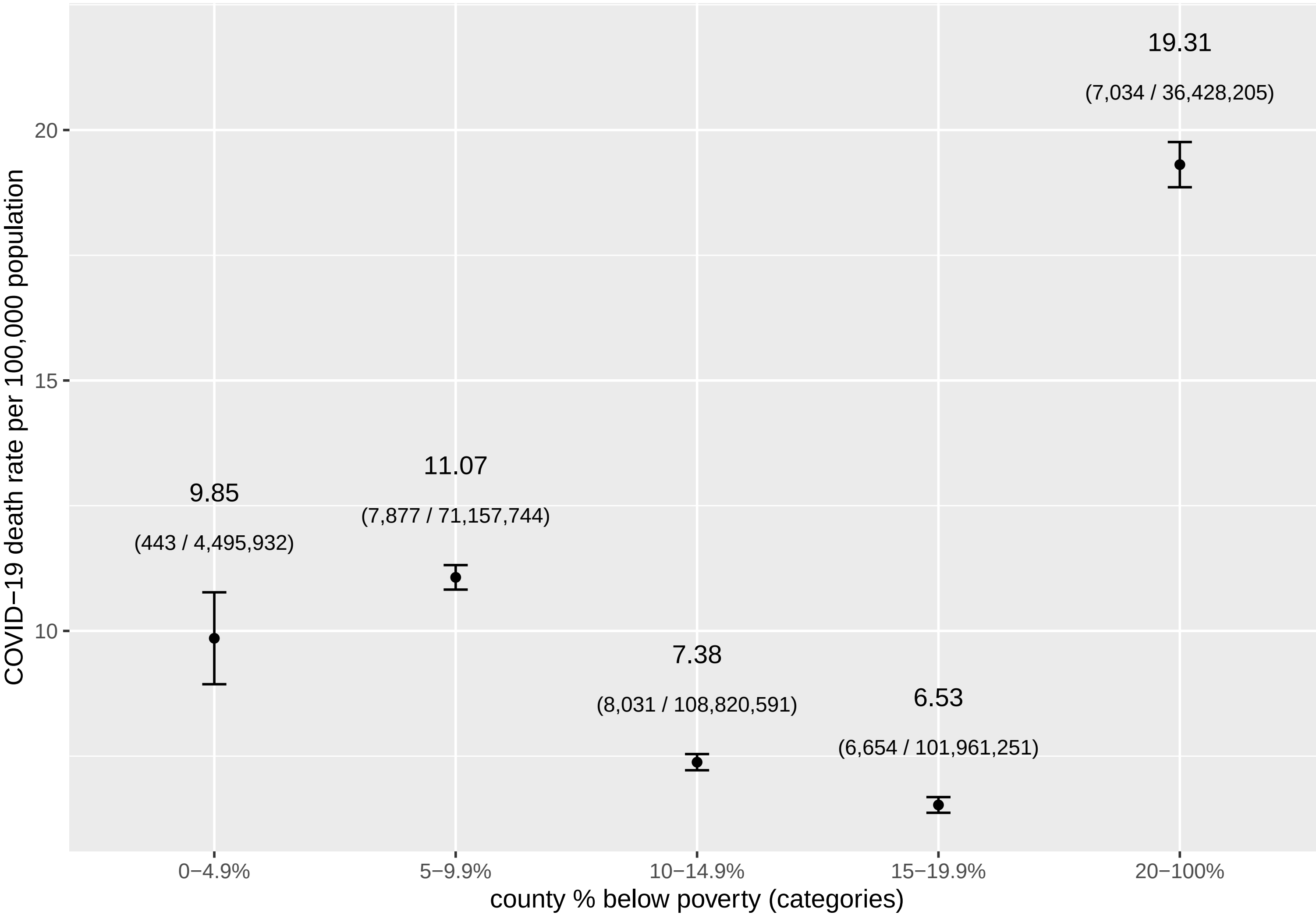
Figure 1a: US COVID−19 deaths per 100,000 population
by county % below poverty (categories) (as of 4.16.2020)



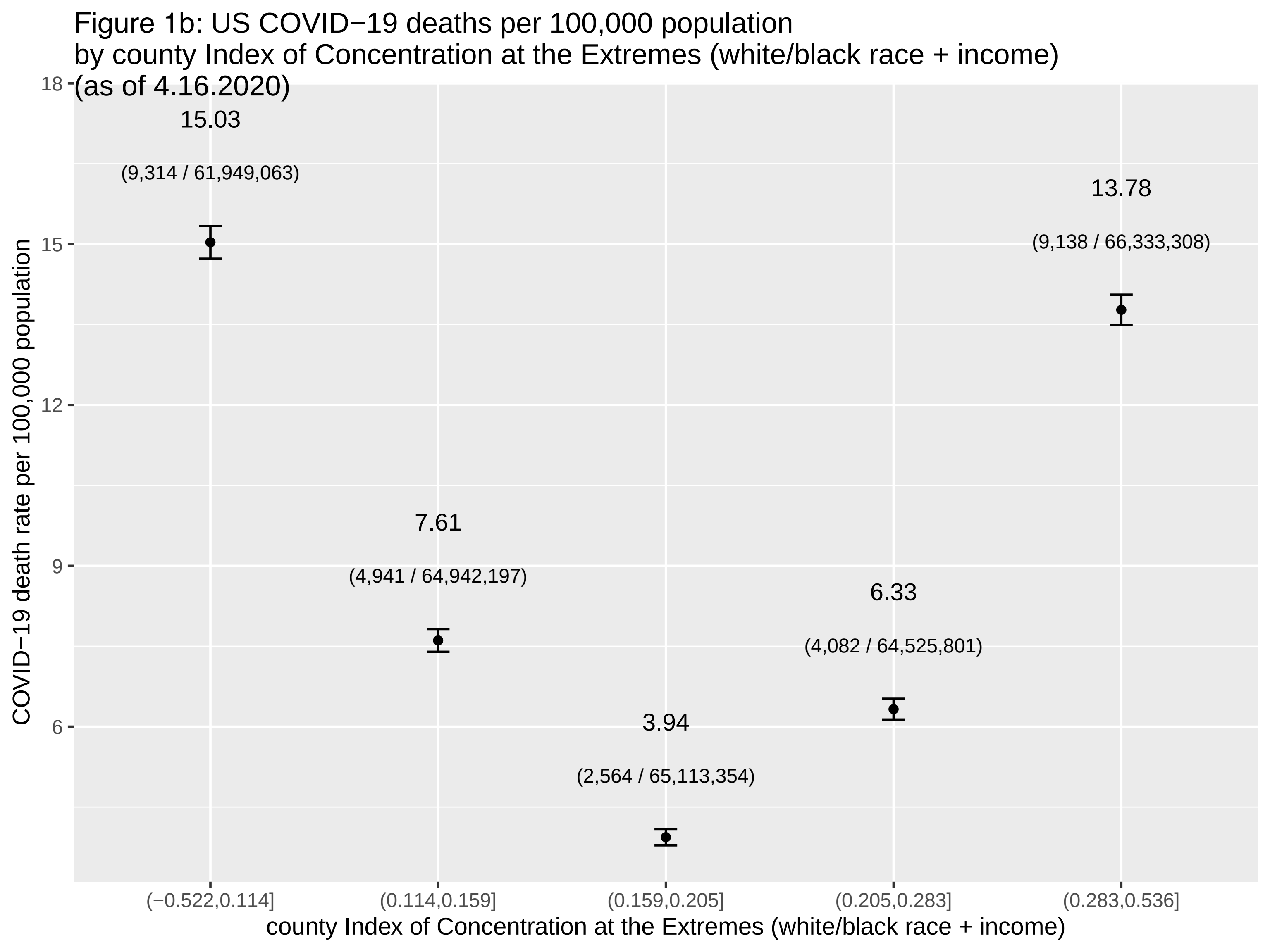


Figure 1b: US COVID−19 deaths per 100,000 population
by county Index of Concentration at the Extremes (white/black race + income)
(as of 4.16.2020)
COVID−19 death rate per 100,000 population
18
15
12
9
6
15.03
(9,314 / 61,949,063)
7.61
(4,941 / 64,942,197)
3.94
(2,564 / 65,113,354)
6.33
(4,082 / 64,525,801)
13.78
(9,138 / 66,333,308)
(−0.522,0.114]
(0.114,0.159]
(0.159,0.205]
(0.205,0.283]
(0.283,0.536]
county Index of Concentration at the Extremes (white/black race + income)

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

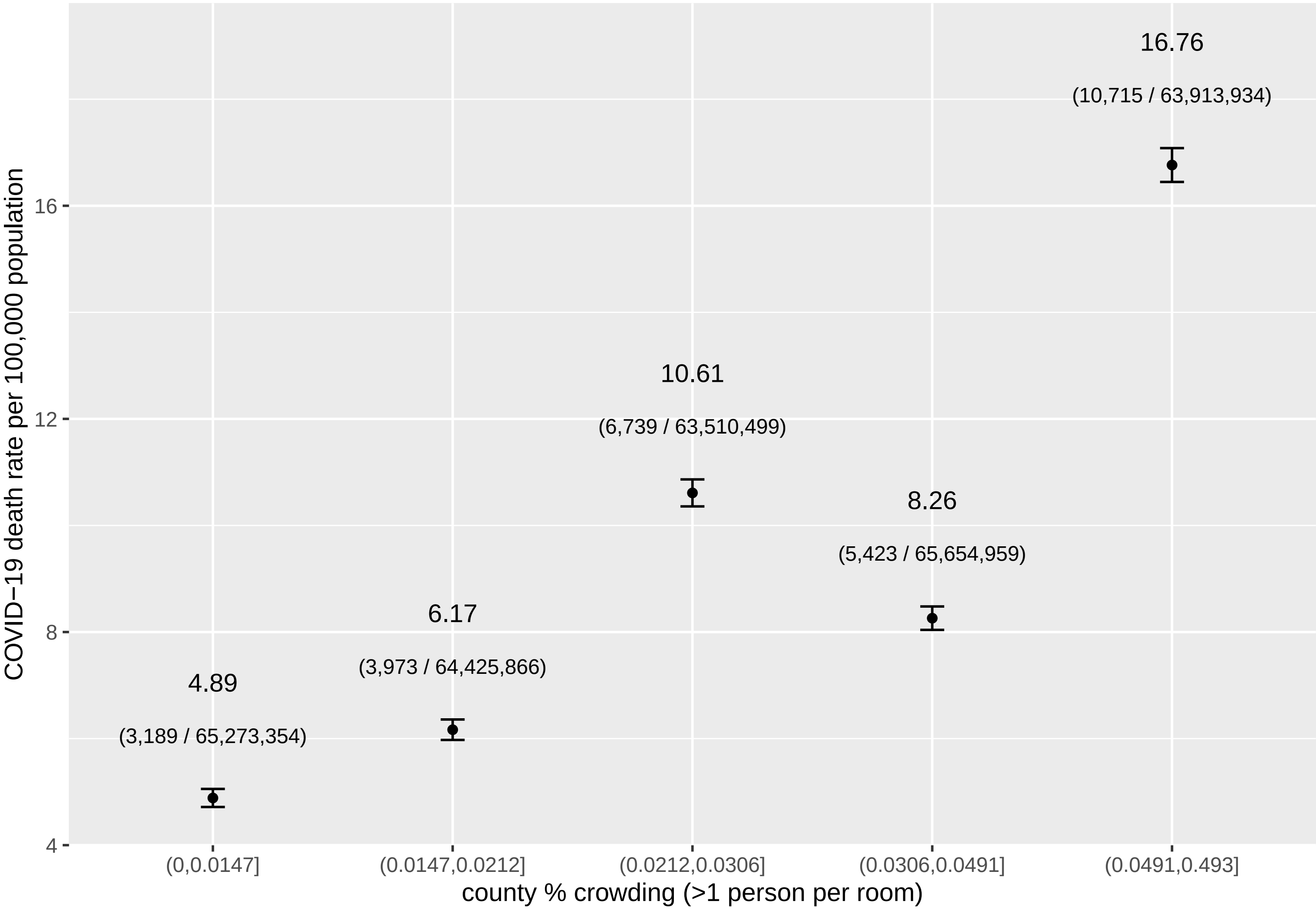


Figure 1d: US COVID−19 deaths per 100,000 population
by county % population of color (as of 4.16.2020)

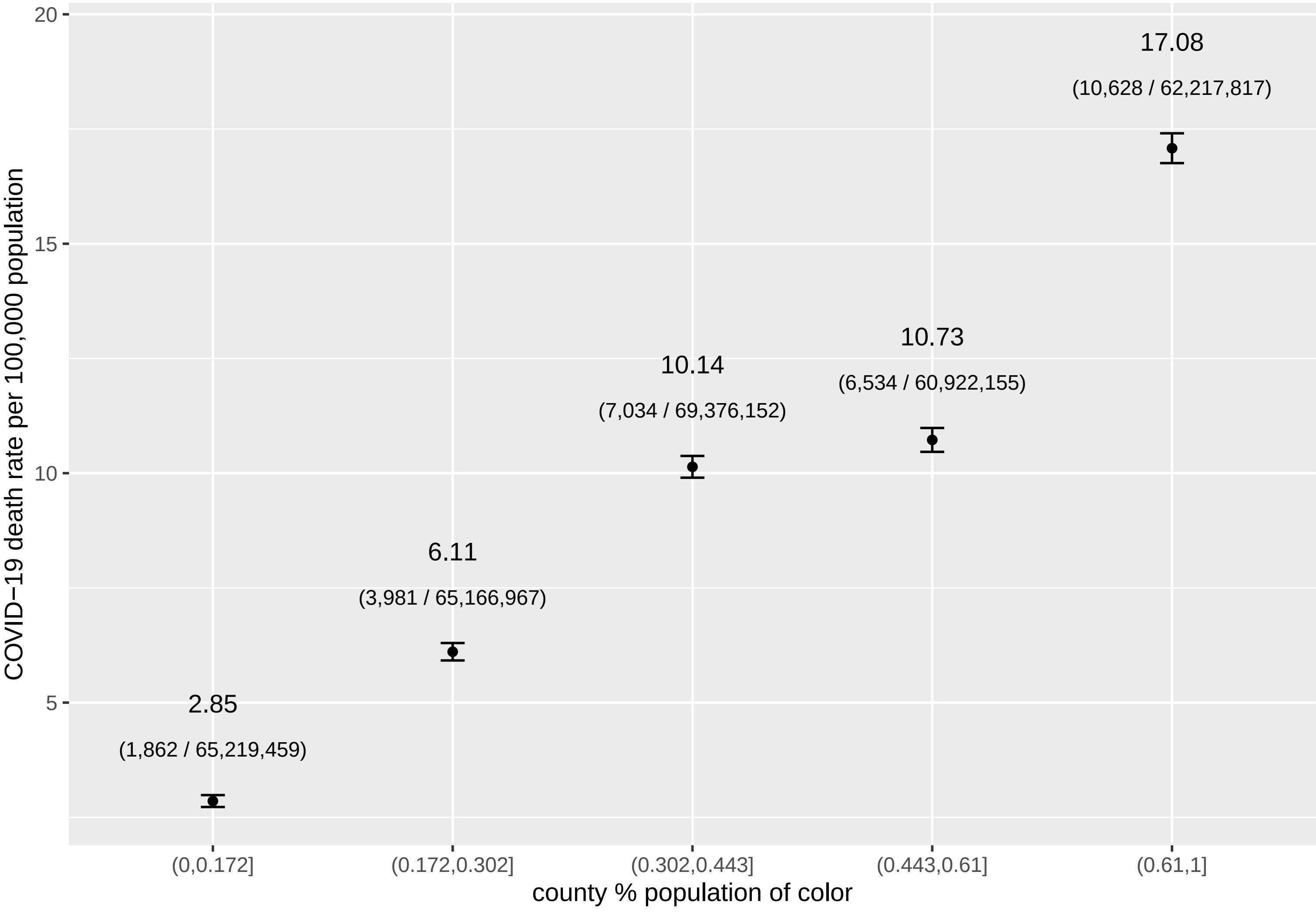


Figure 2a: Illinois COVID−19 confirmed cases per 100,000 population by ZIP code % below poverty (categories) (as of 4.16.2020)

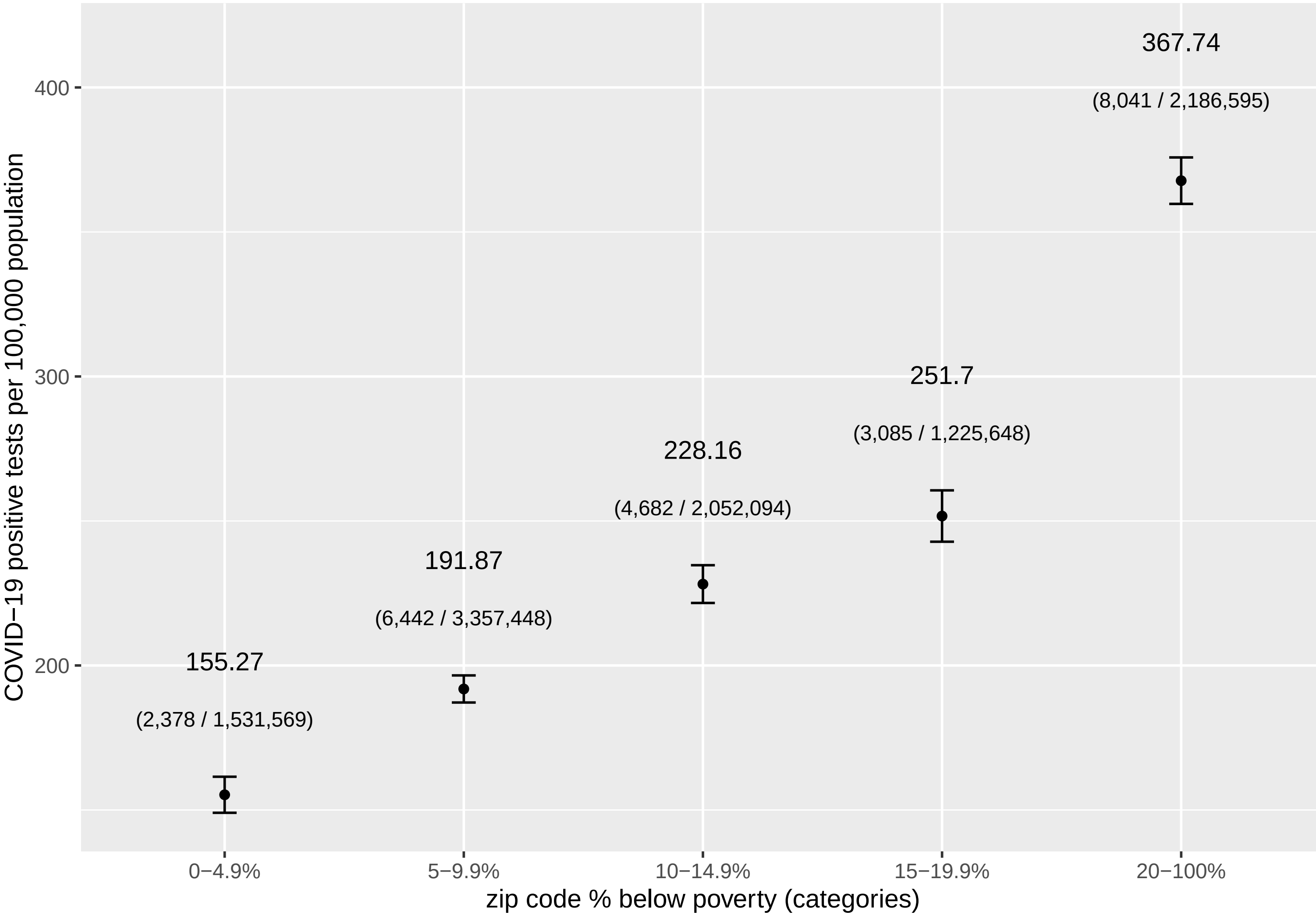


Figure 2b: Illinois COVID−19 confirmed cases per 100,000 population
by ZIP code Index of Concentration at the Extremes (white/black race + income)
(as of 4.16.2020)

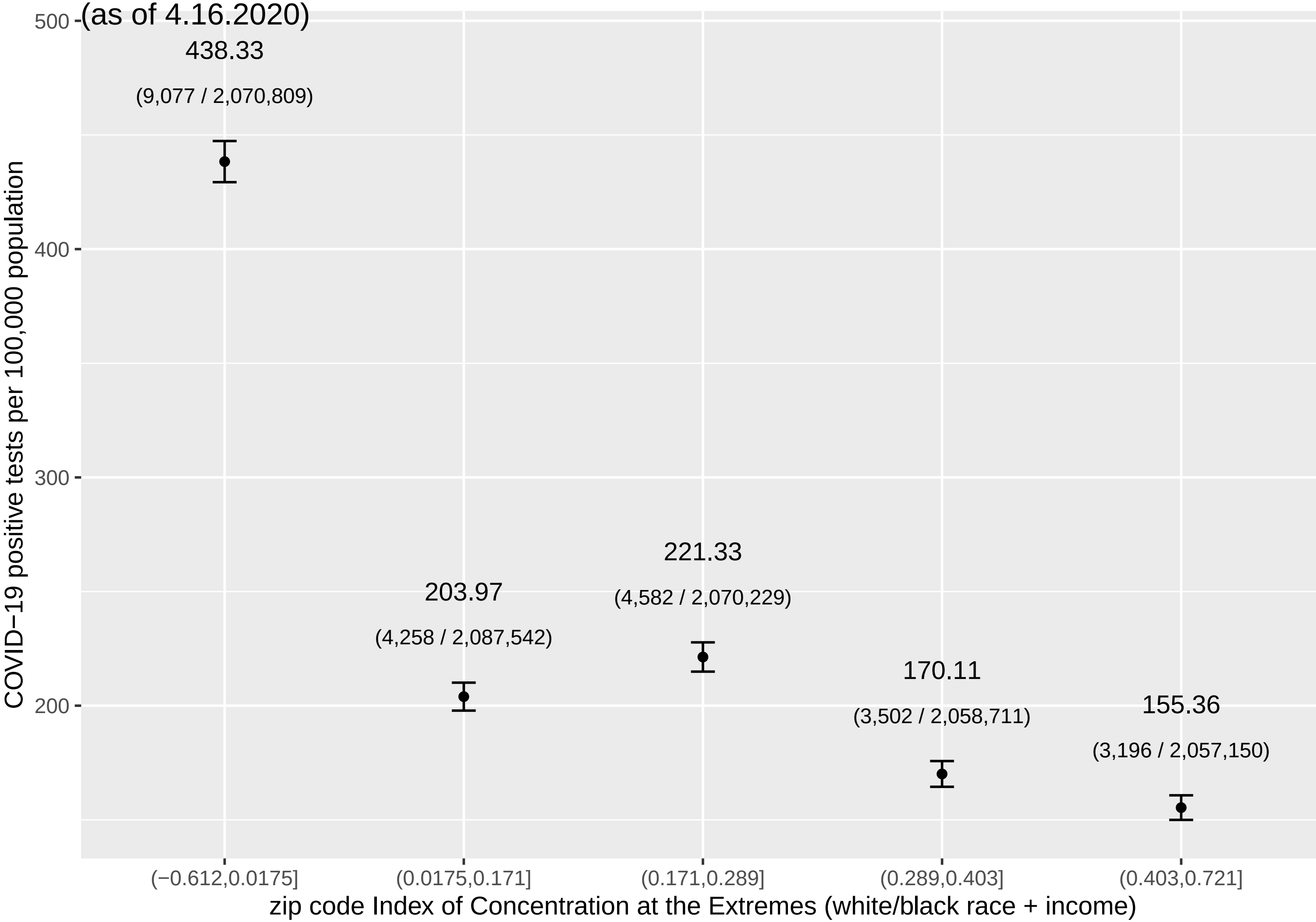


Figure 2c: Illinois COVID−19 confirmed cases per 100,000 population by ZIP code % crowding (>1 person per room) (as of 4.16.2020)

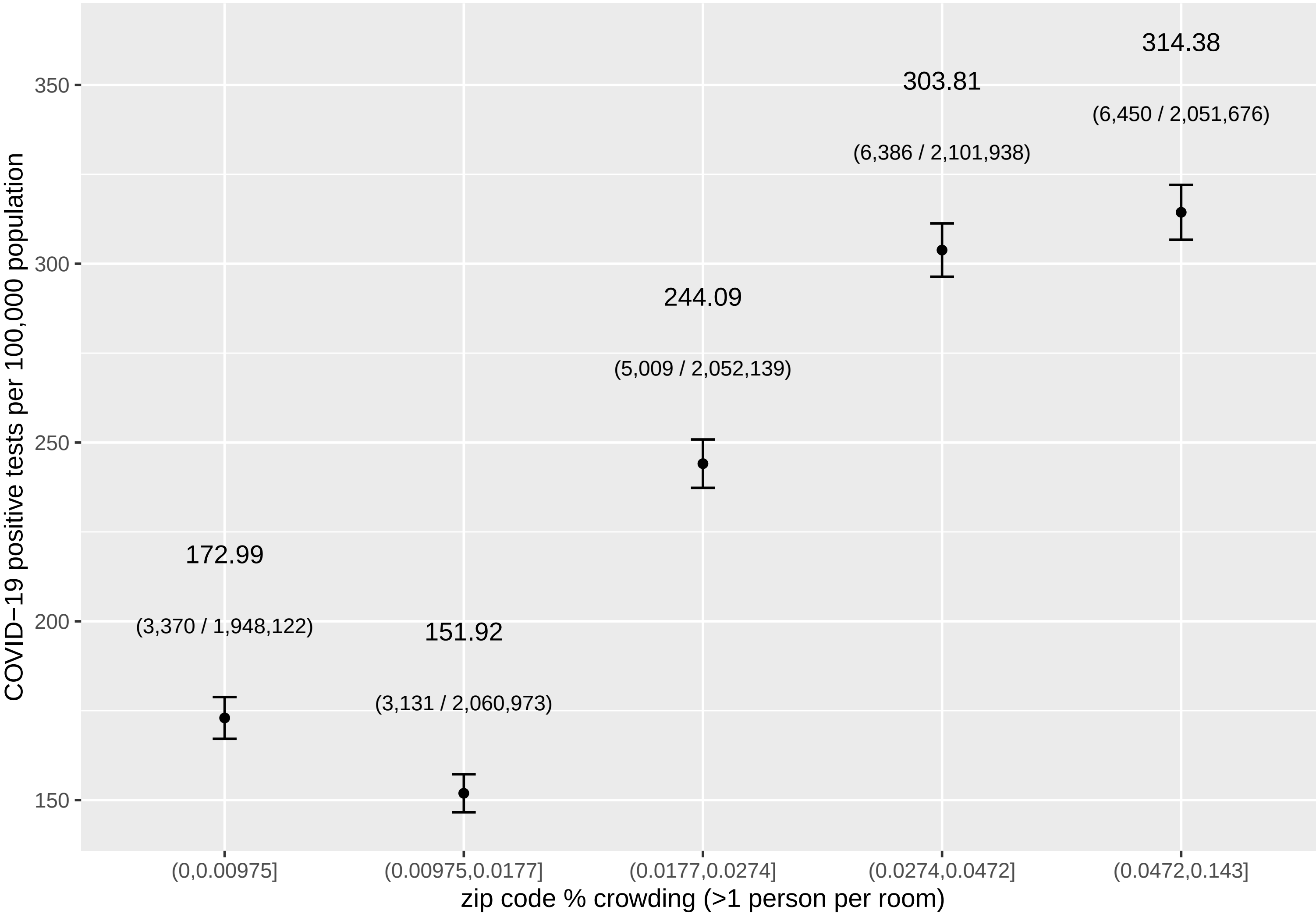


Figure 2d: Illinois COVID−19 confirmed cases per 100,000 population
by ZIP code % population of color (as of 4.16.2020)

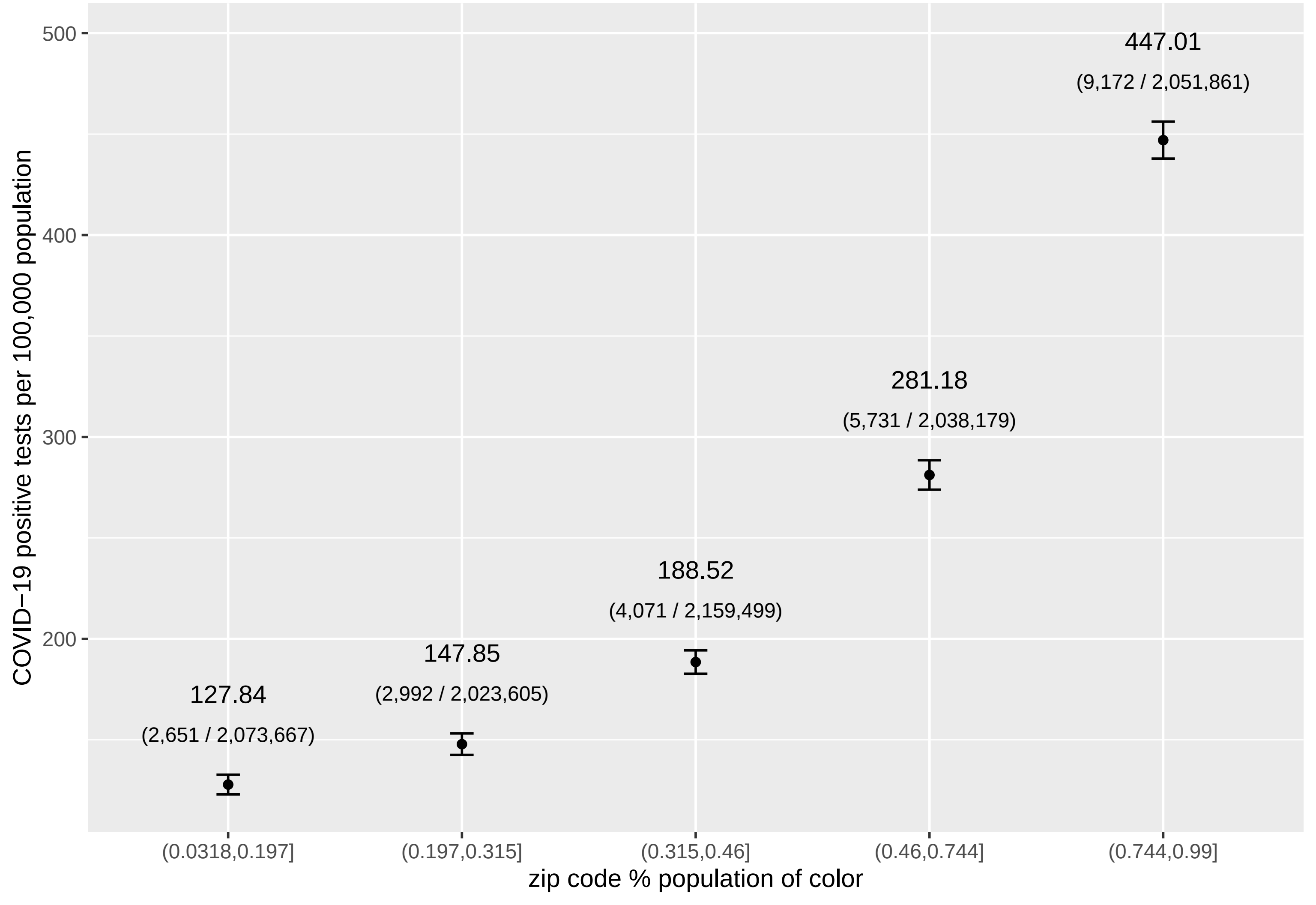


Figure 3a: NYC COVID−19 positive tests per 100,000 population
by ZIP code % below poverty (categories) (as of 4.16.2020)

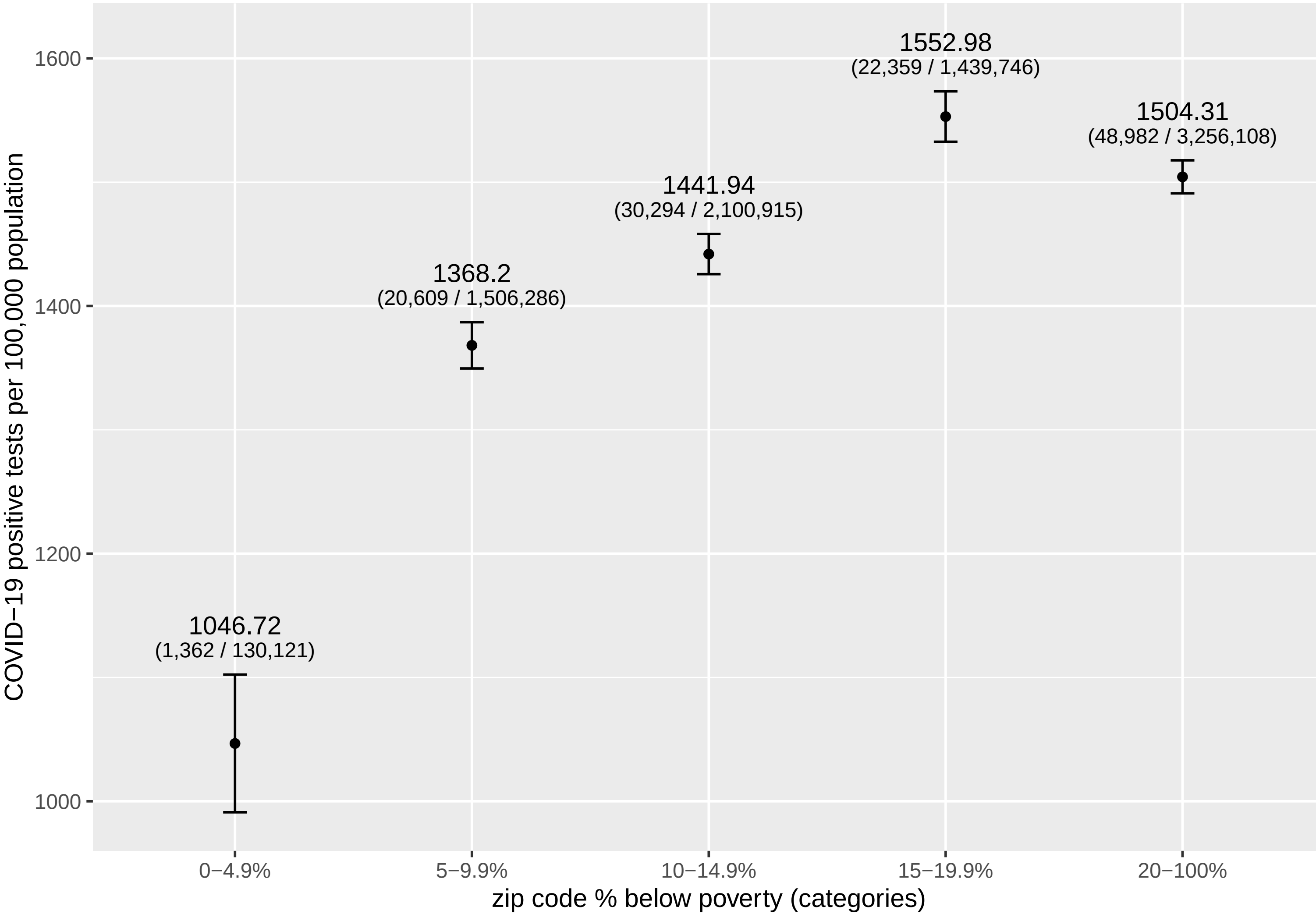


Figure 3b: NYC COVID−19 positive tests per 100,000 population
by ZIP code Index of Concentration at the Extremes (white/black race + income)
(as of 4.16.2020)

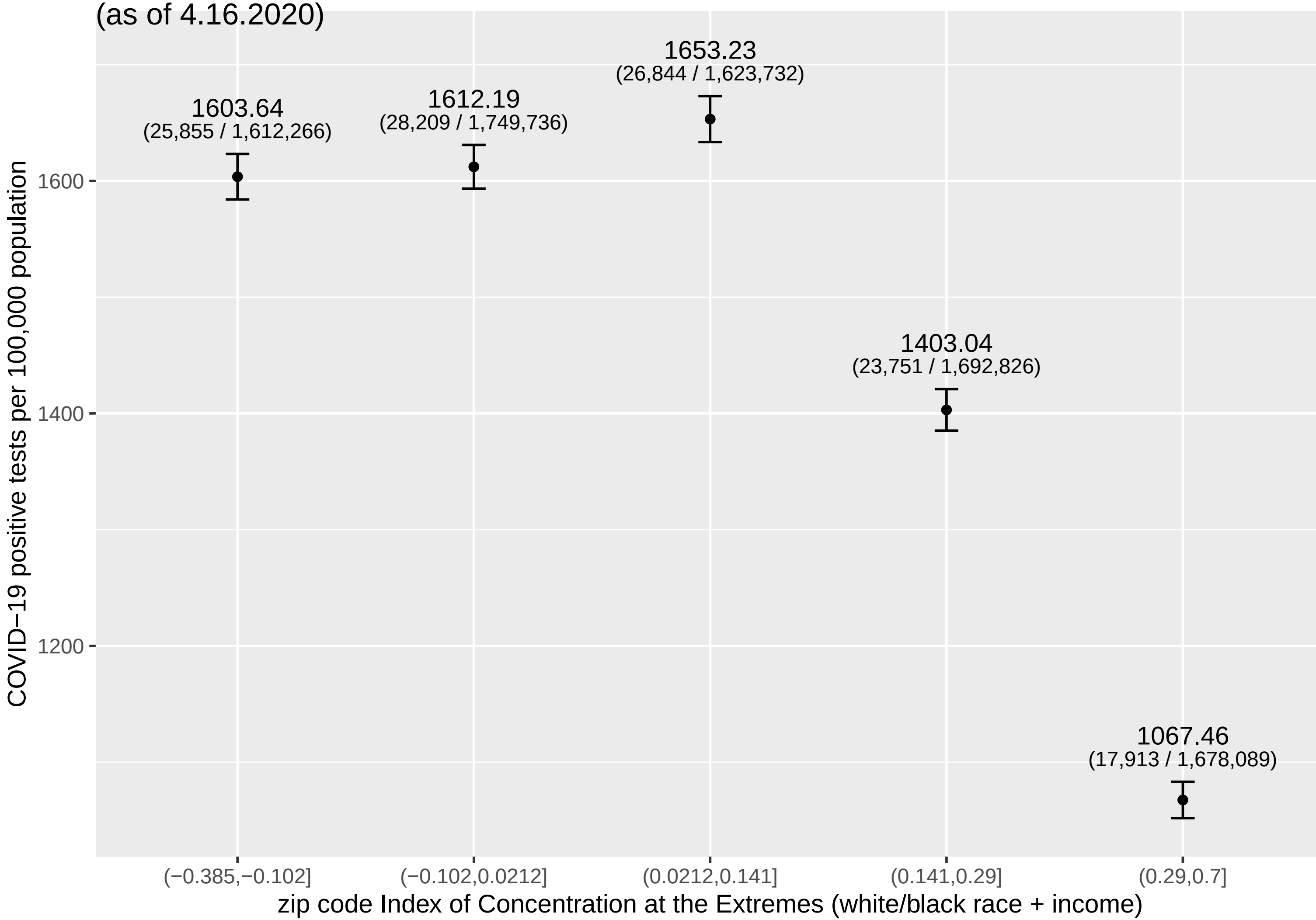


Figure 3c: NYC COVID−19 positive tests per 100,000 population
by ZIP code % crowding (>1 person per room) (as of 4.16.2020)

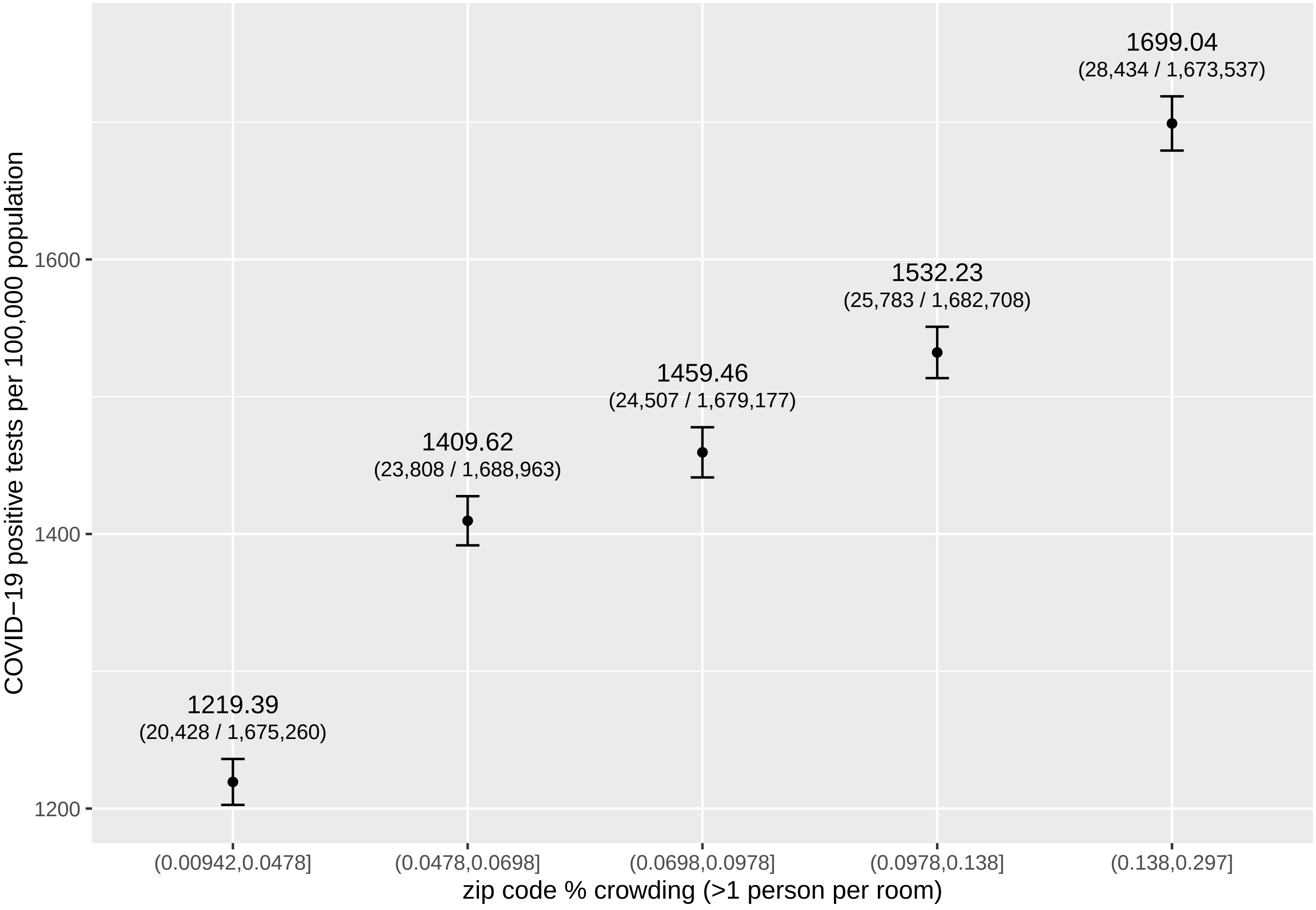
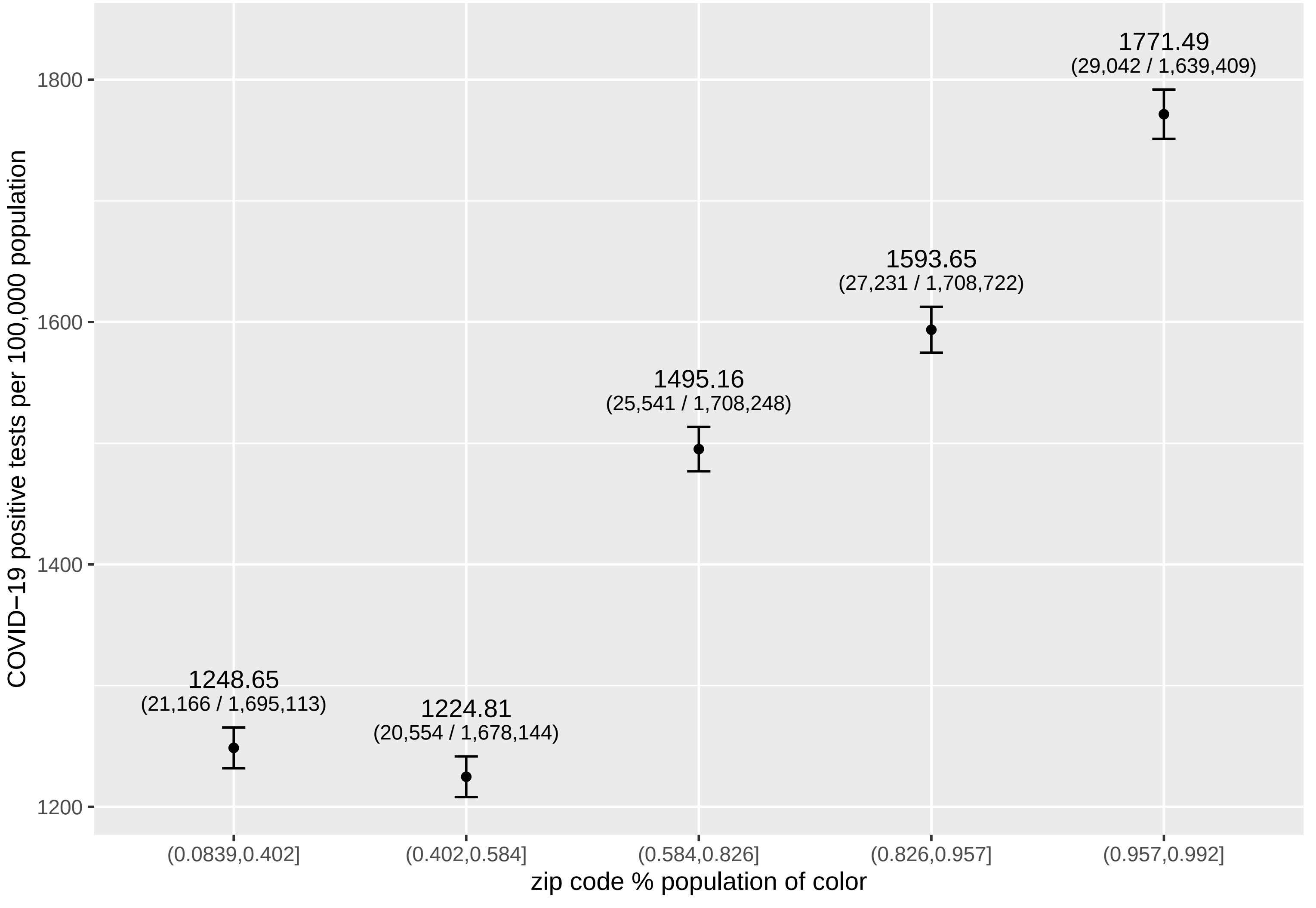


Figure 3d: NYC COVID−19 positive tests per 100,000 population
by ZIP code % population of color (as of 4.16.2020)



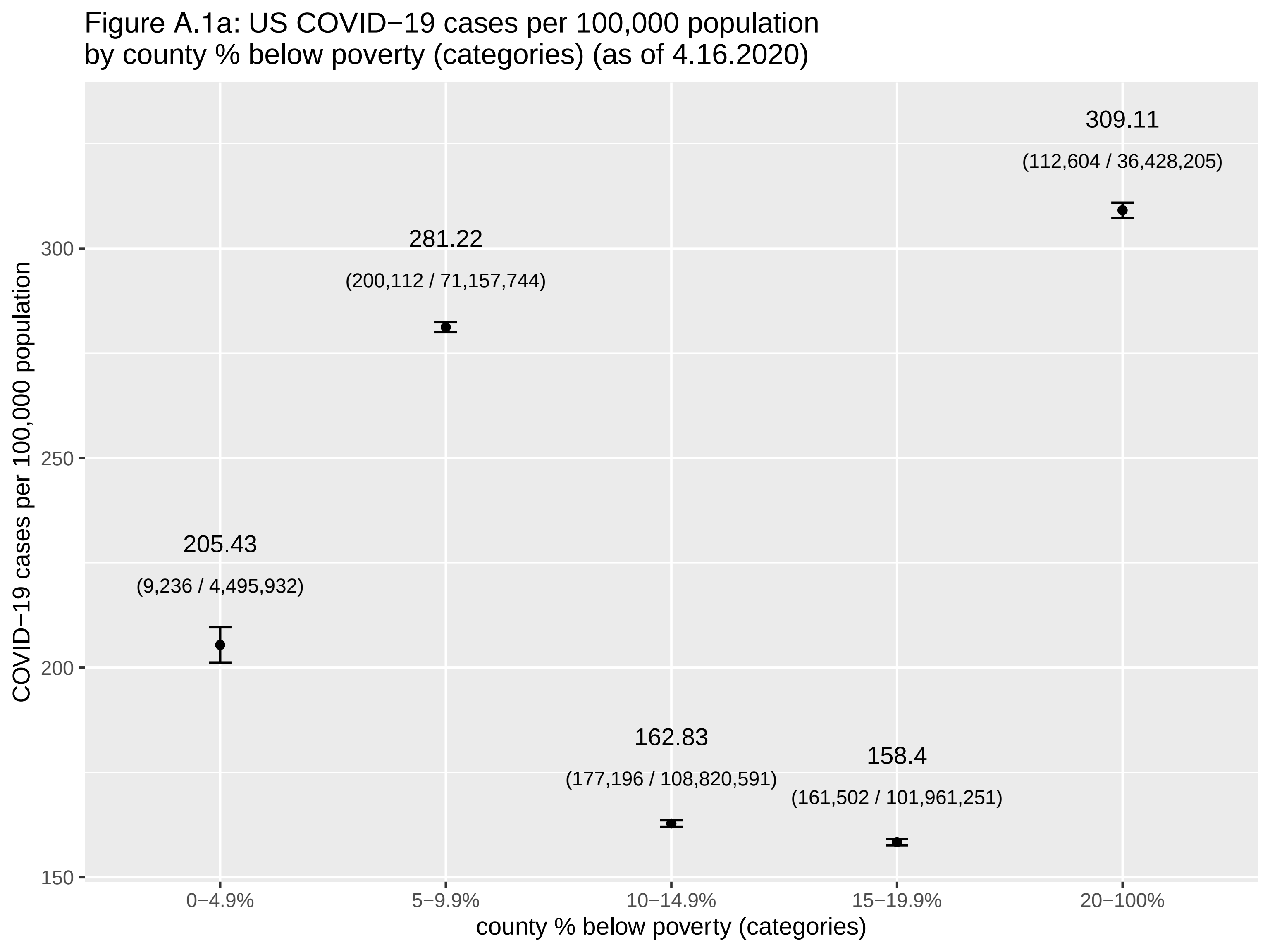
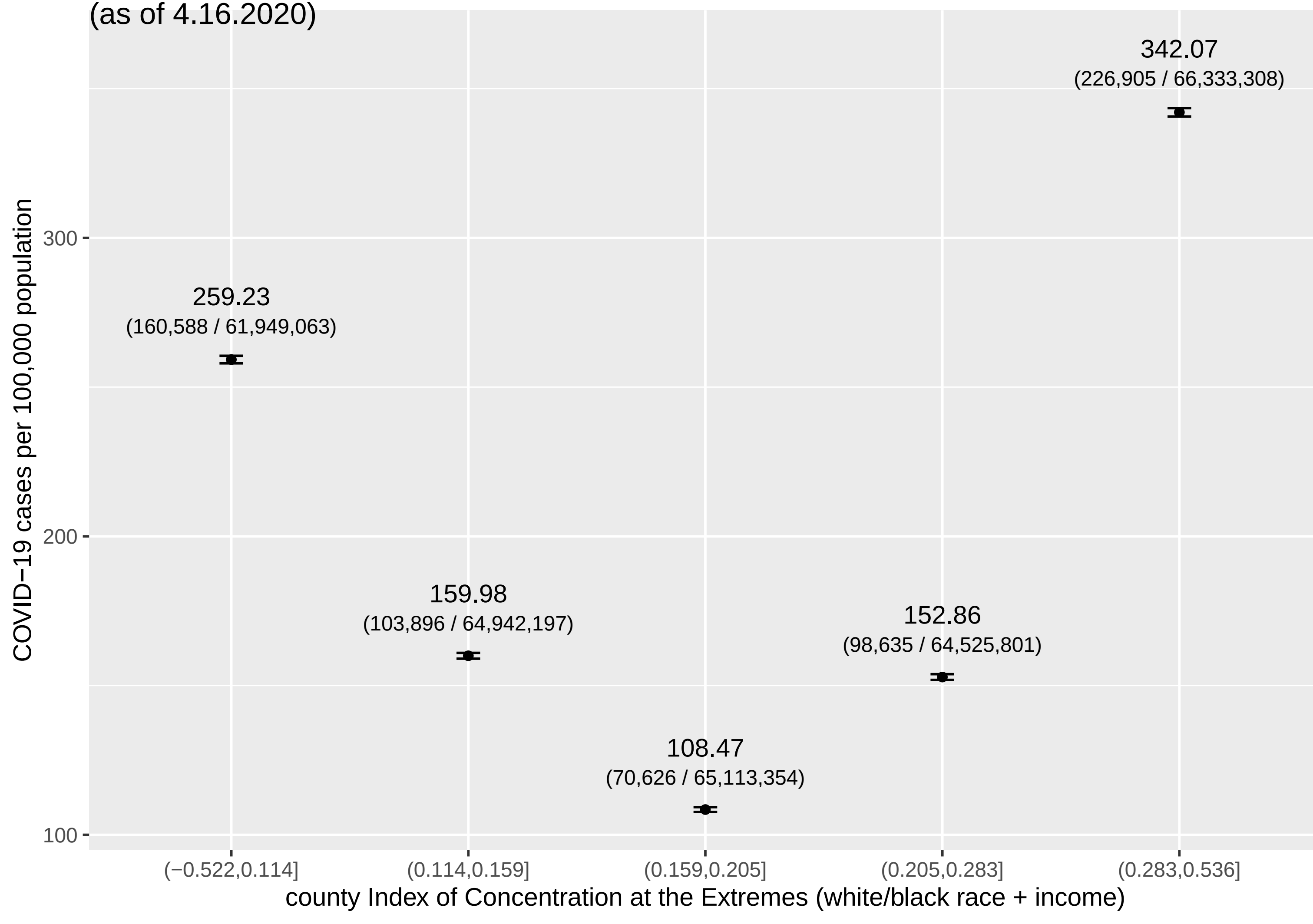


Figure A.1a: US COVID−19 cases per 100,000 population
by county % below poverty (categories) (as of 4.16.2020)
309.11
(112,604 / 36,428,205)
281.22
(200,112 / 71,157,744)
205.43
(9,236 / 4,495,932)
162.83
(177,196 / 108,820,591)
158.4
(161,502 / 101,961,251)
COVID−19 cases per 100,000 population
300
250
200
150
0−4.9%
5−9.9%
10−14.9%
15−19.9%
20−100%
county % below poverty (categories)

Figure A.1b: US COVID−19 cases per 100,000 population
by county Index of Concentration at the Extremes (white/black race + income)
(as of 4.16.2020)



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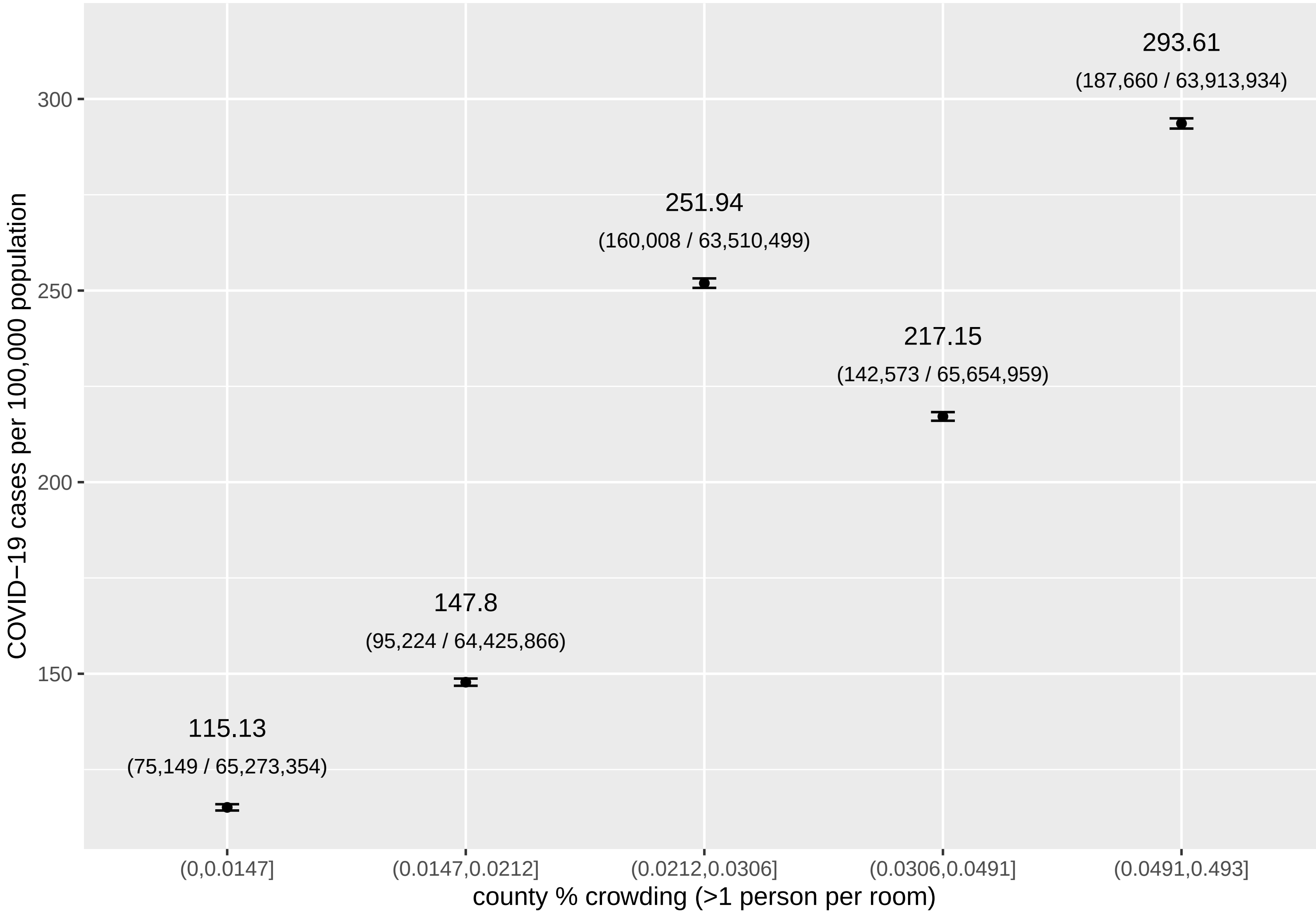
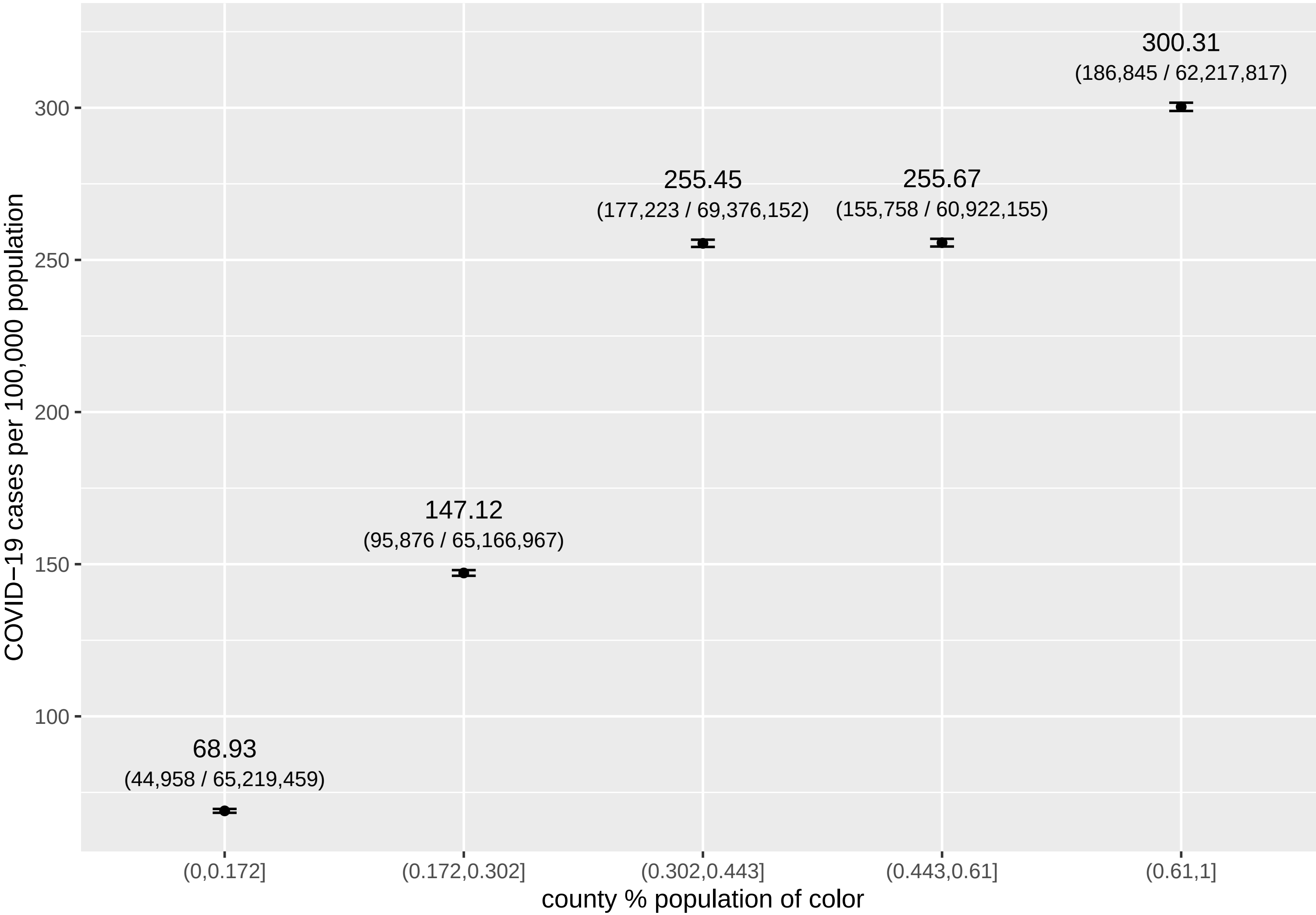


Figure A.1d: US COVID−19 cases per 100,000 population
by county % population of color (as of 4.16.2020)



BMJ Open

US-county level variation in intersecting individual, household and community characteristics relevant to COVID-19 and planning an equitable response: a cross-sectional analysis

Taylor Chin ,[1] Rebecca Kahn ,[1] Ruoran Li ,[1] Jarvis T Chen ,[2] Nancy Krieger ,[2] Caroline O Buckee,[1] Satchit Balsari,[3,4] Mathew V Kiang [4,5,6]

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For numbered affiliations see end of article.

Correspondence to
Taylor Chin;
taylorchin@g.harvard.edu

ABSTRACT

Objectives To illustrate the intersections of, and intercounty variation in, individual, household and community factors that influence the impact of COVID-19 on US counties and their ability to respond.

Design We identified key individual, household and community characteristics influencing COVID-19 risks of infection and survival, guided by international experiences and consideration of epidemiological parameters of importance. Using publicly available data, we developed an open-access online tool that allows county-specific querying and mapping of risk factors. As an illustrative example, we assess the pairwise intersections of age (individual level), poverty (household level) and prevalence of group homes (community-level) in US counties. We also examine how these factors intersect with the proportion of the population that is people of colour (ie, not non-Hispanic white), a metric that reflects histories of US race relations. We defined 'high' risk counties as those above the 75th percentile. This threshold can be changed using the online tool.

Setting US counties.

Participants Analyses are based on publicly available county-level data from the Area Health Resources Files, American Community Survey, Centers for Disease Control and Prevention Atlas file, National Center for Health Statistic and RWJF Community Health Rankings.

Results Our findings demonstrate significant intercounty variation in the distribution of individual, household and community characteristics that affect risks of infection, severe disease or mortality from COVID-19. About 9% of counties, affecting 10 million residents, are in higher risk categories for both age and group quarters. About 14% of counties, affecting 31 million residents, have both high levels of poverty and a high proportion of people of colour.

Conclusion Federal and state governments will benefit from recognising high intrastate, intercounty variation in population risks and response capacity. Equitable responses to the pandemic require strategies to protect those in counties at highest risk of adverse COVID-19 outcomes and their social and economic impacts.

Strengths and limitations of this study

- ► By demonstrating the high intercounty variation in a range of risk factors across US counties, including their intersection with communities of colour, this study highlights the need for policy-makers to consider their local context when addressing the COVID-19 pandemic.
- ► Approximately 9% of counties, affecting 10 million residents, are in higher risk categories for both age and group quarters, while approximately 14% of counties, affecting 31 million residents, have both high levels of poverty and a high proportion of people of colour.
- ► This study provides scientific guidance and an interactive data exploration tool to assist county-level and state-level policy-makers in planning an equitable response to COVID-19.
- ► While the list of variables examined is not exhaustive, an interactive online tool is made available for users to examine and compare 24 county-level characteristics.
- ► The study does not attempt to assign weights to these various risk factors, as it is not yet clear to how they will differentially impact risk of infection from COVID-19, and subsequent morbidity and mortality from it.

INTRODUCTION

The spread of COVID-19 across the USA confirms that not all Americans are equally at risk of infection, severe disease, or mortality. Researchers have noted significant disparities in the availability of critical medical resources that impact COVID-19 survival, such as ventilators, hospital beds and intensive care unit (ICU) beds.[1–4] However, a range of individual, household and community characteristics also influence risk of COVID-19 infection and its lethality. Preliminary data from the epidemic demonstrate a convergence of these risk factors in communities with high proportions of low-income households, people of colour or both, differentially affecting counties across the USA.[5–7]

In this paper, we demonstrate wide intercounty variation in individual, household and community factors that influence risk of COVID-19 outcomes and provide an online tool for policy-makers to examine county-specific risk factors to plan an appropriate response (https://ccdd-hsph-harvard.shinyapps.io/county-risk/).

Current literature indicates that individual-level factors like age and pre-existing health conditions influence COVID-19 susceptibility and survival.[5 8 9] March 2020 data from a hospital-based surveillance system (COVID-NET) confirmed that 75% of all hospitalisations across 14 states in the USA were among those aged ≥50 years, with the highest hospitalisation rates among those aged ≥65.[5] Approximately 89% of COVID-19-associated hospitalised patients had one or more underlying conditions, including hypertension, obesity, chronic lung disease, diabetes and cardiovascular disease.[5]

Household characteristics such as household size, household composition (eg, grandparents living with grandchildren) and household crowding may affect contact patterns and transmission rates.[10] Moreover, poverty and job insecurity determine people's ability to work from home and 'shelter in place', at a time when non-pharmaceutical interventions are currently the primary defence against the outbreak.[11 12] Poverty heightens susceptibility to COVID-19 infection and risk of severe outcomes, due to its association with higher risk of comorbidities,[13] decreased access to care[13 14] and reduced ability to practice social distancing.[15 16] By April 2020, the Bronx, Philadelphia and Orleans Parish—counties with approximately one-fourth or more of its population below the poverty line—were among the counties with the highest cumulative death counts in the USA.[17] Community characteristics involving the presence of group quarters,[18] such as correctional facilities,[19 20] nursing homes[21–23] and homeless shelters,[24 25] are also implicated in COVID-19 risks. Local hospital-bed and ICU-bed capacity further determines a community's ability to respond to COVID-19.[3]

The intersection of these individual, household and community characteristics among communities of colour, created and perpetuated by the pervasive structural inequities in the USA, results in poor health outcomes.[26–28] Communities of colour are more likely to include low-income essential workers who cannot stay home, thereby increasing risk of exposure at work or on public transportation while commuting, as well as to live in more crowded housing.[29] In addition to increased risk of infection and mortality, communities of colour have increased risk of chronic diseases[30] and experience unequal access to healthcare,[6 31 32] further compounding risk of COVID-19 mortality. Populations of colour are also disproportionately unemployed[33] and incarcerated,[34] which independently increase the risk of COVID-19 infection and severe outcomes. These disparities, as manifestations of the effects of systemic racism in the USA, contribute to higher COVID-19 death rates among predominantly black counties relative to predominantly white counties,[35] as well as to their higher age-specific risks of mortality among working-age adults.[36] Data from Detroit, New York City, New Orleans and Chicago—all cities with significant minority populations—reveal that African Americans comprise a disproportionate proportion of COVID-19 cases and deaths, relative to their share of the population.[31 35 37]

Understanding the distribution of these intersecting county-specific risk factors is critical to mounting an equitable, adequate, timely and comprehensive response. Inter-county differences are particularly important to consider in the context of supportive local policies around social distancing as the epidemic unfolds, and for the relaxation of social distancing in the coming months. Counties often have flexibility in determining the stringency of their COVID-19 response relative to their respective state orders[38 39]; therefore, counties represent a spatial and administrative unit ideal for localised response. Local response measures include both mobilisation of healthcare resources and optimisation of policies for social distancing and reopening. We provide an illustrative example of the convergence of individual, household and community factors, including their racial/ethnic composition, across all US counties to identify counties at heightened COVID-19 risk.

METHODS

Using publicly available county-specific data from the Area Health Resources Files,[40] American Community Survey,[41] Centers for Disease Control and Prevention Atlas file,[42] National Center for Health Statistics[43] and RWJF Community Health Rankings,[44] we identified a range of key individual, household and community factors influencing susceptibility to COVID-19, guided by international experiences and consideration of epidemiological parameters of importance. As an illustrative example, we examine the different pairwise intersections of age (an individual characteristic), poverty (a household characteristic) and prevalence of group homes (a community characteristic) in counties across the USA. We also examine how these factors intersect with the proportion of the population that is people of colour (ie, population other than non-Hispanic white), a metric that reflects histories of US race relations.

The accompanying open-access online tool (online supplementary materials text S1) is populated with each of these covariates and allows county-specific querying of different pairs of risk factors. In addition to displaying the county's rank relative to other counties, we display bivariate maps that illustrate the intersection of risk factors across the USA. All our data and code are publicly available to facilitate more nuanced analysis, inform existing models and shape policy (online supplementary materials text S1). For all covariates, we define low, medium and high risk as the below the 25th percentile, the 25–75th percentiles and above the 75th percentile, respectively. These thresholds can be changed using the online tool.

Patient and public involvement

Patients and the public were not involved in any way.

RESULTS

Age and poverty

With respect to age, each county in the top quartile had at least 15% of their population over 70 years of age, compared with the median county of 12.8%. These older counties are clustered in the Midwest, Idaho, Florida and Nevada (online supplementary figure S1). For poverty, each county in the top quartile had at least 19% of their households under the poverty line, compared with the median county of 14.8%. These high poverty counties are clustered around Appalachia, Deep South states and along the USA–Mexico border (online supplementary figure S2). About 4% of US counties (135 of 3106), affecting over 2 million people, have both an older population and high rates of poverty (figure 1A). These counties are geographically dispersed, with little signs of clustering. The most impacted states are Florida (295 718 people in 7 of 67 counties), Arizona (198 858 people in 3 of 15 counties) and Arkansas (159 733 people in 14 of 75 counties).

Poverty and group quarters

For group quarters, each county in the top quartile had at least 4% of the resident population living in group quarters, compared with the median county of 1.9%. These counties are geographically dispersed across the entire USA (online supplementary figure S3). Nearly 4% of US counties (112 of 3111), affecting 2.2 million people, have both high poverty rates and are in the top quartile of proportion of the population living in group quarters (figure 1B). While these counties are clustered in Louisiana, Florida and New Mexico, the states with the most people affected are Pennsylvania (290 418 people in 6 of 67 counties), Florida (218 325 people in 6 of 67 counties) and New York (191 031 people in 4 of 62 counties).

Age and group quarters

Over 9% of US counties (285 of 3106), affecting over 10 million people, have both an older population and are in the top quartile of proportion of the population living in group quarters (figure 1C). These counties are geographically dispersed and show few signs of clustering. The most impacted states are Texas (1.4 million people in 40 of 254 counties), Georgia (1.2 million people in 20 of 67 counties) and Florida (711 168 people in 20 of 67 counties).

Intersections of individual, household and community characteristics in communities with a high proportion of people of colour

Regarding the composition of county populations, one quarter of counties in the USA (761) have at least 35% of their resident populations that are populations of colour (online supplementary figure S4). In 3% of US counties (89 of 3111), affecting 3.5 million people, the counties include both a high proportion of people of colour and a high proportion of older residents (figure 2A). In 14% of US counties (424 of 3106), affecting 31 million people, the counties include both a high proportion of people of colour and a high proportion of households living under the poverty line (figure 2B). In about 7% of US counties (229 of 3111), affecting 14 million people, the counties have both a high proportion of people of colour and are in the top quartile of proportion of people living in group quarters (figure 2C). Across the three risk factors, the intersection with counties with a high proportion of people of colour exhibits geographical variation. For example, clusters of counties with large populations of colour and older populations are found in Arizona, New Mexico and Colorado, but pockets also exist in Texas and Florida. This pattern is similar for counties with a high proportion of people of colour and proportion of people living in group quarters. By contrast, clusters of counties with a high proportion of people of colour and high poverty rates exist in the Deep South, in addition to Arizona, New Mexico and Texas.

DISCUSSION

Principal findings

Many Americans with chronic comorbidities, lack (and recent loss) of health insurance, inability to work from home and limited access to care are likely to be disproportionately affected by COVID-19, due to their increased risk of both infection and severe disease. Our findings demonstrate significant intercounty variation in the distribution of these risks, including their intersection with communities of colour.

Meaning of the study

Many of the counties that carry intersecting risks are located in states that have been tepid in their social-distancing response or in a haste to re-open.[6 45–47] In the absence of measures to enable social distancing and provision of adequate personal protective equipment to those that cannot stay home, communities of colour will likely continue to bear a disproportionately high burden of infection, severe disease and mortality.[6 31 35 37]

Areas with greater COVID-19 risk will likely have greater demand for hospital beds, and the ability of counties to mount a medical response to the outbreak will depend on local bed capacity. However, there is substantial geographical variation in hospital bed capacity. The median county has approximately 185 hospital beds per 100 000 population (mean: 294; IQR: 69–357; online supplementary figure S5). According to a May 2020 report from the US Society for Critical Care Medicine, only 1% (963) of all ICU beds are located in rural areas.[48] (See online supplementary figures S6–S9 for intersection of factors examined above and bed capacity.) In anticipation of heightened demands on healthcare systems during future waves of COVID-19 in counties that are multiply

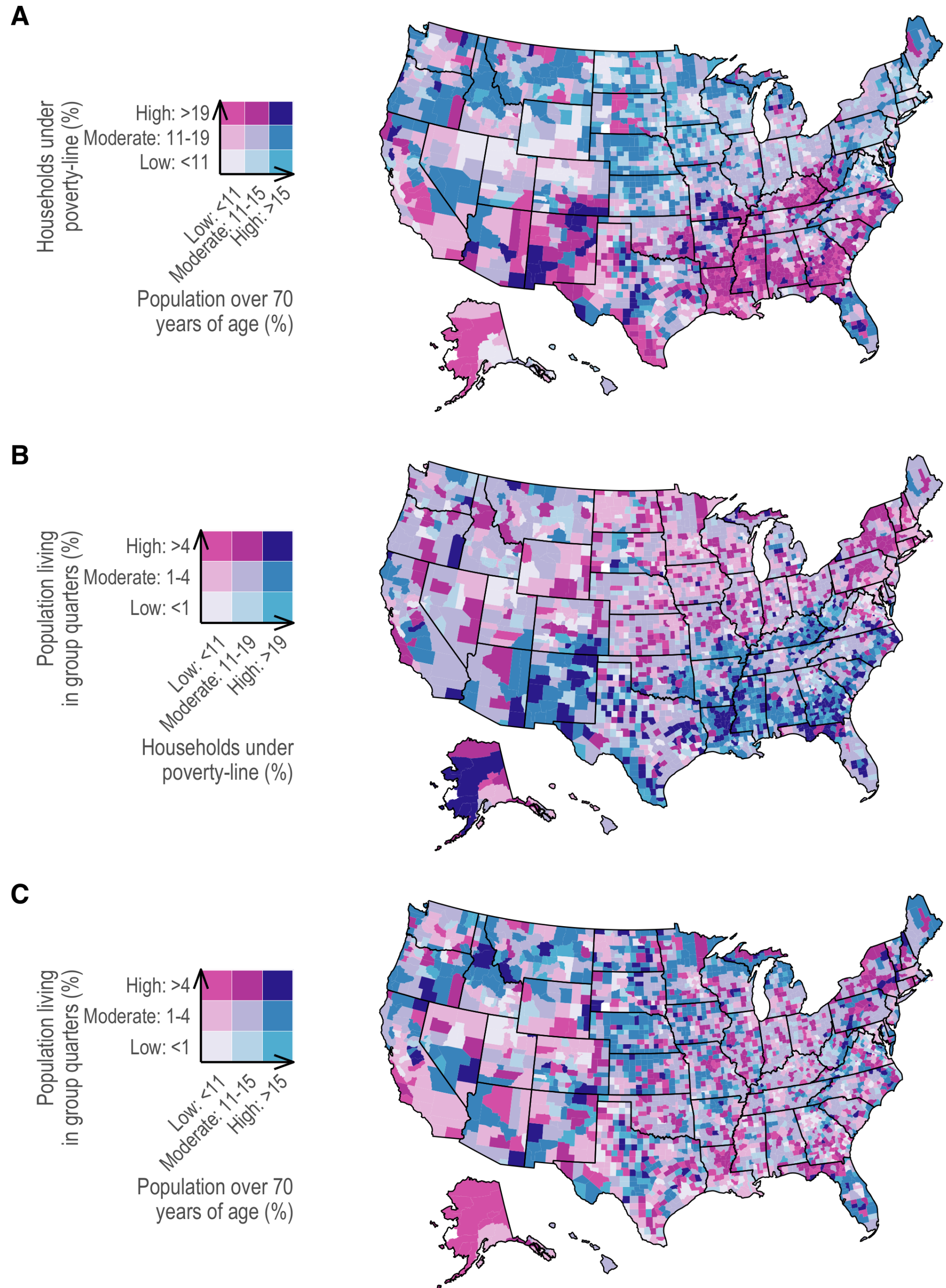

Figure 1 (A) Percentage of households living in poverty, 2016 (Source: CDC Atlas via the Census Small Area Income and Policy Estimates) and percentage of population 70 years or older, 2018 (Source: National Center for Health Statistics Bridged Race Population Estimates 2018, Vintage 2018). (B) Percentage of population living in group quarters, 2018 (Source: American Community Survey) and percentage of households living in poverty, 2016 (Source: CDC Atlas via the Census Small Area Income and Policy Estimates). (C) Percentage of population living in group quarters, 2018 (Source: American Community Survey) and percentage of population 70 years or older, 2018 (Source: National Center for Health Statistics Bridged Race Population Estimates 2018, Vintage 2018).

at risk of having high COVID-19 burden, states and the federal government need to ramp up interjurisdictional coordination efforts to move supplies and personnel to meet rapidly shifting local demands.

Limitations and future research

The risk factors described here are by no means a comprehensive list. Other important county-level characteristics are shown in online supplementary figures S10–S22 and can be found in the online dashboard. Additional risk factors on the county level that are not included in this analysis, such as the proportion of workers in industries that preclude working remotely, language, immigration status, numbers of incarcerated and homeless persons, measures of inequality like the Gini coefficient and Index of Concentration at the Extremes, and density of residential drug treatment programmes and residential mental health

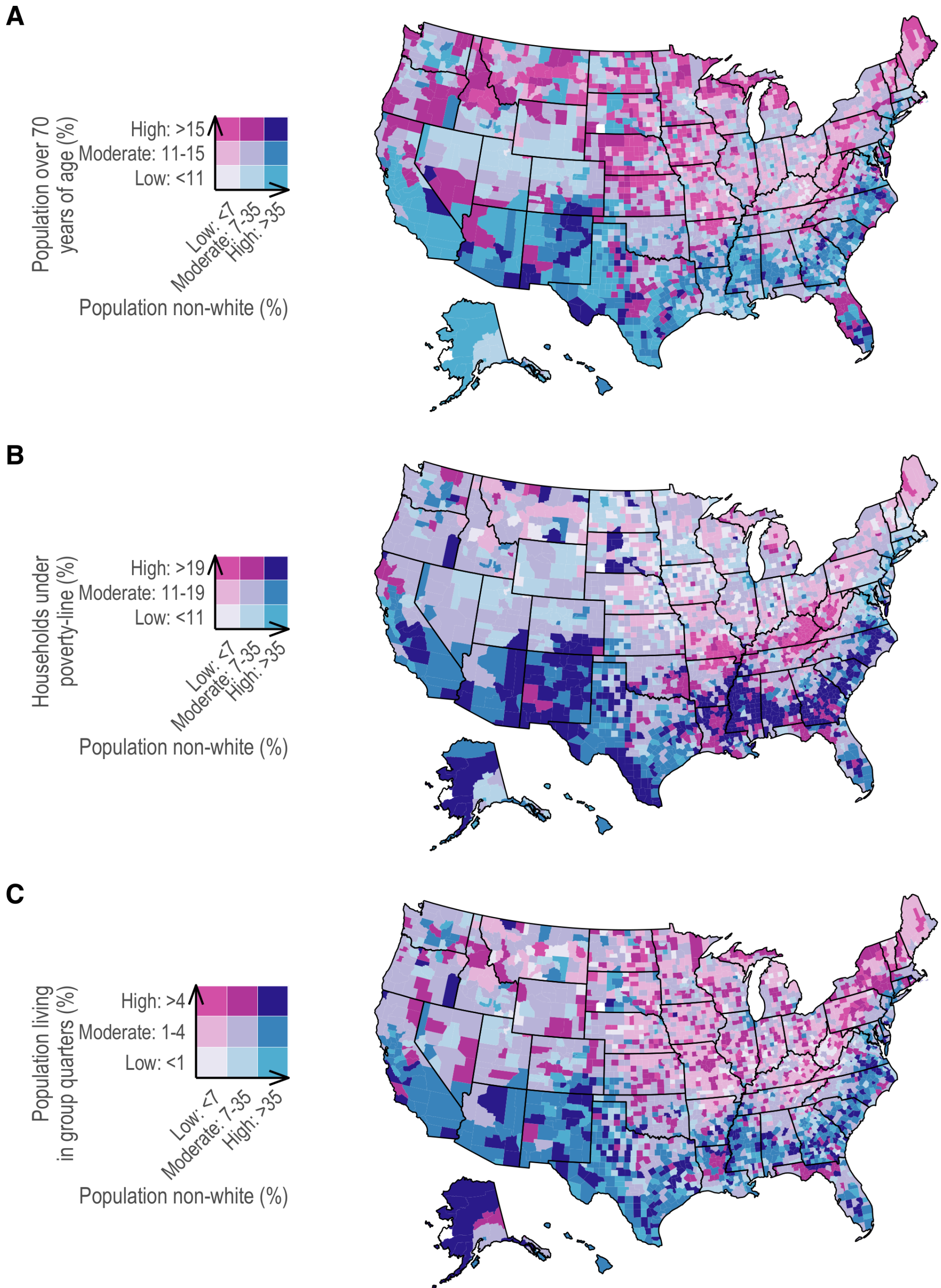

Figure 2 (A) Percentage of population 70 years or older, 2018 (Source: National Center for Health Statistics Bridged Race Population Estimates 2018, Vintage 2018) and percentage of population non-Hispanic and non-white, 2018 (Source: National Center for Health Statistics). (B) Percentage of households living in poverty, 2016 (Source: CDC Atlas via the Census Small Area Income and Policy Estimates) and percentage of population non-Hispanic and non-white, 2018 (Source: National Center for Health Statistics). (C) Percentage of population living in group quarters, 2018 (Source: American Community Survey) and percentage of population non-Hispanic and non-white, 2018 (Source: National Center for Health Statistics).

facilities, may all contribute to how counties are affected and respond. Currently, there is insufficient evidence to justify assigning importance weights to different risk factors; however, as more data become available, future research may expand on our analysis by, for example, constructing and evaluating a polysocial risk score.[49]

Conclusion

By July 6, there were more than 2.9 million cases in the USA, across all states, Washington D.C., and four US territories.[50] County, state and national planners will benefit from examining and preparing for the local factors that are likely to influence their counties' ability to respond. The need for actionable, contextually relevant data that allows for equitable distribution of resources to prevent, mitigate and treat COVID-19 is imperative. Collecting and sharing data on COVID-19 outcomes by race and ethnicity, which surveillance systems have not systematically reported for testing or hospitalisation (but which are increasingly including these data for mortality), will be crucial to understanding and rectifying inequities in the distribution of COVID-19 outcomes.[17 51]

The clustering of counties with high concentrations of people of colour and high rates of poverty can be traced back to legacies of Jim Crow and race relations in the South.[27 28] In the absence of concerted, aggressive and proactive local responses, supported by state and federal agencies, the final morbidity and mortality toll, as early numbers indicate, will be disproportionately borne by these communities. Inaction will only perpetuate the structural inequities that are deeply entrenched in the USA.

Author affiliations
[1]Epidemiology, Harvard University T H Chan School of Public Health, Boston, Massachusetts, USA
[2]Social and Behavioral Sciences, Harvard TH Chan School of Public Health, Boston, MA, United States
[3]Emergency Medicine, Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, Massachusetts, USA
[4]FXB Center for Health and Human Rights, Harvard University, Cambridge, Massachusetts, USA
[5]Center for Population Health Sciences, Stanford University, Palo Alto, California, USA
[6]Epidemiology and Population Health, Stanford University, Stanford, California, USA

Twitter Rebecca Kahn @rebeccajk13, Ruoran Li @ruoranepi and Mathew V Kiang @mathewkiang

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ORCID iDs
Taylor Chin http://orcid.org/0000-0001-6852-1169
Rebecca Kahn http://orcid.org/0000-0001-9511-6142
Ruoran Li http://orcid.org/0000-0001-7575-2758
Jarvis T Chen http://orcid.org/0000-0002-7412-1783
Nancy Krieger http://orcid.org/0000-0002-4815-5947
Mathew V Kiang http://orcid.org/0000-0001-9198-150X

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Q. & A.

The Interwoven Threads of Inequality and Health

By Isaac Chotiner

April 14, 2020

The coronavirus crisis is revealing the inequities inherent in public health due to societal factors, Nancy Krieger, a professor of social epidemiology, says. Photograph by Johannes Eisele / AFP / Getty

According to preliminary data about the coronavirus pandemic, African-Americans are bearing a strikingly disproportionate share of the suffering in the United States. In Illinois, where fourteen per cent of the population is African-American, black Americans represent more than forty per cent of the state's confirmed coronavirus deaths. Coronavirus fatalities have a similar breakdown in Michigan, and several Southern states show even greater disparities. The possible reasons for these inequities are myriad: African-Americans are less likely than white Americans to have the option of working from home and to receive high-quality medical care, and more likely to have preëxisting medical conditions that lead to worse outcomes from the novel coronavirus. New research links coronavirus deaths to air quality, which is often worse in poor communities and communities of color.

Nancy Krieger is a professor of social epidemiology at the Harvard T. H. Chan School of Public Health. Her work focusses on health disparities between demographic groups and the social structures that help determine those disparities. We recently spoke by phone about how American health inequities are playing out during the pandemic. During our conversation, which has been edited for length and clarity, we discussed why the field of social epidemiology is crucial to understanding inequality, the causes of racial disparity in health outcomes, and what can be done to ameliorate the suffering of the most vulnerable Americans during this crisis.

Is the spread of the coronavirus, and especially its disproportionate impact on the African-American community, teaching us new things about racial disparities in health care and health outcomes or confirming things we have long known?

More the latter. What the virus is doing is pulling a thread that is showing how many things are actually connected, and how deeply people are actually connected. But it's also revealing the very different conditions in which we live because of social structures that are inequitable, both within the United States and between countries. By pulling the thread, it's revealing patterns that have been long known in public health.

So, when you think about something like this coronavirus, you have to think about who's exposed in the first place and where they are exposed—at work, at home, and what are the conditions? You have to think about, if they're exposed, do they get infected? You have to think about, if they get infected, do they get ill? And you have to think about, if they're ill, do they actually die?

And you take each of those steps, which are all different steps in this process, and turn to what are the preliminary—and, I emphasize, preliminary—data on the excessive death rates. My state, Massachusetts, just released the first reports that have any racial or ethnic data. The amount of missing data is horrific. Fifty-three per cent of confirmed cases and deaths have no race or ethnicity recorded. So this is really stunning. Thank goodness for what the journalists are doing compared with what the actual health agencies are doing. And I could trace that back to issues like funding cuts in public health that have been pronounced over the past two decades, if not more.

But what you can do is use this to look at what the coronavirus is exposing. So let's start with who's being exposed. Well, if you are living in crowding households—and household crowding is intimately related to lack of living wage and unaffordable housing—what do you have when people are living in crowded spaces? An increased risk of exposure and transmission. If you work in certain kinds of service jobs, which require you to be in close proximity to all kinds of people without sufficient barriers, you're going to be more likely to be exposed. Who is able to stay at home to do their work and who is not? Who is being given protective gear?

Just think about the amount of work that has been done to organize among, for example, people in grocery stores to make sure that they're provided with protective gear. They're considered essential workers now, many of them. Are they essential enough to give protective gear? And then think about the steps that people are being asked to take to protect themselves, including not only physical distancing, while keeping social connections, but also washing your hands. So it's important to note that there have been calls, for example, for not letting utilities cut people's water off. In Detroit, that's been particularly pronounced, because if people don't have running water how can they wash their hands?

I was just looking at the C.D.C. guidelines on masks, which say that the way to clean masks is with a washer. That is the only thing they listed, and a lot of people don't even have washers, and certainly not in their homes or apartment units.

I don't know if you saw the postcard that was sent out to all residents, all people that are domiciled and have a mailing address in the United States, from the Trump Administration about COVID-19. Have you seen that?

I haven't.

Oh, well, you should've got it in your mail. It's called "The President's Coronavirus Guidelines for America." And it says things like, if you feel sick, stay at home—do not go to work. Who can afford to do that? What is this showing about sick leave, and family leave? It says that, if your children are sick, keep them at home and contact your medical provider. Who can watch them at home? Do you have a medical provider? Do you have health insurance? It says that, if someone in your household has tested positive, keep the entire household at home. Again, what are the social conditions that allow people to do that? What are the social policies and what are the glaring gaps that do not allow people to do that equitably in our society? And washing your hands—again, who has access to running water?

So the thing is you can go through each step of what happens with this virus—and we haven't even got to whether you get ill—and, at each step in this process, you can say, "How is this showing what the threads are that connect us, and who's not equitably treated?"

It’s interesting that you keep talking about this thread, because I had been thinking that maybe it would be helpful to disaggregate some of these things, even if they have some of the same root causes. So, on the one hand, you have things like people of color being more likely to live in conditions that make preventing exposure difficult. And then you have specific ways in which people of color may not be treated equally once they get sick, or once they’re in a hospital.

Yes. The way that I frame things is what is called the eco-social theory of disease distribution, which asks the question “How do we embody our societal and ecological context?” And the thing about that is that our bodies could give a fig about how people want to parse things out and call this transportation-related, that related to housing, that related to the conditions in the schools, et cetera. Our thinking needs to be integrated, as we are living organisms who are biological and social, constantly interacting with the environs in which we live, which are both biophysical and also social. And it’s never an either/or. It’s always a both/and.

Can you talk about specifically some of the ways in which coronavirus data may be showing people of color being hurt disproportionately?

First, I want to step back and emphasize that the data are really inadequate right now. They are suggestive, but part of the problem is the drastic cuts to public health, and that ties to a framework that somehow one doesn’t need governance and public-health regulations in order to have healthy societies. And I think that this COVID-19 is manifestly showing why that is not the case. In public health, there may have been a lot of attention paid in certain ways to “preparedness,” but it’s also really important that this shows what the gaps are in public-health funding. Public-health workforces are depleted, and that’s part of why we have these extraordinary gaps in data. But it also doesn’t totally make sense, because some of the data that are missing are things that are routinely on death certificates, like race, ethnicity, sex, gender, age, and also education level. But the data are clearly showing racial and ethnic inequities.

From what we know about existing health disparities, what are some of the reasons that, once people of color contract the coronavirus, they are dying of it at higher rates than other groups?

There are two pieces to your question. There's one piece, which is what's going on in people's bodies—the conditions that they have when they present themselves to the health system. And then, given that they get to the health system, what happens to them? So, if a concern is how come they get a lot sicker and are more at risk of dying, some of it may not be about the medical care they receive but because they have so many so-called preëxisting conditions. For example, it's well documented that cardiovascular disease happens at earlier ages among people who are part of social groups subjected to discrimination and economic deprivation compared with people who are more privileged. It's the same disease, but it starts earlier. So one of the things that's happening is that someone who is fifty in a worse-off group can be biologically, in terms of what their health status is, like somebody who's seventy and in a more privileged group. People are getting infected at a point where there already are massive health inequities in things like diabetes, cardiovascular disease, like respiratory diseases. When you get COVID-19, those make you more likely to have worse mortality.

And what about once you show up in a hospital?

I don’t know right now, because people are on such emergency standing and doing what they can. The question is hospital crowding and hospital resources, as well as the interactions they’re having with hospital staff. So there’s a question of which hospitals now have sufficient ventilators. Separate from the question of what was being worked out and is still being worked out, for example, is who’s going to pay for all this? Who has health insurance that covers it? What’s going to happen with the costs? The tests are allegedly supposed to be covered and not cost anybody, but there was just an article today in my local newspaper, the Boston *Globe*, about someone being told that they had to pay for their COVID test, a Latinx woman who also didn’t speak English. And that’s a part that matters with some of the treatment issues: To what extent are hospital facilities able to deal with questions of translation?

I think a key point to get across is that there are two different kinds of inequities happening here. One is inequities in health status. The other’s an inequity in health care. And they’re not the same thing—they then collide with each other, and it’s much worse.

Without undermining anything you’re saying about how important it is to stress the interconnectedness of all these things, what are some smaller-scale things that could be done to ameliorate some of the disparities we are seeing with the coronavirus?

There has been a lot of activity among public-health people calling attention to people who are incarcerated and detained, whether it's for early release or whether it's about what the standards are for people who are basically in conditions that are not compatible with being safe from COVID-19. There are people who are advocating right now for making sure that there are the income supplements that go to all people. Those efforts are not overturning the entire system. They are about getting remedies right now in a way that the states actually can provide economic relief.

There are public-health actions that are being taken, in terms of doing good education that's not going to scare people, about how to help keep communities safe and how people can stay safe, and making that available in multiple languages. It's about helping to make sure that elderly people are being checked on, to make sure that nobody is isolated in their apartments or where they live. There's work that's being done imminently and immediately about attending to the needs and health issues of people who are homeless.

And, also, I think another important part where public health has helped is with regard to the fact that people are mandated or advised, depending on which state they live in, to shelter at home, but not everybody's home is a safe refuge. Homes are also a site of domestic violence and other kinds of abuse. And so there's been increased attention to what needs to happen with regard to support for domestic-violence hotlines, which have calls increasing. And also the calls to make sure that people who are now deemed essential workers—whether they are undocumented farm workers in California or people like grocery clerks—have sufficient protective equipment.

There was an interesting article in the *Times* saying, essentially, that you could be more vulnerable to coronavirus if you are in an area with bad air pollution.

My colleagues Francesca Dominici and Rachel Nethery, whom I'm working with, did that study. I've done research to show how residential segregation has a link to certain patterns of air pollution. So there's real neighborhood variation in air pollution, and there's more and more work that shows that different types of air pollution play a major role in cardiovascular disease, and also potentially birth outcomes. There's been huge literature on that. And that has to do with what kinds of roads people are living next to and transportation issues. There can be industrial pollution, as well, and that gets back to how different areas are zoned and what that means. There is a lot of literature that makes clear that even something that's ambient, literally floating around in the air, ends up being socially structured.

I recently came across the concept of "weathering." Can you explain to people what that is and how it might be manifesting itself here?

Weathering is a metaphor, an idea that was developed by a colleague, Arline Geronimus. And the idea behind that is similar to what I was saying to you before. She construed basically that there's faster aging among people who are worse off. That would be the simplest way to explain it. This gets back to the idea of the differences between biological age and chronological age, or how people are looking at different kinds of markers of accelerated aging. You can use markers based on epigenetics, for example. There are these things now called epigenetic clocks—you can actually look at places that are getting methylated on the DNA and see that people who are the same chronological age look like they have different epigenetic ages, and those clocks can be related in terms of both how much they correspond to chronological age and also to risk of mortality. So the idea is that just to say that somebody's fifty is not enough—you don't know what fifty means unless you know about the context. For example, to be fifty and to be someone who is very privileged is very different than being someone who is fifty and who has been working-class and belongs to a group that's subjected to racial discrimination. To be fifty in 1940 was still something else in terms of the kinds of health profiles that you could expect to see. So it's really disabusing people of the idea that there's this fundamental biology totally distinct from society. What you see, what you interact with, how you live is your phenotype. It's the way your biology is expressed in societal context.

A lot of people have become familiar recently with what epidemiology is and what an epidemiologist is. But what is the field of social epidemiology, and how would you define what it is you do, separate from anything involving the coronavirus?

Epidemiology is the study of the distribution and determinants of population health, with an eye toward gaining knowledge that can lead to interventions to make things better. That's a crude answer. It's not merely a descriptive science, the science that gets into causes—it's causes with an idea that you're trying to change that which you are studying. So that makes it very different than if you're studying the speed of light.

But there are different strands. There is clinical epidemiology, and that's looking into the impact of health services on health outcomes and can relate to trials of drugs, and it starts wandering off more to the field of medicine. In social epidemiology, you have a focus on what is key to understanding the societal exposures that matter for shaping population health. So social epidemiologists may be involved in doing policy-impact assessments, or health-equity-impact assessments. How does this policy end up affecting, for good or for bad, different groups in society? Others doing social epidemiology are focussed much more on studies that are based on individuals and looking at how their experiences of discrimination may be related to different kinds of biomarkers. But the key point is the fundamental claim that society and the way societies are structured by the people in them, not by random forces, are shaping the patterns of health in that society.

How far back do we have data on things that would be helpful to a social epidemiologist?

Epidemiology as a field earned its name in the seventeen-hundreds, in relation to infectious disease. But, in terms of concerns about the social aspects of health, I can take it back to the Hippocratic texts in 400 B.C.E., in Greece. I can take you back to texts that are even in some of the much earlier Egyptian documents, some of the first papyri about health, that link people's working conditions to their health. It's not a huge thing to ask people to observe that, if people are living under worse conditions and working in hard jobs, it's going to end up harming their health. And that's in the earliest texts that you find in medical literature.

In terms of social epidemiology as a field and public health, that really got born in the mid-eighteen-hundreds, and it was intimately involved with concerns about differential rates of infectious-disease outbreaks, but also mortality in relation to economic divides. I chair a caucus that I helped found within the American Public Health Association that's called the Spirit of 1848. And the reason that we chose that name is that it is fundamentally concerned about the links between social justice and public health, and 1848 was when England passed the first public-health act, which was the first time that anyone passed such national legislation setting up public-health boards. This was inspired, in part, by the cholera epidemics. It was fundamentally tied to questions or concerns of poverty, but there were real debates back then. Was poverty the cause of illness, or was immorality the cause of both poverty and illness?

So those kinds of debates are back then and they are now. But the thing is that 1848 was also a period of revolts throughout Europe. People who were working on suffrage, people who were working on abolition, were all making connections between the ways their societies were structured inequitably and what that meant for inequitable health outcomes. These are fundamental themes that are core to public health.

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Isaac Chotiner is a staff writer at The New Yorker, where he is the principal contributor to Q. & A., a series of interviews with major public figures in politics, media, books, business, technology, and more.

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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

Tori L. Cowger, MPH; Brigette A. Davis, MPH; Onisha S. Etkins, MS; Keletso Makofane, MPH; Jourdyn A. Lawrence, MSPH; Mary T. Bassett, MD, MPH; Nancy Krieger, PhD

Author affiliations and article information are listed at the end of this article.

Introduction

Surveillance and mortality data show large inequities in the impact of coronavirus disease 2019 (COVID-19) by race/ethnicity.[1] Currently, the US Centers for Disease Control and Prevention (CDC) does not report mortality rates by race/ethnicity. Instead, the percentage distribution of COVID-19 deaths by race/ethnicity is presented alongside a weighted distribution of the population from the CDC's National Center for Health Statistics,[2] which weights each county's population by its share of COVID-19 deaths, not population (**Figure**). We investigated whether the resulting magnitude of inequities using the weighted population underestimates those observed using the total population (unweighted).

Methods

This cross-sectional study used publicly available, aggregated data downloaded May 13, 2020.[2] Because the data were deidentified, institutional review board approval and informed consent were not required, in accordance with 45 CFR §46. This study follows the relevant portions of the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines.

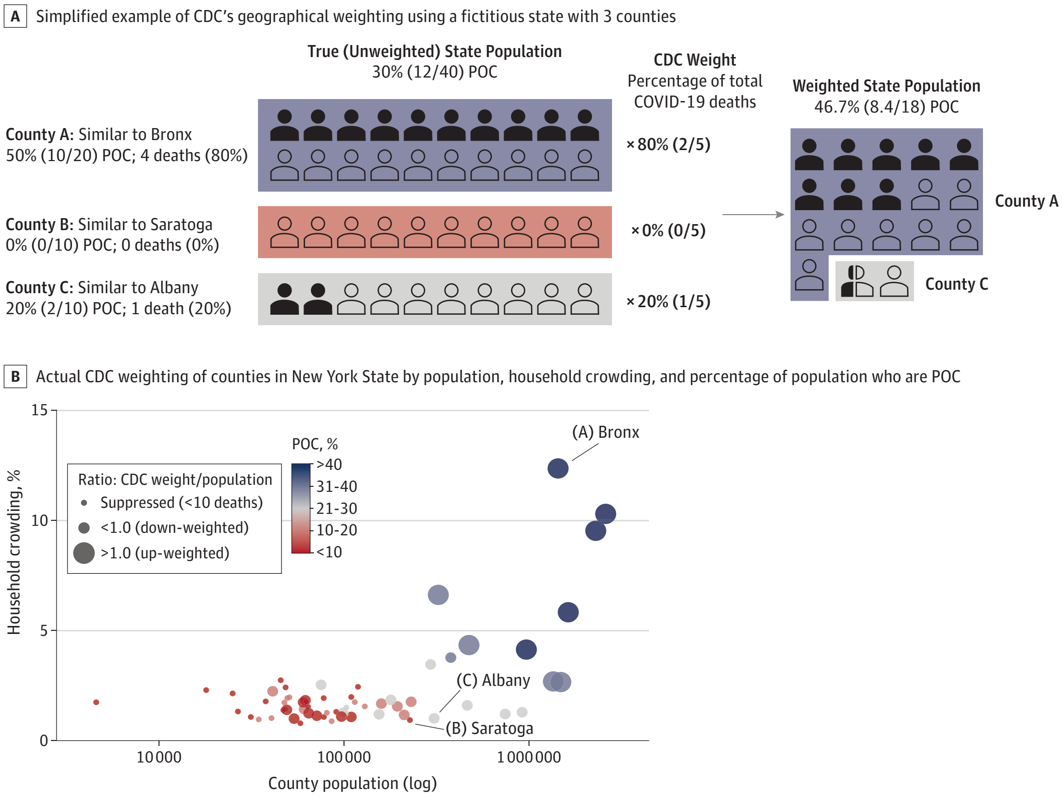
We compared the distribution of COVID-19 deaths by race/ethnicity with 2 separate population distributions provided by the CDC: National Center for Health Statistics weighted population and US Census unweighted population. Data analysis was performed from May to June 2020 using R statistical software version 3.6.3 (R Project for Statistical Computing).

Results

In total, 54 861 COVID-19 deaths were reported as of May 13, 2020. Applying the US Census population distribution, Black individuals were the most overrepresented among COVID-19 deaths, accounting for 9.9% greater than their share of the US Census population, whereas White individuals were underrepresented (−8.1%). In contrast, comparisons with the weighted data suggest that White individuals are most overrepresented among COVID-19 deaths (10.9%) (**Table**). Discrepancies were also noted when comparing deaths with the unweighted vs weighted populations among Latinx (−1.7% vs −10.2%) and Asian (0.1% vs −5.7%) individuals (Table).

The CDC's weighting approach inflates the proportion of residents of color in the weighted population, as shown in our hypothetical example in panel A of the Figure, where the state's true population is 30% people of color, but the CDC's weighted population is 46.7% people of color. For example, in New York, large urban counties with higher percentages of crowded households and residents of color are weighted more heavily compared with their share of the population than smaller, suburban, and rural counties, where residents are predominantly White, as shown in panel B of the Figure.

Figure. Examples of US Centers for Disease Control and Prevention (CDC) Geographical Population Weighting



The figure shows examples of CDC geographical population weighting using a fictitious state with 3 counties (A) and actual CDC weighting of counties in New York State (B) by population, household crowding, and percentage of county population who are people of color (POC). The impact of the CDC's method of geographical reweighting is demonstrated by juxtaposing the hypothetical example in panel A with actual county population data in panel B. By up-weighting counties such as county A (eg, Bronx), down-weighting counties such as county C (eg, Albany), and excluding counties such as county B (eg, Saratoga), the CDC inflates the proportion of residents of color in the weighted population, making their risk of death appear lower, while deflating the proportion of White residents, making their risk of death appear greater.

Table. Percentage Distribution by Race/Ethnicity for COVID-19 Deaths, CDC-NCHS–Weighted Population, and US Census Population and Absolute and Relative Differences Using Data as of May 13, 2020

	Distribution, %			Comparison with CDC-NCHS–weighted population		Comparison with US Census population (unweighted)	
Race/ethnicity[a]	COVID-19 deaths[b]	CDC-NCHS–weighted population	US Census population	Difference, %[c]	Ratio[d]	Difference, %[e]	Ratio[f]
American Indian and Alaska Native[g]	0.4	0.2	0.7	0.2[h]	2.00[h]	−0.3	0.57
Asian American	5.8	11.5	5.7	−5.7	0.50	0.1[h]	1.02[h]
Black	22.4	18.2	12.5	4.2[h]	1.23[h]	9.9[h]	1.79[h]
Latinx	16.6	26.8	18.3	−10.2	0.62	−1.7	0.91
Other race[i]	2.5	1.9	2.4	0.6[h]	1.32[h]	0.1[h]	1.04[h]
White	52.3	41.4	60.4	10.9[h]	1.26[h]	−8.1	0.87

Abbreviations: CDC, Centers for Disease Control and Prevention; COVID-19, coronavirus disease 2019; NCHS, National Center for Health Statistics.

[a] All racial/ethnic groups are shown directly as presented by the CDC in their weekly provisional death counts for COVID-19.

[b] In total, 54 861 COVID-19 deaths were reported to the CDC as of May 13, 2020.

[c] Percentage of COVID-19 deaths minus percentage CDC-NCHS–weighted population.

[d] Percentage of COVID-19 deaths divided by percentage CDC-NCHS–weighted population.

[e] Percentage of COVID-19 deaths minus percentage US Census population.

[f] Percentage of COVID-19 deaths divided by percentage US Census population.

[g] The American Indian and Alaska Native data should be viewed as likely inaccurate, given well-known issues with undercount of deaths and problems with US Census counts of these populations.

[h] Indicates an excess in absolute or relative COVID-19 mortality compared with the population distribution (ie, overrepresentation among COVID-19 deaths).

[i] Includes Native Hawaiian and other Pacific Islander, more than 1 race, race unknown, and Hispanic/Latinx origin unknown.

Discussion

Use of the CDC's weighted population distributions to evaluate racial/ethnic inequities in COVID-19 mortality underestimates the excess burden of COVID-19 among Black and Latinx individuals compared with analyses conducted using the total population (unweighted) in the US Census data. According to the CDC, weighting was conducted because "COVID-19 deaths are concentrated in certain geographic locations where the racial and ethnic population distribution differs from that of the United States overall."[2]

The indirect standardization procedure implemented by the CDC is misleading and obviates a key mechanism by which structural racism operates to produce health inequities: social segregation.[3] The CDC approach heavily weights large, urban counties because of their high proportion of COVID-19 deaths (eg, New York City) and excludes counties without any COVID-19 deaths (Figure). In effect, the CDC treats the geographical clustering of COVID-19 deaths as a nuisance parameter that must be controlled for to accurately compare the distribution of deaths across racial groups in the same geographical areas. However, the same mechanisms that pattern the geographical distribution of COVID-19 mortality also operate to produce racial/ethnic inequities in mortality.

From macrogeographical regions to microneighborhoods within cities, structural racism has determined the distribution of Black, Latinx, and Native American communities and is a key mechanism that produces and maintains inequities in infectious disease outcomes.[3-5] Specifically, historical and contemporary policies and processes, including land theft, racial terrorism, redlining, and gentrification, determine the location, quality, and density of residence for people of color.[3,5] Consequently, Black and Latinx individuals are clustered in the same high-density, urban locations hardest hit in the first months of the pandemic, with these areas weighted most heavily by the CDC's procedure (Figure). By adjusting for the geographical distribution of racial groups, the CDC effectively compares inequities that would remain had all racial and ethnic groups lived in the same geographical areas. Controlling for this major pathway understates COVID-19 mortality among Black, Latinx, and Asian individuals and overstates the burden among White individuals.

This study is limited by the fact that conclusions comparing inequities in weighted and unweighted populations may change as the epidemic evolves. However, as of July 7, 2020, the CDC's weighting method remains unchanged.

In summary, the CDC's presentation of data on race/ethnicity and COVID-19 deaths is misleading, with consequences for resource allocation for mitigating health inequities.[6] We urge the CDC to drop the misleading weighted counts and publish mortality rates per race/ethnicity group stratified by age, gender, education, and ZIP code characteristics[1] to adequately equip epidemiologists and policy makers with the data to mitigate inequities.

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Corresponding Author: Tori L. Cowger, MPH, FXB Center for Health and Human Rights, Harvard T.H. Chan School of Public Health, 677 Huntington Ave, Boston, MA 02115 (vcowger@g.harvard.edu).

Author Affiliations: FXB Center for Health and Human Rights, Harvard T.H. Chan School of Public Health, Boston, Massachusetts (Cowger, Davis, Etkins, Makofane, Lawrence, Bassett); Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, Massachusetts (Cowger); Population Health Sciences Department, Harvard Graduate School of Arts and Sciences, Cambridge, Massachusetts (Cowger, Davis, Etkins, Makofane, Lawrence); Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health, Boston, Massachusetts (Davis, Etkins, Makofane, Lawrence, Bassett, Krieger).

Author Contributions: Ms Cowger and Mr Makofane had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Ms Cowger, Ms Davis, Ms Etkins, Mr Makofane, and Ms Lawrence contributed equally to this work.

Concept and design: Cowger, Davis, Etkins, Makofane, Bassett, Krieger.

Acquisition, analysis, or interpretation of data: Cowger, Davis, Etkins, Lawrence.

Drafting of the manuscript: Cowger, Davis, Etkins, Makofane, Lawrence, Krieger.

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Statistical analysis: Cowger, Davis.

Administrative, technical, or material support: Davis, Etkins, Lawrence.

Supervision: Bassett, Krieger.

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Working Paper Series

COVID-19 and the unequal surge in mortality rates in Massachusetts, by city/town and ZIP Code measures of poverty, household crowding, race/ethnicity,and racialized economic segregation

Jarvis T. Chen, ScD[1], Pamela D. Waterman, MPH[2], Nancy Krieger, PhD[3]

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Affiliations

1. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

2. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

3. Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

Corresponding Author

Nancy Krieger, PhD
Professor of Social Epidemiology
American Cancer Society Clinical Research Professor
Department of Social and Behavioral Sciences
Harvard T.H. Chan School of Public Health
677 Huntington Avenue
Boston, MA 02115
Email: nkrieger@hsph.harvard.edu

Abstract

Despite the paucity of adequate data on race/ethnicity – and no data on socioeconomic position – in US national data on COVID-19 mortality, both investigative journalism and some state and local health departments are beginning to document evidence of the greater mortality burden of COVID-19 on communities of color and low-income communities. To date, such documentation has been in relation to deaths categorized as due to COVID-19. However, in a context when assignment of cause of death to COVID-19 is dynamic and incomplete, given developing scientific evidence, one important strategy for assessing differential impacts of COVID-19 is that of evaluating the overall excess of deaths, as compared to the same time period in prior years. We employ this approach in this working paper and provide a transparent, easy-to-replicate methodology that relies on the reported data (i.e., no model-based estimates or complex modeling assumptions) and that can be readily used by any local or state health agency to monitor the social patterning of excess mortality rates during the COVID-19 pandemic. Key findings are that the surge in excess death rates, both relative and absolute, was evident starting in early April, and was greater in city/towns and ZCTAs with higher poverty, higher household crowding, higher percentage of populations of color, and higher racialized economic segregation. These data provide the backbone to a story that is being published in the Boston Globe, with this Working Paper released following publication of this story (on May 9, 2020), available at: https://www.bostonglobe.com/2020/05/09/nation/disparities-push-coronavirus-death-rates-higher/

Title: COVID-19 and the unequal surge in mortality rates in Massachusetts, by city/town and ZIP Code measures of poverty, household crowding, race/ethnicity, and racialized economic segregation

Authors: Jarvis T. Chen, ScD
Pamela D. Waterman, MPH
Nancy Krieger, PhD

Corresponding author:
Nancy Krieger, PhD
Professor of Social Epidemiology
American Cancer Society Clinical Research Professor
Department of Social and Behavioral Sciences
Harvard T.H. Chan School of Public Health
677 Huntington Avenue
Boston, MA 02115
Email: nkrieger@hsph.harvard.edu

ABSTRACT

Despite the paucity of adequate data on race/ethnicity – and no data on socioeconomic position – in US national data on COVID-19 mortality, both investigative journalism and some state and local health departments are beginning to document evidence of the greater mortality burden of COVID-19 on communities of color and low-income communities. To date, such documentation has been in relation to deaths categorized as due to COVID-19. However, in a context when assignment of cause of death to COVID-19 is dynamic and incomplete, given developing scientific evidence, one important strategy for assessing differential impacts of COVID-19 is that of evaluating the overall excess of deaths, as compared to the same time period in prior years. We employ this approach in this working paper and provide a transparent, easy-to-replicate methodology that relies on the reported data (i.e., no model-based estimates or complex modeling assumptions) and that can be readily used by any local or state health agency to monitor the social patterning of excess mortality rates during the COVID-19 pandemic. Key findings are that the surge in excess death rates, both relative and absolute, was evident starting in early April, and was greater in city/towns and ZCTAs with higher poverty, higher household crowding, higher percentage of populations of color, and higher racialized economic segregation. These data provide the backbone to a story that is being published in the *Boston Globe*, with this Working Paper released following publication of this story (on May 9, 2020), available at: https://www.bostonglobe.com/2020/05/09/nation/disparities-push-coronavirus-death-rates-higher/

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Author contributions: NK and JTC conceptualized the study; NK led data acquisition and contributed to framing the study; JTC led analytic design, conducted the data analysis, and led drafting the methods; PDW contributed to generating the area-based socio-economic measures (ABSMs); all authors contributed to interpreting the results and approve the final version of this working paper.

INTRODUCTION

Despite the paucity of adequate data on race/ethnicity – and no data on socioeconomic position – in US national data on COVID-19 mortality [1-7], both investigative journalism and some state and local health departments are beginning to document evidence of the greater mortality burden of COVID-19 on communities of color and low-income communities [3-6]. To date, such documentation has been in relation to deaths categorized as due to COVID-19. However, in a context when assignment of cause of death to COVID-19 is dynamic and incomplete, given developing scientific evidence, one important strategy for assessing differential impacts of COVID-19 is that of evaluating the overall excess of deaths, as compared to the same time period in prior years [8]. At issue is capturing not only deaths due to COVID-19 that have been misclassified but also other deaths attributable to the COVID-19 pandemic even if not directly caused by infection by the SARS-COV-2 virus (e.g., deaths due to domestic violence as people are mandated to stay-at-home).

We employ this approach in this working paper and provide a transparent, easy-to-replicate methodology that relies on the reported data (i.e., no model-based estimates or complex modeling assumptions) and that can be readily used by any local or state health agency to monitor the social patterning of excess mortality rates during the COVID-19 pandemic. We emphasize that we focus on excess deaths in relation to age-standardized death rates, not counts of deaths, because the former provide a more accurate gauge of whether social group death rates differ above and beyond their age composition and also their pre-existing rates of mortality, both of which are themselves socially determined [9].

Finally, we note that we share the data in this Working Paper as a complement to the extensive story being published in the *Boston Globe* [10] – with the release of our Working Paper timed to occur after this story is published. The *Boston Globe* reporters both humanize and interpret the data we have generated in discussion with them, in a collaboration forged when one author (NK) reached out to them, on April 24, 2020, having read one of their prior stories about COVID-19 mortality in Massachusetts [11]. That discussion led to The *Boston Globe* sharing with our team the Massachusetts mortality data we have analyzed in this Working Paper. We refer the readers of this Working Paper to the *Boston Globe* article for discussion of our findings and their real-world significance [10].

Our next steps will be to refine the descriptive analyses we present here in two ways. The first is that we have been geocoding the records employed for this study to the census tract level, and we will use the census tract social indicators in our next iteration of this research project. Second, we will also employ more sophisticated statistical models.

METHODS

Data Sources

With the assistance of the *Boston Globe*, we obtained provisional records of all deaths for January 1-April 15 from the Massachusetts Vital Statistics Registry Fact of Death files for 2015-2020. These records included data on the age and sex/gender of the decedents, but not their race/ethnicity, education, or occupation, despite the latter three variables being standard components of death certificate data.

The total number of deaths for the specified time periods (Jan 1 – April 15) was 16,266 for 2020 and 75,842 for 2015-2019. We obtained population estimates by age and sex from the 2014-2018 American Community Survey (ACS) Table B01001. Data on area-based socioeconomic measures (ABSMs) were extracted from the ACS at the ZCTA and census tract (CT) level. To obtain city/town ABSM estimates, we aggregated CT level data to the city/town level for 291 city/towns. For a sixty Massachusetts city/towns, however, multiple towns are located within a single CT. For these towns, we aggregated towns within the same CT and assigned the resulting composite town the ABSMs of the CT (resulting in 21 composite towns). For all analyses, we similarly analyzed deaths and population at risk for the composite town entity (affecting 203 deaths in 2020; 823 deaths in 2015-2019).

Area-based socioeconomic measures

ZCTA and city/town 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 [12]. 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 Non-Hispanic population, versus (b) low-income population of color (i.e. not white non-Hispanic) [12]. 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 ZCTA or city/town attributes in Massachusetts (weighted by population size). Definitions and source variables from the ACS are as follows:

Variable	**Formula: Source Variables**
Population Counts	
Total population	B01003_001E
White Non-Hispanic Population	B01001H_001E
Area-based socioeconomic measures	
% of persons below poverty	B17001_002E/B17001_001E

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,
% crowding (>1 person per room)	(B25014_005E + B25014_006E + B25014_007E + B25014_011E + B25014_012E + B25014_013E) / B25014_001E
% population of color (not White Non-Hispanic)	B01003_001E - B01001H_001E)/ B01003_001E

Statistical Analyses

Aggregated method. Using methods of the Public Health Disparities Geocoding Project, we linked death records to ZCTA or city/town socioeconomic characteristics by ZIP code of residence and city/town as recorded in the Fact of Death files. Note that not all postal ZIP codes have a corresponding ZCTA in the US Census files. There were 62 deaths (0.4% of total) from 2020 and 366 deaths (0.5% of total) from 2015-2019 that were unmatched for this reason. We aggregated deaths by ZCTA or city/town, age category, and gender, and linked them to stratified population estimates from the 2014-2018 American Community Survey and ZCTA or city/town ABSMs.

For 2020 and 2015-2019 data, we then computed all-cause age-standardized mortality rates overall and by categories of ABSMs for two-week periods beginning January 8 and ending April 14, using the year 2000 standard million age standard. To compare 2020 rates to average rates based on 2015-2019 data for the same periods, we calculated age-standardized rate differences and rate ratios. We computed 95% confidence limits for age-standardized rates, rate differences, and rate ratios using standard formulae [13].

RESULTS: see list of Tables & Figures, provided after the References.

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Figure 5e: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town % population of color, 2020 vs. 2015−2019, Jan 8−April 14

Table 1: Age standardized mortality rate per 100,000 person-years for 2015-2019 and 2020, by two week period, for total population and by sex; and crude mortality rate per 100,000 person-years by age category (0-64, 65-79, 80+), Massachusetts

	Period	Age-standardized mortality rate (2015-2019)	(95% CI)	Age-standardized mortality rate (2020)	(95% CI)	Age-standardized rate difference (2020 vs. 2015-2019)	(95% CI)		Age-standardized rate ratio (2020 vs. 2015-2019)	(95% CI)
Total population										
	01-08 to 01-21	657.5	(564.9 , 750.2)	637.2	(545.8 , 728.5)	-20.4	-150.5	109.1	0.97	(0.79 , 1.18)
	01-22 to 02-04	646.1	(554.3 , 737.9)	626.5	(535.4 , 717.5)	-19.6	-148.9	109.0	0.97	(0.79 , 1.19)
	02-05 to 02-18	651.0	(558.7 , 743.3)	643.2	(551.4 , 735.0)	-7.8	-138.0	121.7	0.99	(0.81 , 1.21)
	02-19 to 03-03	574.1	(488.0 , 660.2)	579.9	(495.1 , 664.6)	5.8	-115.0	126.0	1.01	(0.82 , 1.24)
	03-04 to 03-17	607.8	(518.6 , 696.9)	625.8	(535.3 , 716.3)	18.0	-109.0	144.4	1.03	(0.84 , 1.26)
	03-18 to 03-31	599.8	(511.2 , 688.5)	653.6	(560.5 , 746.7)	53.7	-74.8	181.7	1.09	(0.89 , 1.34)
	04-01 to 04-14	609.1	(519.5 , 698.7)	919.5	(810.2 , 1028.8)	310.4	169.1	451.0	1.51	(1.25 , 1.82)
Sex										
female	01-08 to 01-21	550.8	(440.6 , 660.9)	535.6	(425.7 , 645.5)	-15.2	-170.8	139.7	0.97	(0.73 , 1.29)
	01-22 to 02-04	549.0	(438.7 , 659.4)	501.5	(395.2 , 607.7)	-47.6	-200.7	104.9	0.91	(0.68 , 1.22)
	02-05 to 02-18	547.3	(436.9 , 657.7)	528.2	(419.8 , 636.7)	-19.0	-173.8	135.0	0.97	(0.72 , 1.29)
	02-19 to 03-03	479.6	(377.4 , 581.7)	464.3	(366.0 , 562.6)	-15.2	-157.0	125.8	0.97	(0.72 , 1.31)
	03-04 to 03-17	503.4	(397.6 , 609.1)	548.9	(438.6 , 659.3)	45.6	-107.3	197.7	1.09	(0.82 , 1.46)
	03-18 to 03-31	504.3	(398.2 , 610.5)	549.6	(438.6 , 660.7)	45.3	-108.3	198.2	1.09	(0.81 , 1.46)
	04-01 to 04-14	501.1	(395.0 , 607.1)	742.3	(615.3 , 869.2)	241.2	75.7	405.8	1.48	(1.13 , 1.94)
male	01-08 to 01-21	776.3	(618.5 , 934.1)	752.6	(597.9 , 907.3)	-23.7	-244.7	196.2	0.97	(0.73 , 1.29)
	01-22 to 02-04	753.8	(598.5 , 909.0)	776.6	(618.3 , 934.9)	22.8	-198.9	243.4	1.03	(0.77 , 1.37)
	02-05 to 02-18	769.4	(612.3 , 926.4)	770.6	(613.7 , 927.5)	1.3	-220.8	222.1	1.00	(0.75 , 1.33)
	02-19 to 03-03	676.7	(530.3 , 823.1)	712.5	(565.8 , 859.3)	35.8	-171.4	242.0	1.05	(0.78 , 1.42)
	03-04 to 03-17	731.2	(578.2 , 884.3)	693.3	(544.8 , 841.8)	-37.9	-251.2	174.2	0.95	(0.70 , 1.28)
	03-18 to 03-31	705.7	(555.4 , 856.0)	764.4	(607.2 , 921.6)	58.7	-158.8	275.1	1.08	(0.81 , 1.45)
	04-01 to 04-14	734.5	(580.9 , 888.0)	1139.9	(947.6 , 1332.3)	405.5	159.3	650.3	1.55	(1.19 , 2.03)
Age*										

Age0-64	01-08 to 01-21	197.5	(178.9 , 216.0)	186.9	(168.8 , 204.9)	-10.6	-36.5	15.1	0.95	(0.83 , 1.08)
	01-22 to 02-04	196.4	(177.9 , 214.9)	193.2	(174.9 , 211.6)	-3.2	-29.2	22.7	0.98	(0.86 , 1.12)
	02-05 to 02-18	195.2	(176.8 , 213.7)	191.9	(173.6 , 210.1)	-3.4	-29.3	22.5	0.98	(0.86 , 1.12)
	02-19 to 03-03	172.6	(155.4 , 189.8)	164.7	(148.3 , 181.0)	-7.9	-31.7	15.7	0.95	(0.83 , 1.10)
	03-04 to 03-17	187.5	(169.4 , 205.6)	188.2	(170.1 , 206.3)	0.7	-24.9	26.2	1.00	(0.88 , 1.15)
	03-18 to 03-31	194.9	(176.4 , 213.3)	195.0	(176.6 , 213.5)	0.2	-25.9	26.1	1.00	(0.88 , 1.14)
	04-01 to 04-14	196.6	(178.1 , 215.1)	213.2	(193.9 , 232.5)	16.6	-10.1	43.2	1.08	(0.95 , 1.23)
Age65-79	01-08 to 01-21	1693.1	(1546.5 , 1839.7)	1652.8	(1507.9 , 1797.6)	-40.3	-246.5	164.7	0.98	(0.86 , 1.10)
	01-22 to 02-04	1601.2	(1458.6 , 1743.8)	1699.1	(1552.2 , 1845.9)	97.8	-106.9	301.5	1.06	(0.94 , 1.20)
	02-05 to 02-18	1691.1	(1544.6 , 1837.7)	1814.7	(1662.9 , 1966.6)	123.6	-87.4	333.5	1.07	(0.95 , 1.21)
	02-19 to 03-03	1471.1	(1335.4 , 1606.8)	1721.5	(1578.7 , 1864.4)	250.4	53.4	446.4	1.17	(1.03 , 1.32)
	03-04 to 03-17	1593.9	(1451.7 , 1736.2)	1751.9	(1602.8 , 1901.1)	158.0	-48.1	363.1	1.10	(0.97 , 1.24)
	03-18 to 03-31	1505.3	(1367.1 , 1643.6)	1851.1	(1697.8 , 2004.4)	345.8	139.3	551.2	1.23	(1.09 , 1.39)
	04-01 to 04-14	1603.9	(1461.1 , 1746.6)	2637.8	(2454.8 , 2820.9)	1034.0	801.9	1264.9	1.64	(1.47 , 1.84)
Age80+	01-08 to 01-21	10319.5	(9721.3 , 10917.8)	10039.7	(9449.6 , 10629.7)	-279.9	-1120.2	556.1	0.97	(0.90 , 1.06)
	01-22 to 02-04	10310.5	(9712.5 , 10908.5)	9317.4	(8748.9 , 9885.8)	-993.1	-1818.2	-172.3	0.90	(0.83 , 0.98)
	02-05 to 02-18	10180.5	(9586.3 , 10774.7)	9516.0	(8941.5 , 10090.5)	-664.5	-1491.0	157.8	0.93	(0.86 , 1.02)
	02-19 to 03-03	8986.8	(8432.4 , 9541.1)	8435.0	(7912.4 , 8957.5)	-551.8	-1313.6	206.2	0.94	(0.86 , 1.02)
	03-04 to 03-17	9404.0	(8832.9 , 9975.2)	9443.8	(8871.5 , 10016.1)	39.7	-768.8	844.1	1.00	(0.92 , 1.09)
	03-18 to 03-31	9237.9	(8671.9 , 9804.0)	9633.4	(9055.3 , 10211.4)	395.4	-413.6	1200.3	1.04	(0.96 , 1.14)
	04-01 to 04-14	9107.9	(8545.9 , 9670.0)	15068.5	(14345.6 , 15791.4)	5960.6	5044.9	6871.6	1.65	(1.53 , 1.79)

* not age-standardized

Statistically significant excess mortality labelled in red.

Table 2: Age standardized mortality rate per 100,000 person-years for 2015-2019 and 2020, by two week period and ZCTA ABSM, with age-standardied rate differences and rate ratios and 95% confidence limits comparing 2020 period to 2015-2019 period, Massachusetts

ZCTA ABSM category	Two-week period	Age-standardized mortality rate (2015-2019)	(95% CI)	Age-standardized mortality rate (2020)	(95% CI)	Age-standardized rate difference (2020 vs. 2015-2019)	(95% CI)	Age-standardized rate ratio (2020 vs. 2015-2019)	(95% CI)
% below poverty									
0-4.9%	01-08 to 01-21	588.0	(427.8 , 748.2)	554.0	(398.8 , 709.2)	-34.0	-(257.0 , 187.9)	0.94	(0.64 , 1.39)
0-4.9%	01-22 to 02-04	563.9	(407.3 , 720.5)	539.3	(385.7 , 692.9)	-24.6	-(243.9 , 193.6)	0.96	(0.64 , 1.42)
0-4.9%	02-05 to 02-18	570.5	(413.0 , 727.9)	592.9	(432.7 , 753.1)	22.4	-(202.2 , 245.9)	1.04	(0.71 , 1.53)
0-4.9%	02-19 to 03-03	514.9	(365.8 , 664.0)	537.3	(384.8 , 689.8)	22.5	-(190.8 , 234.6)	1.04	(0.70 , 1.56)
0-4.9%	03-04 to 03-17	539.7	(386.6 , 692.7)	586.1	(427.6 , 744.6)	46.4	-(173.9 , 265.6)	1.09	(0.73 , 1.60)
0-4.9%	03-18 to 03-31	506.8	(357.9 , 655.6)	565.7	(408.6 , 722.9)	59.0	-(157.4 , 274.3)	1.12	(0.75 , 1.67)
0-4.9%	04-01 to 04-14	537.1	(383.4 , 690.7)	801.6	(616.8 , 986.4)	264.6	(24.2 , 503.7)	1.49	(1.03 , 2.15)
5-9.9%	01-08 to 01-21	642.5	(481.6 , 803.5)	658.8	(496.0 , 821.7)	16.3	-(212.6 , 244.1)	1.03	(0.72 , 1.46)
5-9.9%	01-22 to 02-04	618.6	(461.3 , 775.9)	628.8	(467.7 , 789.9)	10.1	-(215.0 , 234.1)	1.02	(0.71 , 1.46)
5-9.9%	02-05 to 02-18	623.4	(464.6 , 782.3)	589.2	(436.7 , 741.7)	-34.2	-(254.5 , 184.9)	0.95	(0.66 , 1.36)
5-9.9%	02-19 to 03-03	559.9	(410.3 , 709.5)	567.2	(415.9 , 718.6)	7.3	-(205.5 , 219.0)	1.01	(0.69 , 1.47)
5-9.9%	03-04 to 03-17	584.2	(430.4 , 737.9)	598.6	(443.2 , 754.1)	14.4	-(204.2 , 231.9)	1.02	(0.71 , 1.48)
5-9.9%	03-18 to 03-31	592.6	(438.2 , 747.0)	625.9	(467.3 , 784.4)	33.3	-(188.1 , 253.4)	1.06	(0.73 , 1.52)
5-9.9%	04-01 to 04-14	582.0	(427.8 , 736.2)	915.4	(723.6 , 1107.2)	333.4	(87.3 , 578.2)	1.57	(1.12 , 2.20)
10-19.9%	01-08 to 01-21	687.9	(505.2 , 870.5)	627.6	(452.8 , 802.3)	-60.3	-(313.1 , 191.2)	0.91	(0.62 , 1.34)
10-19.9%	01-22 to 02-04	696.3	(512.4 , 880.2)	660.4	(480.9 , 839.8)	-36.0	-(293.0 , 219.7)	0.95	(0.65 , 1.38)
10-19.9%	02-05 to 02-18	693.7	(510.1 , 877.2)	678.4	(495.2 , 861.6)	-15.3	-(274.6 , 242.7)	0.98	(0.67 , 1.42)
10-19.9%	02-19 to 03-03	616.7	(443.0 , 790.5)	687.0	(502.0 , 872.1)	70.3	-(183.5 , 322.8)	1.11	(0.75 , 1.64)
10-19.9%	03-04 to 03-17	639.0	(462.8 , 815.2)	647.0	(469.0 , 824.9)	8.0	-(242.4 , 257.1)	1.01	(0.69 , 1.49)
10-19.9%	03-18 to 03-31	627.0	(452.3 , 801.7)	722.6	(533.9 , 911.3)	95.6	-(161.5 , 351.5)	1.15	(0.79 , 1.69)
10-19.9%	04-01 to 04-14	647.3	(469.2 , 825.4)	955.1	(740.2 , 1170.1)	307.8	(28.7 , 585.6)	1.48	(1.03 , 2.10)
20-100%	01-08 to 01-21	718.8	(416.3 , 1021.3)	753.5	(440.2 , 1066.7)	34.7	-(400.8 , 467.9)	1.05	(0.58 , 1.89)
20-100%	01-22 to 02-04	731.2	(425.9 , 1036.6)	707.6	(405.2 , 1009.9)	-23.6	-(453.3 , 403.9)	0.97	(0.53 , 1.75)
20-100%	02-05 to 02-18	750.0	(439.9 , 1060.1)	745.5	(436.3 , 1054.7)	-4.5	-(442.4 , 431.2)	0.99	(0.55 , 1.78)
20-100%	02-19 to 03-03	644.1	(356.8 , 931.5)	758.6	(444.9 , 1072.3)	114.5	-(310.9 , 537.8)	1.18	(0.64 , 2.16)

20-100%	03-04 to 03-17	699.9	(401.0 , 998.9)	672.2	(380.0 , 964.4)	-27.7	-(445.7 , 388.2)	0.96	(0.52 , 1.76)
20-100%	03-18 to 03-31	712.9	(410.6 , 1015.1)	696.1	(392.0 , 1000.1)	-16.8	-(445.5 , 409.7)	0.98	(0.53 , 1.79)
20-100%	04-01 to 04-14	707.8	(406.7 , 1008.8)	1070.0	(701.3 , 1438.8)	362.3	-(113.7 , 835.9)	1.51	(0.87 , 2.61)
% crowding									
(0,0.00625]	01-08 to 01-21	592.1	(370.0 , 814.1)	543.6	(333.3 , 753.9)	-48.5	-(354.3 , 255.8)	0.92	(0.54 , 1.57)
(0,0.00625]	01-22 to 02-04	578.3	(358.7 , 797.8)	563.1	(343.9 , 782.4)	-15.1	-(325.4 , 293.6)	0.97	(0.57 , 1.67)
(0,0.00625]	02-05 to 02-18	565.4	(350.2 , 780.6)	583.1	(365.0 , 801.3)	17.7	-(288.7 , 322.6)	1.03	(0.60 , 1.75)
(0,0.00625]	02-19 to 03-03	517.8	(310.9 , 724.7)	543.4	(331.8 , 755.0)	25.6	-(270.3 , 320.0)	1.05	(0.60 , 1.83)
(0,0.00625]	03-04 to 03-17	530.8	(319.7 , 741.9)	640.1	(410.8 , 869.5)	109.3	-(202.4 , 419.5)	1.21	(0.71 , 2.05)
(0,0.00625]	03-18 to 03-31	514.3	(308.0 , 720.6)	560.3	(349.3 , 771.3)	46.0	-(249.2 , 339.6)	1.09	(0.63 , 1.88)
(0,0.00625]	04-01 to 04-14	546.8	(331.9 , 761.8)	830.2	(570.9 , 1089.4)	283.3	-(53.4 , 618.4)	1.52	(0.92 , 2.50)
(0.00625,0.0116]	01-08 to 01-21	641.7	(445.6 , 837.7)	626.4	(432.3 , 820.5)	-15.2	-(291.1 , 259.2)	0.98	(0.63 , 1.51)
(0.00625,0.0116]	01-22 to 02-04	603.7	(413.9 , 793.5)	649.8	(452.7 , 847.0)	46.1	-(227.5 , 318.4)	1.08	(0.70 , 1.66)
(0.00625,0.0116]	02-05 to 02-18	630.3	(435.7 , 824.9)	600.4	(411.8 , 788.9)	-29.9	-(300.9 , 239.6)	0.95	(0.61 , 1.48)
(0.00625,0.0116]	02-19 to 03-03	578.5	(391.9 , 765.0)	600.1	(408.7 , 791.5)	21.6	-(245.7 , 287.6)	1.04	(0.66 , 1.63)
(0.00625,0.0116]	03-04 to 03-17	594.9	(405.3 , 784.6)	588.9	(400.9 , 777.0)	-6.0	-(273.1 , 259.7)	0.99	(0.63 , 1.55)
(0.00625,0.0116]	03-18 to 03-31	567.2	(382.0 , 752.3)	641.1	(442.0 , 840.3)	74.0	-(197.9 , 344.5)	1.13	(0.72 , 1.77)
(0.00625,0.0116]	04-01 to 04-14	600.8	(409.0 , 792.7)	815.1	(594.8 , 1035.5)	214.3	-(77.8 , 505.0)	1.36	(0.89 , 2.06)
(0.0116,0.0189]	01-08 to 01-21	636.9	(438.0 , 835.9)	612.8	(417.1 , 808.5)	-24.1	-(303.2 , 253.5)	0.96	(0.62 , 1.50)
(0.0116,0.0189]	01-22 to 02-04	625.6	(428.1 , 823.1)	575.4	(383.0 , 767.8)	-50.2	-(326.0 , 224.1)	0.92	(0.58 , 1.45)
(0.0116,0.0189]	02-05 to 02-18	636.7	(436.5 , 836.9)	610.2	(414.1 , 806.3)	-26.5	-(306.7 , 252.3)	0.96	(0.61 , 1.50)
(0.0116,0.0189]	02-19 to 03-03	570.0	(381.0 , 758.9)	589.1	(396.4 , 781.7)	19.1	-(250.8 , 287.6)	1.03	(0.65 , 1.64)
(0.0116,0.0189]	03-04 to 03-17	568.6	(380.2 , 757.1)	642.7	(442.0 , 843.4)	74.0	-(201.3 , 347.9)	1.13	(0.72 , 1.78)
(0.0116,0.0189]	03-18 to 03-31	607.3	(411.4 , 803.2)	618.4	(422.1 , 814.6)	11.1	-(266.3 , 287.0)	1.02	(0.65 , 1.60)
(0.0116,0.0189]	04-01 to 04-14	584.4	(392.4 , 776.5)	861.7	(628.8 , 1094.6)	277.3	-(24.7 , 577.6)	1.47	(0.96 , 2.25)
(0.0189,0.0309]	01-08 to 01-21	659.3	(441.3 , 877.2)	638.1	(423.5 , 852.8)	-21.1	-(327.0 , 283.2)	0.97	(0.60 , 1.55)
(0.0189,0.0309]	01-22 to 02-04	667.8	(449.5 , 886.1)	610.3	(398.3 , 822.3)	-57.5	-(361.8 , 245.2)	0.91	(0.57 , 1.47)
(0.0189,0.0309]	02-05 to 02-18	638.2	(423.6 , 852.8)	646.1	(430.5 , 861.7)	7.9	-(296.3 , 310.5)	1.01	(0.63 , 1.62)
(0.0189,0.0309]	02-19 to 03-03	571.5	(369.9 , 773.0)	612.7	(400.7 , 824.6)	41.2	-(251.3 , 332.2)	1.07	(0.65 , 1.75)
(0.0189,0.0309]	03-04 to 03-17	610.4	(401.1 , 819.6)	593.4	(386.7 , 800.0)	-17.0	-(311.1 , 275.6)	0.97	(0.60 , 1.58)
(0.0189,0.0309]	03-18 to 03-31	607.7	(399.5 , 815.9)	664.2	(443.1 , 885.3)	56.5	-(247.2 , 358.7)	1.09	(0.68 , 1.76)
(0.0189,0.0309]	04-01 to 04-14	600.9	(392.5 , 809.2)	946.6	(686.1 , 1207.0)	345.7	(12.1 , 677.6)	1.58	(1.01 , 2.45)

(0.0309,0.454]	01-08 to 01-21	703.3	(467.1 , 939.4)	650.2	(422.0 , 878.4)	-53.1	-(381.5 , 273.6)	0.92	(0.57 , 1.50)
(0.0309,0.454]	01-22 to 02-04	718.0	(479.0 , 956.9)	713.6	(475.7 , 951.6)	-4.3	-(341.6 , 331.2)	0.99	(0.62 , 1.59)
(0.0309,0.454]	02-05 to 02-18	737.0	(494.8 , 979.2)	709.3	(471.7 , 946.8)	-27.8	-(367.0 , 309.7)	0.96	(0.60 , 1.53)
(0.0309,0.454]	02-19 to 03-03	627.8	(404.2 , 851.3)	744.7	(499.6 , 989.8)	116.9	-(214.8 , 447.0)	1.19	(0.73 , 1.92)
(0.0309,0.454]	03-04 to 03-17	675.5	(444.5 , 906.4)	654.1	(426.5 , 881.7)	-21.4	-(345.7 , 301.2)	0.97	(0.59 , 1.57)
(0.0309,0.454]	03-18 to 03-31	663.6	(434.0 , 893.2)	738.9	(493.4 , 984.4)	75.3	-(260.9 , 409.7)	1.11	(0.69 , 1.79)
(0.0309,0.454]	04-01 to 04-14	675.1	(442.9 , 907.3)	1173.6	(868.0 , 1479.2)	498.5	(114.7 , 880.4)	1.74	(1.13 , 2.67)
Index of Concentration at the Extremes (high income white non-Hispanic vs. low income people of color)									
(-0.531,0.0648]	01-08 to 01-21	732.4	(480.4 , 984.5)	709.2	(458.9 , 959.5)	-23.2	-(378.4 , 330.1)	0.97	(0.59 , 1.58)
(-0.531,0.0648]	01-22 to 02-04	720.8	(471.0 , 970.6)	707.1	(459.0 , 955.3)	-13.7	-(365.8 , 336.6)	0.98	(0.60 , 1.60)
(-0.531,0.0648]	02-05 to 02-18	741.3	(487.5 , 995.1)	736.0	(484.9 , 987.1)	-5.3	-(362.3 , 349.9)	0.99	(0.61 , 1.61)
(-0.531,0.0648]	02-19 to 03-03	647.3	(410.0 , 884.5)	807.7	(540.0 , 1075.5)	160.5	-(197.2 , 516.4)	1.25	(0.76 , 2.04)
(-0.531,0.0648]	03-04 to 03-17	686.3	(443.1 , 929.4)	658.9	(421.5 , 896.4)	-27.3	-(367.2 , 310.8)	0.96	(0.58 , 1.59)
(-0.531,0.0648]	03-18 to 03-31	704.8	(457.3 , 952.4)	698.4	(448.8 , 948.0)	-6.4	-(357.9 , 343.3)	0.99	(0.60 , 1.63)
(-0.531,0.0648]	04-01 to 04-14	690.8	(445.6 , 936.0)	1144.1	(829.0 , 1459.2)	453.3	(54.0 , 850.5)	1.66	(1.06 , 2.59)
(0.0648,0.265]	01-08 to 01-21	692.4	(484.7 , 900.2)	661.7	(457.7 , 865.7)	-30.7	-(321.9 , 258.9)	0.96	(0.62 , 1.47)
(0.0648,0.265]	01-22 to 02-04	717.8	(506.0 , 929.6)	682.1	(474.6 , 889.6)	-35.7	-(332.2 , 259.3)	0.95	(0.62 , 1.45)
(0.0648,0.265]	02-05 to 02-18	698.8	(490.1 , 907.6)	694.8	(484.0 , 905.5)	-4.1	-(300.7 , 291.0)	0.99	(0.65 , 1.52)
(0.0648,0.265]	02-19 to 03-03	653.6	(451.0 , 856.1)	649.5	(446.2 , 852.8)	-4.1	-(291.1 , 281.4)	0.99	(0.64 , 1.54)
(0.0648,0.265]	03-04 to 03-17	666.6	(462.1 , 871.0)	691.3	(481.6 , 901.0)	24.7	-(268.1 , 316.1)	1.04	(0.67 , 1.59)
(0.0648,0.265]	03-18 to 03-31	649.0	(446.6 , 851.4)	791.8	(567.3 , 1016.4)	142.8	-(159.5 , 443.6)	1.22	(0.80 , 1.86)
(0.0648,0.265]	04-01 to 04-14	674.0	(467.3 , 880.6)	918.1	(678.8 , 1157.4)	244.1	-(72.1 , 558.7)	1.36	(0.91 , 2.03)
(0.265,0.369]	01-08 to 01-21	646.8	(451.2 , 842.4)	641.3	(445.0 , 837.6)	-5.5	-(282.6 , 270.2)	0.99	(0.64 , 1.52)
(0.265,0.369]	01-22 to 02-04	629.6	(435.7 , 823.5)	611.5	(419.1 , 803.9)	-18.1	-(291.3 , 253.6)	0.97	(0.63 , 1.50)
(0.265,0.369]	02-05 to 02-18	641.6	(446.9 , 836.3)	605.3	(416.3 , 794.4)	-36.2	-(307.6 , 233.8)	0.94	(0.61 , 1.46)
(0.265,0.369]	02-19 to 03-03	547.7	(367.2 , 728.1)	553.0	(371.1 , 734.8)	5.3	-(250.9 , 260.2)	1.01	(0.63 , 1.60)
(0.265,0.369]	03-04 to 03-17	592.3	(403.2 , 781.3)	581.7	(396.6 , 766.7)	-10.6	-(275.1 , 252.6)	0.98	(0.63 , 1.54)
(0.265,0.369]	03-18 to 03-31	592.5	(406.2 , 778.7)	583.3	(396.7 , 769.9)	-9.2	-(272.8 , 253.1)	0.98	(0.63 , 1.54)
(0.265,0.369]	04-01 to 04-14	587.6	(398.9 , 776.3)	835.1	(610.9 , 1059.2)	247.4	-(45.5 , 538.9)	1.42	(0.94 , 2.16)
(0.369,0.46]	01-08 to 01-21	593.8	(403.3 , 784.4)	597.1	(407.8 , 786.5)	3.3	-(265.3 , 270.6)	1.01	(0.64 , 1.58)
(0.369,0.46]	01-22 to 02-04	599.5	(408.5 , 790.5)	542.9	(360.4 , 725.4)	-56.6	-(320.8 , 206.2)	0.91	(0.57 , 1.44)
(0.369,0.46]	02-05 to 02-18	580.1	(391.2 , 769.0)	582.1	(393.9 , 770.3)	2.0	-(264.6 , 267.3)	1.00	(0.63 , 1.58)
(0.369,0.46]	02-19 to 03-03	541.9	(361.2 , 722.7)	562.7	(378.2 , 747.3)	20.8	-(237.5 , 277.8)	1.04	(0.65 , 1.65)

(0.369,0.46]	03-04 to 03-17	550.4	(366.9 , 734.0)	593.3	(404.8 , 781.8)	42.9	-(220.2 , 304.6)	1.08	(0.68 , 1.70)
(0.369,0.46]	03-18 to 03-31	529.5	(349.6 , 709.4)	627.5	(433.2 , 821.9)	98.1	-(166.8 , 361.6)	1.19	(0.75 , 1.87)
(0.369,0.46]	04-01 to 04-14	561.6	(376.4 , 746.8)	914.1	(680.0 , 1148.2)	352.5	(54.0 , 649.4)	1.63	(1.07 , 2.47)
(0.46,1]	01-08 to 01-21	584.9	(389.6 , 780.2)	547.5	(360.4 , 734.6)	-37.4	-(307.8 , 231.6)	0.94	(0.58 , 1.51)
(0.46,1]	01-22 to 02-04	523.8	(340.3 , 707.4)	570.9	(377.2 , 764.7)	47.1	-(219.8 , 312.6)	1.09	(0.67 , 1.77)
(0.46,1]	02-05 to 02-18	555.8	(365.5 , 746.0)	566.8	(375.5 , 758.2)	11.1	-(258.8 , 279.5)	1.02	(0.63 , 1.65)
(0.46,1]	02-19 to 03-03	475.4	(300.9 , 650.0)	524.6	(341.3 , 707.8)	49.1	-(203.9 , 300.9)	1.10	(0.66 , 1.83)
(0.46,1]	03-04 to 03-17	509.5	(329.1 , 689.9)	558.8	(367.6 , 749.9)	49.3	-(213.6 , 310.7)	1.10	(0.67 , 1.79)
(0.46,1]	03-18 to 03-31	491.8	(312.9 , 670.8)	516.8	(332.7 , 700.9)	25.0	-(231.8 , 280.4)	1.05	(0.63 , 1.74)
(0.46,1]	04-01 to 04-14	502.2	(320.8 , 683.6)	798.5	(573.0 , 1023.9)	296.3	(6.9 , 584.2)	1.59	(1.01 , 2.51)
% black population									
(0,0.0138]	01-08 to 01-21	622.3	(420.0 , 824.7)	568.2	(377.3 , 759.0)	-54.2	-(332.4 , 222.6)	0.91	(0.57 , 1.45)
(0,0.0138]	01-22 to 02-04	569.3	(375.9 , 762.8)	568.9	(375.8 , 762.0)	-0.4	-(273.8 , 271.5)	1.00	(0.62 , 1.61)
(0,0.0138]	02-05 to 02-18	590.3	(392.3 , 788.4)	624.1	(420.7 , 827.5)	33.8	-(250.1 , 316.2)	1.06	(0.66 , 1.68)
(0,0.0138]	02-19 to 03-03	523.5	(338.4 , 708.6)	539.7	(352.3 , 727.0)	16.1	-(247.2 , 278.2)	1.03	(0.63 , 1.69)
(0,0.0138]	03-04 to 03-17	540.7	(351.4 , 730.0)	612.8	(411.7 , 814.0)	72.1	-(204.1 , 346.9)	1.13	(0.70 , 1.83)
(0,0.0138]	03-18 to 03-31	522.8	(336.1 , 709.6)	595.1	(394.9 , 795.4)	72.3	-(201.5 , 344.7)	1.14	(0.70 , 1.85)
(0,0.0138]	04-01 to 04-14	556.9	(363.5 , 750.3)	766.2	(543.6 , 988.8)	209.3	-(85.6 , 502.7)	1.38	(0.87 , 2.16)
(0.0138,0.0271]	01-08 to 01-21	636.0	(440.9 , 831.1)	632.6	(438.1 , 827.1)	-3.4	-(278.9 , 270.7)	0.99	(0.64 , 1.53)
(0.0138,0.0271]	01-22 to 02-04	616.9	(425.6 , 808.2)	586.7	(399.0 , 774.4)	-30.2	-(298.2 , 236.5)	0.95	(0.61 , 1.48)
(0.0138,0.0271]	02-05 to 02-18	623.5	(431.2 , 815.9)	609.3	(418.4 , 800.1)	-14.3	-(285.2 , 255.3)	0.98	(0.63 , 1.51)
(0.0138,0.0271]	02-19 to 03-03	567.4	(383.6 , 751.1)	562.1	(379.2 , 744.9)	-5.3	-(264.5 , 252.6)	0.99	(0.63 , 1.56)
(0.0138,0.0271]	03-04 to 03-17	591.2	(403.1 , 779.3)	572.8	(388.8 , 756.8)	-18.4	-(281.5 , 243.4)	0.97	(0.62 , 1.52)
(0.0138,0.0271]	03-18 to 03-31	556.8	(374.7 , 738.8)	630.5	(436.6 , 824.4)	73.7	-(192.3 , 338.4)	1.13	(0.72 , 1.77)
(0.0138,0.0271]	04-01 to 04-14	591.9	(402.4 , 781.3)	879.3	(651.7 , 1106.9)	287.4	-(8.7 , 582.1)	1.49	(0.98 , 2.24)
(0.0271,0.0476]	01-08 to 01-21	656.1	(449.7 , 862.6)	614.0	(412.0 , 816.0)	-42.1	-(330.9 , 245.3)	0.94	(0.59 , 1.47)
(0.0271,0.0476]	01-22 to 02-04	660.3	(452.7 , 867.9)	679.8	(465.4 , 894.3)	19.6	-(278.9 , 316.5)	1.03	(0.66 , 1.60)
(0.0271,0.0476]	02-05 to 02-18	620.6	(419.0 , 822.3)	644.0	(439.7 , 848.2)	23.4	-(263.7 , 308.9)	1.04	(0.66 , 1.63)
(0.0271,0.0476]	02-19 to 03-03	571.7	(378.7 , 764.7)	662.2	(450.3 , 874.1)	90.5	-(196.1 , 375.6)	1.16	(0.73 , 1.84)
(0.0271,0.0476]	03-04 to 03-17	588.3	(393.3 , 783.3)	666.9	(458.2 , 875.5)	78.6	-(207.1 , 362.7)	1.13	(0.72 , 1.78)
(0.0271,0.0476]	03-18 to 03-31	607.3	(407.9 , 806.7)	606.9	(407.7 , 806.1)	-0.5	-(282.3 , 279.9)	1.00	(0.63 , 1.59)
(0.0271,0.0476]	04-01 to 04-14	596.6	(399.2 , 794.1)	959.7	(709.3 , 1210.1)	363.1	(44.2 , 680.3)	1.61	(1.06 , 2.45)

(0.0476,0.0888]	01-08 to 01-21	647.5	(440.8 , 854.2)	643.9	(439.0 , 848.9)	-3.6	-(294.6 , 286.0)	0.99	(0.63 , 1.56)
(0.0476,0.0888]	01-22 to 02-04	658.2	(449.1 , 867.3)	630.4	(425.6 , 835.2)	-27.8	-(320.4 , 263.4)	0.96	(0.61 , 1.51)
(0.0476,0.0888]	02-05 to 02-18	674.7	(463.2 , 886.1)	605.0	(403.7 , 806.3)	-69.7	-(361.6 , 220.8)	0.90	(0.57 , 1.41)
(0.0476,0.0888]	02-19 to 03-03	580.8	(384.8 , 776.8)	648.9	(441.2 , 856.6)	68.1	-(217.5 , 352.2)	1.12	(0.70 , 1.77)
(0.0476,0.0888]	03-04 to 03-17	616.9	(416.0 , 817.8)	615.5	(413.2 , 817.8)	-1.4	-(286.5 , 282.2)	1.00	(0.63 , 1.58)
(0.0476,0.0888]	03-18 to 03-31	620.6	(418.2 , 822.9)	673.7	(460.7 , 886.7)	53.1	-(240.6 , 345.4)	1.09	(0.69 , 1.71)
(0.0476,0.0888]	04-01 to 04-14	626.5	(422.1 , 831.0)	913.5	(669.1 , 1157.9)	287.0	-(31.7 , 604.0)	1.46	(0.96 , 2.22)
(0.0888,0.84]	01-08 to 01-21	690.7	(454.3 , 927.1)	682.5	(445.6 , 919.5)	-8.2	-(342.9 , 324.8)	0.99	(0.61 , 1.61)
(0.0888,0.84]	01-22 to 02-04	697.5	(460.4 , 934.6)	638.7	(409.8 , 867.5)	-58.8	-(388.4 , 269.0)	0.92	(0.56 , 1.50)
(0.0888,0.84]	02-05 to 02-18	705.1	(466.0 , 944.1)	678.8	(444.9 , 912.7)	-26.3	-(360.8 , 306.4)	0.96	(0.59 , 1.56)
(0.0888,0.84]	02-19 to 03-03	629.8	(403.0 , 856.7)	677.3	(439.9 , 914.7)	47.5	-(280.9 , 374.2)	1.08	(0.65 , 1.77)
(0.0888,0.84]	03-04 to 03-17	658.6	(427.7 , 889.6)	619.7	(397.4 , 842.0)	-39.0	-(359.5 , 279.9)	0.94	(0.57 , 1.55)
(0.0888,0.84]	03-18 to 03-31	657.9	(427.2 , 888.6)	745.6	(496.9 , 994.3)	87.7	-(251.5 , 425.2)	1.13	(0.70 , 1.83)
(0.0888,0.84]	04-01 to 04-14	638.7	(410.3 , 867.1)	1079.2	(782.4 , 1375.9)	440.5	(66.0 , 813.1)	1.69	(1.08 , 2.65)
% population of color									
(0,0.0912]	01-08 to 01-21	632.5	(438.6 , 826.5)	614.4	(423.8 , 805.1)	-18.1	-(290.1 , 252.5)	0.97	(0.63 , 1.50)
(0,0.0912]	01-22 to 02-04	607.4	(416.9 , 798.0)	563.9	(378.0 , 749.9)	-43.5	-(309.7 , 221.4)	0.93	(0.59 , 1.46)
(0,0.0912]	02-05 to 02-18	615.3	(422.4 , 808.2)	623.8	(430.6 , 817.0)	8.5	-(264.6 , 280.1)	1.01	(0.65 , 1.57)
(0,0.0912]	02-19 to 03-03	537.5	(358.6 , 716.3)	542.3	(364.2 , 720.3)	4.8	-(247.6 , 255.8)	1.01	(0.63 , 1.61)
(0,0.0912]	03-04 to 03-17	580.9	(393.4 , 768.4)	630.7	(435.4 , 826.0)	49.8	-(220.9 , 319.1)	1.09	(0.69 , 1.69)
(0,0.0912]	03-18 to 03-31	537.7	(358.4 , 717.0)	603.1	(412.8 , 793.5)	65.5	-(196.0 , 325.6)	1.12	(0.71 , 1.77)
(0,0.0912]	04-01 to 04-14	577.3	(389.2 , 765.5)	809.0	(590.4 , 1027.7)	231.7	-(56.8 , 518.7)	1.40	(0.92 , 2.14)
(0.0912,0.164]	01-08 to 01-21	652.8	(459.8 , 845.8)	651.4	(460.6 , 842.1)	-1.4	-(272.8 , 268.6)	1.00	(0.66 , 1.51)
(0.0912,0.164]	01-22 to 02-04	625.5	(438.2 , 812.8)	648.0	(454.1 , 841.9)	22.5	-(247.1 , 290.7)	1.04	(0.68 , 1.58)
(0.0912,0.164]	02-05 to 02-18	635.1	(445.6 , 824.6)	656.3	(464.1 , 848.4)	21.2	-(248.7 , 289.7)	1.03	(0.68 , 1.57)
(0.0912,0.164]	02-19 to 03-03	573.4	(393.4 , 753.4)	619.1	(430.4 , 807.8)	45.7	-(215.1 , 305.1)	1.08	(0.70 , 1.67)
(0.0912,0.164]	03-04 to 03-17	602.4	(417.4 , 787.3)	614.9	(428.7 , 801.1)	12.6	-(249.9 , 273.7)	1.02	(0.66 , 1.57)
(0.0912,0.164]	03-18 to 03-31	586.1	(402.8 , 769.4)	636.5	(447.5 , 825.6)	50.4	-(212.9 , 312.4)	1.09	(0.71 , 1.67)
(0.0912,0.164]	04-01 to 04-14	610.0	(422.4 , 797.6)	878.9	(657.1 , 1100.8)	268.9	-(21.6 , 558.0)	1.44	(0.97 , 2.14)
(0.164,0.27]	01-08 to 01-21	629.3	(428.0 , 830.5)	584.9	(390.8 , 779.1)	-44.3	-(323.9 , 233.9)	0.93	(0.59 , 1.47)
(0.164,0.27]	01-22 to 02-04	616.0	(417.0 , 815.0)	609.7	(410.5 , 808.9)	-6.3	-(287.9 , 273.9)	0.99	(0.63 , 1.56)
(0.164,0.27]	02-05 to 02-18	605.7	(407.0 , 804.3)	554.9	(366.0 , 743.8)	-50.8	-(324.9 , 222.0)	0.92	(0.57 , 1.47)
(0.164,0.27]	02-19 to 03-03	561.9	(371.7 , 752.2)	597.5	(400.8 , 794.3)	35.6	-(238.1 , 307.9)	1.06	(0.66 , 1.70)

(0.164,0.27]	03-04 to 03-17	558.4	(369.1 , 747.8)	577.5	(384.0 , 770.9)	19.0	-(251.6 , 288.4)	1.03	(0.64 , 1.66)
(0.164,0.27]	03-18 to 03-31	580.4	(387.4 , 773.5)	628.7	(425.9 , 831.4)	48.2	-(231.7 , 326.8)	1.08	(0.68 , 1.72)
(0.164,0.27]	04-01 to 04-14	571.6	(379.1 , 764.1)	887.8	(648.3 , 1127.3)	316.2	(9.0 , 621.8)	1.55	(1.01 , 2.39)
(0.27,0.434]	01-08 to 01-21	621.6	(408.1 , 835.1)	589.3	(379.9 , 798.8)	-32.3	-(331.4 , 265.3)	0.95	(0.58 , 1.55)
(0.27,0.434]	01-22 to 02-04	625.3	(409.9 , 840.7)	588.3	(379.6 , 797.1)	-37.0	-(337.0 , 261.4)	0.94	(0.57 , 1.54)
(0.27,0.434]	02-05 to 02-18	624.1	(410.0 , 838.2)	607.7	(394.6 , 820.8)	-16.4	-(318.4 , 284.1)	0.97	(0.60 , 1.59)
(0.27,0.434]	02-19 to 03-03	557.9	(354.8 , 761.1)	589.1	(378.1 , 800.0)	31.2	-(261.7 , 322.5)	1.06	(0.63 , 1.75)
(0.27,0.434]	03-04 to 03-17	585.7	(378.5 , 792.8)	641.0	(424.0 , 858.0)	55.3	-(244.7 , 353.8)	1.09	(0.67 , 1.78)
(0.27,0.434]	03-18 to 03-31	584.7	(376.6 , 792.9)	620.4	(406.7 , 834.0)	35.6	-(262.6 , 332.4)	1.06	(0.65 , 1.74)
(0.27,0.434]	04-01 to 04-14	586.0	(377.2 , 794.7)	858.0	(607.8 , 1108.3)	272.1	-(53.8 , 596.3)	1.46	(0.92 , 2.31)
(0.434,0.971]	01-08 to 01-21	695.6	(459.5 , 931.8)	686.6	(450.6 , 922.6)	-9.0	-(342.9 , 323.1)	0.99	(0.61 , 1.60)
(0.434,0.971]	01-22 to 02-04	715.6	(476.0 , 955.2)	682.6	(448.3 , 917.0)	-33.0	-(368.1 , 300.5)	0.95	(0.59 , 1.54)
(0.434,0.971]	02-05 to 02-18	736.6	(493.3 , 980.0)	712.5	(473.7 , 951.3)	-24.1	-(365.1 , 315.1)	0.97	(0.60 , 1.54)
(0.434,0.971]	02-19 to 03-03	630.6	(405.3 , 855.8)	723.7	(480.4 , 967.0)	93.1	-(238.5 , 423.0)	1.15	(0.70 , 1.87)
(0.434,0.971]	03-04 to 03-17	663.8	(433.9 , 893.8)	618.1	(396.1 , 840.1)	-45.7	-(365.4 , 272.2)	0.93	(0.57 , 1.53)
(0.434,0.971]	03-18 to 03-31	669.1	(437.5 , 900.8)	730.6	(484.2 , 977.1)	61.5	-(276.8 , 398.0)	1.09	(0.67 , 1.77)
(0.434,0.971]	04-01 to 04-14	663.9	(432.1 , 895.7)	1174.6	(867.1 , 1482.1)	510.7	(125.6 , 893.9)	1.77	(1.14 , 2.73)

Statistically significant excess mortality labelled in red.

Table 3: Age standardized mortality rate per 100,000 person-years for 2015-2019 and 2020, by two week period and city/town ABSM with age--standardized rate differences and rate ratios and 95% confidence limits comparing 2020 period to 2015-2019 period, Massachusetts

City/town ABSM % below poverty	Two-week perio	Age-standardized mortality rate (2015-2019)	(95% CI)	Age-standardized mortality rate (2020)	(95% CI)	Age-standardized rate difference (2020 vs. 2015-2019)	(95% CI)	Age-standardized rate ratio	(95% CI)
0-4.9%	01-08 to 01-21	580.0	(416.8 , 743.2)	536.1	(379.6 , 692.6)	-43.9	-(270.0 , 181.0)	0.92	(0.62 , 1.38)
0-4.9%	01-22 to 02-04	551.7	(392.9 , 710.5)	536.5	(379.4 , 693.5)	-15.3	-(238.6 , 206.9)	0.97	(0.64 , 1.46)
0-4.9%	02-05 to 02-18	565.7	(404.8 , 726.6)	581.2	(418.7 , 743.6)	15.5	-(213.2 , 243.0)	1.03	(0.69 , 1.53)
0-4.9%	02-19 to 03-03	499.9	(350.3 , 649.4)	502.0	(355.8 , 648.2)	2.1	-(207.0 , 210.2)	1.00	(0.66 , 1.52)
0-4.9%	03-04 to 03-17	528.3	(373.2 , 683.5)	587.0	(424.4 , 749.5)	58.7	-(166.1 , 282.2)	1.11	(0.74 , 1.66)
0-4.9%	03-18 to 03-31	502.2	(350.1 , 654.2)	553.5	(394.6 , 712.4)	51.3	-(168.6 , 270.1)	1.10	(0.73 , 1.67)
0-4.9%	04-01 to 04-14	531.9	(375.4 , 688.4)	801.7	(612.1 , 991.4)	269.8	(24.0 , 514.5)	1.51	(1.03 , 2.19)
5-9.9%	01-08 to 01-21	659.8	(497.4 , 822.1)	664.9	(502.2 , 827.5)	5.1	-(224.7 , 233.7)	1.01	(0.71 , 1.42)
5-9.9%	01-22 to 02-04	642.8	(482.4 , 803.2)	637.1	(474.4 , 799.8)	-5.7	-(234.2 , 221.6)	0.99	(0.69 , 1.41)
5-9.9%	02-05 to 02-18	643.4	(482.4 , 804.3)	612.1	(457.0 , 767.2)	-31.3	-(254.8 , 191.1)	0.95	(0.67 , 1.36)
5-9.9%	02-19 to 03-03	562.5	(414.0 , 711.0)	557.0	(412.2 , 701.8)	-5.5	-(212.9 , 200.8)	0.99	(0.68 , 1.43)
5-9.9%	03-04 to 03-17	600.8	(445.2 , 756.5)	592.3	(437.8 , 746.8)	-8.6	-(227.9 , 209.6)	0.99	(0.68 , 1.42)
5-9.9%	03-18 to 03-31	594.4	(440.4 , 748.4)	639.4	(479.2 , 799.5)	45.0	-(177.2 , 266.0)	1.08	(0.75 , 1.54)
5-9.9%	04-01 to 04-14	601.9	(445.4 , 758.5)	915.1	(723.8 , 1106.5)	313.2	(66.0 , 559.2)	1.52	(1.09 , 2.12)
10-19.9%	01-08 to 01-21	698.8	(495.4 , 902.1)	702.0	(497.8 , 906.2)	3.2	-(285.0 , 289.9)	1.00	(0.67 , 1.51)
10-19.9%	01-22 to 02-04	714.0	(509.0 , 919.1)	683.8	(483.4 , 884.2)	-30.2	-(316.9 , 255.0)	0.96	(0.64 , 1.44)
10-19.9%	02-05 to 02-18	711.7	(506.5 , 916.9)	684.5	(481.6 , 887.5)	-27.2	-(315.8 , 260.0)	0.96	(0.64 , 1.45)
10-19.9%	02-19 to 03-03	630.5	(438.0 , 823.1)	628.0	(440.3 , 815.6)	-2.6	-(271.4 , 264.9)	1.00	(0.65 , 1.52)
10-19.9%	03-04 to 03-17	676.1	(475.8 , 876.4)	670.6	(470.3 , 870.9)	-5.5	-(288.8 , 276.4)	0.99	(0.65 , 1.51)
10-19.9%	03-18 to 03-31	655.2	(457.8 , 852.5)	742.1	(530.6 , 953.5)	86.9	-(202.3 , 374.7)	1.13	(0.75 , 1.71)
10-19.9%	04-01 to 04-14	676.1	(474.9 , 877.3)	944.5	(709.0 , 1180.0)	268.5	-(41.3 , 576.6)	1.40	(0.95 , 2.06)

20-100%	01-08 to 01-21	691.0	(453.0 , 929.0)	632.7	(402.3 , 863.1)	-58.3	-(389.6 , 271.2)	0.92	(0.55 , 1.51)
20-100%	01-22 to 02-04	687.3	(449.9 , 924.6)	661.9	(426.9 , 896.9)	-25.4	-(359.4 , 306.9)	0.96	(0.59 , 1.58)
20-100%	02-05 to 02-18	693.5	(454.8 , 932.2)	693.6	(454.3 , 932.9)	0.1	-(337.9 , 336.3)	1.00	(0.61 , 1.62)
20-100%	02-19 to 03-03	602.0	(381.0 , 822.9)	646.3	(421.5 , 871.2)	44.4	-(270.9 , 358.1)	1.07	(0.65 , 1.78)
20-100%	03-04 to 03-17	634.8	(407.2 , 862.3)	653.4	(422.4 , 884.5)	18.7	-(305.6 , 341.3)	1.03	(0.62 , 1.70)
20-100%	03-18 to 03-31	665.2	(430.9 , 899.5)	678.4	(440.0 , 916.7)	13.2	-(321.1 , 345.7)	1.02	(0.62 , 1.67)
20-100%	04-01 to 04-14	635.4	(406.9 , 863.8)	1048.1	(755.0 , 1341.3)	412.8	(41.1 , 782.5)	1.65	(1.05 , 2.60)
% crowding									
(0,0.00695]	01-08 to 01-21	608.2	(395.2 , 821.3)	576.5	(372.0 , 781.0)	-31.7	-(327.0 , 262.1)	0.95	(0.58 , 1.56)
(0,0.00695]	01-22 to 02-04	589.2	(380.2 , 798.2)	574.6	(365.7 , 783.5)	-14.6	-(310.1 , 279.4)	0.98	(0.59 , 1.62)
(0,0.00695]	02-05 to 02-18	565.0	(360.6 , 769.4)	601.7	(392.6 , 810.8)	36.7	-(255.7 , 327.6)	1.06	(0.64 , 1.75)
(0,0.00695]	02-19 to 03-03	530.0	(333.3 , 726.7)	526.7	(335.7 , 717.6)	-3.4	-(277.5 , 269.4)	0.99	(0.59 , 1.66)
(0,0.00695]	03-04 to 03-17	538.9	(338.1 , 739.8)	621.2	(407.8 , 834.7)	82.3	-(210.8 , 373.9)	1.15	(0.69 , 1.91)
(0,0.00695]	03-18 to 03-31	514.9	(319.4 , 710.4)	550.3	(352.4 , 748.1)	35.4	-(242.8 , 312.1)	1.07	(0.63 , 1.80)
(0,0.00695]	04-01 to 04-14	561.8	(355.9 , 767.7)	847.9	(599.4 , 1096.4)	286.1	-(36.6 , 607.2)	1.51	(0.94 , 2.41)
(0.00695,0.(	01-08 to 01-21	625.9	(434.2 , 817.6)	625.8	(434.6 , 816.9)	-0.1	-(270.9 , 269.2)	1.00	(0.65 , 1.54)
(0.00695,0.(	01-22 to 02-04	593.9	(407.8 , 779.9)	651.3	(454.0 , 848.7)	57.5	-(213.8 , 327.3)	1.10	(0.71 , 1.69)
(0.00695,0.(	02-05 to 02-18	635.3	(441.2 , 829.3)	605.1	(418.0 , 792.3)	-30.1	-(299.8 , 238.1)	0.95	(0.62 , 1.47)
(0.00695,0.(	02-19 to 03-03	549.2	(371.3 , 727.1)	521.3	(350.5 , 692.2)	-27.9	-(274.5 , 217.5)	0.95	(0.60 , 1.50)
(0.00695,0.(	03-04 to 03-17	587.9	(401.9 , 774.0)	580.0	(394.1 , 765.8)	-8.0	-(270.9 , 253.7)	0.99	(0.63 , 1.54)
(0.00695,0.(	03-18 to 03-31	567.0	(383.8 , 750.1)	657.7	(459.3 , 856.2)	90.7	-(179.3 , 359.4)	1.16	(0.75 , 1.80)
(0.00695,0.(	04-01 to 04-14	568.2	(384.0 , 752.4)	806.6	(590.9 , 1022.4)	238.4	-(45.3 , 520.7)	1.42	(0.93 , 2.16)
(0.0128,0.0	01-08 to 01-21	663.3	(465.5 , 861.0)	633.0	(439.1 , 827.0)	-30.2	-(307.2 , 245.3)	0.95	(0.62 , 1.46)
(0.0128,0.0	01-22 to 02-04	668.4	(469.7 , 867.1)	576.6	(390.0 , 763.1)	-91.8	-(364.4 , 179.3)	0.86	(0.56 , 1.34)
(0.0128,0.0	02-05 to 02-18	659.2	(461.6 , 856.8)	598.8	(410.3 , 787.3)	-60.5	-(333.6 , 211.3)	0.91	(0.59 , 1.40)
(0.0128,0.0	02-19 to 03-03	588.3	(402.5 , 774.1)	607.5	(423.9 , 791.0)	19.2	-(242.0 , 279.0)	1.03	(0.67 , 1.60)

(0.0128,0.0	03-04 to 03-17	628.1	(434.5 , 821.7)	617.5	(427.5 , 807.6)	-10.6	-(281.9 , 259.3)	0.98	(0.64 , 1.52)
(0.0128,0.0	03-18 to 03-31	611.4	(420.7 , 802.2)	603.7	(413.1 , 794.3)	-7.7	-(277.4 , 260.5)	0.99	(0.63 , 1.54)
(0.0128,0.0	04-01 to 04-14	639.6	(443.5 , 835.7)	898.9	(668.4 , 1129.3)	259.3	-(43.3 , 560.3)	1.41	(0.94 , 2.09)
(0.0196,0.0358]									
	01-08 to 01-21	673.5	(445.4 , 901.5)	651.5	(425.7 , 877.4)	-21.9	-(342.9 , 297.4)	0.97	(0.60 , 1.57)
(0.0196,0.0	01-22 to 02-04	673.8	(445.3 , 902.4)	627.7	(407.1 , 848.3)	-46.1	-(363.7 , 269.9)	0.93	(0.57 , 1.51)
(0.0196,0.0	02-05 to 02-18	679.5	(449.9 , 909.1)	699.1	(464.3 , 933.9)	19.6	-(308.8 , 346.3)	1.03	(0.64 , 1.65)
(0.0196,0.0	02-19 to 03-03	597.7	(384.0 , 811.3)	623.3	(408.4 , 838.3)	25.7	-(277.4 , 327.2)	1.04	(0.63 , 1.71)
(0.0196,0.0	03-04 to 03-17	608.0	(391.6 , 824.5)	666.1	(440.0 , 892.3)	58.1	-(255.0 , 369.5)	1.10	(0.67 , 1.79)
(0.0196,0.0	03-18 to 03-31	639.6	(416.2 , 863.1)	708.2	(472.0 , 944.4)	68.5	-(256.6 , 392.0)	1.11	(0.68 , 1.79)
(0.0196,0.0	04-01 to 04-14	625.4	(404.1 , 846.6)	995.4	(716.0 , 1274.8)	370.0	(13.7 , 724.6)	1.59	(1.01 , 2.49)
(0.0358,0.1	01-08 to 01-21	687.6	(453.4 , 921.9)	627.1	(401.5 , 852.8)	-60.5	-(385.8 , 263.1)	0.91	(0.56 , 1.49)
(0.0358,0.1	01-22 to 02-04	700.2	(463.5 , 936.9)	710.0	(470.4 , 949.7)	9.9	-(327.0 , 345.0)	1.01	(0.63 , 1.63)
(0.0358,0.1	02-05 to 02-18	697.0	(460.6 , 933.4)	708.5	(470.3 , 946.8)	11.5	-(324.1 , 345.5)	1.02	(0.63 , 1.63)
(0.0358,0.1	02-19 to 03-03	587.2	(372.3 , 802.0)	616.2	(400.4 , 832.1)	29.1	-(275.5 , 332.1)	1.05	(0.63 , 1.74)
(0.0358,0.1	03-04 to 03-17	649.1	(422.1 , 876.0)	627.4	(403.1 , 851.8)	-21.6	-(340.8 , 295.9)	0.97	(0.59 , 1.59)
(0.0358,0.1	03-18 to 03-31	646.2	(419.2 , 873.2)	712.1	(470.5 , 953.7)	65.9	-(265.6 , 395.7)	1.10	(0.68 , 1.79)
(0.0358,0.1	04-01 to 04-14	638.9	(412.7 , 865.0)	1098.1	(802.5 , 1393.7)	459.2	(87.0 , 829.5)	1.72	(1.10 , 2.68)

Index of Concentration at the Extremes (high income white non-Hispanic vs. low income people of color)

(-0.21,0.03	01-08 to 01-21	703.2	(474.1 , 932.3)	654.4	(431.6 , 877.1)	-48.9	-(368.4 , 269.1)	0.93	(0.58 , 1.49)
(-0.21,0.03	01-22 to 02-04	705.1	(475.8 , 934.5)	666.7	(442.6 , 890.8)	-38.4	-(359.1 , 280.6)	0.95	(0.59 , 1.51)
(-0.21,0.03	02-05 to 02-18	716.5	(484.9 , 948.1)	720.8	(487.9 , 953.6)	4.2	-(324.2 , 331.0)	1.01	(0.64 , 1.59)
(-0.21,0.03	02-19 to 03-03	616.1	(402.7 , 829.5)	668.5	(449.8 , 887.2)	52.4	-(253.2 , 356.4)	1.09	(0.67 , 1.74)
(-0.21,0.03	03-04 to 03-17	654.9	(434.3 , 875.5)	667.6	(444.4 , 890.7)	12.6	-(301.1 , 324.8)	1.02	(0.63 , 1.63)
(-0.21,0.03	03-18 to 03-31	670.6	(446.4 , 894.9)	698.4	(467.1 , 929.8)	27.8	-(294.4 , 348.4)	1.04	(0.65 , 1.66)
(-0.21,0.03	04-01 to 04-14	645.5	(425.7 , 865.3)	1060.1	(777.9 , 1342.2)	414.6	(56.9 , 770.4)	1.64	(1.07 , 2.52)
(0.0388,0.2	01-08 to 01-21	722.5	(486.8 , 958.3)	726.7	(489.2 , 964.2)	4.1	-(330.5 , 337.0)	1.01	(0.63 , 1.59)

(0.0388,0.2	01-22 to 02-04	739.4	(501.0 , 977.7)	735.1	(495.2 , 975.0)	-4.3	-(342.4 , 332.2)	0.99	(0.63 , 1.57)
(0.0388,0.2	02-05 to 02-18	723.5	(487.8 , 959.2)	680.1	(449.8 , 910.5)	-43.4	-(373.0 , 284.5)	0.94	(0.59 , 1.50)
(0.0388,0.2	02-19 to 03-03	669.9	(442.9 , 897.0)	637.0	(422.2 , 851.8)	-32.9	-(345.5 , 278.1)	0.95	(0.59 , 1.53)
(0.0388,0.2	03-04 to 03-17	697.7	(466.0 , 929.3)	703.2	(467.9 , 938.4)	5.5	-(324.7 , 334.0)	1.01	(0.63 , 1.61)
(0.0388,0.2	03-18 to 03-31	681.7	(451.3 , 912.0)	799.1	(549.0 , 1049.3)	117.5	-(222.6 , 455.8)	1.17	(0.74 , 1.85)
(0.0388,0.2	04-01 to 04-14	705.2	(470.4 , 940.0)	909.3	(645.5 , 1173.1)	204.1	-(149.1 , 555.4)	1.29	(0.83 , 2.00)
(0.242,0.36	01-08 to 01-21	649.9	(456.3 , 843.5)	631.3	(440.0 , 822.6)	-18.6	-(290.8 , 252.1)	0.97	(0.64 , 1.48)
(0.242,0.36	01-22 to 02-04	632.2	(440.5 , 823.8)	609.0	(420.0 , 798.0)	-23.2	-(292.3 , 244.6)	0.96	(0.62 , 1.48)
(0.242,0.36	02-05 to 02-18	655.8	(460.2 , 851.4)	642.3	(449.8 , 834.9)	-13.5	-(287.9 , 259.6)	0.98	(0.64 , 1.49)
(0.242,0.36	02-19 to 03-03	562.1	(382.7 , 741.5)	543.2	(371.3 , 715.1)	-18.9	-(267.3 , 228.3)	0.97	(0.62 , 1.51)
(0.242,0.36	03-04 to 03-17	618.1	(427.3 , 809.0)	575.0	(393.8 , 756.2)	-43.1	-(306.3 , 218.7)	0.93	(0.60 , 1.44)
(0.242,0.36	03-18 to 03-31	606.4	(419.6 , 793.1)	621.5	(431.5 , 811.6)	15.2	-(251.3 , 280.2)	1.03	(0.66 , 1.58)
(0.242,0.36	04-01 to 04-14	607.8	(418.2 , 797.4)	880.5	(653.5 , 1107.5)	272.7	-(23.1 , 566.9)	1.45	(0.97 , 2.17)
(0.363,0.46	01-08 to 01-21	610.8	(417.0 , 804.7)	636.5	(440.0 , 832.9)	25.6	-(250.4 , 300.2)	1.04	(0.67 , 1.62)
(0.363,0.46	01-22 to 02-04	616.8	(422.2 , 811.4)	557.7	(372.1 , 743.2)	-59.1	-(328.0 , 208.3)	0.90	(0.57 , 1.43)
(0.363,0.46	02-05 to 02-18	606.0	(412.8 , 799.2)	591.9	(402.1 , 781.8)	-14.1	-(285.0 , 255.4)	0.98	(0.62 , 1.53)
(0.363,0.46	02-19 to 03-03	546.4	(365.6 , 727.2)	543.0	(366.6 , 719.4)	-3.4	-(256.0 , 247.9)	0.99	(0.63 , 1.58)
(0.363,0.46	03-04 to 03-17	555.1	(370.0 , 740.2)	614.5	(422.0 , 806.9)	59.4	-(207.7 , 325.0)	1.11	(0.70 , 1.75)
(0.363,0.46	03-18 to 03-31	531.8	(350.9 , 712.7)	624.3	(428.9 , 819.7)	92.5	-(173.8 , 357.4)	1.17	(0.74 , 1.86)
(0.363,0.46	04-01 to 04-14	586.2	(395.7 , 776.8)	869.9	(640.7 , 1099.0)	283.6	-(14.4 , 580.1)	1.48	(0.98 , 2.25)
(0.465,0.70	01-08 to 01-21	580.0	(385.5 , 774.5)	523.2	(340.0 , 706.5)	-56.7	-(324.0 , 209.1)	0.90	(0.56 , 1.46)
(0.465,0.70	01-22 to 02-04	525.3	(341.4 , 709.2)	572.5	(377.3 , 767.7)	47.2	-(221.0 , 314.0)	1.09	(0.67 , 1.77)
(0.465,0.70	02-05 to 02-18	541.4	(353.4 , 729.4)	546.0	(358.1 , 733.9)	4.6	-(261.1 , 269.0)	1.01	(0.62 , 1.64)
(0.465,0.70	02-19 to 03-03	464.7	(293.1 , 636.3)	482.1	(311.1 , 653.2)	17.4	-(224.9 , 258.4)	1.04	(0.62 , 1.73)
(0.465,0.70	03-04 to 03-17	504.2	(324.8 , 683.7)	556.0	(365.3 , 746.8)	51.8	-(210.2 , 312.3)	1.10	(0.67 , 1.80)
(0.465,0.70	03-18 to 03-31	492.5	(313.1 , 671.8)	525.6	(340.8 , 710.5)	33.2	-(224.4 , 289.4)	1.07	(0.64 , 1.77)
(0.465,0.70	04-01 to 04-14	494.4	(315.0 , 673.9)	831.1	(600.5 , 1061.7)	336.7	(44.5 , 627.4)	1.68	(1.06 , 2.65)

% black population									
(0,0.0155]	01-08 to 01-21	606.8	(408.4 , 805.2)	596.3	(402.8 , 789.8)	-10.5	-(287.7 , 265.2)	0.98	(0.62 , 1.55)
(0,0.0155]	01-22 to 02-04	567.8	(375.1 , 760.5)	539.8	(353.7 , 726.0)	-28.0	-(295.9 , 238.6)	0.95	(0.59 , 1.54)
(0,0.0155]	02-05 to 02-18	600.6	(402.2 , 799.1)	612.6	(413.8 , 811.5)	12.0	-(268.9 , 291.5)	1.02	(0.64 , 1.62)
(0,0.0155]	02-19 to 03-03	525.0	(342.3 , 707.7)	515.4	(339.4 , 691.5)	-9.6	-(263.3 , 242.8)	0.98	(0.60 , 1.59)
(0,0.0155]	03-04 to 03-17	539.4	(352.2 , 726.5)	613.8	(413.5 , 814.1)	74.4	-(199.7 , 347.2)	1.14	(0.71 , 1.83)
(0,0.0155]	03-18 to 03-31	528.9	(342.2 , 715.6)	595.6	(396.5 , 794.8)	66.7	-(206.3 , 338.3)	1.13	(0.69 , 1.83)
(0,0.0155]	04-01 to 04-14	562.6	(369.8 , 755.5)	795.0	(569.4 , 1020.6)	232.4	-(64.4 , 527.6)	1.41	(0.91 , 2.20)
(0.0155,0.0	01-08 to 01-21	653.6	(455.7 , 851.5)	644.6	(447.5 , 841.6)	-9.0	-(288.3 , 268.8)	0.99	(0.64 , 1.51)
(0.0155,0.0	01-22 to 02-04	642.4	(447.2 , 837.7)	641.5	(443.8 , 839.2)	-0.9	-(278.8 , 275.5)	1.00	(0.65 , 1.54)
(0.0155,0.0	02-05 to 02-18	635.7	(441.2 , 830.3)	619.1	(427.1 , 811.1)	-16.6	-(290.0 , 255.3)	0.97	(0.63 , 1.50)
(0.0155,0.0	02-19 to 03-03	574.9	(390.7 , 759.1)	526.8	(355.0 , 698.7)	-48.1	-(300.0 , 202.6)	0.92	(0.58 , 1.44)
(0.0155,0.0	03-04 to 03-17	616.5	(423.3 , 809.8)	629.4	(436.4 , 822.5)	12.9	-(260.3 , 284.6)	1.02	(0.66 , 1.58)
(0.0155,0.0	03-18 to 03-31	570.2	(386.3 , 754.1)	672.9	(473.3 , 872.4)	102.7	-(168.7 , 372.6)	1.18	(0.76 , 1.82)
(0.0155,0.0	04-01 to 04-14	594.4	(404.8 , 784.0)	873.2	(647.1 , 1099.3)	278.8	-(16.3 , 572.4)	1.47	(0.97 , 2.21)
(0.0298,0.0	01-08 to 01-21	673.3	(469.4 , 877.2)	625.3	(427.4 , 823.1)	-48.0	-(332.1 , 234.7)	0.93	(0.60 , 1.44)
(0.0298,0.0	01-22 to 02-04	663.7	(461.3 , 866.1)	675.3	(466.5 , 884.2)	11.7	-(279.2 , 301.0)	1.02	(0.66 , 1.57)
(0.0298,0.0	02-05 to 02-18	641.2	(442.0 , 840.4)	671.4	(467.0 , 875.8)	30.2	-(255.2 , 314.2)	1.05	(0.68 , 1.61)
(0.0298,0.0	02-19 to 03-03	571.0	(383.9 , 758.0)	636.5	(442.0 , 831.0)	65.5	-(204.3 , 333.9)	1.11	(0.71 , 1.74)
(0.0298,0.0	03-04 to 03-17	606.9	(413.6 , 800.2)	653.3	(450.7 , 856.0)	46.4	-(233.7 , 325.0)	1.08	(0.69 , 1.68)
(0.0298,0.0	03-18 to 03-31	612.5	(416.8 , 808.2)	586.7	(394.8 , 778.7)	-25.8	-(299.9 , 247.0)	0.96	(0.61 , 1.51)
(0.0298,0.0	04-01 to 04-14	626.5	(428.4 , 824.7)	924.9	(687.1 , 1162.7)	298.4	-(11.1 , 606.3)	1.48	(0.98 , 2.21)
(0.0516,0.1	01-08 to 01-21	679.6	(473.9 , 885.4)	672.2	(467.8 , 876.5)	-7.5	-(297.4 , 281.0)	0.99	(0.64 , 1.52)
(0.0516,0.1	01-22 to 02-04	687.9	(480.0 , 895.7)	608.3	(413.1 , 803.4)	-79.6	-(364.7 , 204.0)	0.88	(0.57 , 1.37)
(0.0516,0.1	02-05 to 02-18	689.5	(481.6 , 897.4)	602.4	(407.1 , 797.7)	-87.1	-(372.3 , 196.6)	0.87	(0.56 , 1.36)
(0.0516,0.1	02-19 to 03-03	598.2	(405.7 , 790.7)	618.5	(427.5 , 809.5)	20.3	-(250.9 , 290.1)	1.03	(0.66 , 1.61)
(0.0516,0.1	03-04 to 03-17	637.7	(438.2 , 837.1)	578.5	(389.2 , 767.8)	-59.2	-(334.2 , 214.4)	0.91	(0.58 , 1.42)

(0.0516,0.1:	03-18 to 03-31	648.0	(446.8 , 849.3)	700.0	(488.6 , 911.5)	52.0	-(239.9 , 342.4)	1.08	(0.70 , 1.66)
(0.0516,0.1:	04-01 to 04-14	649.0	(446.6 , 851.3)	948.2	(704.8 , 1191.6)	299.2	-(17.3 , 614.2)	1.46	(0.98 , 2.18)
(0.131,0.42:	01-08 to 01-21	648.1	(403.5 , 892.6)	613.5	(373.8 , 853.2)	-34.5	-(377.0 , 306.2)	0.95	(0.55 , 1.63)
(0.131,0.42:	01-22 to 02-04	652.7	(407.8 , 897.7)	652.4	(406.2 , 898.7)	-0.3	-(347.7 , 345.3)	1.00	(0.59 , 1.70)
(0.131,0.42:	02-05 to 02-18	671.3	(422.3 , 920.3)	679.0	(429.5 , 928.4)	7.7	-(344.8 , 358.3)	1.01	(0.60 , 1.70)
(0.131,0.42:	02-19 to 03-03	578.7	(348.8 , 808.6)	578.0	(352.8 , 803.2)	-0.7	-(322.5 , 319.5)	1.00	(0.57 , 1.74)
(0.131,0.42:	03-04 to 03-17	617.2	(379.5 , 854.9)	622.1	(383.2 , 861.0)	4.8	-(332.2 , 340.1)	1.01	(0.59 , 1.73)
(0.131,0.42:	03-18 to 03-31	621.0	(381.9 , 860.1)	705.8	(447.9 , 963.7)	84.8	-(266.9 , 434.7)	1.14	(0.67 , 1.93)
(0.131,0.42:	04-01 to 04-14	590.8	(356.6 , 825.1)	1076.3	(760.5 , 1392.2)	485.5	(92.3 , 876.8)	1.82	(1.11 , 2.98)
% population of color									
(0.0129,0.0!	01-08 to 01-21	641.2	(445.4 , 837.1)	624.3	(431.8 , 816.8)	-16.9	-(291.5 , 256.3)	0.97	(0.63 , 1.50)
(0.0129,0.0!	01-22 to 02-04	628.5	(433.9 , 823.1)	577.6	(388.5 , 766.8)	-50.9	-(322.2 , 219.1)	0.92	(0.59 , 1.44)
(0.0129,0.0!	02-05 to 02-18	633.2	(436.8 , 829.6)	613.5	(422.1 , 804.8)	-19.7	-(293.9 , 253.0)	0.97	(0.62 , 1.50)
(0.0129,0.0!	02-19 to 03-03	535.1	(357.3 , 712.9)	518.8	(349.5 , 688.0)	-16.3	-(261.8 , 227.9)	0.97	(0.61 , 1.54)
(0.0129,0.0!	03-04 to 03-17	586.8	(398.2 , 775.5)	630.3	(434.4 , 826.1)	43.4	-(228.5 , 314.0)	1.07	(0.69 , 1.68)
(0.0129,0.0!	03-18 to 03-31	546.8	(365.1 , 728.6)	638.6	(441.8 , 835.3)	91.8	-(176.1 , 358.3)	1.17	(0.74 , 1.83)
(0.0129,0.0!	04-01 to 04-14	588.4	(398.2 , 778.6)	816.0	(595.0 , 1036.9)	227.6	-(64.0 , 517.7)	1.39	(0.91 , 2.11)
(0.0933,0.1(	01-08 to 01-21	664.3	(469.4 , 859.2)	654.7	(463.0 , 846.4)	-9.6	-(283.0 , 262.4)	0.99	(0.65 , 1.49)
(0.0933,0.1(	01-22 to 02-04	633.4	(444.3 , 822.5)	668.6	(470.7 , 866.4)	35.2	-(238.5 , 307.5)	1.06	(0.69 , 1.60)
(0.0933,0.1(	02-05 to 02-18	638.5	(448.4 , 828.6)	677.4	(481.7 , 873.2)	38.9	-(233.9 , 310.4)	1.06	(0.70 , 1.60)
(0.0933,0.1(	02-19 to 03-03	580.1	(400.1 , 760.2)	565.1	(390.8 , 739.3)	-15.1	-(265.6 , 234.2)	0.97	(0.63 , 1.51)
(0.0933,0.1(	03-04 to 03-17	619.5	(431.1 , 807.8)	632.8	(443.8 , 821.7)	13.3	-(253.5 , 278.7)	1.02	(0.67 , 1.56)
(0.0933,0.1(	03-18 to 03-31	589.1	(405.4 , 772.7)	632.9	(444.8 , 821.1)	43.9	-(219.1 , 305.5)	1.07	(0.70 , 1.65)
(0.0933,0.1(	04-01 to 04-14	621.7	(432.0 , 811.3)	861.9	(642.4 , 1081.3)	240.2	-(49.8 , 528.7)	1.39	(0.93 , 2.06)
(0.163,0.27!	01-08 to 01-21	627.3	(427.7 , 827.0)	640.3	(438.5 , 842.2)	13.0	-(270.9 , 295.5)	1.02	(0.65 , 1.59)
(0.163,0.27!	01-22 to 02-04	616.9	(419.3 , 814.5)	584.3	(392.3 , 776.3)	-32.6	-(308.1 , 241.5)	0.95	(0.60 , 1.50)

(0.163,0.27	02-05 to 02-18	612.9	(415.2 , 810.6)	581.5	(389.6 , 773.4)	-31.4	-(306.9 , 242.7)	0.95	(0.60 , 1.50)
(0.163,0.27	02-19 to 03-03	558.8	(371.7 , 746.0)	567.8	(384.0 , 751.6)	9.0	-(253.4 , 270.0)	1.02	(0.64 , 1.62)
(0.163,0.27	03-04 to 03-17	562.2	(373.7 , 750.8)	568.4	(378.6 , 758.2)	6.2	-(261.3 , 272.3)	1.01	(0.63 , 1.62)
(0.163,0.27	03-18 to 03-31	591.8	(398.2 , 785.5)	600.2	(403.8 , 796.6)	8.3	-(267.5 , 282.8)	1.01	(0.64 , 1.61)
(0.163,0.27	04-01 to 04-14	571.6	(380.7 , 762.5)	905.1	(665.7 , 1144.4)	333.5	(27.3 , 638.0)	1.58	(1.03 , 2.42)
(0.279,0.51	01-08 to 01-21	651.5	(438.5 , 864.5)	605.0	(398.9 , 811.0)	-46.5	-(342.9 , 248.3)	0.93	(0.58 , 1.49)
(0.279,0.51	01-22 to 02-04	658.9	(443.5 , 874.3)	608.2	(401.8 , 814.6)	-50.7	-(349.0 , 246.1)	0.92	(0.58 , 1.48)
(0.279,0.51	02-05 to 02-18	665.2	(449.4 , 880.9)	605.1	(397.7 , 812.4)	-60.1	-(359.4 , 237.6)	0.91	(0.57 , 1.45)
(0.279,0.51	02-19 to 03-03	590.0	(387.3 , 792.7)	601.6	(401.0 , 802.2)	11.5	-(273.7 , 295.2)	1.02	(0.63 , 1.64)
(0.279,0.51	03-04 to 03-17	616.9	(409.4 , 824.4)	627.0	(418.0 , 836.0)	10.1	-(284.4 , 303.1)	1.02	(0.63 , 1.63)
(0.279,0.51	03-18 to 03-31	621.7	(412.4 , 831.1)	661.7	(444.1 , 879.3)	40.0	-(262.0 , 340.4)	1.06	(0.66 , 1.70)
(0.279,0.51	04-01 to 04-14	633.2	(421.0 , 845.4)	873.3	(626.8 , 1119.8)	240.1	-(85.2 , 563.8)	1.38	(0.89 , 2.13)
(0.512,0.85	01-08 to 01-21	674.4	(431.2 , 917.7)	611.1	(377.3 , 844.8)	-63.4	-(400.7 , 272.3)	0.91	(0.54 , 1.53)
(0.512,0.85	01-22 to 02-04	675.8	(432.5 , 919.2)	676.9	(432.0 , 921.8)	1.0	-(344.2 , 344.5)	1.00	(0.60 , 1.66)
(0.512,0.85	02-05 to 02-18	688.8	(442.6 , 935.1)	701.4	(453.9 , 948.9)	12.6	-(336.6 , 359.9)	1.02	(0.62 , 1.68)
(0.512,0.85	02-19 to 03-03	575.4	(352.1 , 798.7)	629.3	(399.7 , 858.9)	53.9	-(266.4 , 372.5)	1.09	(0.64 , 1.86)
(0.512,0.85	03-04 to 03-17	632.6	(398.0 , 867.1)	629.1	(394.8 , 863.4)	-3.5	-(335.0 , 326.4)	0.99	(0.59 , 1.68)
(0.512,0.85	03-18 to 03-31	633.3	(397.5 , 869.0)	706.5	(454.3 , 958.6)	73.2	-(272.0 , 416.6)	1.12	(0.67 , 1.86)
(0.512,0.85	04-01 to 04-14	612.6	(380.5 , 844.8)	1190.0	(865.9 , 1514.2)	577.4	(178.7 , 974.1)	1.94	(1.22 , 3.09)

Figure 1a: Massachusetts age−standardized death rates by two−week period, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

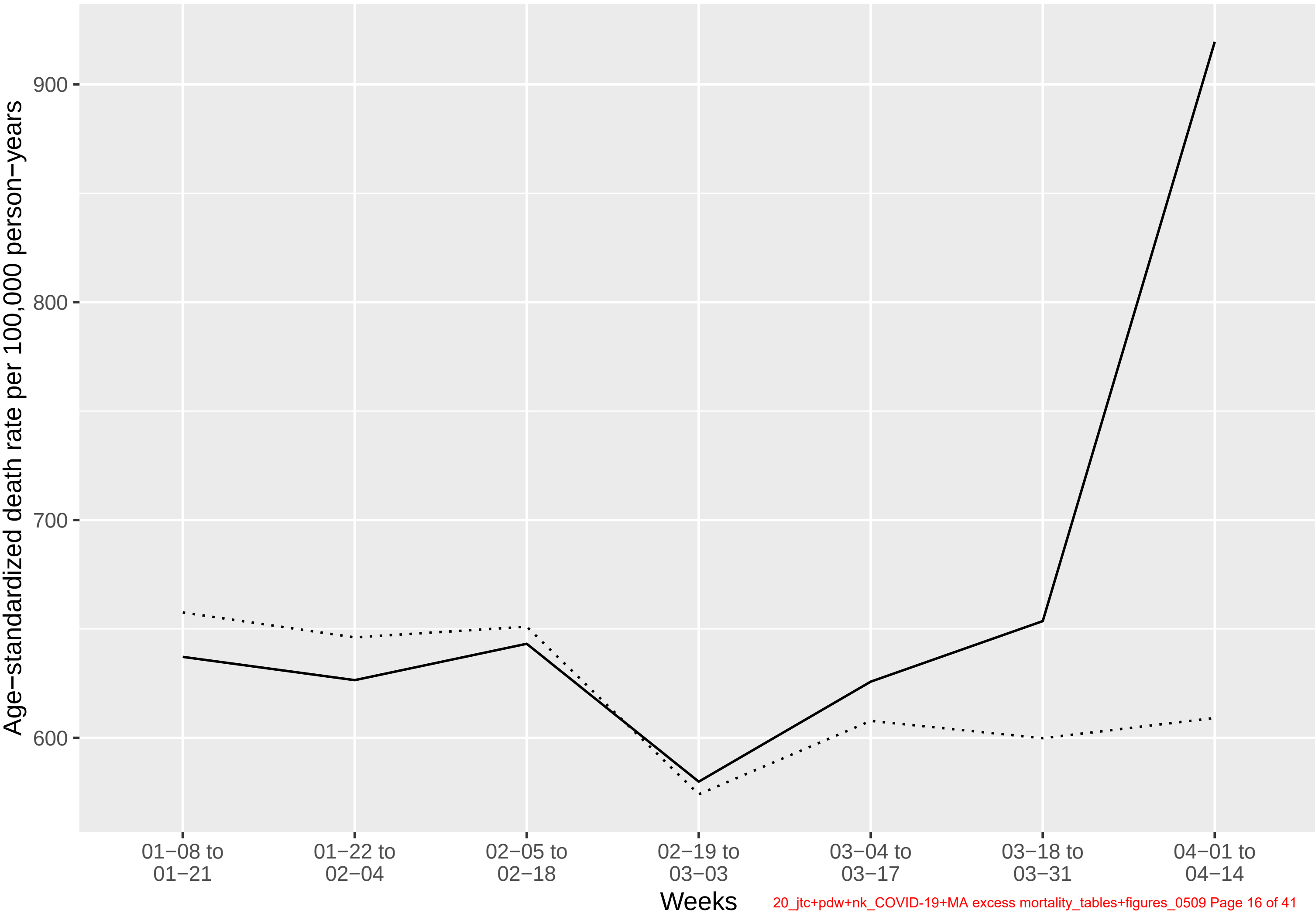


Figure 1b: Massachusetts age−standardized mortality rate differences by two−week period, 2020 vs. 2015−2019, Jan 8−April 14

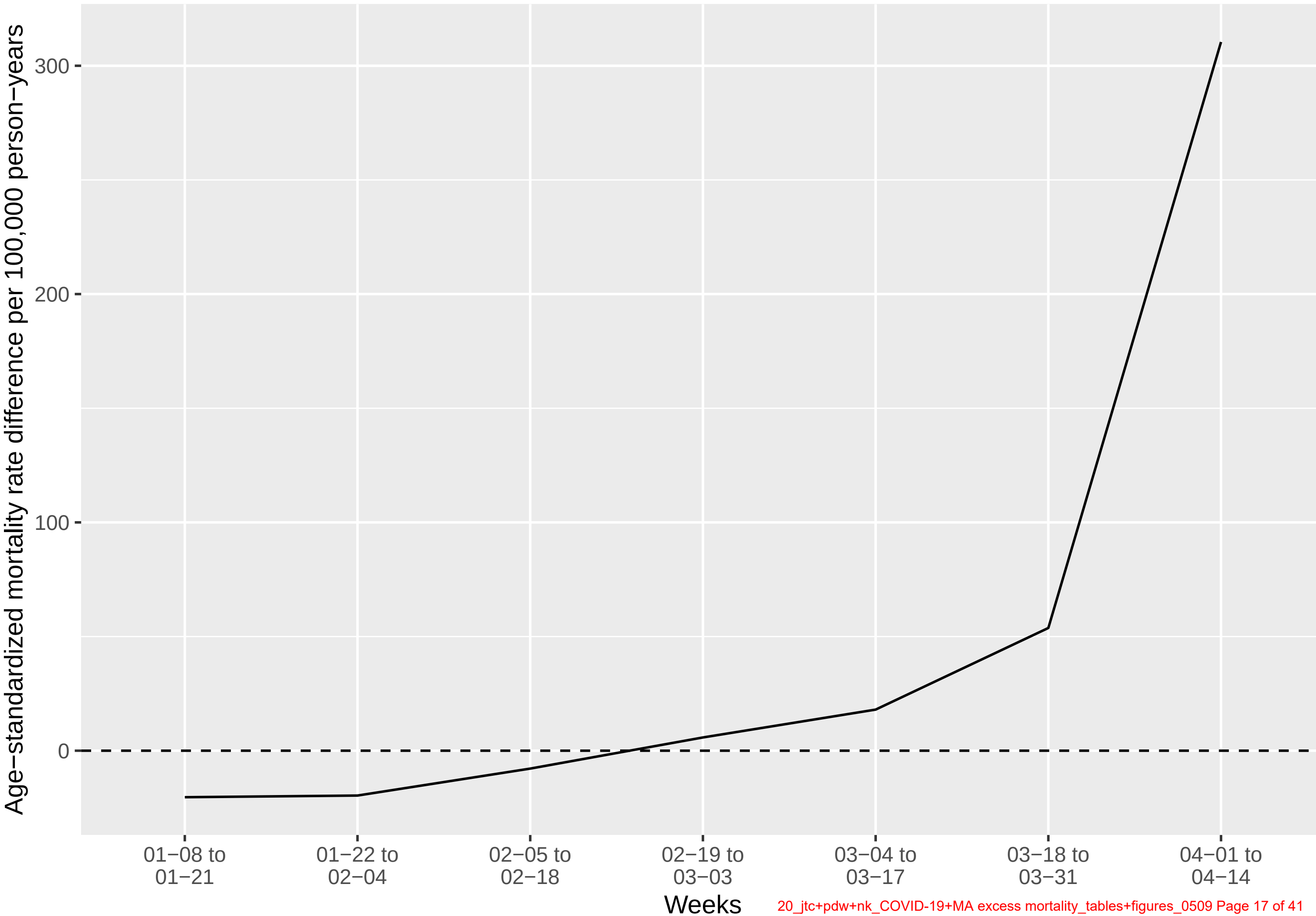
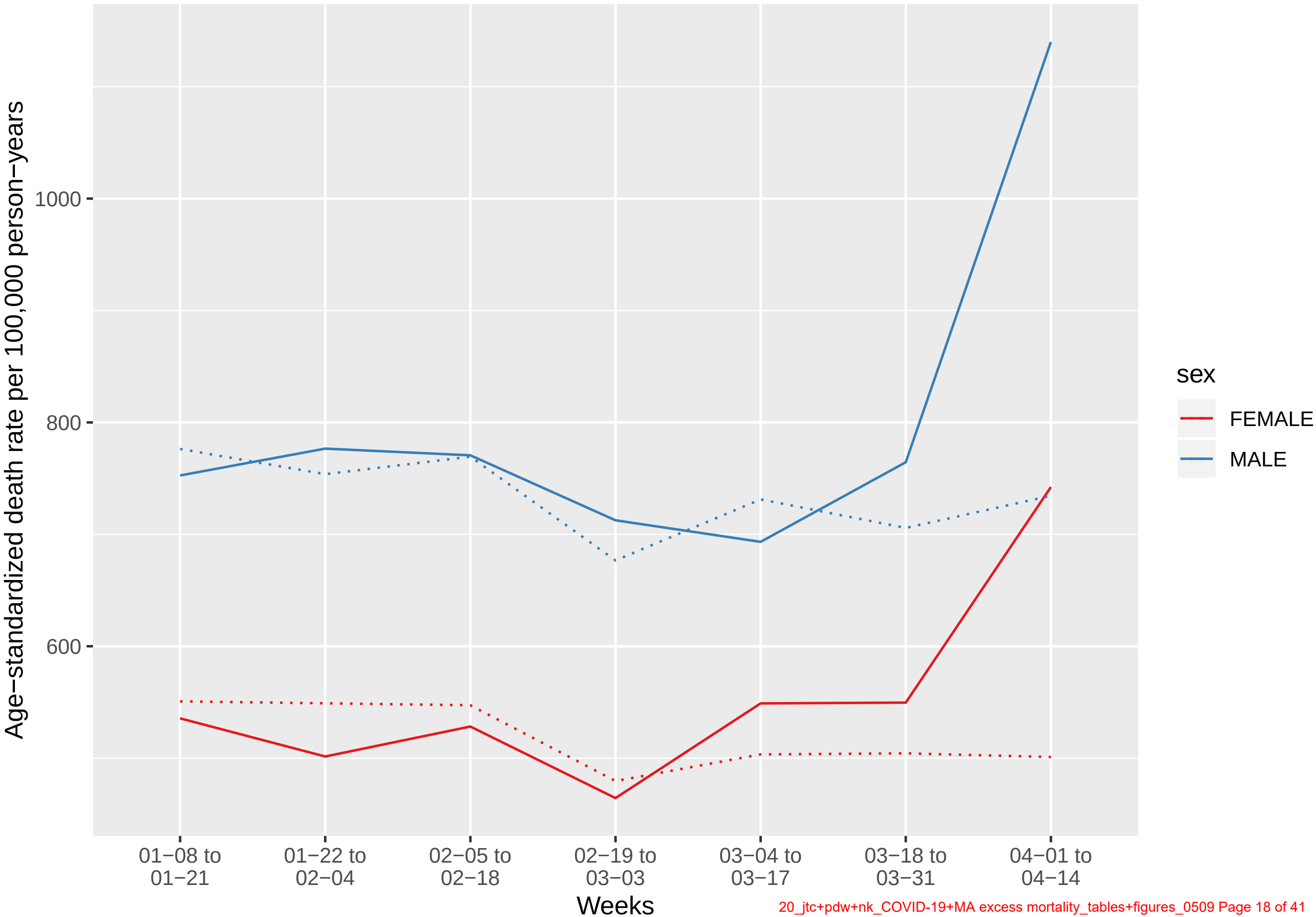


Figure 1c: Massachusetts age−standardized death rates by two−week period and sex, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14



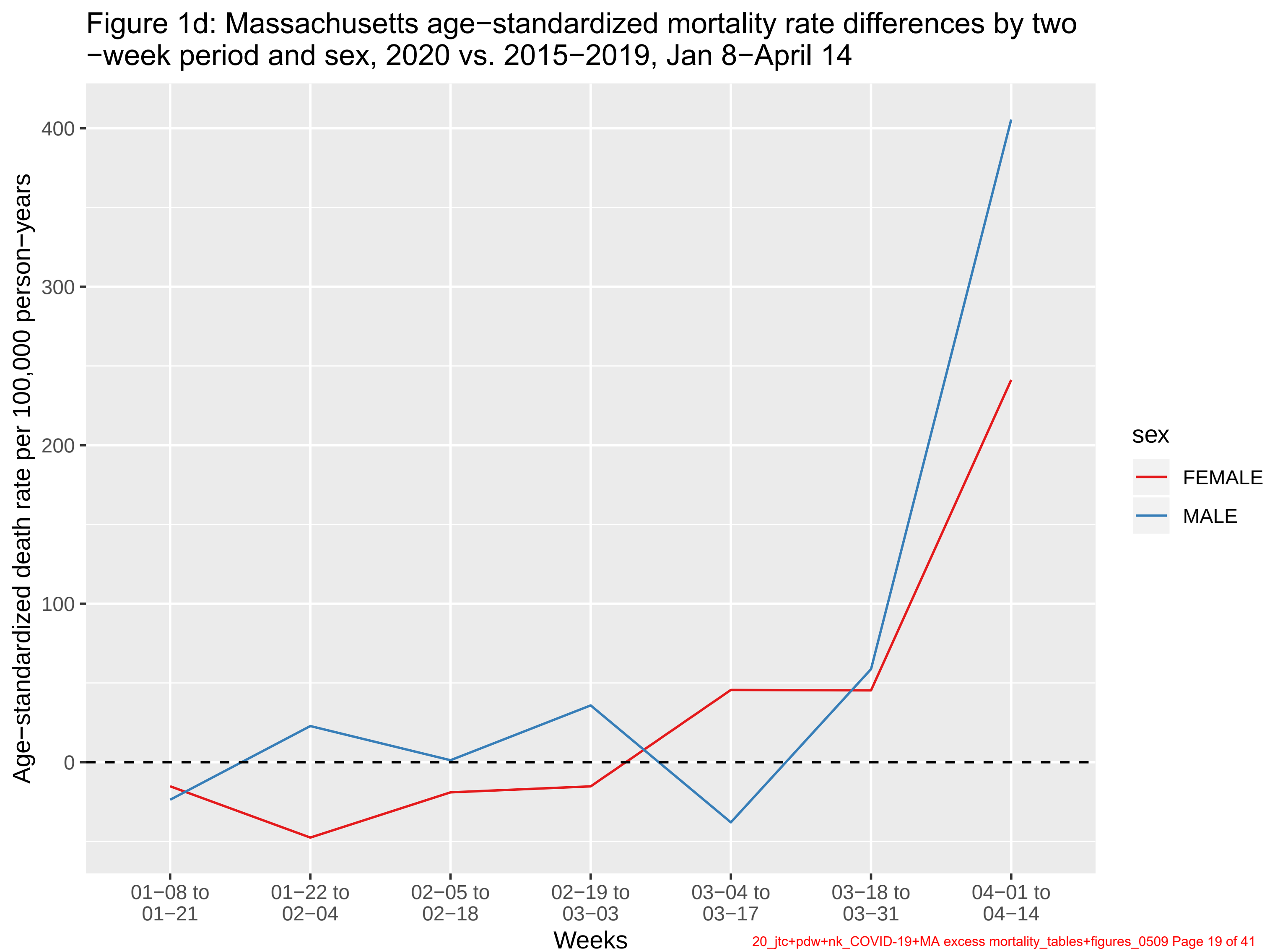


Figure 1d: Massachusetts age−standardized mortality rate differences by two
−week period and sex, 2020 vs. 2015−2019, Jan 8−April 14
Age−standardized death rate per 100,000 person−years
400
300
200
100
0
01−08 to
01−21
01−22 to
02−04
02−05 to
02−18
02−19 to
03−03
03−04 to
03−17
03−18 to
03−31
04−01 to
04−14
Weeks
sex
FEMALE
MALE

Figure 1e: Massachusetts crude death rates per 100,000 person−years by two−week period and age, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

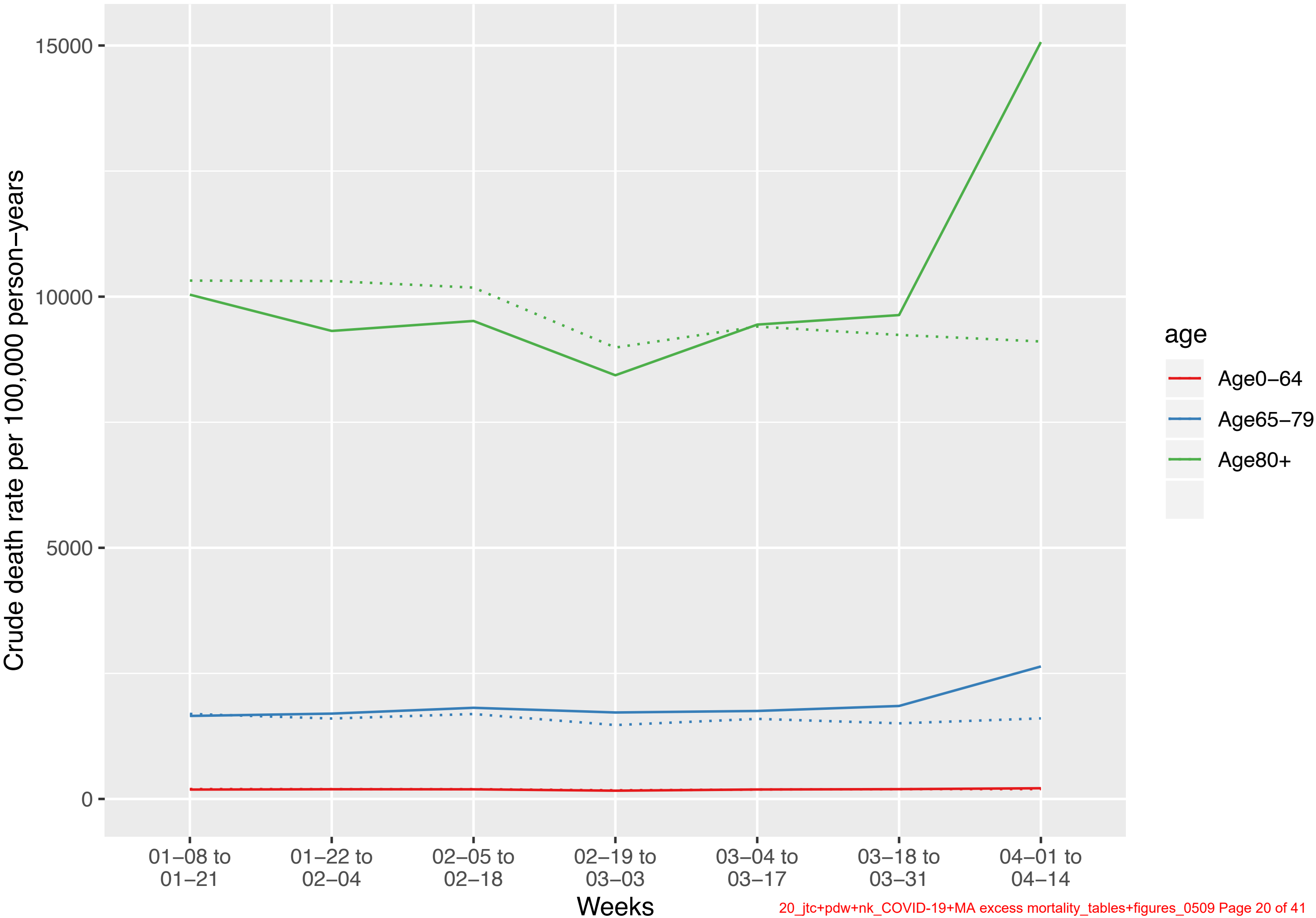


Figure 1f: Massachusetts crude mortality rate differences per 100,000 person-years by two−week period and age, 2020 vs. 2015−2019, Jan 8−April 14

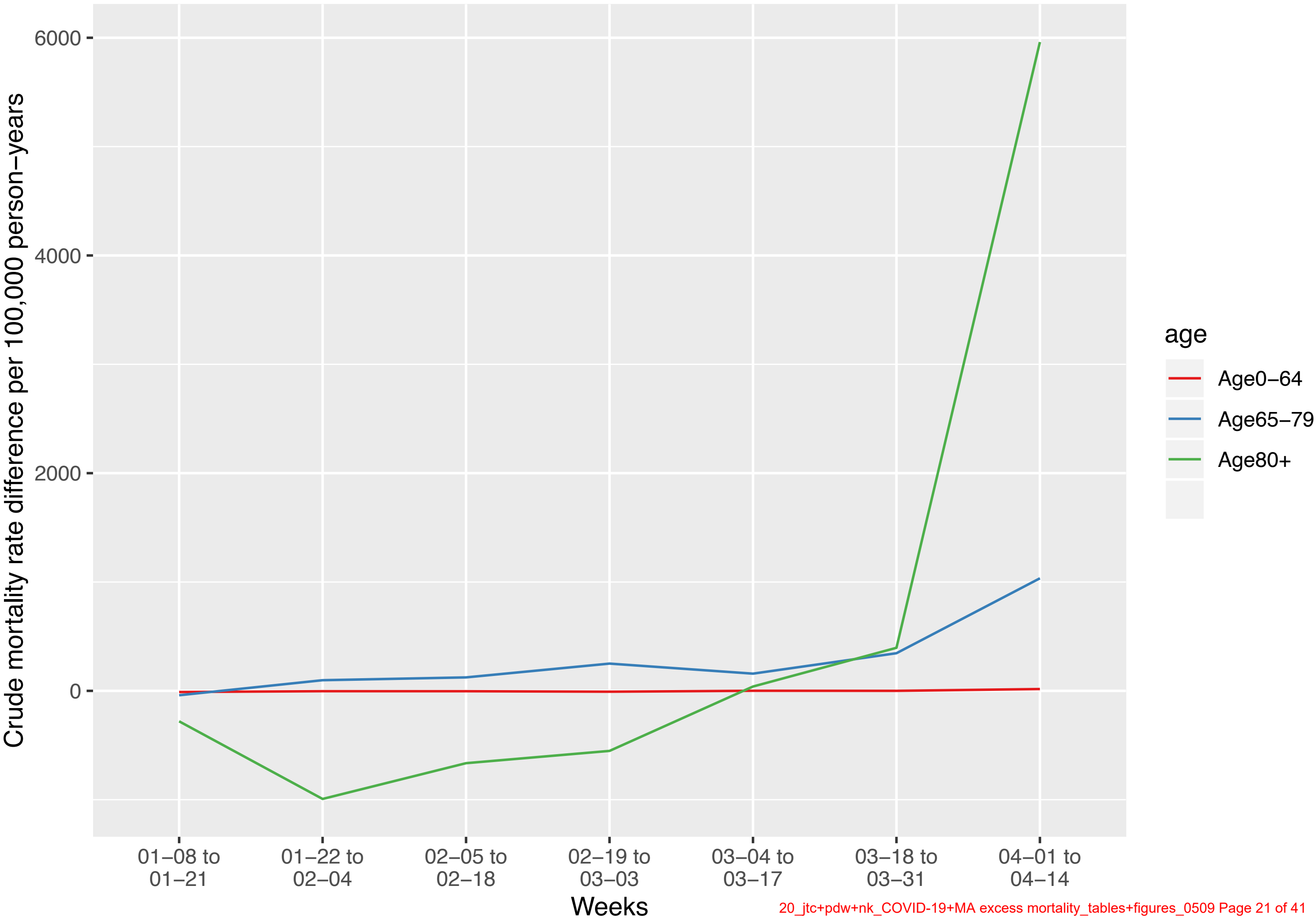


Figure 2a: Massachusetts age−standardized death rates by two week period and ZCTA % poverty, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

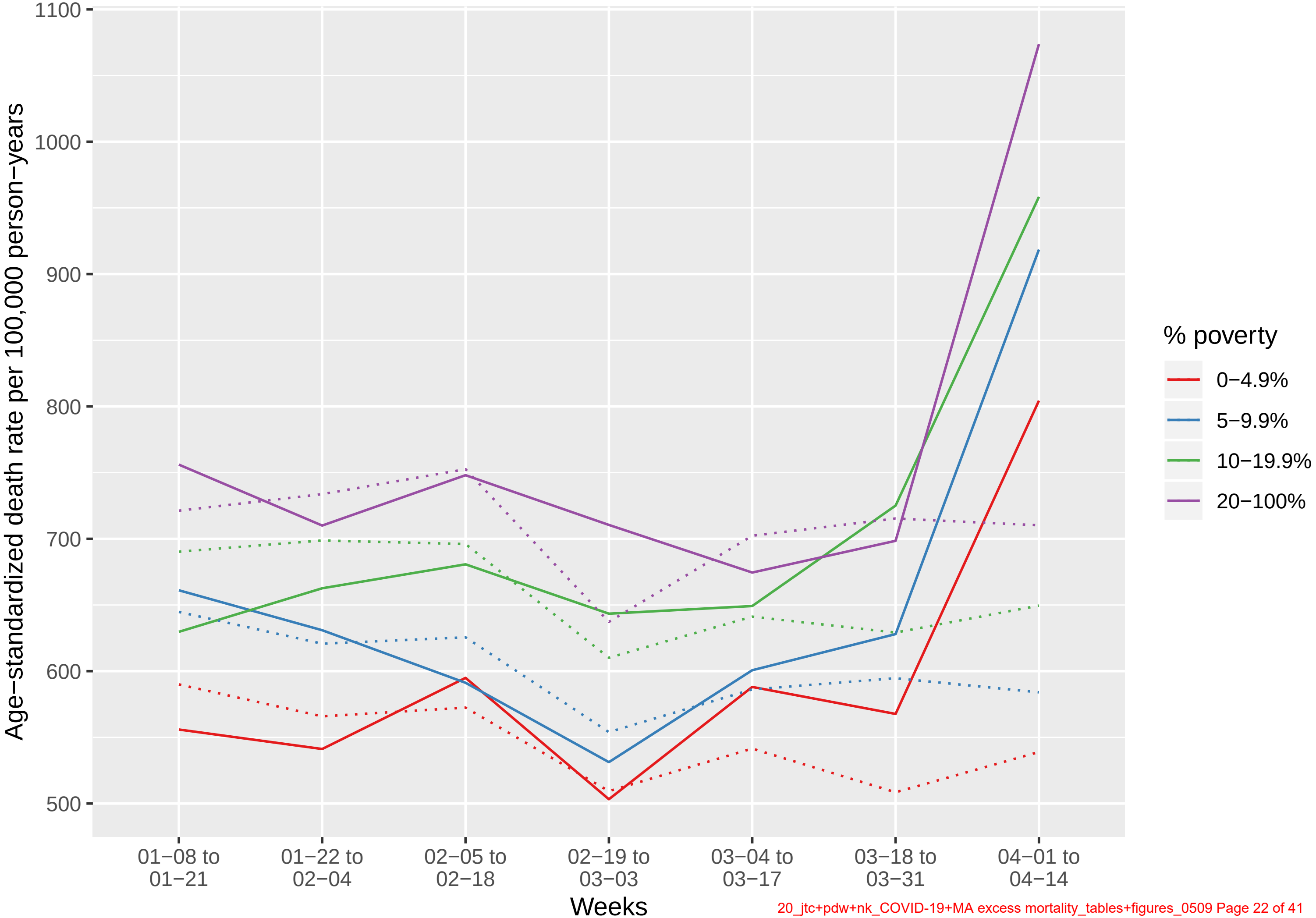


Figure 2b: Massachusetts age−standardized death rates by two week period and ZCTA % crowding, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

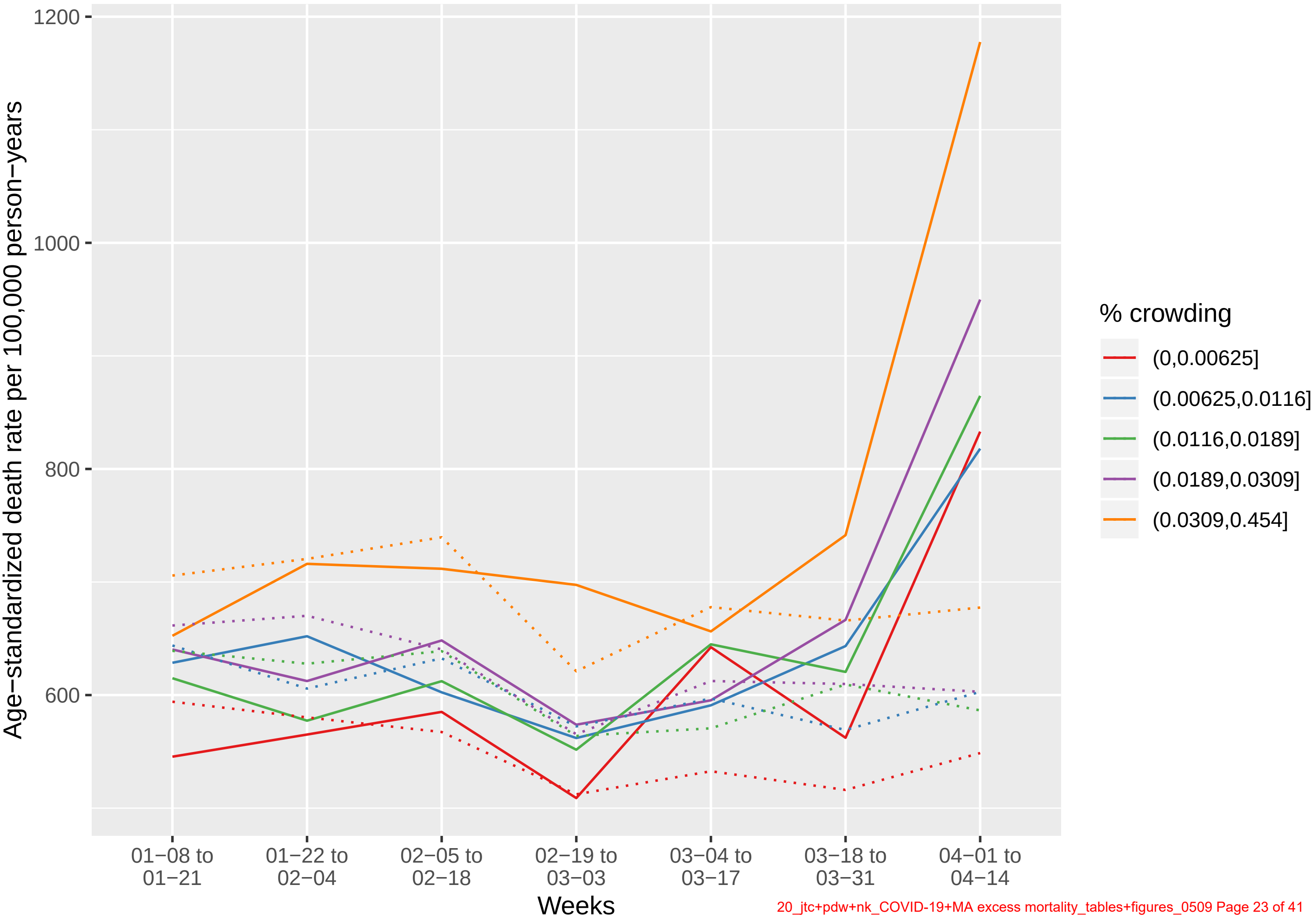


Figure 2c: Massachusetts age−standardized death rates by two week period and ZCTA ICE, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

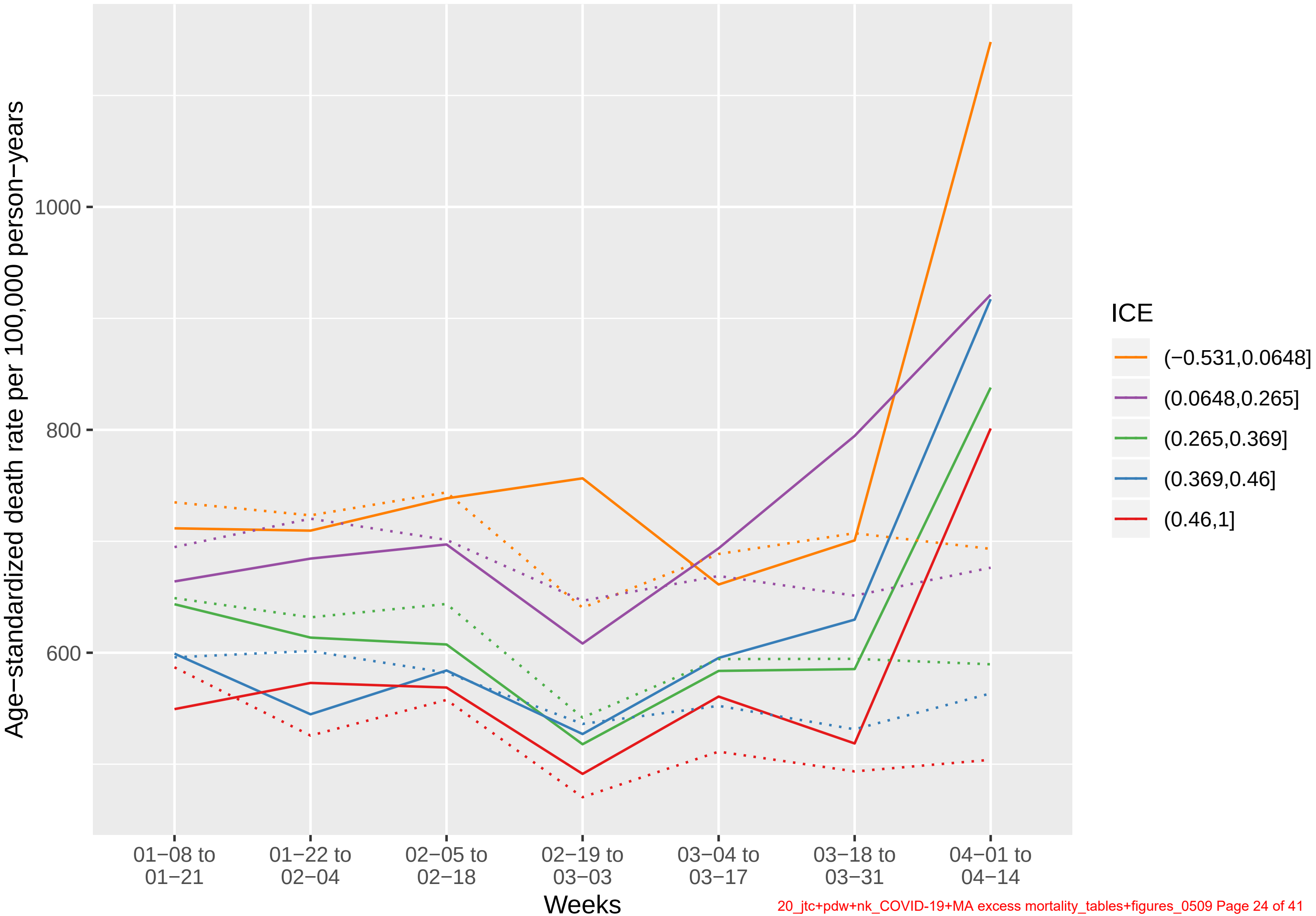


Figure 2d: Massachusetts age−standardized death rates by two week period and ZCTA % black population, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

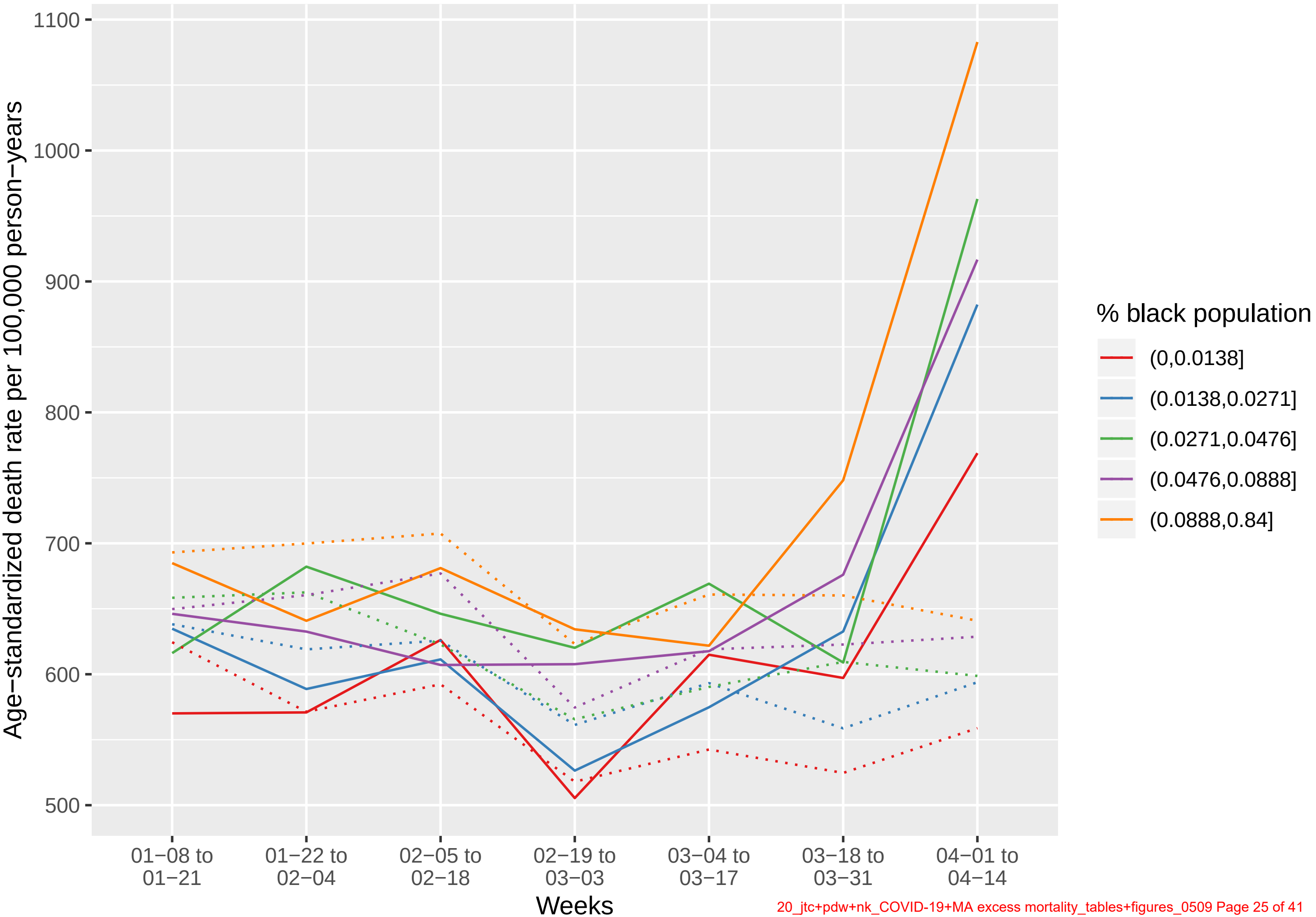


Figure 2e: Massachusetts age−standardized death rates by two week period and ZCTA % population of color, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

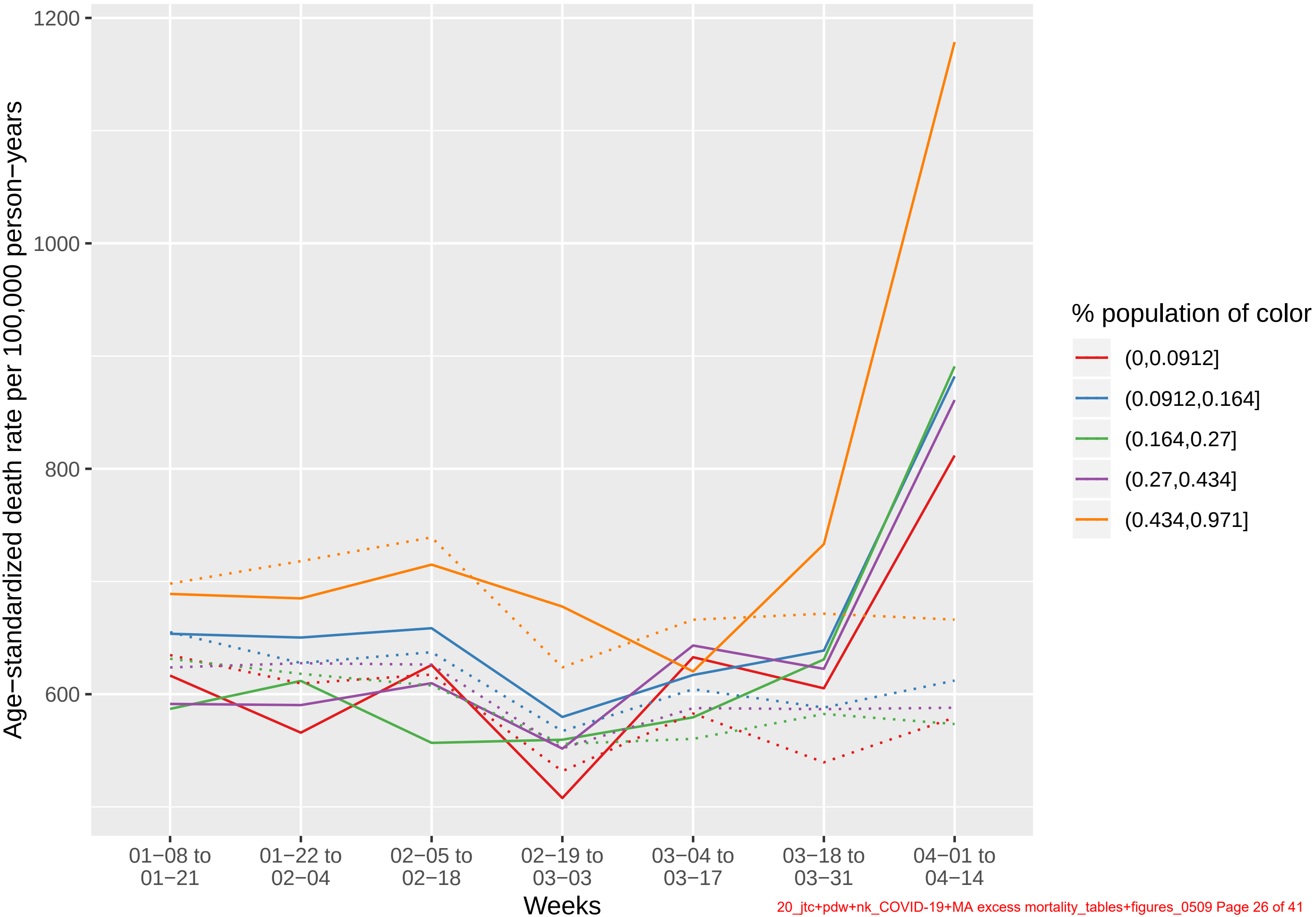


Figure 3a: Massachusetts age−standardized mortality rate differences by two week period and ZCTA % poverty, 2020 vs. 2015−2019, Jan 8−April 14

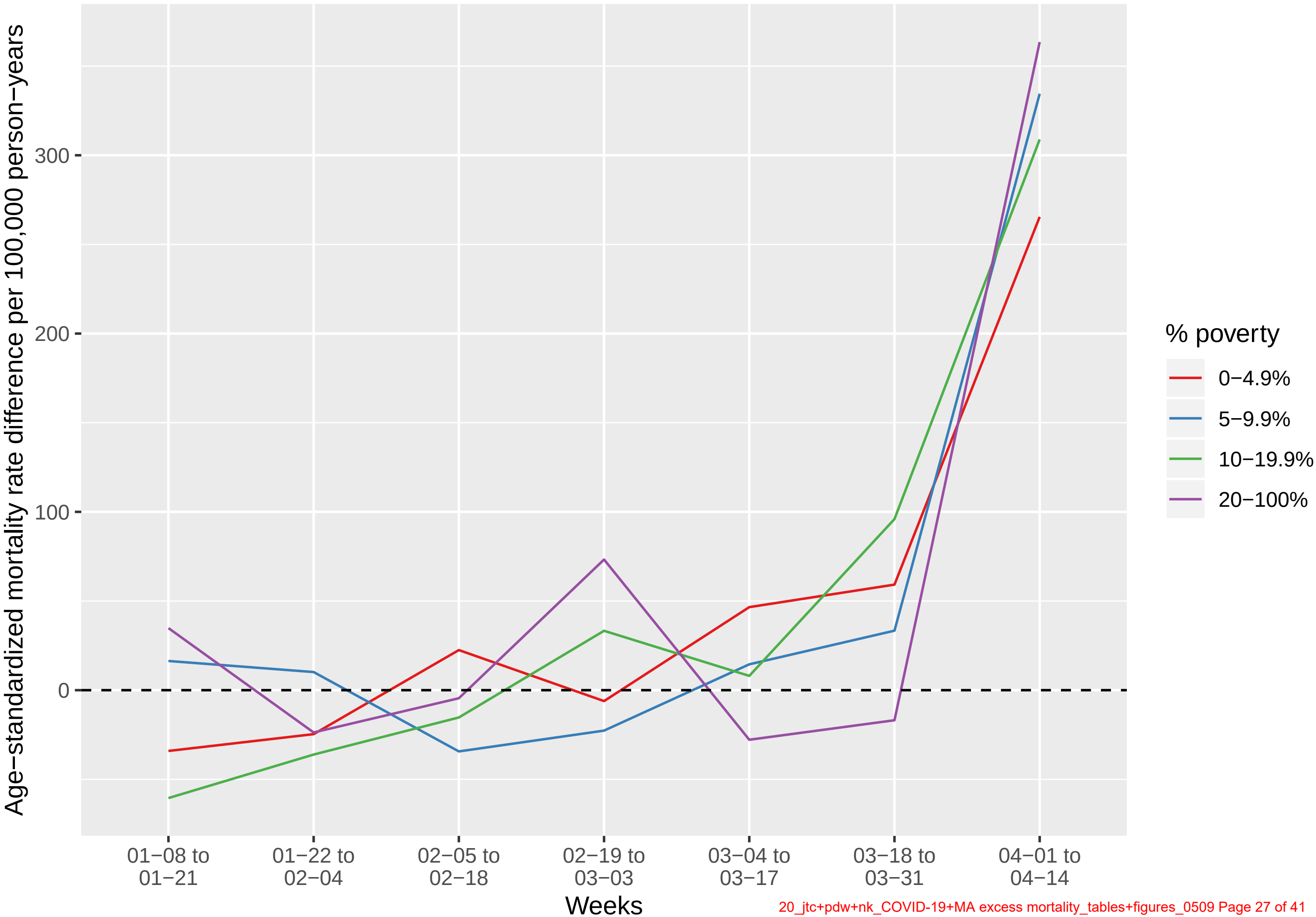


Figure 3b: Massachusetts age−standardized mortality rate differences by two week period and ZCTA % crowding, 2020 vs. 2015−2019, Jan 8−April 14

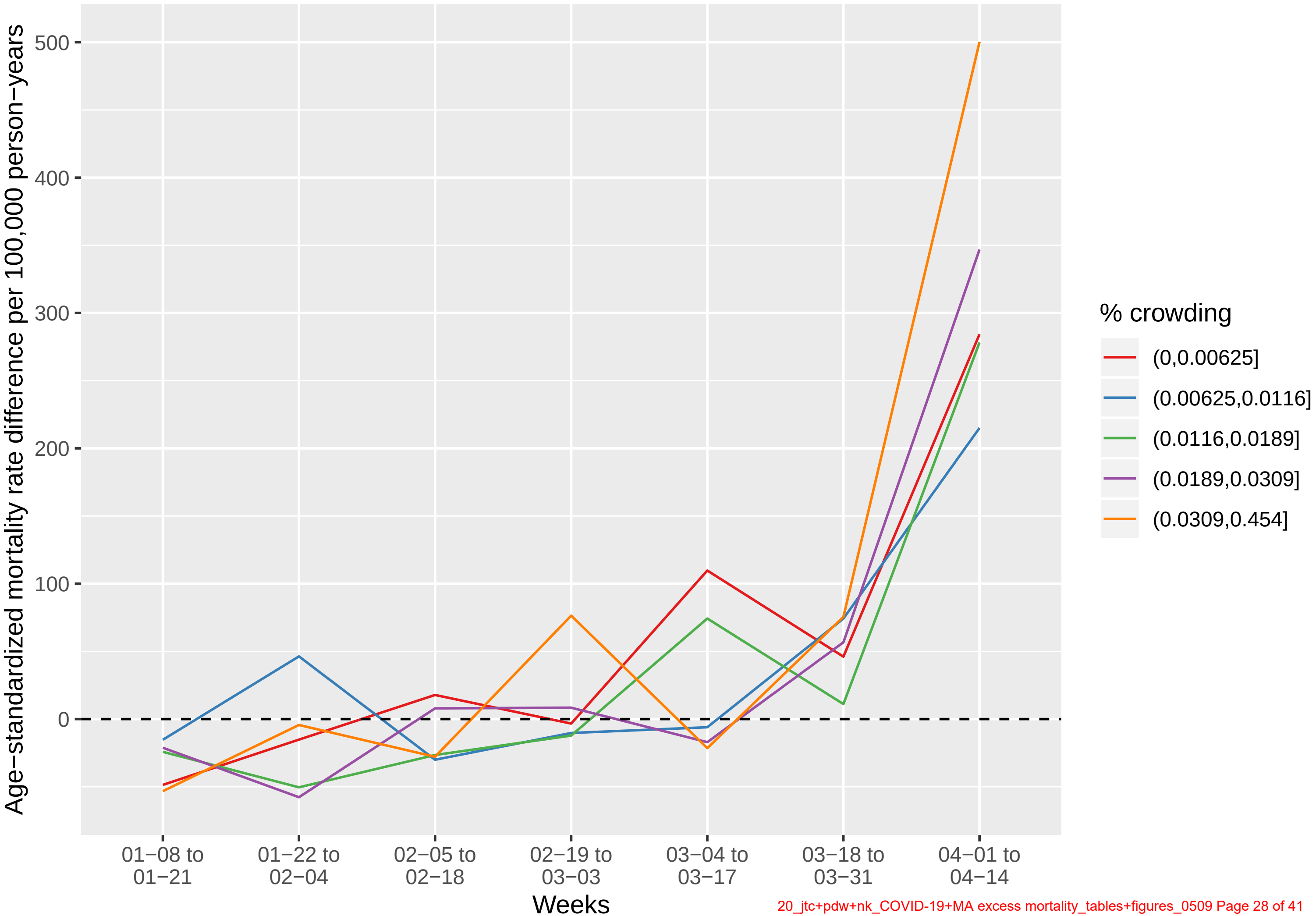


Figure 3c: Massachusetts age−standardized mortality rate differences by two week period and ZCTA ICE, 2020 vs. 2015−2019, Jan 8−April 14

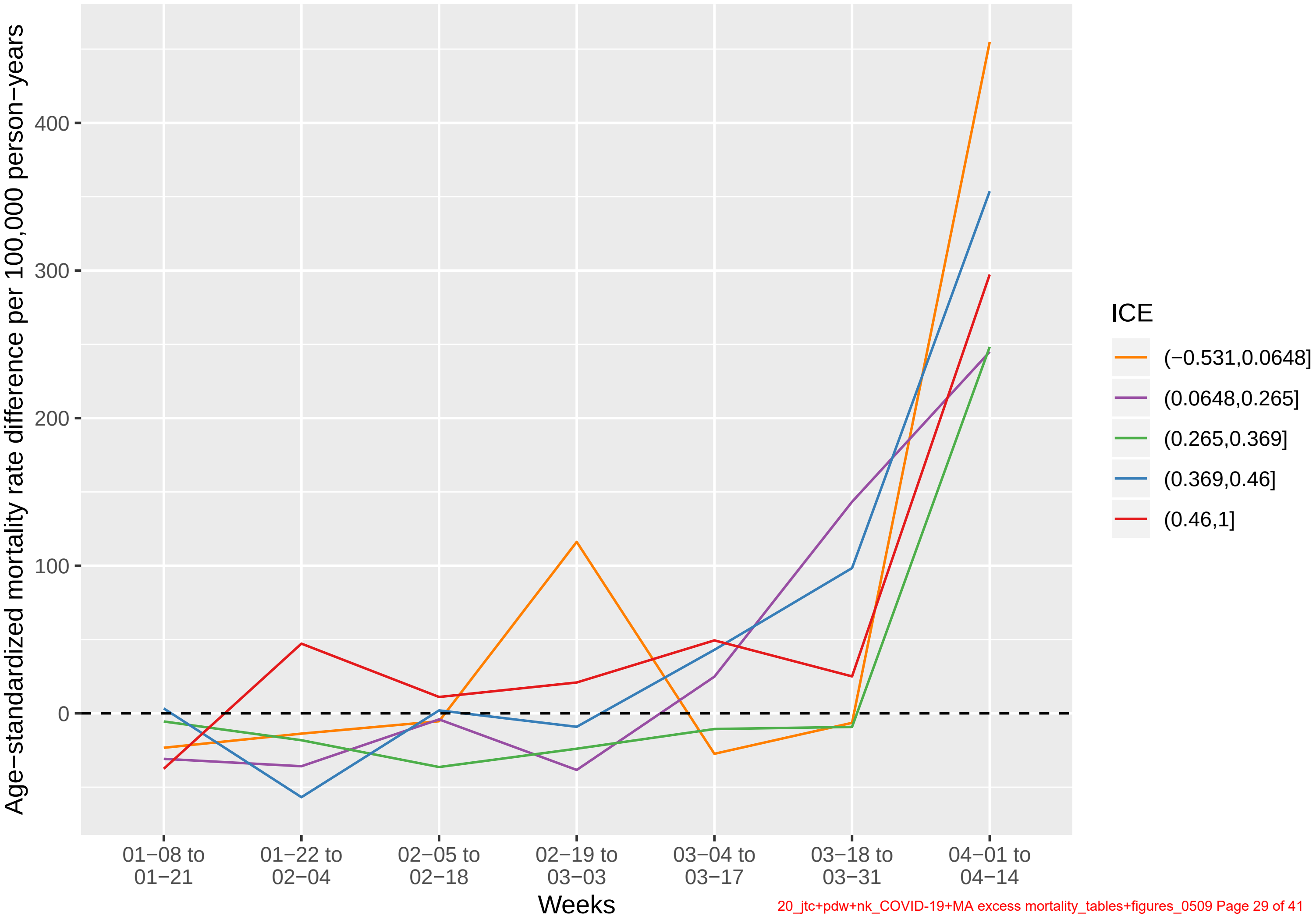


Figure 3d: Massachusetts age−standardized mortality rate differences by two week period and ZCTA % black population, 2020 vs. 2015−2019, Jan 8−April 14

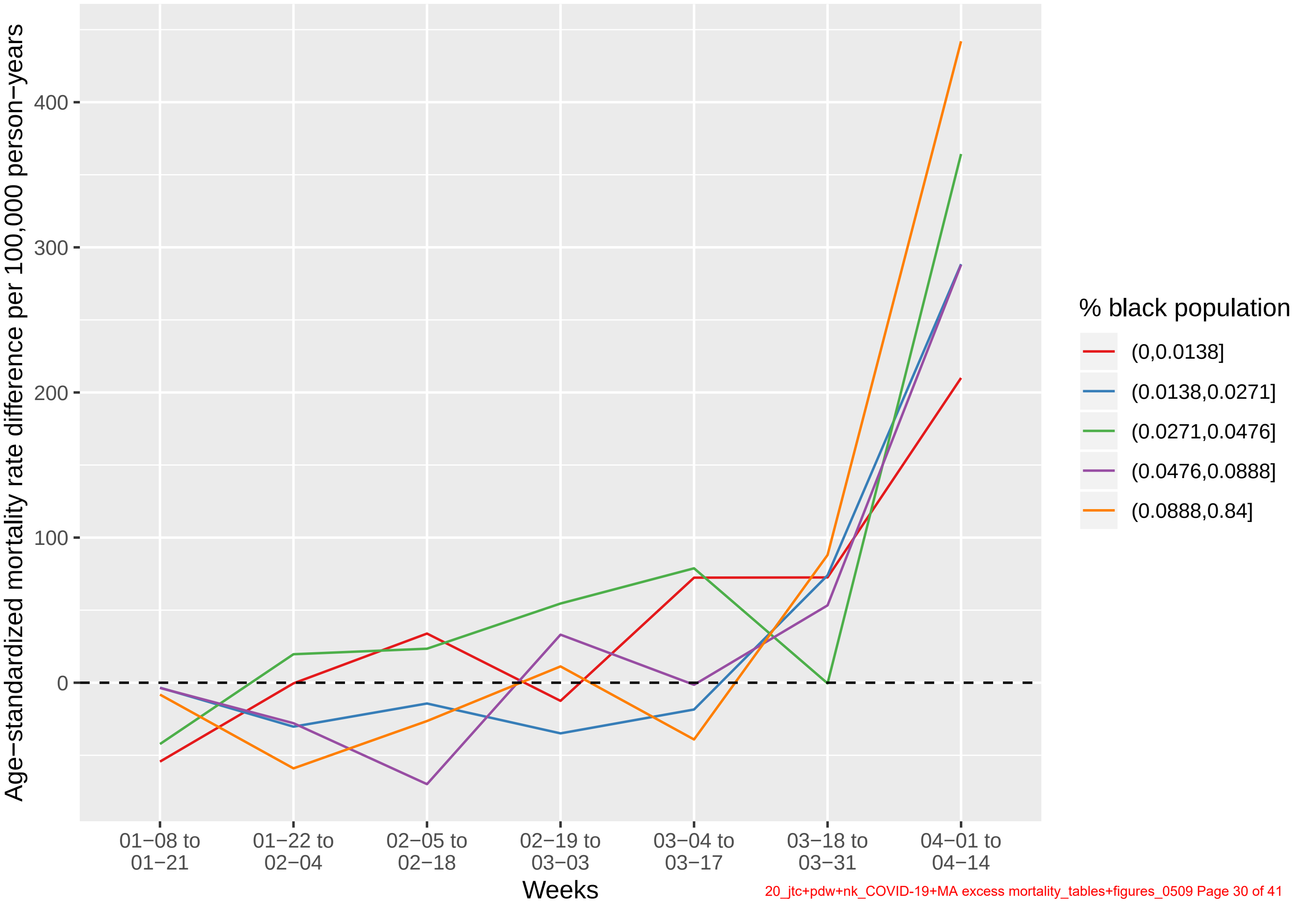


Figure 3e: Massachusetts age−standardized mortality rate differences by two week period and ZCTA % population of color, 2020 vs. 2015−2019, Jan 8−April 14

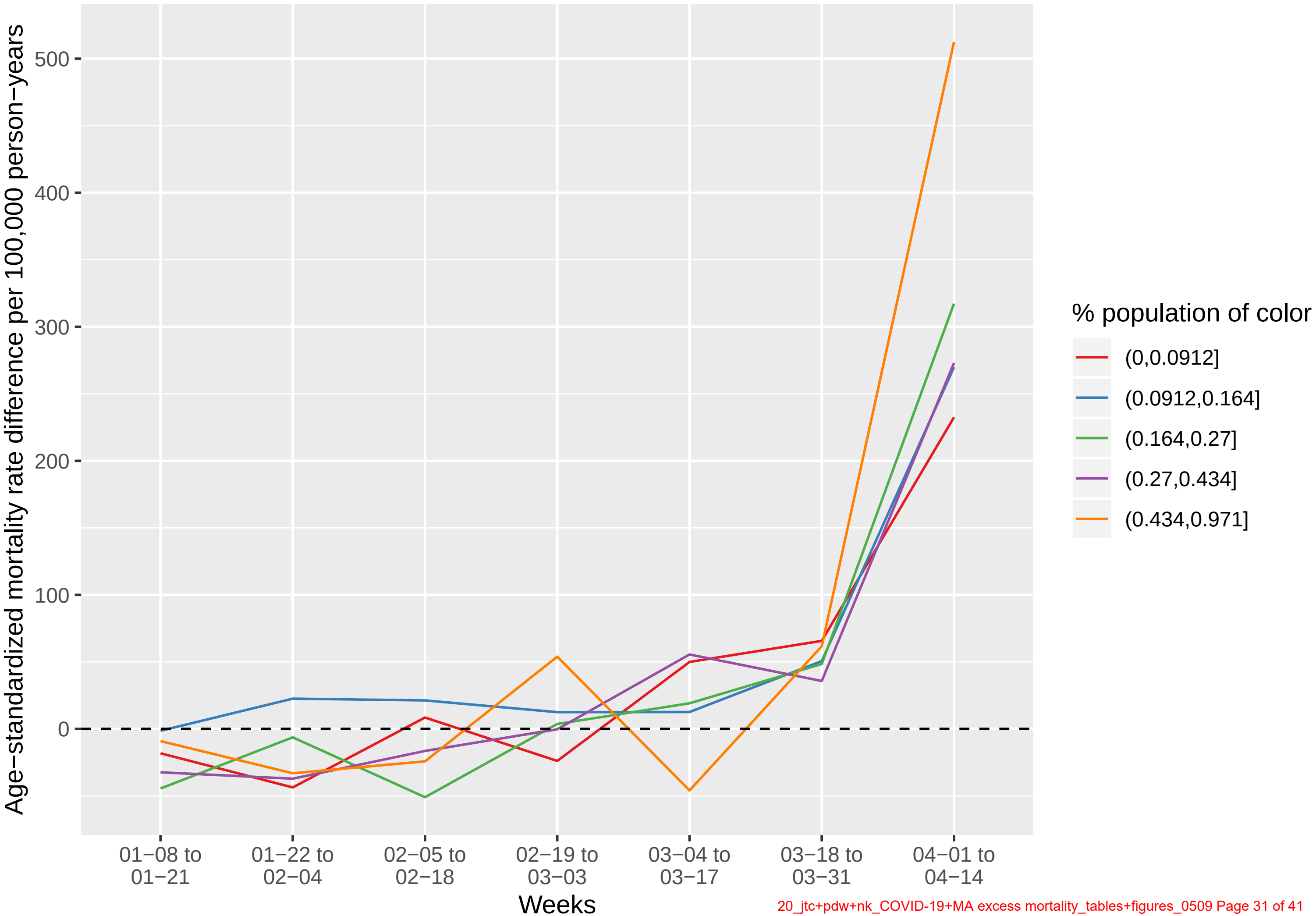


Figure 4a: Massachusetts age−standardized death rates by two−week period and city/town % poverty, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

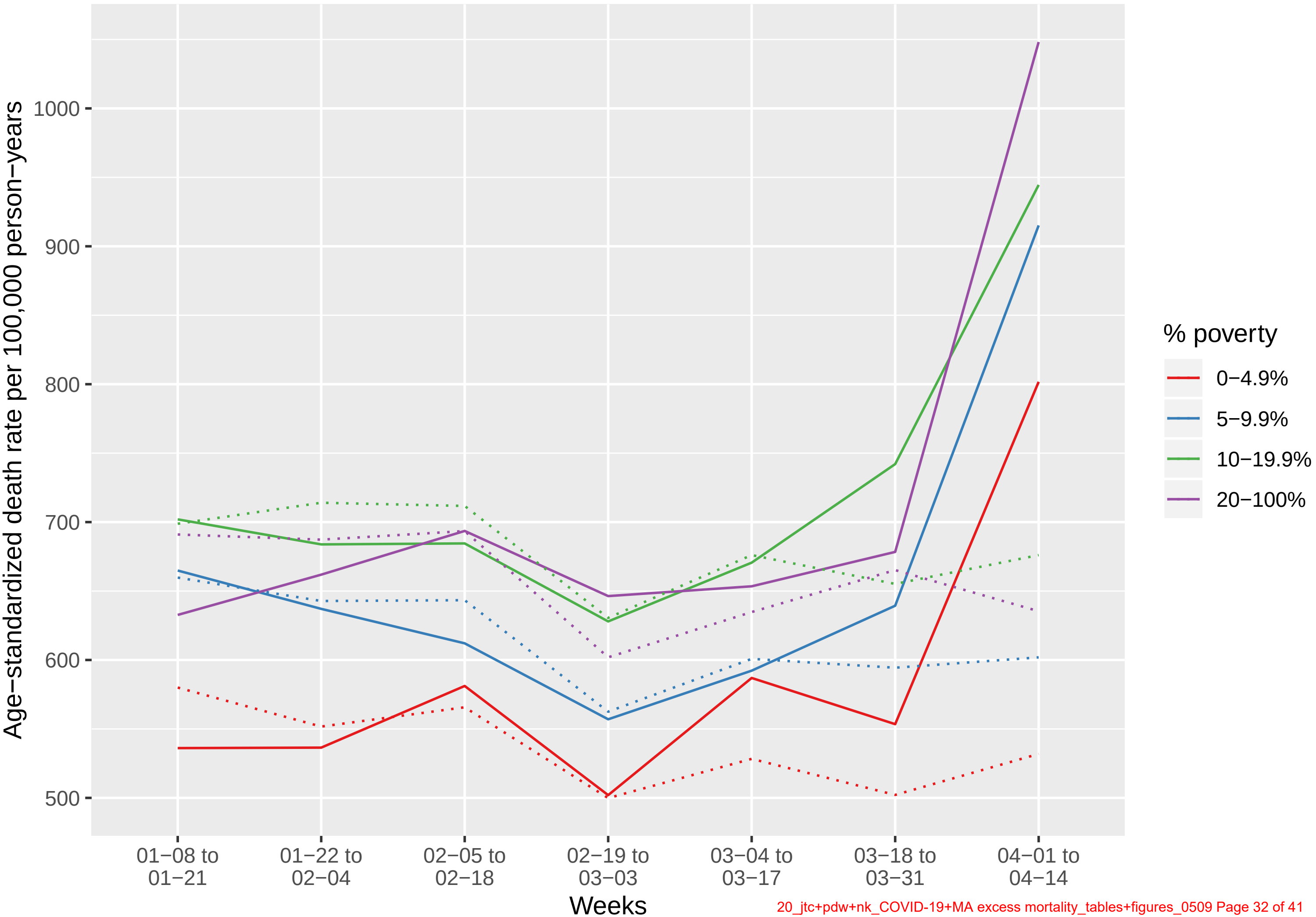


Figure 4b: Massachusetts age−standardized death rates by two−week period and city/town % crowding, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

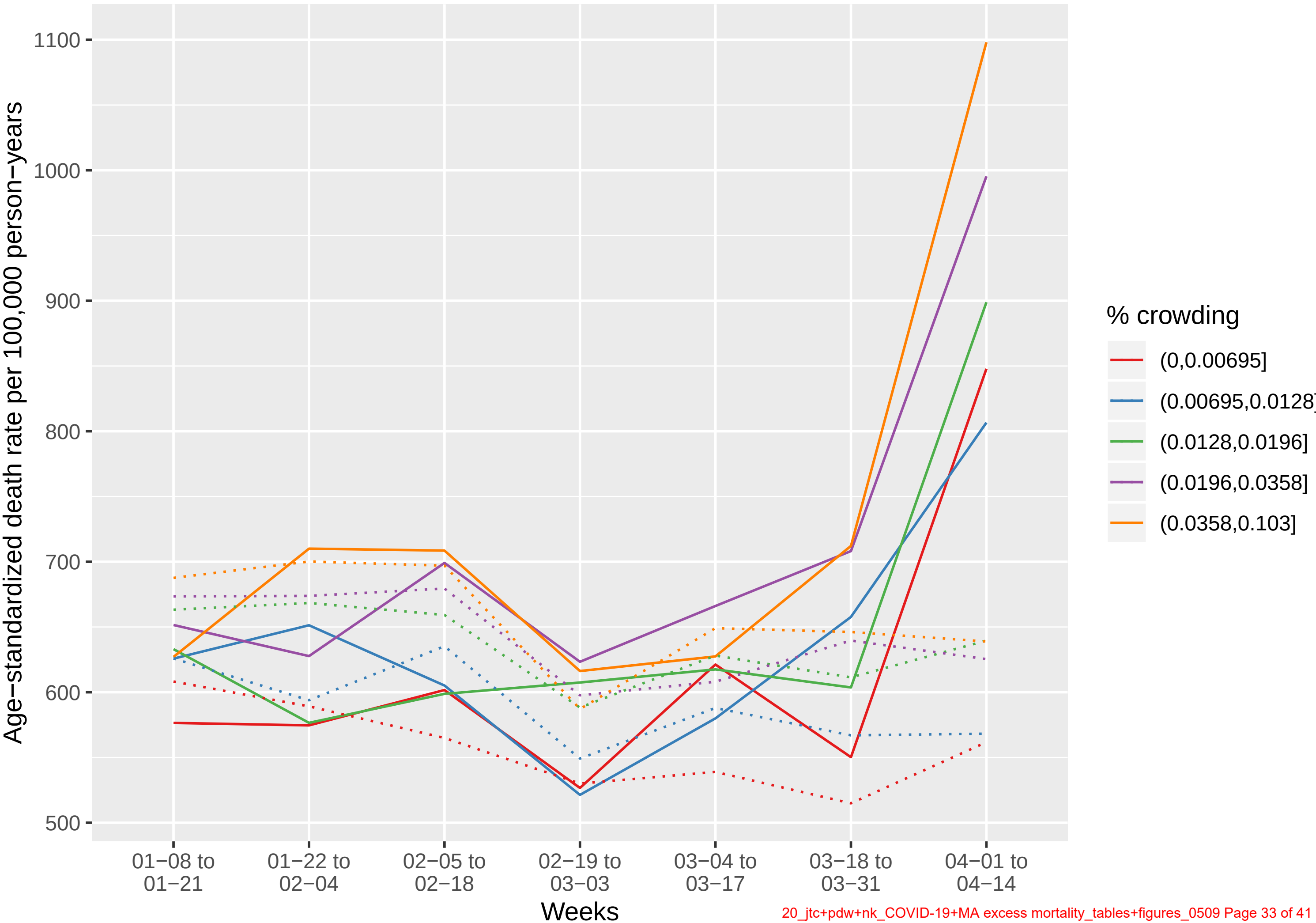


Figure 4c: Massachusetts age−standardized death rates by two−week period and city/town ICE, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

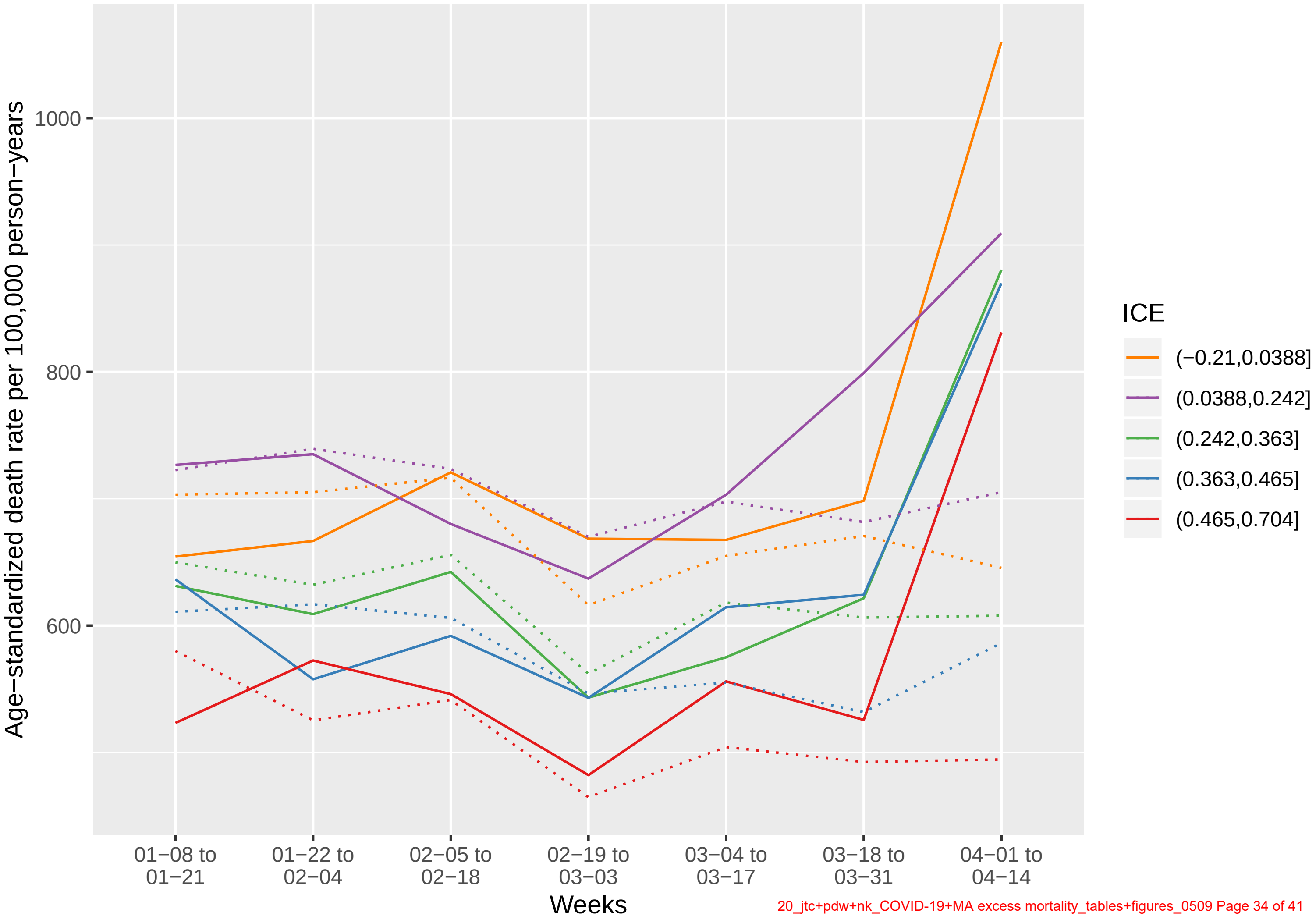


Figure 4d: Massachusetts age−standardized death rates by two−week period and city/town % black population, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

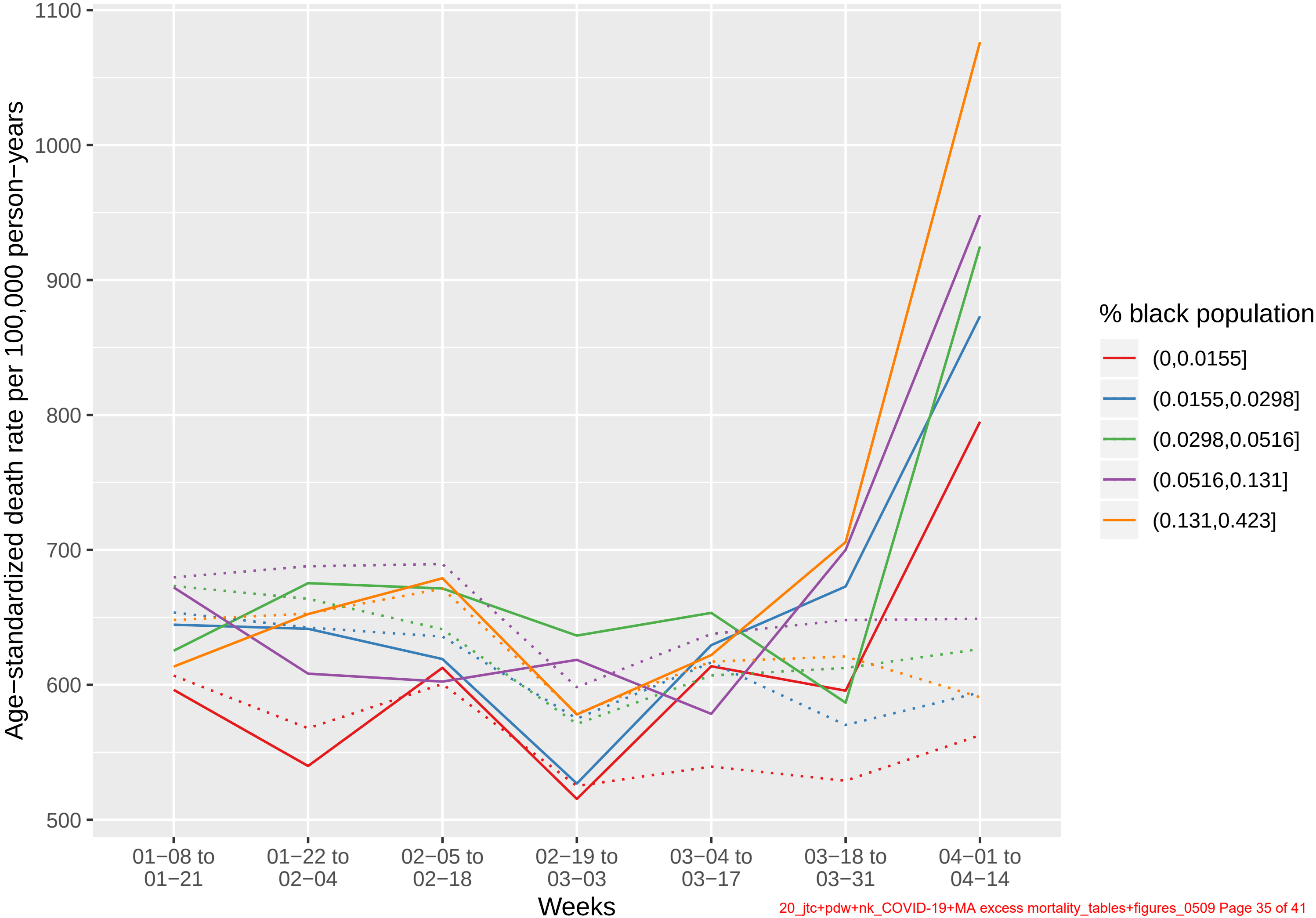


Figure 4e: Massachusetts age−standardized death rates by two−week period
and city/town % population of color, 2020 (solid) and 2015−2019 (dotted), Jan 8−April 14

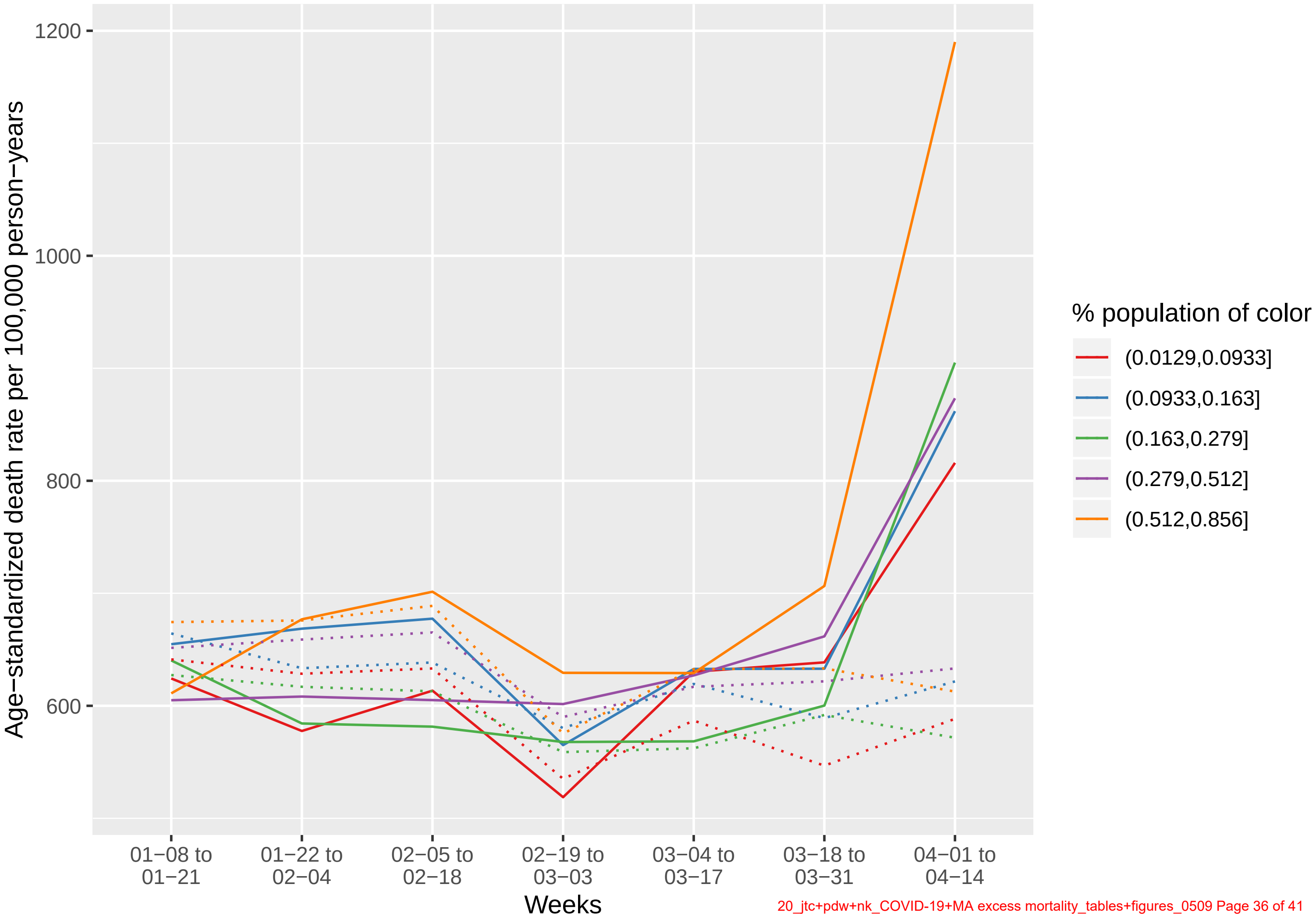


Figure 5a: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town % poverty, 2020 vs. 2015−2019, Jan 8−April 14

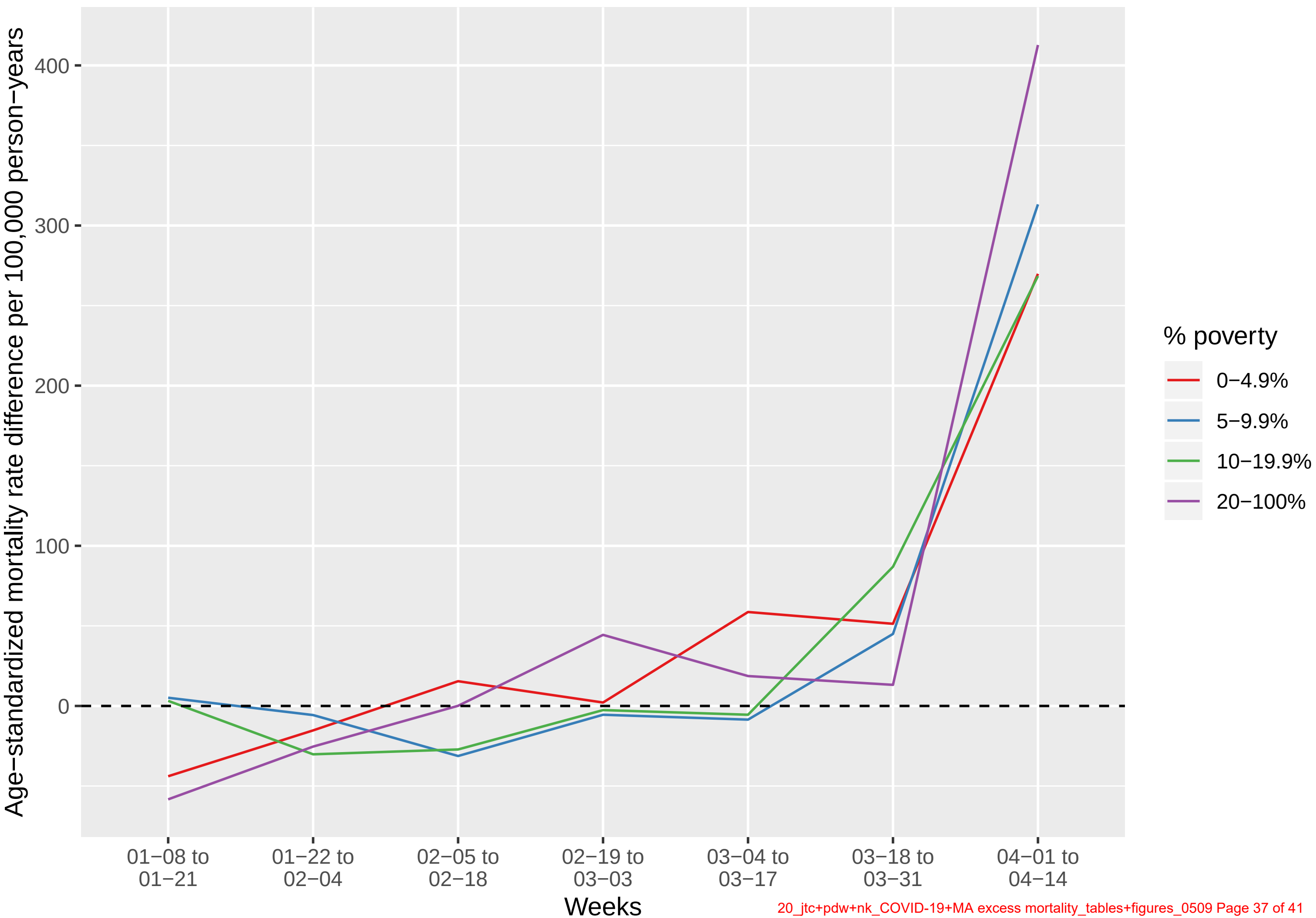


Figure 5b: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town % crowding, 2020 vs. 2015−2019, Jan 8−April 14

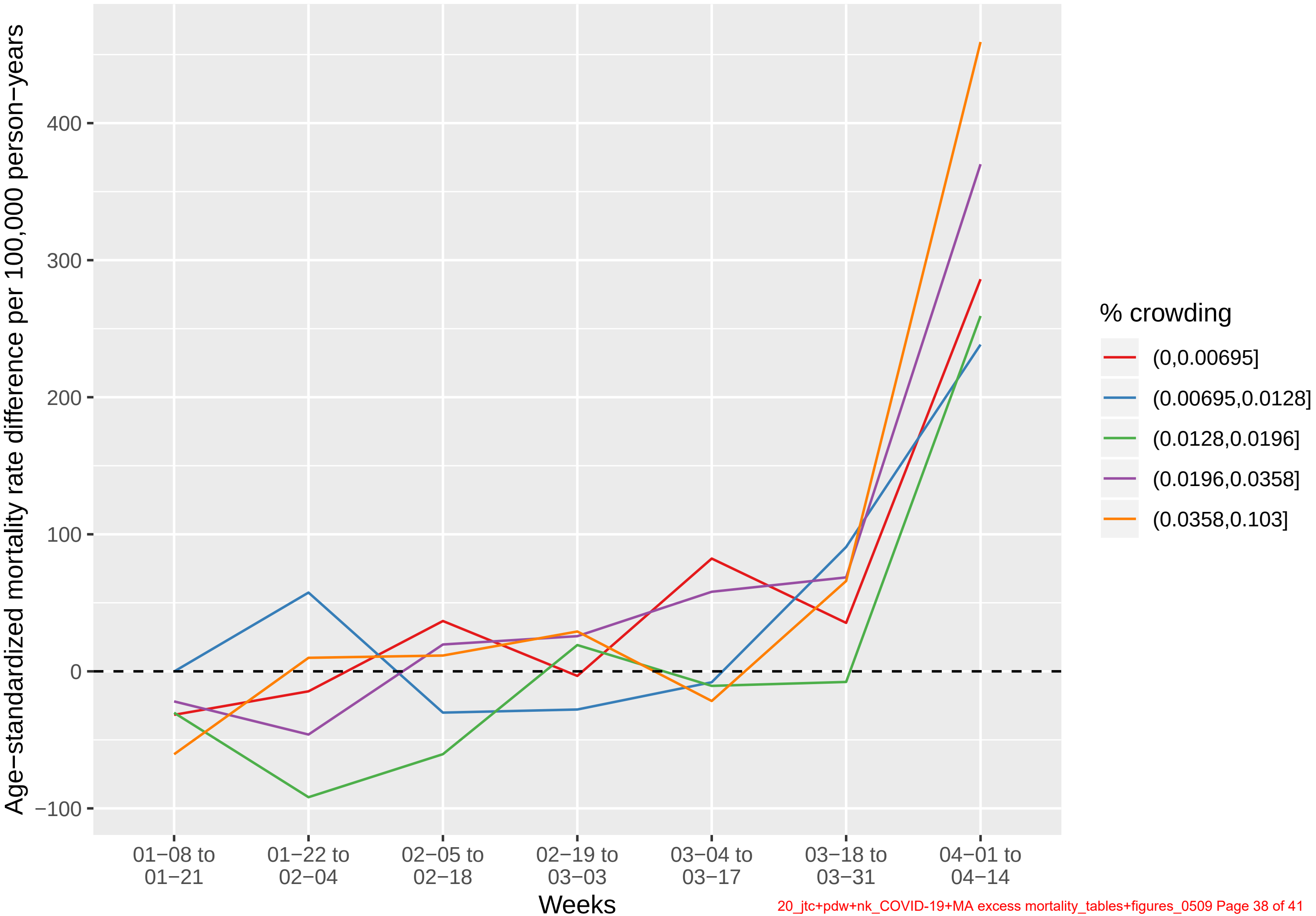


Figure 5c: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town ICE, 2020 vs. 2015−2019, Jan 8−April 14

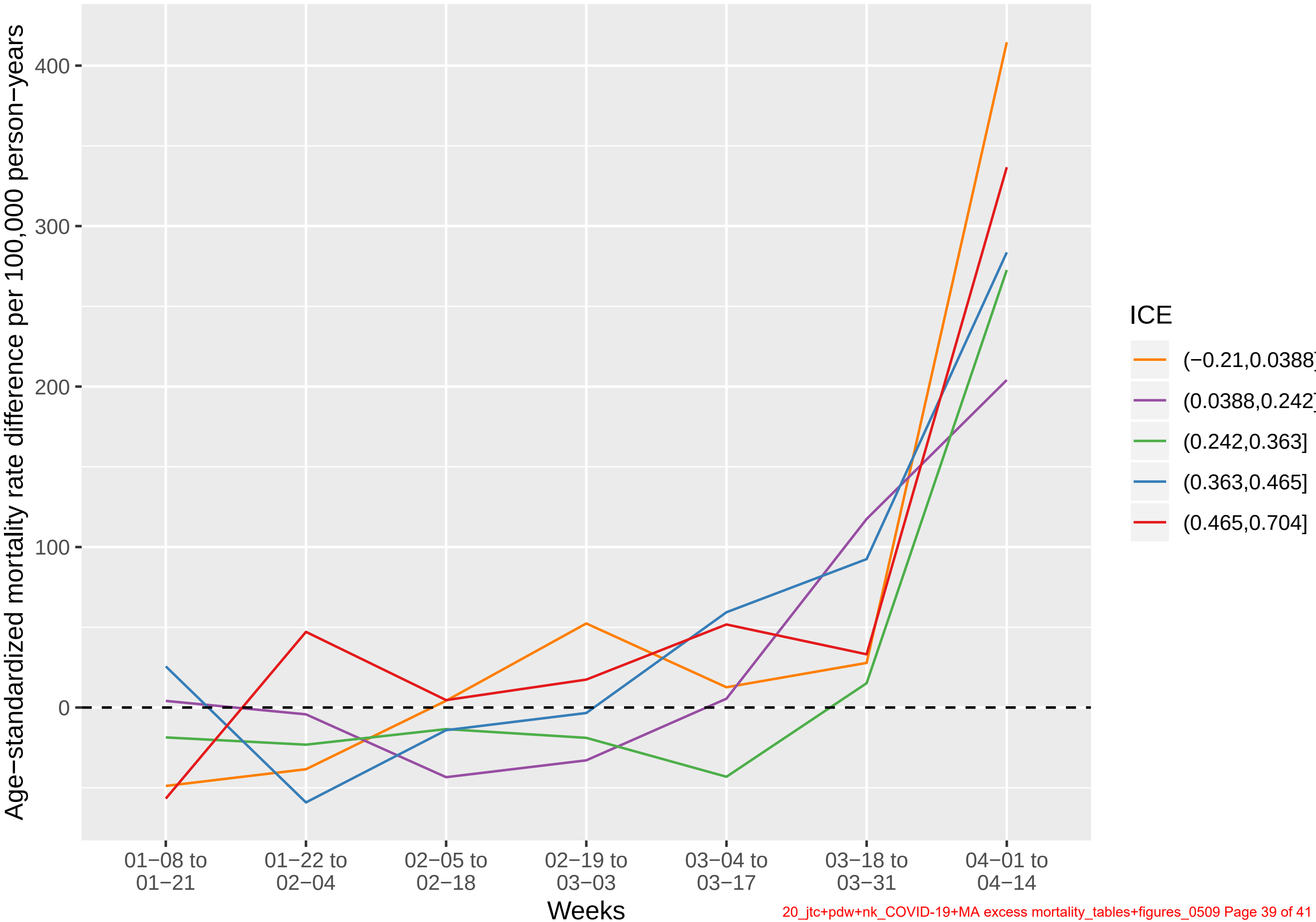


Figure 5d: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town % black population, 2020 vs. 2015−2019, Jan 8−April 14

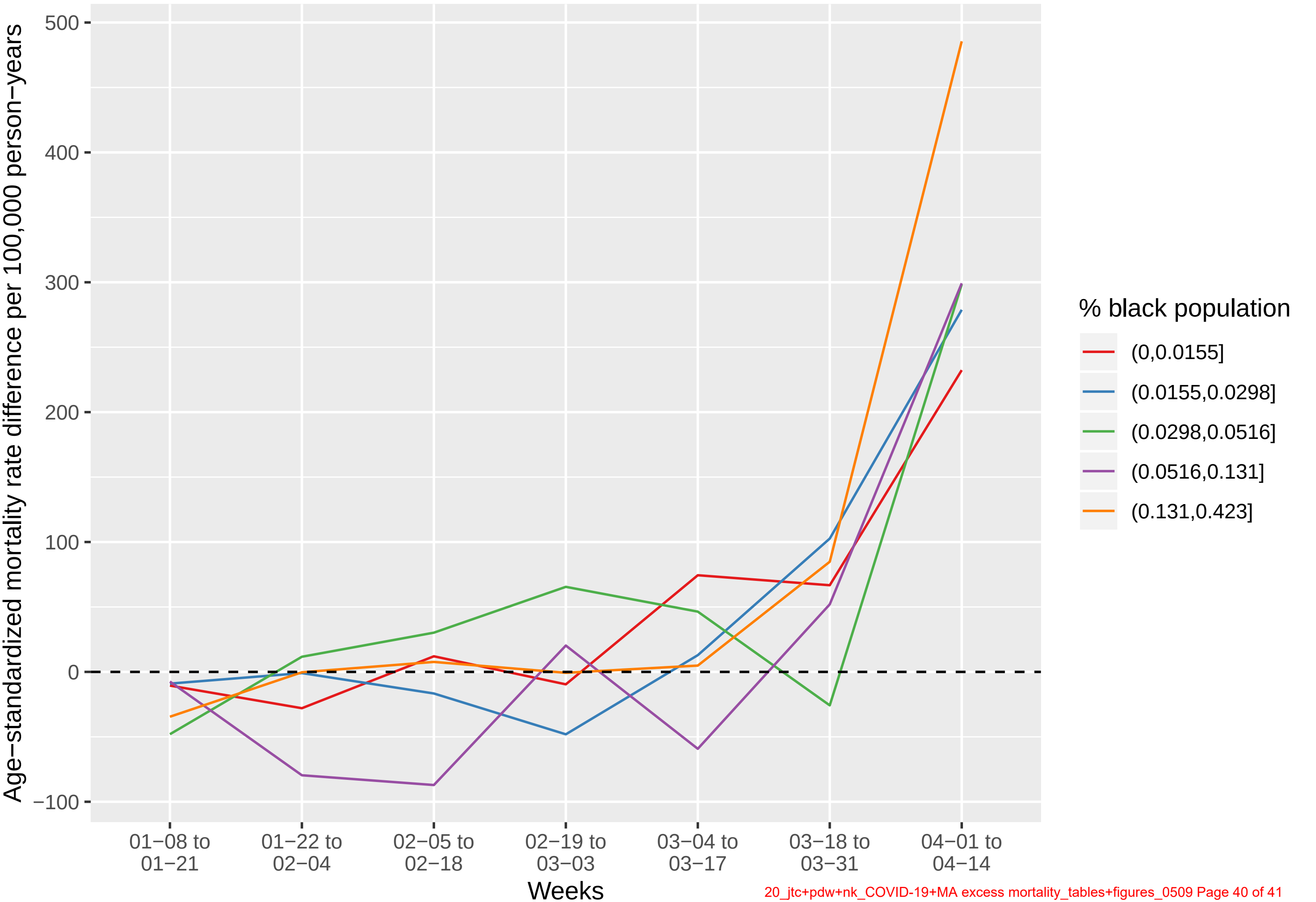
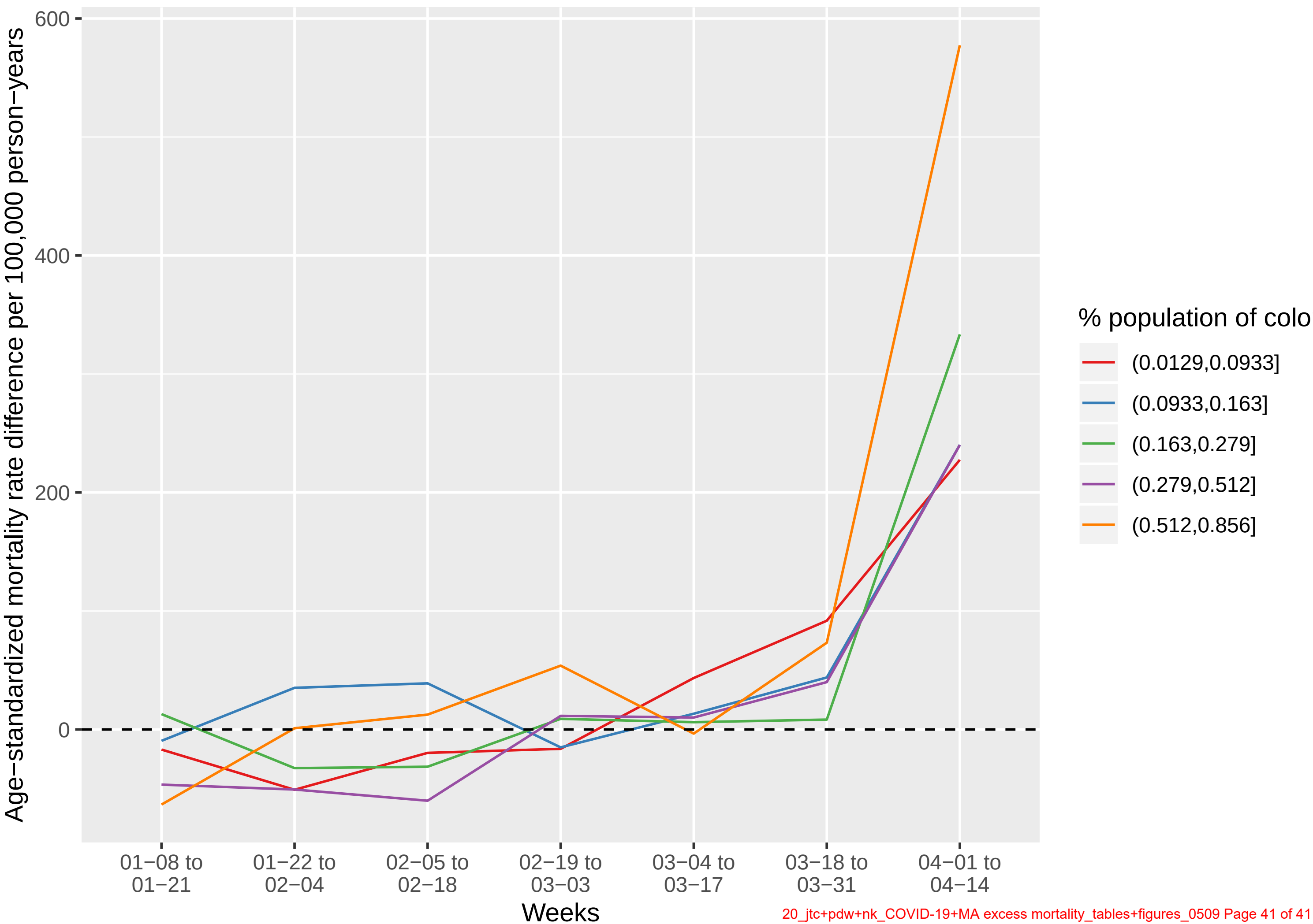


Figure 5e: Massachusetts weekly age−standardized mortality rate differences by two−week period and city/town % population of color, 2020 vs. 2015−2019, Jan 8−April 14



The Public Health Disparities Geocoding Project Monograph

THE PUBLIC HEALTH DISPARITIES GEOCODING PROJECT MONOGRAPH

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COVID-19 Resources

Using the Methods of the Public Health Disparities Geocoding Project to Monitor COVID-19 Inequities and Guide Action for Health Justice

Introduction

The COVID-19 pandemic is once again pointing to the need for systematic monitoring and analysis of health inequities – especially in a context of health data lacking social and economic information – to guide both understanding and action. In our latest publications, we have been using the methods of the Public Health Disparities Geocoding Project to document inequities in the population distribution of COVID-19 cases, hospitalizations, and deaths in the United States. In this update to our website, we provide the following resources, to assist others in carrying out this vital work – to clarify who, in what communities, are being hit hardest by COVID-19, and hence where:

(a) resources for testing, screening, and prevention (including adequate provision of personal protective equipment, especially for essential workers at their jobs and for use in transportation to & from these jobs) are urgently needed;

(b) locales to assist self-isolation of people who are positive should be based (e.g., if it is not possible for people to self-isolate at home, given household crowding); and

(c) support is needed to assist people with COVID-19 & their families, especially if they are in communities and social groups already burdened inequitably by premature morbidity and mortality from chronic diseases which exacerbate the severity of COVID-19.

We provide below our relevant conceptual and empirical publications.

We also provide an ACS/ABSM variable table that lists the relevant area-based socioeconomic measures we constructed using 5-year (2014-2018) US Census American Community Survey data which we supply here at the county, ZCTA (ZIPcode tabulation area), and census tract levels (for the entire United States). We request that if you use these data, please cite this webpage.

Lastly, we provide code in R to:

- extract ABSMs from the US Census American Community Survey
- replicate the analyses we conducted in our empirical papers using these variables
- replicate excess mortality analyses by ZIPcode social metrics

— Prepared by Nancy Krieger, Jarvis T. Chen, Pamela D. Waterman (May 15, 2020)

Definitions and Source Variables from the American

Community Survey

Total Population	B01003_001E
White Non-Hispanic Population	B01001H_001E
% of persons below poverty	B17001_002E / B17001_001E
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
Index of Concentration at the Extremes (high income white non-Hispanic households versus low income people of color households)*	(B19001H_014E + B19001H_015E + B19001H_016E + B19001H_017E) – [(B19001_002E + B19001_003E + B19001_004E + B19001_005E) – (B19001H_002E + B19001H_003E + B19001H_004E + B19001H_005E)]
% crowding (>1 person per room)	(B25014_005E + B25014_006E + B25014_007E + B25014_011E + B25014_012E + B25014_013E) / B25014_001E
% population of color (not White Non-Hispanic)	B01003_001E -B01001H_001E) / B01003_001E

*High-income refers to the top quintile for US household income and low-income refers to the bottom quintile for US household income, during the years specified.

Publications

Conceptual:

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COVID-19 Publications

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Chen JT, Waterman PD, Krieger N. COVID-19 and the unequal surge in mortality rates in Massachusetts, by city/town and ZIP Code measures of poverty, household crowding, race/ethnicity, and racialized economic segregation. *Harvard Center for Population and Development Studies Working Paper Series,* Volume 19, Number 2. May 9, 2020.

- with data used in: Ryan A, Lazar K. Disparities push coronavirus death rates higher. Harvard analysis finds mortality surged higher in communities with more poverty, people of color, and crowded housing. Boston Globe, May 9, 2020.
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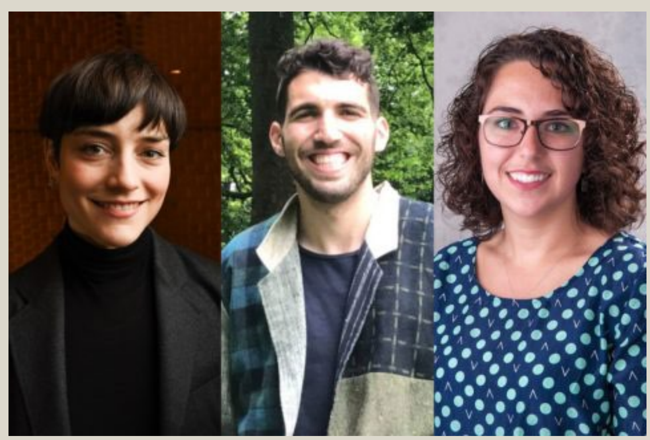

More men than women are dying from COVID-19. Why?

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Excess mortality in men and women in Massachusetts during the COVID-19 pandemic

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May 27, 2020
https://doi.org/10.1016/S0140-6736(20)31234-4

Suggestions that more men than women are dying from COVID-19 have appeared in scientific journals[1] and newspapers.[2,3] To our knowledge, however, no comparisons have been made of relative or absolute mortality differences between women and men. Both matter: a small relative increase in rates applied to a high baseline rate can lead to the same excess counts of deaths as a large relative increase applied to a lower baseline rate.

When assignment of cause of death to COVID-19 is dynamic and incomplete, given developing scientific evidence, one important strategy for assessing differential impacts of COVID-19 is that of evaluating the overall excess of deaths, as compared to the same time period in previous years.[4] We obtained Massachusetts mortality data for the period Jan 1 to April 14 for the years 2015–20. For people categorised as women and as men, we computed their age-standardised 2020 mortality rates and compared them, in both relative and absolute terms, to their average rates for 2015–19, by 2-week intervals.

Notably, the sharp rise in excess mortality observed during the first 2 weeks of April, 2020, was similar for women and men (appendix), whereby the age-standardised rate ratio for 2020 versus 2015–19 equalled 1·48 (95% CI 1·13–1·94) for women and 1·55 (1·19–2·03) for men. The corresponding age-standardised rate differences equalled 240·4 deaths per 100 000 person-years (95% CI 75·5–404·4) for women and 404·1 (158·8–648·1) for men, compared to the 2015–19 baseline age-standardised rates of 499·3 (95% CI 393·6–605·1) for women and 732·0 (578·9–885·0) for men.

See Online for appendix

Women and men in Massachusetts therefore experienced virtually identical relative increases in the rise in the total burden of mortality as deaths from COVID-19 began their quick ascent, even though the absolute difference in mortality rates was larger for men. One implication is that it might be misleading to focus solely on men's higher death counts for COVID-19,[1–3] since absolute differences, by definition, will be higher, despite similar relative risk, given men's higher baseline mortality rates.

Debates over the extent to which biological expressions of gender, sex-linked biology, both, or neither matter for exposure, susceptibility, and health outcomes is long standing.[5] In the case of COVID-19, speculation has focused on both social aspects of gender (eg, greater likelihood of smoking and less handwashing among men compared to women) and biological susceptibility (eg, as perhaps related to sex hormones).[1–3] Robust evidence regarding both relative and absolute difference in rates is needed to inform these debates.

We declare no competing interests. We thank *The Boston Globe* for their assistance (uncompensated) in obtaining the Massachusetts mortality data. This research project was exempt from institutional review board review (decedents only; 45 CFR 46.102(f)).

**Nancy Krieger, Jarvis T Chen, Pamela D Waterman*
nkrieger@hsph.harvard.edu

Department of Social and Behavioral Sciences, Harvard TH Chan School of Public Health, Boston, MA 02115, USA

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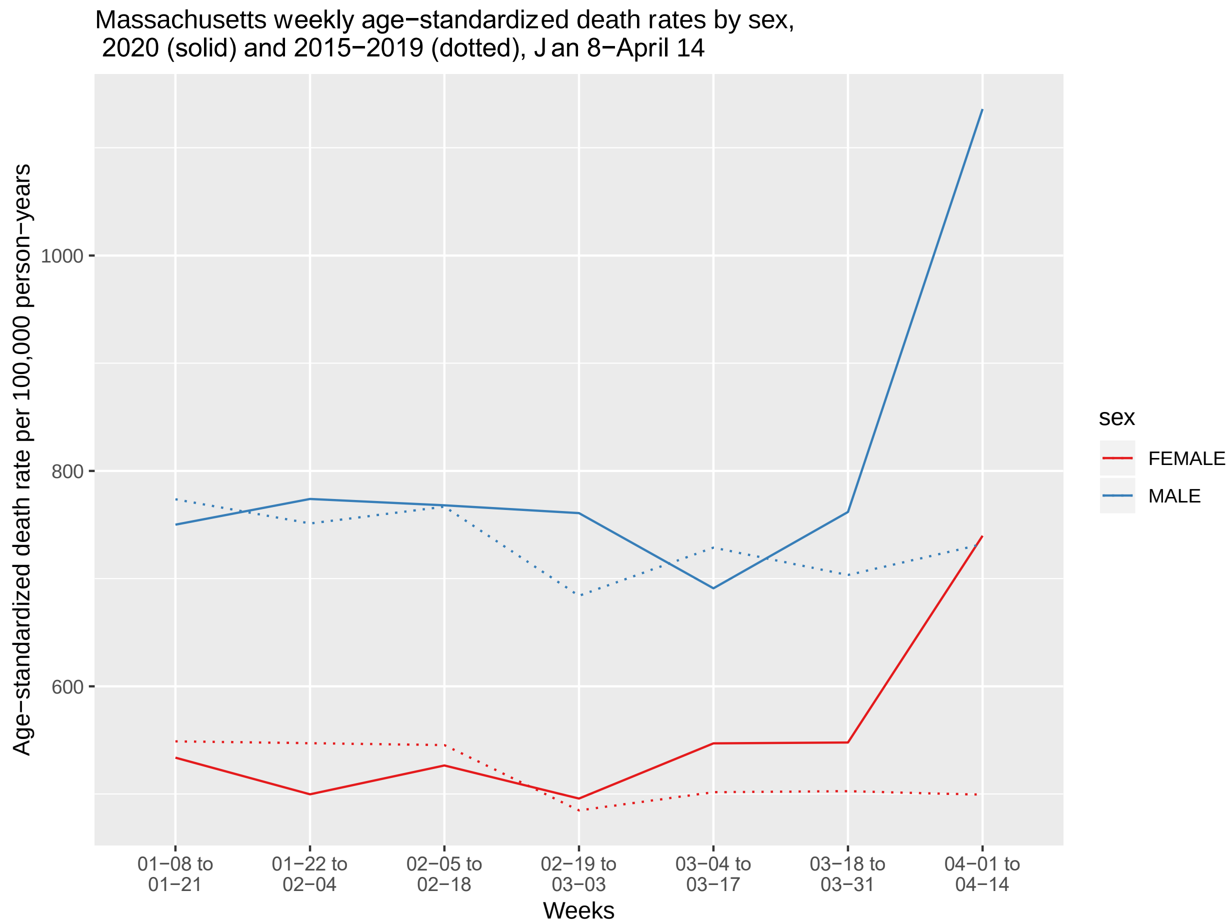
Supplementary appendix

This appendix formed part of the original submission. We post it as supplied by the authors.

Supplement to: Krieger N, Chen JT, Waterman PD. Excess mortality in men and women in Massachusetts during the COVID-19 pandemic. *Lancet* 2020; published online May 27. http://dx.doi.org/10.1016/S0140-6736(20)31234-4.


Massachusetts weekly age−standardized death rates by sex,
2020 (solid) and 2015−2019 (dotted), Jan 8−April 14
Age−standardized death rate per 100,000 person−years
1000
800
600
01−08 to 01−21
01−22 to 02−04
02−05 to 02−18
02−19 to 03−03
03−04 to 03−17
03−18 to 03−31
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The Fierce Urgency Of Now: Closing Glaring Gaps In US Surveillance Data On COVID-19

Nancy Krieger, Gregg Gonsalves, Mary T. Bassett, William Hanage, Harlan M. Krumholz

APRIL 14, 2020 10.1377/hblog20200414.238084

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CONTENT

Where are the data on COVID-19 to understand who in the US population is being tested, who is ill, and who is dying? The sole data being reported by the US Centers for Disease Control and Prevention (CDC) is for the total population only, and just for the country as a whole and by state. Worse: case counts at the county level—for just a small subset of the 3242 US counties—are available not from the CDC, but from the websites of a private university (Johns Hopkins) using data credited to the CDC and

those of several newspapers and volunteer groups frantically trying to track down data.. All in this reporting hodgepodge are grappling with inconsistencies and gaps in state reporting on COVID-19, including some states publicly reporting only the number of confirmed cases without data on the number of persons tested (e.g., CA, NY, WA), or not reporting on the number of persons hospitalized.

Nor are any data are available—at the national state, county, city, neighborhood, or health system levels—to enable monitoring and interpretation of testing patterns (including who is being tested), likelihood of positive tests (which will be related to testing strategy), or mortality (which is related to definitions and ascertainment of what

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is COVID-19 related) – especially in relation to core sociodemographic variables, such as age, race/ethnicity, sex/gender, and socioeconomic position. Health equity is literally off the map, made invisible because data to document inequities are unavailable, even as journalism and social media vividly attest to the risks of those who do not have the luxury to shelter safely at home and who cannot afford the economic disruption.

This is unacceptable and threatens prudent public health action.

The Inadequacy Of Current Data

It is insufficient to ask simply whether the virus is or is not present. Social data about who is infected are crucial for responding to needs now and will allow for better estimation of the likely spread and impact of COVID-19, the toll of which will be measured not only in deaths but also in the second-order, socially disparate spill-over effects on people's economic well-being and safety. Real-time fast journalistic reporting and advocacy groups in the US and other countries are pointing to the critical importance of racial/ethnic, economic, and gender inequities to shaping COVID-19 risks. In the past week, calls for data on COVID-19 by race/ethnicity have been issued by leading politicians, including Senator Elizabeth Warren and Congresswoman Ayana Pressley, the Congressional Black Caucus, the National Lawyers Committee for Civil Rights Under the Law, and by journalists. Why aren't the public health data documenting these risks available?

Granted, the CDC has developed a detailed intake form, valid through April 23, 20202, which does include data on a several social variables (race/ethnicity, sex/gender, age, county, and state), along with numerous questions about travel, clinical presentation, and respiratory diagnostic testing. Our understanding, however, is that this form (which the CDC estimated takes 30 minutes to complete – difficult when cases number in the thousands) is not being used and that a short form may be in development to replace it.

The New York City Department of Health and Mental Hygiene laudably has just produced one of the few neighborhood-level maps to show the percent of patients testing positive for COVID-19. This map vividly documents differential rates by neighborhood and makes clear that the distribution of positive tests is far from random, with higher positivity rates in lower-income areas. But without any social data, the map is also completely uninterpretable. Do the results shown reflect that public hospitals are reporting more sick people? That wealthy people are getting screened who are not symptomatic and less likely infected? There is no way to know. The spatial patterns presented cry out for explication and informed intervention. But the available data cannot provide the information needed.

Recognition of the critical importance of societal determinants of health is now commonplace in public health, globally by the World Health Organization and within US health agencies as well. It is not a mystery that social inequalities become embodied as health inequities. Failing to collect and report critical social data necessary to mitigate and prevent COVID-19 will hamper efforts to control the first wave and to handle the uncertain future ahead.

It might perhaps be understandable that data collection in the rapid exponential first phase of the epidemic has been imperfect, although adequately funded preparedness planning could have anticipated and addressed many problems. Going forward, the federal government must provide both leadership and sufficient funding to ensure there is a strong coordinated response so that the relevant social and clinical data are collected and swiftly made nationally available at the national, state, and local levels.

A Call To Action: Improving Collection And Reporting Of COVID-19 Sociodemographic Data

We accordingly urge rapid adoption of a uniform *short* digital form for COVID-19 testing and surveillance that is up to the task. The federal government should mandate that all testing data are provided to the CDC, in real time, and that data are publicly reported, in real time, in relation to total cases and stratified by race/ethnicity, sex/gender, age, educational level, at the national, state, county, and Zip Code levels. Federal funding is essential for this work, which necessarily will be carried out by a combination of state and local health departments and the CDC.

We emphasize this digital form should be used nationally by every private, academic, and public laboratory doing COVID-19 testing. Additionally, the expedient short list of social variables we have enumerated—already available in death certificates (i.e., age, race/ethnicity, sex/gender, educational level, and Zip Code)—must also be included in COVID-19 hospital intake forms and in population-based seroprevalence surveys when they become feasible. A minimal goal is to have all testing, hospital, and mortality data for COVID-19 publicly reported for both the total population and by these social variables, minimally at the national, state, and county level.

Of course, we have visions of what more comprehensive social data for COVID-19 monitoring would entail, relevant to both modeling the course of the epidemic and policy impacts. But we recognize the fierce urgency of getting core basic data now, so that communities and health professionals can plan and do their best to control and mitigate the community spread now well-underway across the US. Examples of additional social variables, all supported by growing accounts of inequitable risks and burdens, would pertain to employment status, housing status (e.g., private home, incarcerated, other institution, homeless), health insurance, income level, food insecurity, transportation access, safety at home (for oneself and one's children, given abuse that can happen in a context of remanding people to stay at home), and residential address (for more precise geocoding and linkage to neighborhood social and economic data). In a better world, obtaining such data would be recognized as an intervention, with appropriate resources provided at the time of data collection (e.g., referrals to a social worker if domestic violence or child abuse is reported, especially for people who have to self-quarantine at home).

But we are realistic. Grounded in concerns both for population health overall and health equity, and acutely aware of the perils of this pandemic, we assert the time is now for the COVID-19 public health surveillance system to record and publicly share the critical data needed to protect the people's health and prevent health inequities. Protecting all communities, especially those most harmed by COVID-19 and its social consequences, is imperative.

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COVID-19, Data, and Health Justice

April 16, 2020 | Nancy Krieger

LIBRARY PRINT

As COVID-19 rips through the United States and many other countries, it exposes the fault lines of social injustice and divisions that determine whether people have necessary resources. In the face of critical stay-at-home orders, who has a job with sick-leave benefits? Health insurance? A living wage? Or a home with Internet access?

Exposing these inequities requires people who can systematically collect, organize, and publicly report the evidence. But in the U.S., the available population health data are not up to the task. The COVID-19 data reported by the U.S. Centers for Disease Control and Prevention (CDC) are solely for the national and state level, and for total population only. The first data sets to document the count of confirmed cases and deaths by U.S. county, released on March 27, were produced not by a government agency, but by the *New York Times* and *Washington Post*. This is the second time in five years that independent journalists have filled glaring gaps in public health data. In 2015, *The Guardian* began publishing "The Counted" to compile systematic data on the number of people killed by the police in the U.S., which had been previously unavailable.

Notably, the CDC website provides no data on COVID-19 stratified by gender or race and ethnicity, and only recently began reporting data stratified by age. Yet it is now excluding "testing results for persons repatriated to the United States from Wuhan, China and Japan," suggesting that the CDC does have access to detailed individual-level data. In addition, data on age, gender, race, ethnicity, and education are

Toplines

The U.S. lacks the necessary population health data to understand how COVID-19 affects different populations and social groups

To better understand how the pandemic is making health inequities worse, we need to create and publicly report data on different populations and social groups routinely included in death certificate data. Why are these data absent for COVID-19?

Since March 31, a growing number of health professionals, politicians, and advocates have begun to call for COVID-19 data to be reported in relation to race and ethnicity, as journalists have begun to reveal starkly higher burdens of COVID-19 mortality among African American, Latinx, and American Indian communities. Even state and local health departments that are attempting to release these data are finding, however, that racial and ethnic data are missing for well over half to two-thirds of the COVID-19 case reports. Systemic problems run deep.

Age is featuring prominently in national discussions about COVID-19, in terms of infection, severity of illness, and death. The initial supposition that only people 60 and older are at elevated risk is shifting with reporting of hospitalizations and deaths of people in their 20s through 50s.

However, age and its relation to risk of COVID-19 mortality is not the same across all social groups. In the U.S., risk of premature onset of and death because of chronic diseases, which may increase risk of mortality because of COVID-19, is greatest for African Americans, American Indians, Alaska Natives, and people with low incomes. Risk for people in their 50s in these groups may be more akin to that of people in their 70s in more privileged groups. The adverse health impacts of economic deprivation and discrimination built on a past of enslavement and colonization cannot be underestimated.

For accurate guidance on risk, testing and mortality data should be stratified by age, race, ethnicity, socioeconomic position, and gender. We also need data on type of work or unemployment, insurance status, sickness benefits, housing and homelessness, incarceration, nativity and citizenship status, sexual orientation, gender identity, and exposure to domestic violence. These all matter for risk, care, and prevention of COVID-19.

Data are also vital to capturing other effects of the pandemic. How is COVID-19 disrupting care of patients with chronic diseases? Consider lupus — a disease that disproportionately affects people subjected to economic deprivation and discrimination. They are routinely prescribed hydroxychloroquine, but access to this drug has been compromised since President Trump led the charge to tout it with scant evidence as a potential COVID-19 cure. Or, what about the immediate and enduring effects of stay-at-home mandates on physical and sexual abuse and violence within households; can these consequences be mitigated?

To ensure that COVID-19 work is grounded in health justice, we must generate and publicly report data on how it affects different populations and social groups and use a health equity lens to examine how the pandemic is exacerbating inequities.

The Commonwealth Fund Recommends

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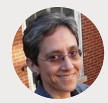

Nancy Krieger
Professor of Social Epidemiology, Department of Social and Behavioral Sciences, Harvard T.H. Chan School of Public Health

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ENOUGH: COVID-19, Structural Racism, Police Brutality, Plutocracy, Climate Change—and Time for Health Justice, Democratic Governance, and an Equitable, Sustainable Future

"History never really says goodbye. History says, see you later."

—*Eduardo Galeano*[1]

COVID-19 starkly reveals how structural injustice cuts short the lives of people subjected to systemic racism and economic deprivation.[2–4] It is not, however, the only crisis at hand.

Since the May 25, 2020, murder of George Floyd, a 46-year-old African American man, by the Minneapolis, Minnesota, police, protests have coursed through cities and towns across the United States, denouncing structural racism and police violence,[5–7] fueled, too, by COVID-19's disproportionate toll on US populations of color.[2–4] In a context in which US police kill upwards of 1000 people per year—nearly three per day, disproportionately Black Americans, and vastly more than in any other wealthy country[5,6]—the last straw was Floyd's horrific murder.[7] Floyd died because he could not breathe, because police officer Derek Chauvin knelt on his neck for an agonizing 8 minutes and 46 seconds—in open view, as videoed for all to see, while three other police standing nearby failed to intervene.

The current upsurge of protest builds on the leadership of so many groups, perhaps most prominently Black Lives Matter, founded in 2013 by three radical Black women organizers—Alicia Garza, Patrisse Cullors, and Opal Tometi—in response to the acquittal of Trayvon Martin's vigilante murderer, George Zimmerman, and which rapidly grew in the wake of Michael Brown's killing by Ferguson, Missouri, police officer Darren Wilson in 2014.[8] Also feeding these protests is the post-2016 rise in hate crimes,[9] coupled with overt expressions of racism, both by word and by policies, at the highest levels of the US government.[2,10]

COVID-19: TERRIBLE INEQUITIES, TERRIBLE DATA

The inequitable context of the COVID-19 pandemic in the United States is not a mystery.[2,11] In 2019, 53 million US workers, including 44% of all workers aged 18 to 64 years, were employed in low-wage jobs, earning an median hourly wage of $10.22, yielding median annual earnings of only $17 950.[12] Meanwhile, a 2017 analysis reported that "[t]he three wealthiest people in the United States—Bill Gates, Jeff Bezos, and Warren Buffett—now own more wealth than the entire bottom *half* of the American population combined," while 20% of US households, and 30% of Black and 27% of Latinx households, have "zero or negative net worth."[11(p4)]

The stunning COVID-19 inequities—which are inequities, because health inequities comprise differences in health status across social groups that are unjust, avoidable, and, in principle, preventable[13]—are, thus, no surprise. Reflecting the impacts of structural racism, including the origins of the United States as a settler–colonial nation and slave republic, US Black and American Indian populations have long lived sicker and shorter lives than the US White non-Hispanic population.[3,14,15] Despite serious problems affecting the accuracy of COVID-19 data,[16] the pattern repeats with COVID-19.[2–4,17–23] Higher burdens of COVID-19 cases and deaths, especially among working-age adults—and in surges of death overall—are documented among communities with high proportions of people of color, high poverty, crowded housing, and high levels of racialized economic segregation,[4,17–23] even as their reduced access to COVID-19 testing (used also to classify COVID-19 deaths) would mitigate against such findings.[2,16] This high excess toll at younger ages, moreover, cannot be discerned from counts of deaths, or crude or age-standardized mortality rates, as typically reported by health department and other COVID-19 data dashboards.[4,19] These data gaps themselves are an injustice.

The new US Census Household Pulse Survey offers additional

ABOUT THE AUTHOR

Nancy Krieger is professor of social epidemiology and American Cancer Society clinical research professor in the Department of Social and Behavioral Sciences, Harvard T. H. Chan School of Public Health, Boston, MA.

Correspondence should be sent to Nancy Krieger, PhD, Professor of Social Epidemiology, American Cancer Society Clinical Research Professor, Department of Social and Behavioral Sciences (Kresge 717), Harvard T. H. Chan School of Public Health, 677 Huntington Ave, Boston, MA 02115 (e-mail: nkrieger@hsph.harvard.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

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insights into the inequitable social and economic tolls of COVID-19.[24] It found that, for the week of May 28 to June 2, 2020, fully 44% of Black non-Hispanic and Hispanic households reported they had no or little confidence they could pay the next month's rent, more than twice the already alarming 20% reported for White non-Hispanic households.[24] In addition, household food insecurity—defined as often or sometimes not having enough to eat in the previous week—was reported by 20% of Hispanic and 26% of Black non-Hispanic households, versus 9.3% of White non-Hispanic households[24]—with levels for all groups higher than in 2018.[25] Overall, among households with persons aged 18 years or older, rent insecurity was reported by 35% versus 13% of persons with less than versus four or more years of college; the corresponding proportions for food insecurity were 14% versus 3%.[24] These metrics of misery, and the inequities in this misery, are severe.

What do these terrible data mean for public health? The data are terrible in two ways. First, the data literally are terrible. High levels of missing racial/ethnic data plague the extant (and selectively obtained[16]) testing and hospitalization data; these limited racial/ethnic data are rarely, if ever, cross-stratified by age or sex/gender,[19,20,26] and it has taken months of agitation to secure federal legislation mandating that SARS-CoV-2 laboratory tests must report data on race/ethnicity.[26,27] To date, no national, state, or local health agencies report any data on COVID-19 by cases' income or educational level, occupation (with the exception, in some locales, of data on health care worker vs not), disability status, sexual orientation or gender identity, incarceration status, or nativity.[26] Yet, despite all of these data caveats, there are good grounds to be concerned about disproportionate impact across these social groups.[2,3,28]

Second, even the scant data that do exist terribly expose the lethal politics that treat people of color and other low-income essential workers nevertheless as expendable, who matter solely to keep businesses open, not because their own lives matter.[2–4,29,30] At issue are not only hospital workers (including janitors, orderlies, and other staff—not just health care workers) and first responders, but also grocery store workers, warehouse workers, bus drivers, subway conductors, postal workers, security workers, custodians, factory workers, home health aides, and the many others whose work must be done at their workplace and is vital for society to function.[28–32] Fully 75% of US workers, comprising 108.4 million people, have jobs that cannot be done from home, and these tend to be lower-income jobs, disproportionately filled by workers of color—for whom lack of a living wage and lack of affordable housing translate to crowded households.[2,3,31,32] Meatpacking plants have been the site of terrible COVID-19 outbreaks, reflecting industry opposition to supplying adequate personal protective equipment and to creating conditions in which workers could safely do their jobs and stay home if sick.[33] A similar disregard exists for the lives of inmates and immigrant detainees—who, reflecting policies of mass incarceration, are disproportionately Black, Brown, and low-income.[34,35]

Tellingly, the same conservative groups who have been funding scientific denialism about climate change, attacking environmental regulation, and distorting democratic governance by abetting voter suppression and gerrymandering—all to protect their private interests—have also been contributing to funding anti–lockdown protests and related public health COVID-19 regulations that interfere with their ability to maximize profits.[36–38] These deathly plutocratic politics are antithetical to protecting people's health, let alone promoting health equity.[36]

SOCIAL MOVEMENTS AND EMBODYING HEALTH JUSTICE

This past June, propelled by the massive protests over police brutality, the COVID-19 pandemic, and the intensification of economic inequities disproportionately harming US communities of color and their health, 20 US cities and counties and three states have declared or are in the process of declaring that racism is a public health crisis.[39,40] Major public health, epidemiological, and medical societies have, for the first time ever, made similar declarations.[41–43] New conversations are erupting in mainstream media, in city councils, in state legislature, and in Congress over the longstanding but previously marginalized vision of shifting funds from excessive militarized policing to community investment and community safety, informed by principles of social justice, human rights, and participatory budgeting,[5–8,35,44–47] Whether this new awareness translates into meaningful change will depend on the sustained mobilization of social movements that recognize both painful histories of past injustice and powerful histories of resistance, thereby inspiring hope for repair and a better equitable and sustainable future.[44–47]

COVID-19, like previous pandemics, has pulled the thread, revealing profound inequities in every country it touches—while also pointing to our common humanity.[3] As with COVID-19, so too with climate change: all humans are threatened, but these risks are deeply and inequitably societally structured.[3,36,46,47] If the past is any guide, unjust systems that people have made can be unmade and transformed.

Clear analysis of the sociopolitical context of COVID-19 inequities is crucial for engaging with the multi–racial/ethnic upsurge of people across the United States and globally,[7,47] especially youths, demanding justice and a world in which they can literally breathe. I am heartened by how they are making visible the embodied connections our bodies make each and every day, between our health and our societal and ecological contexts.[3,48] They will propel public health forward.

Between COVID-19, structural racism, police brutality, climate change, plutocratic politics, and threats to democratic governance, it is time—past time—to say ENOUGH.

In 2001, the first World Social Forum, held in Porto Alegre, Brazil, declared "Another world is possible."[49] This was a rejoinder to the "There is no alternative" (TINA) mantra of the 1980s' architects of a hyperglobalized market economy devoted to maximizing private wealth, coupled with deregulation, austerity budgets, and destruction of the welfare state—which, in the United States, was done in racialized terms—and this agenda still wreaks woe for the many and riches for the few.[49–51] Yet, as the current shocks of COVID-19 and the past weeks of protest underscore, the future is not a fact foretold: it is what people shape, by our actions, mindful—or ignorant—of our histories.

For those of us in public health, one way to contribute our skills and insights to the changes so urgently needed—in both society overall and the institutions where we work—is to start by respecting the leadership of the myriad groups in coalition, nationally and locally, who are together propelling the current social movement, such as the Movement for Black Lives, the Poor People's Campaign, and the Green New Deal.[47,52–54] Engaging with their integrative policy platforms—which all call for social justice in its myriad forms, including health justice[47,52–54]—offers needed vision and concrete paths toward fruitful action, so that everyone can thrive.

May George Floyd—who at the time of his death was infected (but not killed) by SARS-CoV-2, Ahmaud Arbery, Breonna Taylor, and the thousands and thousands whose lives were cut short by police violence rest in justice. May the untold numbers of families, friends, neighbors, and networks of all who have sickened and died from COVID-19 come together in their grief to help repair this world. And for all of us in public health, as we ratchet up our work for the people's health, we would do well to remember the wise words of Frederick Douglass (1818–1895), who in 1857, in his "West Indian Emancipation" speech, declared: "Power concedes nothing without a demand. It never did and it never will."[55(p22)] Or as Mother Jones (1837–1930), the famous (and to the wealthy, infamous) socialist community and labor organizer, rousingly said, at age 88 in her 1925 autobiography, the time is now to "pray for the dead, and fight like hell for the living!"[56(p41)] AJPH

Nancy Krieger, PhD

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CONFLICTS OF INTEREST

The author has no conflicts of interest to report.

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9	**What this document is all about: Resources and organized efforts responding to COVID19** Public Health Awakened (www.publichealthawakened.com), in collaboration with The Spirit of 1848 (www.spiritof1848.org), are crowdsourcing this database to inform a public health response to COVID19 that centers equity, racial justice, collective care, and community and power building — we know these are what create conditions for health, in this pandemic and beyond. We are both national public health groups that center social justice, health equity, and action in our work. Our members represent the broad field of public health; we are researchers, educators, students, non-profit workers, healthcare providers, government workers, and more. In this current moment, it is more clear than ever that our public health work must focus on the social and structural determinants of health. We see all the topics and issues in this document as public health issues that those of us inside and outside of public health must take action on both during the COVID-19 pandemic and beyond. We have included resources in a number of languages in this document. We hope that you find this a useful resource and you will both share resources you find here as well as add resources you are seeing elsewhere. If you have any questions, comments, or suggestions, please email sari@humanimpact.org and sophia@humanimpact.org.
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From:	Sharon Bradford Franklin
To:	NCVHS Mail (CDC)
Cc:	Sharon Bradford Franklin; Lauren Sarkesian
Subject:	Submission on Privacy, Confidentiality and Security Considerations for Data Collection and Use During a Public Health Emergency
Date:	Wednesday, September 9, 2020 5:05:29 PM
Attachments:	NewAmericaSafraCenterforEthicsWhitePaper22e.pdf

To Whom It May Concern:

I write to make a submission in connection with the review by the National Committee on Vital and Health Statistics (NCVHS), Subcommittee on Privacy, Confidentiality, and Security considering data privacy and security in light of the COVID-19 Public Health Emergency (PHE). In July 2020, our team at New America released a white paper entitled *Digital Tools for COVID-19 Contact Tracing: Identifying and Mitigating the Equity, Privacy, and Civil Liberties Concerns*, which is available here and also attached in PDF.

I am pasting the abstract of the paper below. The paper addresses several of the questions the Committee poses. In particular:

- On the proper scope of data collection, analysis, and sharing in an emergency: We explain that government entities and tech companies should minimize the amount of personal data they collect to that which is actually needed by public health authorities, and to strictly limit what entities have access to the data. While the amount and types of data collected may increase to address the public health emergency, the collection must still be limited and tied to what is needed for public health purposes.

- On best practices for properly cabining emergency authorities: We include a series of recommendations to enact appropriate privacy safeguards, and urge that any data collection conducted for pandemic response should be time-limited. When the pandemic ultimately ends, any such data collection authority should expire and the data should be deleted.

- On what data organizations should collect: We explain that government and private entities should only collect the data that they need to for specific pandemic response purposes. Thus, for digital apps to assist with contact tracing, they should only collect proximity information, such as from Bluetooth apps, which can show whether two people have come close enough together to transmit the virus, and should not collect actual location information (CSLI or GPS).

- On when aggregate data is more appropriate: We explain that aggregate location data may be helpful for heat maps for overall pandemic response, but individual location information is not sufficiently precise for contact tracing and tracking the movement of specific individuals is privacy invasive.

Thank you for your consideration of our paper. Please let us know if you have any questions. Thank you.

Sincerely,

Sharon Bradford Franklin
Policy Director
New America's Open Technology Institute

Paper Abstract:

Many state governments and public health authorities in the United States are turning to digital tools to assist contact tracing efforts in response to the coronavirus pandemic despite equity, privacy, and civil liberties concerns. The digital divide, pronounced lack of trust in government among certain communities, and privacy risks posed by collecting personal data at scale make effective deployment of digital contact tracing tools challenging. But if governments decide they need to supplement manual contact tracing due to capacity issues, digital tools that use exclusively Bluetooth-based technology may be useful, as long as public health authorities implement proper safeguards. This paper outlines the equity, privacy, and civil liberties risks posed by digital tools as well as safeguards that policymakers can adopt to mitigate these concerns. Further, the paper recommends that policymakers take affirmative steps to address vulnerable populations that are unlikely to be reached by digital apps, partner with developers and community organizations, promote public education campaigns when deploying digital tools, take steps to close the digital divide, and pass comprehensive privacy legislation with effective enforcement mechanisms.

Sharon Bradford Franklin
Policy Director
New America's Open Technology Institute
740 15th Street NW, Suite 900
Washington, DC 20005
Pronouns: she/her/hers

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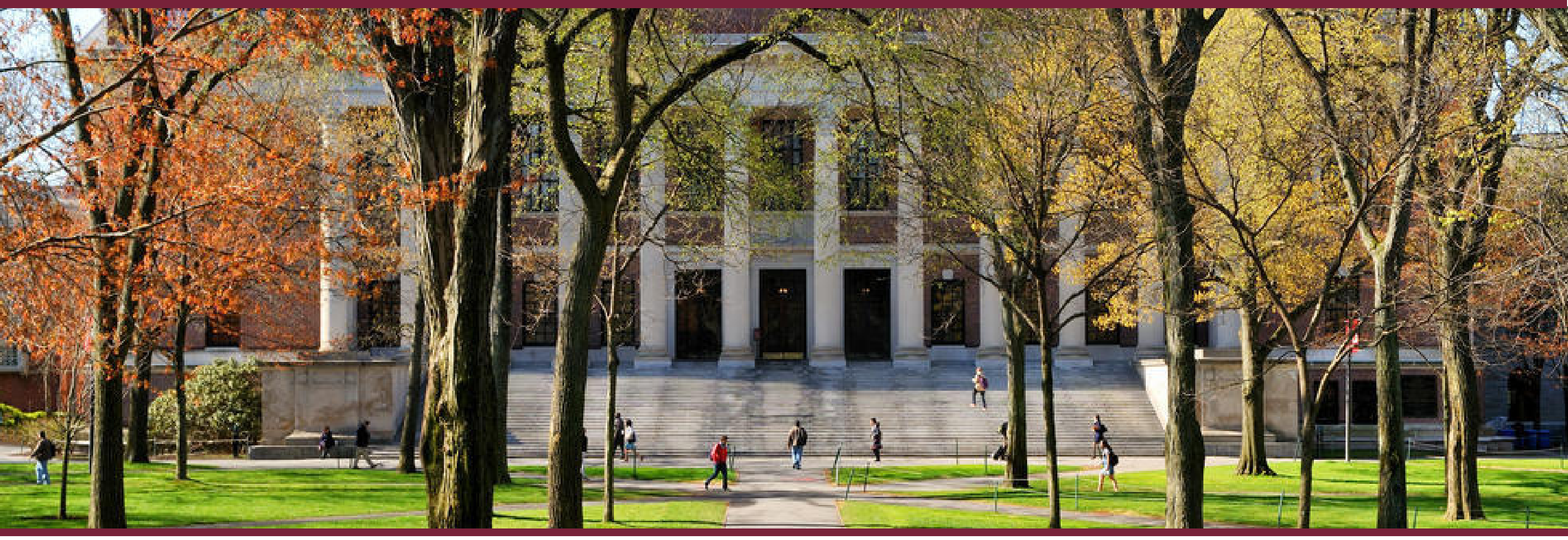
Digital Tools for COVID-19 Contact Tracing:

Identifying and Mitigating the Equity, Privacy, and Civil Liberties Concerns

July 2, 2020



Koustubh “K.J.” Bagchi[1]
Christine Bannan[2]
Sharon Bradford Franklin[3]
Heather Hurlburt[4]
Lauren Sarkesian[5]
Ross Schulman[6]
Joshua Stager[7]

Abstract

Many state governments and public health authorities in the United States are turning to digital tools to assist contact tracing efforts in response to the coronavirus pandemic despite equity, privacy, and civil liberties concerns. The digital divide, pronounced lack of trust in government among certain communities, and privacy risks posed by collecting personal data at scale make effective deployment of digital contact tracing tools challenging. But if governments decide they need to supplement manual contact tracing due to capacity issues, digital tools that use exclusively Bluetooth-based technology may be useful, as long as public health authorities implement proper safeguards. This paper outlines the equity, privacy, and civil liberties risks posed by digital tools as well as safeguards that policymakers can adopt to mitigate these concerns. Further, the paper recommends that policymakers take affirmative steps to address vulnerable populations that are unlikely to be reached by digital apps, partner with developers and community organizations, promote public education campaigns when deploying digital tools, take steps to close the digital divide, and pass comprehensive privacy legislation with effective enforcement mechanisms.

[1] Senior Policy Counsel, New America's Open Technology Institute
[2] Policy Counsel, New America's Open Technology Institute
[3] Policy Director, New America's Open Technology Institute
[4] Director, New Models of Policy Change, New America's Political Reform Program
[5] Senior Policy Counsel, New America's Open Technology Institute
[6] Senior Counsel & Senior Policy Technologist, New America's Open Technology Institute
[7] Senior Policy Counsel, New America's Open Technology Institute

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01 Introduction

As states, counties, and foreign governments move to reopen society amid the ongoing coronavirus pandemic, most are relying upon models that center around testing and extensive contact tracing. The Safra Center's "Roadmap to Pandemic Resilience,"[8] released in April 2020, sets out a comprehensive approach to enabling society to reopen, based on testing, tracing, and supported isolation (TTSI). The contact tracing envisioned in the Roadmap involves a robust combination of traditional manual approaches and reliance on digital tools. Likewise, as state governments are now planning and implementing their reopenings, many are considering combined approaches that supplement manual tracing with digital tools. A number of Asian and European countries have also instituted such mixed systems in recent months.

A variety of policy experts, technology companies, and public health officials have argued that digital tools may be able to expand the reach of traditional manual contact tracing systems and provide a rapid alert system that enables potentially exposed individuals to seek testing.[9] While, as this paper describes, it is not clear that such tools can be effective given the scale and rapid spread of the coronavirus pandemic, we should consider how they might play a role in the United States' pandemic response. This white paper aims to examine the equity, privacy, and civil liberties concerns raised by digital contact tracing tools, to outline safeguards that promise to mitigate these concerns, and where possible, to explain how to incorporate these safeguards.

We recognize that traditional manual contact tracing techniques also present equity, privacy, and civil liberties issues. Traditional contact tracing requires the collection of personal medical and behavioral

[8] Allen et al., "Roadmap to Pandemic Resilience: Massive Scale Testing, Tracing, and Supported Isolation (TTSI) as the Path to Pandemic Resilience for a Free Society."
[9] Simpson and Conner. "Digital Contact Tracing To Contain the Coronavirus"; Kahn and Johns Hopkins, *Digital Contact Tracing for Pandemic Response: Ethics and Governance Guidance*.

Introduction

information from infected individuals, and just as with digital data, this collected information is subject to risks of misuse and oversharing. For example, the Cook County Board of Commissioners passed a resolution—later vetoed by the Board's president—that would have required the personal information of those who tested positive for COVID-19 be disclosed to law enforcement.[10] Such a requirement would have severe implications for equity, privacy, and civil liberties.

However, an extended discussion of the risks associated with manual contact tracing techniques is beyond the scope of this paper. This paper focuses on the issues presented by digital tools because they create novel and additional risks relative to traditional manual contact tracing. First, digital tools collect an exponentially greater volume of data, including data on vast numbers of individuals who are not infected and have not even been in contact with infected individuals. Manual contact tracing, by contrast, is limited to infected individuals and their contacts. Second, because public health agencies generally lack in-house technical expertise and capacity, digital tools are designed and operated by private companies in partnership with public health authorities, rather than by public health authorities directly. This creates questions about corporate access to data that do not arise in manual contact tracing. Third, the risk of data breach is much more significant: an attack could expose the data of millions of individuals. And finally, while law enforcement access is also a risk in manual systems, the volume and types of data collected by digital tools make these systems more attractive to law enforcement and more vulnerable to mission creep.

Before seeking to outline a rights-protective approach to using digital tools for contact tracing, we must set forth some key principles that frame our analysis. First, when policymakers use big data solutions as part of pandemic response, they should follow the guidance of public health experts to determine

[10] Yin, "Cook County Board President Toni Preckwinkle Vetoes 'Extraordinarily Bad' Plan to Share Coronavirus-Positive Addresses with First Responders."
[11] Amnesty International USA, "Contact Tracing App Exposed Sensitive Personal Details of over One Million."

what is necessary and efficacious in combating the virus. Technology is not the solution for every problem, and we must be guided by experts in epidemiology and public health in designing solutions that will work.

Additionally, while effectiveness of contact tracing may come in degrees, three conditions should be met for a large-scale contact tracing system to be most effective. First, very widespread and accessible testing must be available, as laid out in the first pillar of the "Roadmap to Pandemic Resilience." If people cannot easily get tested, tracing will be far from complete. Countries that have had some success with limiting the spread of the coronavirus (albeit with setbacks in the cases of Singapore and South Korea, and with invasive government surveillance approaches in China and South Korea) have first had widespread testing available. There is no model for successful COVID-19 containment that does not include an extensive testing regime. Although some states are making progress in developing testing capacity,[12] it is not clear if or when the necessary level of testing will be available across the United States.[13] Second, the structures to permit supported isolation—the third pillar of the Roadmap—must also be in place, so as not to create disincentives for individuals to either get tested or to participate in contact tracing efforts. These supports include job protection and income compensation, health care and family support, and protection for vulnerable communities reluctant to engage with the authorities. Third, global and U.S. experience suggests that contact tracing regimes are more effective when they are designed and implemented in partnership with vulnerable communities and those most impacted by the virus.

Each of these conditions brings with it important equity concerns that cannot be ignored, especially as our nation wrestles with the consequences of structural racism and inequality across all of public life. For example, protest leaders have issued COVID response demands, highlighting what is needed to allow Black and other marginalized communities to benefit equally from a contact tracing regime:

[12] TestAndTrace, "What U.S. States Are Ready To Test & Trace?"
[13] Osterholm and Olshaker. "Let's Get Real About Coronavirus Tests."

universal paid leave, provision of shelter, food, housing and healthcare for all, decarceration, and limitation of law enforcement powers.[14] Developing and implementing contact tracing tools now requires a process of equity and inclusion very different from how the health tech industry usually operates; established manual tracing best practices will provide some guidance, but the challenge is significant.

[14] Movement for Black Lives, "National Demands for COVID-19."

02 The Components of Contact Tracing

Traditional Contact Tracing Methods and New Challenges

Contact tracing is a traditional public health technique used to combat infectious disease outbreaks. It enables public health officials to identify individuals who have been exposed to someone who has contracted an infectious disease, so that exposed individuals can get tested and can quarantine themselves if needed. Traditionally, contact tracing involves trained public health personnel speaking directly with individuals who have been exposed to and identified by an infected person. Public health officials have long used contact tracing to break chains of transmission of infectious diseases, but the COVID-19 pandemic has posed unprecedented challenges due to its scale and the speed of its transmission worldwide.

Two elements of COVID-19 make contact tracing especially important in this pandemic, but likewise especially challenging: the long incubation period and the frequency of asymptomatic transmission. As compared with other viruses, COVID-19 has a relatively long incubation period: the median time from infection to onset of symptoms is five days, but nearly all infected persons who will show symptoms will do so within twelve days.[8] More problematic yet, recent coronavirus data demonstrate that a substantial proportion of transmissions, perhaps as high as 50 percent, occur between individuals who are not symptomatic.[9] Because health experts now believe that asymptomatic spread of COVID-19 is a significant source of infection, health authorities know that they need to work to identify potentially infected people before they show symptoms.

Accordingly, speed is essential for contact tracing, but state, county, and municipal health authorities have only limited personnel available for manual contact tracing. Former director of the Centers for

[15] Lauer et al., "Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application."
[16] Hub Staff, "Asymptomatic Spread Makes COVID-19 Tough to Contain."

The Components of Contact Tracing

Traditional Contact Tracing Methods and New Challenges

Disease Control (CDC) Tom Frieden has reportedly estimated that "[w]e need an army of 300,000 people"[17] to trace the coronavirus in the United States, but as of late April, we only had about 8,000 contact tracers working nationwide.[18] Promisingly, there are new initiatives to train contact tracers, such as ones through Johns Hopkins University, which has established a new online course to train numerous people to work as contact tracers,[19] and UC San Francisco, which is partnering with the California Department of Public Health to provide similar training.[20] Moreover, some states are quickly working to hire manual contact tracers to make up for this shortfall,[21] but states will likely still have difficulty hiring and training contact tracers at the necessary rate.

Contact tracers undergo training to develop the skills needed to deal with the highly sensitive and complex issues associated with infectious disease and human behavior. These skills have been described as "somewhat of an art" that technology may not be able to replicate.[22] The CDC notes that "contact tracing is a specialized skill. To be done effectively, it requires people with the training, supervision, and access to social and medical support for patients and contacts."[23] The current pandemic is placing these skills under added pressures as public health authorities are not able to conduct these manual approaches with available resources.

For these reasons, during the current coronavirus pandemic, various countries, public health authorities, researchers, and app developers have designed digital tools to assist in contact tracing efforts.

[17] Fox, "We Need an Army': Hiring of Coronavirus Trackers Is Likely Set to Soar."
[18] Haskins et al., "We Need An 'Army' Of Contact Tracers To Safely Reopen The Country. We Might Get Apps Instead."
[19] Pearce, "Johns Hopkins Launches Online Course to Train Army of Contact Tracers to Slow Spread of COVID-19."
[20] Kurtzman, "UCSF Partners with State to Develop Public Health Workforce for COVID-19 Response."
[21] Nadi, "Inside an 'Army' of COVID-19 Contact Tracers in Massachusetts"; and Simmons-Duffin, "States Nearly Doubled Plans For Contact Tracers Since NPR Surveyed Them 10 Days Ago."
[22] Holder, "Who Wants to Be a Contact Tracer?"
[23] CDC, "Coronavirus Disease 2019 (COVID-19)."

The Components of Contact Tracing

Traditional Contact Tracing Methods and New Challenges

Proponents of these digital tools aim to increase the speed and reach of traditional contact tracing methods, which can be slow, labor-intensive, and costly. Italy's minister for technological innovation views the country's app Immuni as a tool with the potential for a "major impact" on public health.[24] The academics at University of Washington helping to develop an exposure notification app known as CovidSafe view these apps as tools that can augment traditional contact tracing but not replace it.[25] An infectious disease specialist at Mayo Clinic who has contributed to the SafePlaces app believes that "contact tracing is a critical intervention" and that digital tools can enhance contact tracing capabilities and help public health officials to intervene expeditiously.[26] Similarly, the dean of UAB School of Medicine and chair of the re-entry task force for the University of Alabama system views the state's app as their "best chance for actually surviving through this without undue damage and havoc, [a]nd having a chance to move into a future where we may eventually get a vaccine."[27]

However, as this paper outlines, there are many open questions regarding the efficacy of such digital tools. Moreover, there is little to no precedent for automating the delicate work of contact tracing. Accordingly, digital tools should be considered as methods to augment, but not replace, traditional manual contact tracing by public health officials.

At this stage, we cannot yet know the relative reach of traditional contact tracing methods and digital tools, or the extent to which digital tools will enable contact tracing to be conducted at scale. Nonetheless, if they are implemented in a rights-protective way, digital tools to support contact tracing have the potential to assist public health authorities in combating this pandemic.

[24] Horowitz and Satariano, "Europe Rolls Out Contact Tracing Apps, With Hope and Trepidation."
[25] McQuate, "Contact-Tracing App That Helps Public Health Agencies and Doesn't Compromise Your Privacy."
[26] MIT Media Lab, "Safe Paths: A Privacy-First Approach to Contact Tracing."
[27] Pillion, "Alabama Balances Privacy against Accuracy in Contact Tracing App."

What Digital Tools May Be Helpful

There are a variety of digital tools under consideration for supporting contact tracing efforts. Some tools may assist contact tracers in managing caseloads[28] and in coordinating outreach to ensure that people with the necessary language skills are assigned where needed. Other digital tools are being proposed and developed with the goal of assisting public health authorities to identify people who may have been exposed to an infected person. These tools have been referred to as "digital contact tracing apps," although more recently, many proponents have adopted the more precise description of "exposure notification apps." Developers are designing such apps to use data generated by smartphones in ways that can expand the reach of manual contact tracing approaches.

In deciding what digital tools, if any, to adopt, health authorities must carefully consider what specific data is useful. Digital tools should not collect individuals' location data through cell site location information (CSLI) or Global Positioning System (GPS) information. These types of data are generated by individual cellphones and collected by phone providers and various apps in connection with the services they offer. Contrary to what some have argued,[29] collecting such location information is neither useful nor appropriate. It is not useful because phone location data is not precise enough to allow assessments of whether particular individuals came close enough for transmission of the virus;[30] and while GPS is more accurate than CSLI, it only works when people are outside, its accuracy can vary depending on a number of factors, and its drastic negative impact on battery life means that uptake will be seriously hampered. Use of CSLI and GPS is not appropriate because collecting such information about specific individuals would be extremely privacy invasive, as it can reveal their paths of travel

[28] Bourdeaux et al., "How Human-Centered Tech Can Beat COVID-19 through Contact Tracing."
[29] Albergotti and Harwell, "Apple and Google Are Building a Virus-Tracking System. Health Officials Say It Will Be Practically Useless."
[30] Landau, "Location Surveillance to Counter COVID-19: Efficacy Is What Matters."

The Components of Contact Tracing

What Digital Tools May Be Helpful

and intimate details about their daily lives.[31] As a result, contact tracing apps should not rely on CSLI or GPS, and governments should not be collecting this data for individuals. However, it may be appropriate for public health authorities to seek such location data in aggregate anonymized form; heat maps and analytical tools that rely upon aggregate location data may provide helpful information for planning pandemic responses.[32]

Contact tracing tools that rely on Bluetooth technology to measure proximity should provide a better proxy for determining exposure to the virus, though their accuracy is uncertain. There are several models for such apps, most of which have been inspired by Singapore's TraceTogether app initiated in March.[33] In May, Apple and Google launched interoperable Application Programming Interfaces (APIs) that will support exposure notification apps as long as they are approved by public health authorities and comply with the Apple/Google privacy requirements.[34] The TCN Coalition, an international coalition of technologists formed in April, has developed and promoted recommendations to incorporate privacy safeguards into the design of such exposure notification tools.

These Bluetooth-enabled apps, once voluntarily downloaded on individuals' smartphones, would cause the phones to send out anonymized signals that other phones in close proximity and also running the app would detect and catalog. Whenever an app user later tests positive for the coronavirus, the user is then able to report the test result, with a certification, to the relevant public health authority. That authority could then denote this in the app so that the app could alert all other phones that had detected a signal from the infected person's phone over the past fourteen days. An app user receiving such an alert would then know to seek testing.

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31 Franklin, "Right and Wrong Ways to Use Location Data in the Pandemic."
32 See ibid.
33 Ungku, "Singapore Launches Contact Tracing Mobile App to Track Coronavirus Infections."
34 Google, "Exposure Notification API Launches to Support Public Health Agencies."

The Components of Contact Tracing

What Digital Tools May Be Helpful

While many questions remain about their operation, these Bluetooth systems are inherently more effective and privacy protective as tools to support contact tracing than the collection of individuals' CSLI or GPS data. Bluetooth technology can measure the much shorter distances necessary for contact tracing, and with Bluetooth apps, the phones are simply measuring their proximity to one another and not the precise location of either phone. There are also several critical components that should be incorporated into the design of such apps to ensure that they are as rights-protective as possible. In particular, the apps must be voluntary, with individuals choosing to download and use them. In addition, implementation must be decentralized, so that there is no central government authority collecting all the emitted Bluetooth signals; rather, the signals generated and detected by each phone should be stored on individual devices. Another critical safeguard is to ensure that the apps generate random, anonymized, and constantly changing signals to avoid any risk that individuals can be reidentified or tracked. Finally, no data from these apps should ever be used commercially.

Some have proposed apps that rely upon Bluetooth proximity data combined with individual location data. However, it is the Bluetooth proximity information, not GPS or CSLI data, that can show whether two individuals have come close enough to one another to create a risk of exposure. Public health authorities should not collect individuals' actual location information even as part of hybrid systems. Location data that shows an individual's actual path of travel can much more easily lead to reidentification and tracking of specific people, and it is unclear that it would provide any improved efficacy. For example, North Dakota has introduced an exposure notification app called Care19 that relies on such a hybrid approach involving Bluetooth and GPS, but it has been riddled with accuracy issues due to both its inconsistent recording of GPS data and the insufficient granularity of the GPS data it does record.[35]

[35] Morse, "North Dakota Launched a Contact-Tracing App. It's Not Going Well."

03 Equity and Effectiveness Issues with Contact Tracing

The greatest challenges for digital exposure notification systems are the intertwined issues associated with equity and effectiveness. First, despite its relative benefits over the use of CSLI or GPS data, the effectiveness of Bluetooth technology to support contact tracing remains unconfirmed—for both reasons related to the technology itself and much larger issues related to adoption of such technology. Further, digital tools, even more so than traditional manual contact tracing approaches, are not equally available to—or trusted by—all communities, and reliance on such tools risks exacerbating inequities already present across the United States. Moreover, to the extent that digital tools are not equally available and widely adopted, this will hinder their effectiveness in assisting public health authorities to conduct contact tracing at scale.

Certain strategies—such as building in privacy safeguards when designing digital tools, combating misinformation, and conducting public education campaigns—can help minimize these obstacles, although real change will likely require long-term efforts and investment. Meanwhile, awareness of these issues can assist public health authorities to design solutions that will be as rights-protective, widely adopted, and effective as possible.

Effectiveness Issues in Bluetooth Technology

Bluetooth signals may lead to both false positives and false reassurances of a lack of exposure. For instance, exposure notification apps can cause false positives because Bluetooth signal strength varies depending on the phone's position and whether a person carries the device in a pocket or a bag.[37]

[36] Sarkesian, "Amid Reopenings, Technology Alone Won't Stop the Coronavirus."
[37] There is also an open question as to whether measuring the strength of a Bluetooth signal gives any information as to the distance between devices at all. Leith and Farrell, "Coronavirus Contact Tracing: Evaluating The Potential Of Using Bluetooth Received Signal Strength For Proximity Detection."

Equity and Effectiveness Issues with Contact Tracing

Effectiveness Issues in Bluetooth Technology

Bluetooth signals may show connections when individuals are too far apart to transmit the virus (even as far as 30 feet apart) and are separated by walls—these crucial details make all the difference in terms of one's exposure risk, and cause false positives.[38] Individuals living in apartment buildings may therefore be more likely to encounter false-positive notifications, as Bluetooth can ping nearby phones through walls and even floors, meaning that Bluetooth could indicate a possible exposure among neighbors who did not actually breathe the same air.[39]

Conversely, it is also likely that the apps will undercount potential exposures. Even if people widely adopted and used Bluetooth exposure notification apps—which, as discussed below, is far from certain—there will be an undercount of exposures both because Bluetooth technology can be unreliable and because public health officials are constantly learning more about the novel coronavirus and its symptoms.[40] As of March, many believed that fevers were a nearly requisite symptom of coronavirus, but since then evidence has mounted showing that presymptomatic and asymptomatic people could also pass the virus to other individuals. Significantly, Bluetooth applications can merely inform individuals that they have not been around an individual who was diagnosed positive (and who is also using the app), but certainly cannot detect undiagnosed cases. Bluetooth apps could consequently lead to a false sense of security among the public, though the apps can only, at best, inform individuals of recent exposures.

Further, some elements of disease transmission may be challenging for Bluetooth or any technology to trace: because it is an airborne respiratory virus, coronavirus is mostly transmitted when individuals are indoors and the viral load, or amount of virus one carries when infected, is significant. In a study from China of over 7,300 cases, only one case was transmitted outdoors.[41] And while it has not yet been

[38] Newton, "Why Bluetooth Apps Are Bad at Discovering New Cases of COVID-19."
[39] Landau, Lopez, and Moy, "The Importance of Equity in Contact Tracing."
[40] Landau, "Looking Beyond Contact Tracing to Stop the Spread."
[41] Qian et al., "Indoor Transmission of SARS-CoV-2."

definitively proven, a study from China shows that higher exposure doses lead to higher viral loads, which lead to more severe cases of COVID-19.[42] Both of these elements—whether individuals are in proximity outdoors or indoors, and how much of the virus one may have been exposed to—are difficult if not impossible for the current technology to measure. However, as discussed below, the most significant challenges to overcome in order for exposure notification apps to be effective are obstacles that affect how widely the public, in particular the most vulnerable populations, will adopt and use them.

Biggest Hurdles: Public Trust & Equity Issues Which Impact Effectivenes

For a Bluetooth-based contact tracing system to be effective, many epidemiologists estimate that roughly 50 to 70 percent of a population would need to participate for the app to be used to replace rather than supplement manual contact tracing.[43] In order to participate, individuals will need to own a smartphone made in the last five years,[44] download an app, and carry their phone with them at all times, with Bluetooth enabled. However, of the several countries that have created COVID-19 contact tracing apps, the highest adoption rate is in Iceland, where only 38 percent of residents have downloaded the app.[45] Yet some experts, such as an infectious disease specialist at Oxford University's Big Data Institute, estimate that an adoption rate of slightly more than 10 percent of a population could cut down on infections, because one infection could be prevented for every one to two users.[46]

Public Trust

Public trust will play a significant role in promoting robust participation. However, as discussed further

[42] Hogan, "How Much of the Coronavirus Does It Take to Make You Sick?"
[43] Fussell and Knight, "The Apple-Google Contact Tracing Plan Won't Stop Covid Alone."
[44] Bradshaw, "2 Billion Phones Cannot Use Google and Apple Contact-Tracing Tech."
[45] O'Neill et al. "A Flood of Coronavirus Apps Are Tracking Us. Now It's Time to Keep Track of Them"; Johnson, "Nearly 40% of Icelanders Are Using a Covid App—and It Hasn't Helped Much."
[46] Horowitz and Satariano, "Europe Rolls Out Contact Tracing Apps, With Hope and Trepidation."

below, much of the public lacks such trust both in the government and in big tech companies, and a troubling combination of misinformation around COVID-19 and justified historical grievances have fueled a heightened sense of mistrust. In some communities, public health responses have become identified with partisan politics, while others may experience contract tracing methods as a continuation of histories of heavy policing and surveillance. A lack of public trust can also pose barriers to manual tracing efforts, but these challenges are compounded for digital tools that also require trust in companies. Indeed, the companies involved in the development of contact tracing applications will have to prove their trustworthiness after many years of technology companies disappointing consumers with their poor handling of personal data. The proliferation of various apps purporting to assist with contract tracing, many of which do not incorporate the safeguards recommended in this paper, is compounding this trust problem.

Combatting the misinformation surrounding the many varying app proposals moving forward will be a challenge for governments and app providers alike, and will affect much of the public. Already, misinformation has been having a detrimental effect in the spread of coronavirus, and those with less access to reliable resources are likely to suffer the most.[47] The proliferation of misinformation in the time of COVID-19 has spread harmful claims that appear, in some cases, to have been specifically targeted at marginalized communities.[48] One study indicated that a number of factors play into the spread of the false belief that the coronavirus was created in a lab, including education level, political affiliation, and race.[49] In particular, those with a bachelor's degree or more education were less likely than those with a high school diploma or less education to believe the coronavirus was created in a lab. Addressing the spread of misinformation and properly educating the public regarding coronavirus will be critical to reaching vulnerable communities with any digital tracing tools.

47 Bursztyn, "Misinformation During a Pandemic."
48 Ross, "From White Conservatives to Black Liberals, Coronavirus Misinformation Poses Serious Risks."
49 Schaeffer, "Nearly Three-in-Ten Americans Believe COVID-19 Was Made in a Lab."

Equity and Effectiveness Issues with Contact Tracing

Biggest Hurdles: Public Trust & Equity Issues Which Impact Effectivenes - Public Trust

Unfortunately, the public health system has a record of discrimination, mistreatment, and inconsistency toward communities of color.[50] For example, in the 1972 Tuskegee Study conducted by the U.S. Public Health Service doctors knowingly failed to treat Black men diagnosed with syphilis, though treatment was readily available at the time.[51] The outrage and mistrust generated by this discriminatory study still impact the Black community to this day.[52] Using health services also leaves some already-vulnerable individuals further exposed, as they risk encountering immigration and law enforcement personnel. In a recent example, a man was arrested by U.S. Immigration and Customs Enforcement (ICE) agents as he left an emergency room,[53] even though hospitals have been considered “sensitive locations” by ICE and should be avoided for immigration enforcement.[54] While ICE has stated that it will modify its enforcement efforts during COVID-19 around “sensitive locations,”[55] the agency’s past actions do not raise the public’s confidence—and data from across the country shows that anxious immigrants are avoiding testing and treatment for this reason.

In addition to mistrusting government entities, the general public has consistently indicated an overall skepticism of the technology sector in recent years. Prior to the onset of the pandemic, tech companies had developed a negative reputation for gathering users’ personal data and selling or transferring that data to third parties without informing users. The most infamous example of this improper secondary use of information is the Facebook and Cambridge Analytica scandal,[56] but there are numerous other examples, including cases involving the misuse of location information. Indeed, earlier this year, the Federal Communications Commission (FCC) fined the nation’s four largest wireless carriers for selling

[50] Hardeman et al., “Structural Racism and Supporting Black Lives: The Role of Health Professionals.”
[51] CDC, “U.S. Public Health Service Syphilis Study at Tuskegee.”
[52] O’Donnell, “Coronavirus: Some Fear Black People Won’t Get Vaccine. Here’s Why.”
[53] Hall, “ICE Criticized for Arrest at Scranton Hospital.”
[54] See Morton, Memorandum,”Enforcement Actions at or Focused on Sensitive Locations,” Oct. 24, 2011; and Aguilar, Memorandum, “U.S. Customs and Border Protection Enforcement Actions at or Near Certain Community Locations,” Jan. 18, 2013.
[55] ICE, “ICE Guidance on COVID-19.”
[56] Confessore, “Cambridge Analytica and Facebook:The Scandal and the Fallout So Far.”

their customers' location information without the customers' consent.[57] A Pew Research Institute study conducted in June 2019 found that 79 percent of adults surveyed said they were at least somewhat concerned about how companies were using the data collected about them.[58] In addition, that study found that 70 percent of those surveyed felt their personal information was less secure than it was five years ago. The Pew results indicate an overall lack of trust in the access that app developers have to user data, and may imply a reluctance to use digital tools to support contact tracing if those tools require users to share data with a tech company.

This dynamic of mistrust toward tech companies, especially with regard to privacy, has not been alleviated even as tech companies attempt to provide solutions for combating the pandemic. Even though many members of the public have been sacrificing their civil liberties due to the need for ongoing isolation, Americans seem skeptical of digital contact tracing tools—though they vary on whom they trust, with what information, and for what purpose. In a recent *Washington Post* survey, three in five adults surveyed indicated that they would be either unable or unwilling to use the exposure-alert system under development by Apple and Google.[59] And a May Axios survey showed that who is providing the apps is significant: while 51 percent of Americans would participate in apps provided by the CDC or public health officials, only 33 percent would participate if the providers were big tech companies, and even fewer would partake if the federal government were providing them.[60]

A further complication is that Americans are very unclear on who, in fact, is the entity providing these apps. Many apps will be offered on Apple and Google's interfaces, but they will be created by various

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[57] FCC, "FCC Proposes over $200 Million in Fines against Four Largest Wireless Carriers for Apparently Failing to Adequately Protect Consumer Location Data."
[58] Auxier, "How Americans See Digital Privacy Issues amid the COVID-19 Outbreak."
[59] Timberg, Harwell, and Safarpour, "Most Americans Are Not Willing or Able to Use an App Tracking Coronavirus Infections. That's a Problem for Big Tech's Plan to Slow the Pandemic."
[60] Talev, "Americans Highly Resistant to Participating in a Contact Tracing Program."

app developers in conjunction with different state and local governments. With many varying apps being offered—one for each state, if not more—the patchwork of apps with different approaches (some following the Apple/Google API, some collecting location data, and perhaps some in between) will likely confuse Americans' analysis of whether they trust the provider and are willing to participate.

Equity Issues

Any contact tracing tools that rely on smartphones risk exacerbating a wide range of inequities in American society that stem from disparities in income, age, race, language proficiency, and geography, among other factors. Many of these inequities are deep-seated and not easily remedied. Accordingly, relying on digital tools for contact tracing risks focusing our public health response on the most digitally connected, while neglecting precisely the populations that are most at risk for infection.

It is important to note that manual contact tracing also presents equity considerations that can decrease the likelihood of robust participation. Manual contact tracing requires significant investment by public health authorities to hire a multitude of contact tracers and to subsequently supply them with the case management tools necessary to conduct in-depth surveys of affected individuals. The first step in manual contact tracing involves interviewing the infected person to make a list of all the persons with whom they may have come in contact. With this pandemic, due to the contagiousness of the virus and the lack of any vaccine or proven treatment, there has been increased reliance on interviews conducted over the phone. This exacerbates certain obstacles such as outdated contact information, lack of language comprehension, and a mistrust of the contact tracer.[61] However, the personal approach that manual contact tracers provide can be more effective in building trust with marginalized communities than digital approaches.[62]

[61] Greiner et al. "Addressing Contact Tracing Challenges—Critical to Halting Ebola Virus Disease Transmission."
[62] Sellers and Guarino, "Contact Tracing Is 'Best' Tool We Have until There's a Vaccine, Health Experts Say."

Equity and Effectiveness Issues with Contact Tracing

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In addition, the entire contact tracing enterprise assumes that, once a risk is identified, individuals will self-quarantine and get tested and treated as necessary. Inequitable distribution of access to sick leave, health care, housing, and food will depress participation in every stage of a tracing regime unless jurisdictions plan ahead to put those services in place—and make the most vulnerable communities aware that they exist and are safe to use.[63]

Yet contact tracing through digital tools is subject to additional and heightened equity concerns, particularly given the need for smartphone ownership and digital literacy to participate. While 81 percent of Americans own a smartphone, this means that nearly one-fifth of the population does not.[64] Moreover, it is unclear how many Americans own smartphones that support the technology that contact-tracing apps may require, such as low-power Bluetooth chips, the newest operating systems, and sufficiently robust batteries—but the number is likely well below 81 percent. Moreover, the population without smartphones is largely made up of lower-income communities[65] and seniors[66]—precisely the demographics that are most at risk of COVID-19 infection. Older Americans are also more likely to lack sufficient digital literacy skills.[67] These skills would be critical for maneuvering a digital exposure notification system, which requires familiarity with Bluetooth functionality, engaging with a phone's notification system, and correctly deploying a phone's contact tracing app to alert others of their potential exposure to coronavirus. Further, in the public debates over what role digital tools can play in contact tracing, not enough analysis has been provided on how individuals with lower levels of English proficiency will be able to participate in the system.

To the extent that exposure notification apps may induce people living in proximity to older Americans

[63] The experience of Chelsea, Massachusetts is sobering in this regard. See Barry, "In a Crowded City, Leaders Struggle to Separate the Sick from the Well."
[64] Pew Research Center, "Mobile Fact Sheet."
[65] Anderson and Kumar, "Digital Divide Persists Even as Lower-Income Americans Make Gains in Tech Adoption."
[66] Anderson and Perrin. "Technology Use among Seniors."
[67] Fields, "We Are Leaving Older Adults out of the Digital World."

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or others who lack smartphones to get tested or self-quarantine, the apps may provide some benefit to individuals who do not themselves participate in the system. However, any smartphone-based application to assist contact tracing will be far less effective in reaching minority and vulnerable communities, thereby having a serious impact on the efficacy of the tool.

For a multitude of reasons, COVID-19 is disproportionately impacting racial and ethnic minority groups, which makes it even more important to develop a system that will not leave these communities behind.[68] As noted, misinformation about the virus has already spread particularly widely among marginalized groups, and it has also been rampant on platforms reaching a variety of demographics across the country. This mistrust between government entities and marginalized communities, as well as lower levels of digital literacy in such communities, must also be accounted for in developing an adoption strategy.

Implementing a system where users are *required* to download an exposure notification app or other digital contact tracing tool in order to access public spaces would exacerbate these equity issues. Policies mandating app usage have been adopted in other countries, and some employers in the United States are considering plans to require exposure notification apps for employees returning to work.[69] If downloading and using an exposure notification app becomes a requirement to determine access to certain spaces, those who do not possess a smartphone or knowledge of how to utilize a contact tracing app would be excluded from basic aspects of everyday life, potentially including their place of employment, schools, and grocery stores. The disparities that already existed pre-pandemic would become compounded as a result.

Digital exposure notification apps also risk leaving behind large swaths of rural America that lack cellular

[68] CDC, "COVID-19 in Racial and Ethnic Minority Groups."
[69] Mozur et al., "In Coronavirus Fight, China Gives Citizens a Color Code, With Red Flags; Coombs," "Microsoft and UnitedHealth Offer Companies Free App to Screen Employees for Coronavirus";. Leswing, "Companies Could Require Employees to Install Coronavirus-Tracing Apps like This One from PwC before Coming Back to Work."

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wireless connectivity, which these apps would require for cross-referencing identifiers regularly and notifying the exposed. While much of the wireless industry touts the "race to 5G," the next generation of wireless technology, many communities in rural and geographically isolated areas have "no G," as one U.S. senator explained.[70] These communities have no wireless service of any kind, and many providers are loath to invest in them due to high infrastructure costs. Despite the inherent physical distancing in rural areas, these regions are not immune to the pandemic, as demonstrated by the ongoing spread of COVID-19 in meat processing plants in low-density areas like rural Nebraska.

Given these realities, digital exposure notification tools risk leaving behind precisely the people who are most difficult for public health officials to identify, warn, and treat. If public health officials decide to pursue smartphone-based tracing tools, they must address these equity concerns. As described further in our recommendations below, public health officials should confer with minority community leaders in developing a targeted approach toward program implementation, as well as consider investing in digital literacy assistance programs.[71] Digital literacy programs will take time to yield results, but it is still worth beginning that investment now. Further, while manual tracing also presents challenges, the need to reach those communities that may not have the digital literacy skills or smartphone ownership to use digital tools presents yet another reason for public health entities to ensure substantial investment in manual contact tracers. Additional recommendations to mitigate the equity issues posed by digital tracing tools are further discussed below.

[70] "Tester Holds FCC Accountable to Increase Wireless Service in Montana": "'As we work to get 5G across the country, what happens to the places with no G,' Tester said during a Senate Commerce Committee hearing. 'We will never get 1G in Montana if we are focused on bringing 5G to Houston.'"
[71] Landau, Lopez, and Moy, "Importance of Equity in Contact Tracing."

04 Privacy and Cybersecurity/Data Security Threats from Contact Tracing

Privacy Threats

Whenever governments or companies collect personal information about individuals, there are risks that the information will be used for improper secondary purposes, that the information will be abused, including to fuel discrimination, and that there will be a data breach. Therefore, it is of the utmost importance that policymakers and tech companies minimize the amount of personal information collected as part of contact tracing efforts, and safeguard the sensitive health and location information related to coronavirus exposure and disposition under discussion. As discussed above, even manual contact tracing approaches present such privacy threats, since they involve collecting highly personal medical and behavioral information; but these threats are more significant where digital tools collect vast quantities of data, including data on people who never test positive for, or are even exposed to, the coronavirus.

Even where data is only stored or shared in aggregate and anonymized formats, there is a risk of reidentification, a severe privacy risk with real consequences, especially for those who have tested positive for COVID-19. Stigmas and discrimination can develop either when people associate a certain disease with a specific population or toward specific individuals who have been quarantined. Much like in past disease outbreaks, stigmatization has been an issue during the spread of the novel coronavirus in the United States, causing additional stress, fear, and anxiety for certain communities facing discrimination. As Dr. Anthony Fauci and others have pointed out, fear and stigma surrounding positive cases are reminiscent of the AIDS crisis.[72]

For example, across the United States, Asian-Americans have faced discrimination and an uptick in violent attacks during the spread of COVID-19.[73] Similarly, contact tracers in New York City are struggling

[72] Shafer, "Could Lessons From The Early Fight Against AIDS Inform The Coronavirus Response?"
[73] Tavernise and Oppel, "Spit On, Yelled At, Attacked: Chinese-Americans Fear for Their Safety."

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Privacy Threats

to gain the trust of immigrant, Arab, Orthodox Jewish, and other minority communities due to fears that their personal information will be weaponized against them.[74] Additionally, there are already several examples from different countries of the data collected by COVID-19 apps being abused or misused. In South Korea, exposure notifications provided so much detailed information about people who had tested positive that they have turned some citizens into "imperious armchair detectives" who look to track and reidentify individuals.[75] Additionally, the LGBTQ community in Seoul has been the subject of recent tracking, hate, and blame for the latest outbreak.[76] In Norway, the data protection authority ordered the country's public health body to suspend its contact-tracing app due to privacy issues with the app's collection of location data.[77] And Bahrain's BeAware app was used as fodder for state-controlled television: the host of the game show *Are You At Home?* called app users on-air to ask if they were adhering to social distancing guidelines.[78] This stigmatization and fear may also create disincentives for individuals in such communities to even seek testing.

Contact tracing is, by its very nature, intrusive, but digital tools can create additional privacy threats because of the scale of data collected, and the risk that additional entities beyond public health authorities could gain access to the data. Some intrusions into our privacy may be necessary to contain disease—public health professionals may ask infected individuals to look through their phones and recent credit records to help assist in identifying people who may have been exposed. But historically only public health authorities had access to this information, and we have trusted that public health officials' interest is in public health alone.

It is critical that data gathered for contact tracing purposes—whether by traditional methods or through

[74] Eisenberg, "Privacy Fears Threaten New York City's Coronavirus Tracing Efforts."
[75] Thompson, "The Technology That Could Free America From Quarantine."
[76] Kim, "Tracing South Korea's Latest Virus Outbreak Shoves LGBTQ Community into Unwelcome Spotlight."
[77] Manancourt, "Norway Suspends Contact-Tracing App over Privacy Concerns."
[78] Statt, "Gulf States Using COVID-19 Contact Tracing Apps as Mass Surveillance Tools, Report Says."

digital tools such as exposure notification apps—be limited to public health agencies. Neither law enforcement agencies nor technology companies are tasked with securing our public health, and this sensitive personal information should not be shared with them.

Allowing law enforcement access to any of this data would open the door to increased, non-disease-related surveillance, and could permit law enforcement to conduct an end-run around Fourth Amendment safeguards. Further, permitting access to government officials other than public health authorities creates a real risk of mission creep and improper secondary uses of personal data. Once the government obtains new streams of data, it can be very difficult to scale that data collection back and to ensure that it is used properly and in a limited fashion. We should heed these lessons from our experience with the Patriot Act,[79] which created new surveillance authorities post-9/11 and has been a struggle to reform to this very day, nineteen years later. Models taken from counter-terrorism that "fuse" local, state, and national agencies, as was highlighted in the original Safra Center "Roadmap to Pandemic Resilience," are problematic for this reason and require special care and explicit protections for individuals' data.

Tech companies' involvement also raises serious privacy threats and significantly alters the dynamic between public health authorities and the general public. While the majority of Americans trust public health agencies,[80] Americans have largely negative views of tech companies and their impact on society.[81] The business models of many technology companies rely on monetizing user data, which has caused the majority of Americans to feel that they have little control over their personal information.[82] The trove of sensitive health data collected for public health purposes, as well as any location or proximity information collected for exposure notification systems, could also be valuable for commercial

[79] Swire, "Security, Privacy and the Coronavirus: Lessons From 9/11."
[80] Nather, "Exclusive Poll: Public Trusts Health Agencies More than Trump on Coronavirus."
[81] Knight Foundation, "Techlash? America's Growing Concern with Major Technology Companies."
[82] Auxier, "Americans and Privacy: Concerned, Confused and Feeling Lack of Control Over Their Personal Information."

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Privacy Threats

purposes, creating a high risk for secondary uses of this data. Without appropriate guardrails, app developers could use the data for unrelated purposes such as advertising, or sell the data to data brokers who run a lucrative market for personal health information.[83] For example, there is a risk that insurance companies could use the data to deny coverage or raise premiums[84] and pharmaceutical companies could use the data for drug marketing.[85] Already, North Dakota's Care19 app, which collects users' sensitive individual location data, has violated this principle and its own stated privacy protections by sharing location data and unique identifiers (including advertising identifiers) with FourSquare and Google.[86] It will be difficult to earn the public's trust in digital tools without restrictions on such abuses of COVID-19 data, including a ban on use for commercial purposes.

Expanded collection of and access to personal data, whether by government agencies beyond public health authorities or by companies, also increases the risk of harm through data breaches. Indeed, data breaches are a serious risk for the public health authorities and companies collecting and retaining COVID-19 data. The public and private sectors have both been the targets of major security breaches in recent years, such as the OPM data breaches and the Equifax breach. And breaches are so rampant in the healthcare industry that the U.S. Department of Health and Human Services Office for Civil Rights maintains a public list of breaches of unsecured protected health information affecting 500 or more individuals. To mitigate these risks, it is critical to minimize the amount of data collected to that which is actually needed by public health authorities, and to strictly limit what entities have access to the data. Further, all digital contact tracing tools must be designed to meet best practices for securing sensitive health information.

83 Tanner, "For Sale: Your Medical Records."
84 Allen, "Health Insurers Are Vacuuming Up Details About You—And It Could Raise Your Rates."
85 Ornstein, "Big Data + Big Pharma = Big Money."
86 Melendez, "North Dakota's COVID-19 App Has Been Sending Data to Foursquare and Google."

Regulation limiting the entities authorized to access COVID-19 data and the permitted uses will mitigate the privacy risks posed by digital contact tracing systems. Legitimate interests in using the data for public health research can be preserved while preventing inappropriate secondary uses. As discussed in more detail in the Recommendations section below, we must enact legislation to ensure that the app providers have no commercial interest in our coronavirus data.

Anonymization and Cybersecurity Issues

In addition to developing safeguards to mitigate the risks of improper data use and data breaches, public health authorities will need to adopt practices to guard against a variety of cybersecurity threats. Not just the digital exposure notification apps that are the focus of this paper, but all digital tools that may be used in the process of contact tracing present inherent cybersecurity risks. For example, case management systems are an integral part of a public health organization's response toolkit and, as noted above, digital tools are available to assist public health authorities with these systems. Health agencies must adopt best practices for cybersecurity to protect all these tools, as well as the databases that they produce, and keep them as secure and private as possible. Data security concerns are equally, if not more important in the face of an unprecedented pandemic.

As mentioned above, a central privacy concern in Bluetooth contact tracing technologies is maintaining anonymity of those using the apps, particularly for those users who do eventually test positive for COVID-19 and submit that result to the public health authority operating the tracing system. These people are at the highest risk, both because of the way in which some tracing systems necessarily reveal more data about those who test positive and because of the potential for targeted harassment, stigmatization, and even potential violence against them. Keeping users anonymous is therefore crucial for any proposed digital tracing tool.

Privacy and Cybersecurity/Data Security Threats from Contact Tracing

Anonymization and Cybersecurity Issues

The anonymity features of any contact tracing app depend upon what technologies the app uses and how it implements those technologies. For example, some governments are building or have already deployed apps that rely on GPS location information. As noted above, GPS information is not as useful as Bluetooth technology in showing whether two people have possibly transmitted the virus. Additionally, such a system precludes any anonymity because the location information would show the pathways that particular individuals follow, including starting and ending points at their own homes, and because it would deliver absolute location data (as opposed to the relative data that Bluetooth provides).

The cybersecurity threats extend beyond a breach of anonymity. In a recent example, Amnesty International uncovered that Qatar's compulsory exposure notification app EHTERAZ contained security vulnerabilities allowing hackers access to over one million Qatari citizens' sensitive personal information, including names, national IDs, health status, and GPS location data.[87] Moreover, in a June 2020 study, a mobile cybersecurity analysis company assessed seventeen mobile contact tracing apps from around the world on a variety of app security best practices tests and found only one app passed every test, while there was not a single test that even a majority of the apps passed.[88]

Turning to Bluetooth-reliant tools, the Apple/Google proposal is likely to be most prevalent in the United States, not only due to the companies' combined market dominance, but also because it uses cryptography to achieve the exposure alerts without actually turning over names and locations. Despite its focus on retaining anonymity even for those diagnosed with COVID-19, however, there are still some data security concerns with the Apple/Google proposal and with other proposals for digital contact tracing apps. In particular, there are risks that the system could be abused, either by governments seeking to use the data for law enforcement purposes or as another tool for repression in autocratic regimes, or by companies misusing data for commercial purposes to track customer location for advertising or marketing.

[87] Amnesty International UK, "Qatar: 'huge' Security Weakness in COVID-19 Contact-Tracing App."
[88] Goodes, "Report: The Proliferation of COVID-19 Contact Tracing Apps Exposes Significant Security Risks."

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Anonymization and Cybersecurity Issues

In addition, cryptographers and cybersecurity professionals have identified two current lines of attack against the anonymity of the Apple/Google system (and another similar proposal called DP-3T from a coalition of European researchers) that are worth noting. Both involve exploiting the list of infected device identifiers (which each device generates every day and from which can be derived the fifteen-minute rotating identifiers that are broadcast over Bluetooth) that must be distributed in order for each device to determine if they were in close contact with an infected person.

The first attack requires deploying a network of Bluetooth receivers spread around a physical area with enough granularity to follow devices as they move around the area from point to point.[89] While this may seem like a high bar, Bluetooth-enabled urban infrastructure is growing all of the time, including smart meters and street lights. Each receiver could record all of the short-term identifiers it sees over time and put them all in a central database. As people test positive and their infected device identifiers are broadcast to all devices to check for contacts, the database could be used to track which receivers around the area observed the corresponding short-term identifiers and when. In this way, a map of movements of those who test positive could be generated, after which assigning names and addresses is as easy as tracking commutes.

The second attack is even simpler to execute, although it would likely result in identifying fewer subjects than the first.[90] If an attacker hooked a single Bluetooth receiver up to a video camera and stored the identifiers it received over Bluetooth along with the video footage, picking out those who tested positive would be as easy as associating short-term identifiers with frames of the video footage showing those who have tested positive.

[89] Seiskari, Github: Contact Tracing BLE Sniffer POC.
[90] Soltani, Calo, and Bergstrom, "Contact-tracing apps are not a solution to the Covid-19 crisis."

Privacy and Cybersecurity/Data Security Threats from Contact Tracing

Anonymization and Cybersecurity Issues

Both of these attacks are not necessarily mistakes by the authors of the system. Rather they are unavoidable consequences of the need for the system to connect two people together. If it were not for the distribution of the device identifiers of those who test positive, the contact tracing would be impossible. The first of these potential attacks, involving installation of numerous Bluetooth receivers around a wide area, is likely only achievable by government entities like law enforcement. Thus, prohibiting law enforcement access to this data, as discussed elsewhere in this paper, should mitigate this threat. However, the second potential attack could be achieved by a less well-resourced hacker. Thus, these potential breaches of anonymity must be carefully considered and mitigations against them included in any proposal for digital contact tracing tools.

05 Recommendations

Recommendations for Policymakers

We have identified a variety of equity, privacy, and civil liberties concerns that are posed by contact tracing systems, particularly where they rely on digital tools. Policymakers can and should take action to address these concerns, and provide guardrails to ensure that digital tools to support contact tracing are properly designed to provide the information public health officials need, while also protecting individual rights.

While digital tools cannot replace traditional manual methods, they have the potential—if they are implemented with robust safeguards— to assist public health authorities in contact tracing efforts. The most significant hurdle to Bluetooth apps' efficacy will be issues related to adoption, which are deeply intertwined with digital equity issues.

To address these concerns and hopefully improve adoption rates, we recommend that policymakers take steps to: (1) ensure that public health officials develop targeted strategies, possibly including dedicated manual tracers, to address vulnerable populations that are unlikely to be reached by digital apps; (2) encourage partnerships between digital tool developers and community organizations; (3) develop and promote public education campaigns alongside deployment of any apps; (4) take long-overdue steps to close the digital divide; (5) pass comprehensive privacy legislation; and (6) enhance enforcement by the Federal Trade Commission.

Public health authorities should continue to rely upon traditional manual contact tracing methods, and should particularly recognize that digital tools are least likely to be helpful in reaching marginalized and at-risk communities. We recommend that reliance on digital tools be merely supplemental to manual tracing, which will especially be necessary to reach the lower-income and senior populations who are also at highest risk of contracting COVID-19. Immigrant populations, as well, may need more attention from public health authorities. In addition to experiencing lower rates of English proficiency, these communities also have strong concerns about federal policies that disqualify immigrants who have accepted any government benefits from applying for citizenship (the so-called "material support" regulation has been suspended, but community members are often not aware of this) as well as the sharing of data with ICE agents.

Policymakers should encourage partnerships between developers of digital contact tracing tools and community organizations or leaders that represent affected communities. Such partnerships will have crucial inputs in decision-making around the role that app-based contact tracing can play. Developers and providers should consult with community representatives regarding how to design and deploy apps in ways that allay public mistrust. Such partnerships can also be helpful for developing and implementing isolation and treatment plans. For example, the mayor of Chicago created a Racial Equity Rapid Response Team to work with Black and Latino community groups in shaping the response.[91] Maryland's Montgomery County refers Chinese and Spanish speakers to information hotlines run by non-profit organizations. In the hard-hit city of Detroit, a coalition of city agencies, non-profits, and academic institutions has focused on the particular needs of the homeless.[92] Again, such an approach can help to both mitigate risks posed by digital tools, and produce digital tools and practices that are most likely to be used effectively. To achieve these goals, Congress could mandate that funding for tracing regimes be contingent upon partnerships with community organizations. Further, funding to assist tracing efforts should be contingent on localities making equitable and accessible testing and treatment regimes available, again in concert with those most affected.

[91] Malagon, "Latino Communities in Illinois See Uptick in COVID-19 Confirmed Cases: 'Physical Distancing Is a Privilege.'"

[92] Taylor, "Detroit Mobilizes to Protect the Homeless from Coronavirus."

Recommendations

Recommendations for Policymakers

Public health authorities should develop and promote public education campaigns. In order to increase participation, public education campaigns deployed alongside apps will likely be necessary. Early surveys indicate that many Americans of diverse backgrounds are skeptical of the concept of Bluetooth exposure notification apps and are unlikely to participate.[93] Further, as discussed above, there will be many varying approaches throughout the country when it comes to digital tools, as these are state-led efforts. Some states may choose not to use digital tools, some may choose Bluetooth-based approaches and some may, against our recommendations, collect location data. There is already much confusion surrounding both who is developing and providing these tools and what these tools collect and do. Accordingly, each state will need to undertake efforts to correct the many misunderstandings about their particular app offering, and proactively inform the public regarding how they work and what information they collect, if any. These educational efforts will be key to widespread adoption, and demand a concerted, collaborative effort between governments, app providers (and potentially Apple/Google), and community organizations.

The federal government must take long-overdue steps to close the digital divide and connect the millions of people in the United States who lack access to the devices and connectivity upon which any digital tracing system would be built. Congress should pass the Digital Equity Act (S. 1167), a comprehensive bill that would dramatically expand digital literacy training around the country. These training programs are designed to develop precisely the sort of skill sets that people would need to navigate digital apps, Bluetooth functionality, and basic device maintenance.

Furthermore, Congress, in conjunction with the FCC, should significantly expand federal programs to provide emergency connectivity to households that lack internet access during the pandemic. Specifically,

[93] Owens, "Americans Are on Board with Contact Tracing as Long as It Doesn't Involve Cellphone Data"; Timberg et al., "Most Americans Are Not Willing or Able to Use an App Tracking Coronavirus Infections. That's a Problem for Big Tech's Plan to Slow the Pandemic."

Recommendations

Recommendations for Policymakers

Congress should significantly expand funding and eligibility for the Lifeline program, which subsidizes phone and internet service for low-income Americans. The FCC should also work closely with any state that adopts digital exposure notification apps to ensure that Lifeline-supported devices also support such apps, and promulgate any necessary rule changes. Accordingly, the FCC should also abandon its recent proposal to prohibit Lifeline providers from offering free devices in conjunction with Lifeline service.[94] The FCC and Congress should also increase Lifeline's voice and data allowances, at least during the COVID-19 pandemic, to ensure that people can use the program as the literal lifeline it was intended to be. The current caps could deter Lifeline subscribers from downloading contact tracing apps for fear of exceeding data allowances.

Many of these actions are long overdue, but it should be noted that, even in their entirety, these recommendations will not fully ameliorate our equity concerns or bring access to every unserved community. The problems of the digital divide are deep-seated and require long-term investments in infrastructure deployment and affordability that cannot realistically occur in the short-term. Moreover, the only federal agency designed to address these issues—the FCC—has fully retreated from its role over the past three years. In 2017, the FCC deregulated internet providers and wholly abdicated its legal authority to oversee the broadband market. Without this federal cop on the beat, it is difficult to imagine how we can fully close the digital divide in the manner that smartphone-based tracing systems require. Although the enormity of these challenges suggests that we cannot resolve them in the immediate context of the COVID-19 pandemic, the pandemic should provide a new call to action for policymakers. We must begin to implement sorely needed measures to restore FCC enforcement and begin to reduce the digital divide.

[94] FCC, Fifth Report and Order, Memorandum Opinion and Order and Order on Reconsideration, and Further Notice of Proposed Rulemaking; New America's Open Technology Institute, Comments of New America's Open Technology Institute and Public Knowledge.

Congress should pass legislation to provide safeguards and hold governments and companies accountable. Perhaps most crucially, Congress must pass legislation to address the privacy, equity, and civil rights risks posed by digital contact tracing tools. The United States does not have a comprehensive federal privacy law and the inadequacy of the country's sectoral approach to privacy has become particularly pronounced during the pandemic. Significantly, the Health Insurance Portability and Accountability Act (HIPAA) only applies when personal health information is collected by healthcare providers and insurance companies.[95] But when the same information is collected by non-medical entities, such as app providers, HIPAA protections do not apply, leaving Americans' sensitive health data vulnerable in any digital health tools the private sector offers.

As discussed earlier, the pandemic has created privacy threats that cannot wait to be addressed until Congress is able to pass comprehensive privacy legislation, which is unlikely to occur in 2020. Without legal guardrails, the collection of health, proximity, and location data for public health purposes could lead to mission creep by other government entities and threats of commercial use. Therefore, Congress should pursue legislation targeted to the privacy issues specific to public health emergencies, particularly digital exposure notification systems. And state legislatures should fill any gaps Congress leaves to protect the privacy and public health of their residents.

Several different stakeholders—including tech companies, professional associations, and NGOs—have published principles recognizing the need for privacy protections specific to COVID-19.[96] Additionally, a coalition of civil society organizations sent congressional leaders a list of principles addressing the protection of civil rights and privacy of all persons, especially communities of color and other populations

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[95] US HHS, Office for Civil Rights. "Covered Entities and Business Associates."

[96] Gilmor, "Principles for Technology-Assisted Contact-Tracing"; AMA, "AMA Privacy Principles"; Brill and Lee, "Preserving Privacy While Addressing COVID-19"; Massé, "Privacy and Public Health: The Dos and Don'ts for COVID-19 Contact Tracing Apps."

who are at high risk for the virus, when considering the deployment of technological measures to combat COVID-19.[97] There is substantial overlap on broad principles, with some distinctions on how those common values should be reflected in legislation. The following principles should serve as a guide to policymakers developing public health emergency privacy legislation.

1. **Meaningful consent:** All participation in contact tracing applications must be voluntary. Voluntariness requires that participation is not a condition for access to public benefits, work, or educational spaces. Companies must obtain meaningful consent to collect and use personal data. The "notice and consent" model that has characterized much of privacy enforcement in the United States fails to protect user privacy under normal conditions and should not be the consent model used for exposure notification systems.[98]
2. **Transparency:** App providers must be fully transparent with users about the type of data collected, the entities that will have access to the data, and how the data will be used. Congress should require notices to be accessible to those with limited English proficiency and to be available in a machine-readable format.
3. **Data Minimization:** App providers should minimize the collection of personal data and only collect the data necessary for specified public health purposes. As noted above, this means that digital tools to assist contact tracing should only collect proximity information, such as Bluetooth data, and not individual location information, such as CSLI or GPS. Further, only apps developed in partnership with public health authorities should be made available to the public, so that only the types of data necessary to support contact tracing are collected.
4. **Limited Retention Period:** The data collected must not be retained by companies or public health authorities indefinitely. Legislation should define a retention period for personal data. The retention period could be a defined period of time, such as every thirty days, or could be tied to a declaration by public health agencies that the emergency has ended. Legislation could also permit longer retention of aggregated anonymized data by public health authorities for research purposes.

[97] New America's Open Technology Institute, "Civil Rights Groups Call for Protection of Democracy and Privacy as Tech Responds to Pandemic."
[98] Park, "How 'Notice and Consent' Fails to Protect Our Privacy."

5. **Prohibition on Secondary Uses:** Personal data must be used for public health purposes only and legislation should prohibit secondary uses. The data must not be used for commercial purposes such as advertising. Data should not be shared with any government entities other than public health authorities. Law enforcement access should be prohibited, including access for pandemic-related purposes, such as the enforcement of stay-at-home orders. Location data must not be used to track individuals.
6. **Data Security:** Companies must maintain best security practices to safeguard the collected data. Such practices include decentralized implementation, de-identification methods like differential privacy, and encryption.
7. **Equity:** Companies must take steps to prevent disparate impacts on certain populations and demographics. Legislation should include a prohibition on discriminatory uses of data related to protected characteristics, including denial of access to education, housing, and employment opportunities. The data must not be used to restrict or deny voting rights.

Legislation rooted in these principles would help to protect the public from the risks that digital tools for contact tracing pose to individual rights. However, if Congress does not pass legislation (or passes weak legislation), there are existing legal frameworks that can be used to hold companies accountable for the privacy practices of contact tracing apps. Both the Federal Trade Commission and state attorneys general have authority to bring enforcement actions against companies that misrepresent their privacy and security practices to users.

The Federal Trade Commission (FTC) and state agencies should be given the resources necessary to hold companies accountable for any privacy violations or other deceptive practices. Section 5(a) of the FTC Act provides that "unfair or deceptive acts or practices in or affecting commerce . . . are . . . declared unlawful" and the Commission applies this authority to privacy and security. The FTC typically relies on the deceptiveness prong, bringing privacy cases against companies that do not abide by the representations made to their users in privacy policies or other public-facing documents.[99] All states have similar statutes prohibiting deceptive practices and most also prohibit unfair practices.[100] These state statutes empower their attorneys general to pursue actions against companies' unfair and deceptive privacy and security practices.[101]

If app providers or platforms break the promises made to the public, both the FTC and state attorneys general would have the legal authority to pursue legal action for unfair and deceptive trade practices. For example, Apple and Google have characterized their contact tracing partnership as promoting "Privacy-Preserving Contact Tracing" and have stated that their system does not collect location data and the system is only used by public health authorities. Therefore, if the companies were collecting location data or disclosing data to third parties, the federal and state consumer protection agencies would have grounds for an investigation and potential enforcement actions.

But without legislation establishing legal obligations on exposure notification programs, or more resources for enforcement, the ability of the FTC and state attorneys general to regulate privacy during the pandemic will be severely limited.

Recommendations for Platforms and App Designers

If local governments do choose to move forward with deploying Bluetooth exposure notification apps, as many appear to be, we recommend that platforms and app developers take a number of steps that, even in the absence of legislation, could help ensure privacy is protected, mitigate the equity concerns raised above, and increase participation. These are largely system design recommendations, and many are already required by the Apple/Google API. Where Apple/Google have announced that they require

[99] Keegan and Schroeder, "[FTC's Evolving Measures of Privacy Harms.](https://ethics.harvard.edu/digital-tools-for-contact-tracing)"
[100] NCLC, "Consumer Protection in the States: A 50-State Evaluation of Unfair and Deceptive Practices Laws."
[101] Citron, "Privacy Policymaking of State Attorneys General."

these privacy protections, we urge Apple/Google to not retreat on these important protections down the road, but rather to conduct regular oversight to ensure apps' compliance.

Systems relying on digital tools to aid contact tracing should be decentralized. Data must remain decentralized, meaning data should be stored on individual devices rather than in a centralized server. Germany has already waged an instructive debate on this particular element of the Bluetooth app proposals. In their effort to develop an effective and privacy-protective app for the European Union, the Pan-European-Privacy-Preserving Proximity Tracing team of more than 100 international researchers pushed a centralized approach, through which the pseudonymized proximity data would be stored and processed on a server controlled by a national health authority. However, Germany more recently rejected this approach following an outcry from academics and organizations due to concerns about allowing authorities to amass citizens' data and potential government mission creep.[102] Instead, Germany and some other governments in the E.U. are pursuing a decentralized, more privacy-protecting approach known as the DP-3T proposal, which would also incorporate the other safeguards we recommend for platforms and app designers. However, France has more recently deployed a centralized app named StopCovid (which would not be interoperable with its neighbors' decentralized apps as a result) and that app has not gained substantial uptake. While France's centralized app has only been downloaded by 1.9 million citizens since it launched on June 2,[103] Germany's decentralized app has been downloaded by nearly 10 million Germans since it launched on June 16.[104] This suggests that the low adoption rate in France may stem from the centralized approach, and that the most privacy-protective apps are the best way to improve uptake, and therefore improve effectiveness. Under the decentralized contact tracing infrastructure, identifiers are stored locally on individual devices and are only uploaded with a user's permission after a confirmed COVID-19 diagnosis. U.S. app developers should follow suit.

[102] Lomas, "Germany Ditches Centralized Approach to App for COVID-19 Contacts Tracing."
[103] Braun, "French Contact Tracing App Sent Just 14 Notifications After 2M Downloads."
[104] Seythal, "German Coronavirus Tracing App Downloaded Almost 10 Million Times: Government."

Recommendations

Recommendations for Platforms and App Designers

Digital tools must incorporate robust safeguards to protect anonymity of users. Bluetooth-based exposure notification tools rely on phones to generate identifiers that are sent out as beacons and then detected by other phones using the app. Anonymization of these identifiers is key, and the identifiers must be continuously changing, as often as possible, in order to avoid harms related to reidentification. As devices interact via Bluetooth, they will exchange nameless identifiers (again, which will be stored on the devices rather than in a central database). But as outlined above, a significant threat from both a cybersecurity and privacy perspective is reidentification, a threat that can be mitigated by changing identifiers more frequently to make reidentification more challenging. While the central database will keep track of the nameless identifiers (as they change) of the individuals with confirmed cases, the concept is that the database will not be able to track who has been exposed. For example, the Apple/Google API addresses this threat by requiring that identifiers are randomized every fifteen minutes.

Notifications of potential exposure should provide only the minimum information necessary. App providers and governments should work together to ensure that notifications of exposure contain no personally identifiable information. While its collection is not allowed under the Apple/Google infrastructure, location data showing individuals' paths of travel, for instance, can be used to reidentify individuals. Including too much personal or location data in notifications can be problematic, even if not shared with the government.

App designers should partner with local communities to ensure apps are designed to meet community needs. For these system design recommendations, we urge app designers to engage with civil rights and civil liberties advocates as well as community organizations, who can help developers to address community needs and increase reach. Privacy-protective system design should result in higher uptake of the apps, and therefore increased effectiveness. Thus it is important to ensure that the communities most in need of attention—the vulnerable populations at highest risk of coronavirus—have their concerns addressed, and to educate and partner with the relevant communities and organizations in order to spread awareness as to the apps' purposes, privacy protections, and limitations.

Apple and Google should take steps to enforce the safeguards they have announced. Given the predominant market share of Apple and Google, it is likely that exposure notification apps relying on the Apple/Google API will be more widely adopted than other digital tools.[105] As mentioned throughout this section, many of the most crucial privacy protections we recommend are requirements under the Apple/Google API, where apps must: (1) use Bluetooth data only; (2) use frequently-changing anonymous identifiers that only health authorities can temporarily access when necessary; (3) be decentralized; (4) be voluntary; (5) require consent for diagnosis information uploads; and (6) provide transparency to users.[106] Enactment of privacy legislation, as we recommend above, would enable the public to hold these platforms accountable to uphold these privacy safeguards, but with or without such legislation, we strongly urge Apple and Google to conduct regular and conscientious oversight to ensure that app providers strictly comply with these requirements. As the coronavirus battle could rage on for months or potentially years to come, pressure could mount from governments for Apple and Google to scale back these restrictions and allow more access to and collection of data.

Further, Apple and Google may need to consider banning non-API-compliant apps from their app stores to avoid confusion regarding which apps are government-backed and privacy-protective.[107] For example, at present, even though apps using location data are barred from the API, they are allowed in the companies' app stores. In some cases there are multiple apps per state, one complying with the API, one non-compliant.[108] The Apple/Google infrastructure is fairly strong from a privacy perspective, and Apple/Google should maintain these requirements and enforce them by expelling apps that flout the requirements.

[105] Lovejoy, "More Countries Adopting or Switching to Apple/Google Contact Tracing API."
[106] Apple and Google, "Exposure Notification: Bluetooth Specification."
[107] Langley, "Apple and Google Are Facing Pressure from New York's Attorney General to Impose Stricter Privacy Rules on Contact Tracing Apps That Are Currently Flooding Their App Stores."
[108] O'Neill, "Why One US State Will Have Two Coronavirus Tracing Apps."

06 Conclusion

Governments throughout the United States and around the world are turning to contact tracing programs as a critical component of efforts to combat the coronavirus pandemic. The extent to which digital tools can play a meaningful role in expanding the reach of traditional manual contact tracing techniques is not yet clear, and these tools pose a variety of concerns regarding equity, privacy, and civil liberties. Nonetheless, given the scale and impact of this pandemic, digital exposure notification tools may be worth exploring and developing, provided that governments can implement adequate guardrails to control use of these systems.

We have therefore presented a series of recommendations for government officials and for platforms and app developers, to mitigate the risks to privacy and civil liberties, and ensure that use of digital tools for contact tracing is as rights-protective as possible. In addition, we have recommended that public health officials should recognize that digital tools will still exclude vulnerable communities, and should take affirmative steps to both try to reach those communities with digital tools and compensate for the remaining gaps with manual contact tracing.

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From:	Ponce, Ninez
To:	NCVHS Mail (CDC)
Cc:	Mays, Vickie M.; nponce@ucla.edu; Richard Calvin Chang; Corina Penaia; Karla Thomas
Subject:	Sep 14, 2020 Materials Submitted for Virtual Hearing on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency
Date:	Wednesday, September 9, 2020 3:01:24 PM

Dear NCVHS Committee and Distinguished Professor Mays,

Kindly see the attached links related to data collection and use on Native Hawaiians/Pacific Islanders (NHPI) during a Public Health Emergency. The submission is a link to the UCLA Center for Health Policy Research's virtual seminar presenting the NHPI COVID-19 Data Policy Lab. I'm also including a Q&A from UCLA Newsroom related to promoting the seminar and a Health Affairs Blog written by the NHPI members of the NHPI Lab.

Here is the link to the seminar video on YouTube: https://www.youtube.com/watch?v=N34gVBH2y1U.
UCLA Newsroom Q&A: https://newsroom.ucla.edu/stories/covid-19-stark-differences-NHPI
Health Affairs blog: https://www.healthaffairs.org/do/10.1377/hblog20200825.671245/full/

Thanks for your consideration.

Ninez Ponce

Ninez A. Ponce, MPP, PhD (she/her/hers)
Director | UCLA Center for Health Policy Research healthpolicy.ucla.edu
Principal Investigator | California Health Interview Survey
Professor | Department of Health Policy and Management
UCLA Fielding School of Public Health
Email: nponce@ucla.edu
Twitter : @NinezPonce
For immediate assistance please contact Hala Douglas

At UCLA, we pay respect to the Gabrileno/Tongva peoples as the traditional land caretakers of the Los Angeles basin and South Channel Islands.

From:	Ponce, Ninez
To:	Mays, Vickie M.
Cc:	NCVHS Mail (CDC); nponce@ucla.edu; Richard Calvin Chang; Corina Penaia; Karla Thomas
Subject:	Re: Sep 14, 2020 Materials Submitted for Virtual Hearing on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency
Date:	Wednesday, September 9, 2020 4:09:06 PM

Thanks, Dr. Mays, and NCVHS Committee.

For easy reference, here's also the link the NHPI COVID-19 Data Policy Lab dashboard. Please also use this as a submission. Best, and thanks, Ninez

https://healthpolicy.ucla.edu/health-profiles/Pages/NHPI-COVID-19-Dashboard.aspx

From:	beth.pathak@wiise-usa.org
To:	NCVHS Mail (CDC)
Cc:	Hines, Rebecca (CDC/DDPHSS/NCHS/OD)
Subject:	Public Comment on Privacy, Confidentiality and Security Considerations for Data Collection and Use during a Public Health Emergency
Date:	Wednesday, September 9, 2020 11:37:43 PM
Attachments:	COVKID Statement to the NCVHS Subcommittee on Data Privacy FINAL.pdf
Importance:	High

TO: Rebecca Hines, MHS
Designated Federal Officer (DFO)
NCVHS Executive Secretary

Hello Rebecca:

I hope this note finds you well and surviving 2020.

I am writing to submit a public comment from The COVKID Project, a program of the Women's Institute for Independent Social Enquiry (WiiSE). I am available to speak during the public comment section of the agenda, if that would be helpful to the committee.

Warm regards,
Beth Pathak

Elizabeth Pathak, PhD, President
Women's Institute for Independent Social Enquiry
www.wiise-usa.org @wiise_usa
www.covkidproject.org @covkidproject
Mobile 1-813-610-8715

"A very trifling thing can cause the greatest of joys."
Viktor Frankl

Statement to the NCVHS Subcommittee on Data Privacy for the September 14, 2000 Meeting

The COVKID Project Team
Elizabeth B. Pathak, PhD, Jason L. Salemi, PhD, Janelle M. Menard, PhD

Objectives of this meeting are to:
•Understand current policies and practices involving data collection and use with respect to privacy and security during the COVID-19 PHE;
•Understand challenges and potential areas of clarification in light of these practices, new and emerging technology developments, and new and evolving policy directions;
•Identify best practices and areas where additional technical assistance or guidance may be useful

Introduction

The COVKID Project (www.covkidproject.org) is a public-facing COVID-19 data dashboard reporting surveillance data on children and teens aged 0-19 years old in the United States. Since late April, we have pulled data at least 2x/week from 52 jurisdictional health departments (50 states, NYC, and DC) and shared those data on our website. Dr. Salemi has also created a Florida-specific data dashboard (covid19florida.mystrikingly.com) using the COVID-19 case line data file that is released on a daily basis by the Florida Department of Health.

COVID-19 surveillance for children and teens varies widely in extent, detail, and timeliness. There is also needless data suppression at the state level – suppressing death counts less than 5 for demographic groups for an entire state. This misguided omission of specificity for death data impacts only children and teens, because older age groups have sufficient numbers of deaths to avoid suppression. Given that the majority of child decedents are Hispanic or Black, suppressing death counts in this way directly impedes our ability to track and document health disparities at the state level.

The COVKID Project recommends that all states adapt a minimum data table that is updated and reported on their websites daily. The recommended table is in a 4 x 4 x 4 format:

- 4 essential measures (number tested, number positive, number ever hospitalized, number deceased)
- 4 standard age groups (0-4 years, 5-9 years, 10-14 years, 15-19 years)
- 4 major racial/ethnic groups (all combined, Black non-Hispanic, Hispanic, White non-Hispanic, and Mixed-Race), with additional groups per state situation
- View the recommended data table, with additional methodological details, on our website (www.covkidproject.org/state-report-card)

An important COVKID initiative is the State Data Quality Report Card (www.covkidproject.org/state-report-card), which scores each state and DC on their progress in reporting the data in accordance with our recommended table format. As of August 27, the highest earned grade on our report card was a B (Florida, Georgia), and only 4 states had earned a B- (Illinois, Minnesota, North Dakota, California). New York State currently has a grade of D because it reports no case data at all for children and teens (although it does report COVID-19 deaths for two pediatric age groups).

a) What is the proper scope of data collection, analysis, and sharing in an emergency?

Accurate, detailed, and timely data are critically important for public health efforts to end the COVID-19 pandemic. Equally important are data transparency and timely sharing. State health departments simply lack the staff and time to conduct all of the necessary surveillance data compilation, cleaning, and analyses. Key epidemiological measures must be analyzed rapidly to assess contemporaneous trends in an ever-changing environment. Timely public release of data allows the nation to draw on research expertise in university and non-profit settings to inform important public health policy decisions with data-driven evidence.

b) What are fair information principles for a pandemic?

Fair information practice principles for a pandemic provide a framework for data reporting methods to ensure patient confidentiality in keeping with HIPAA laws. Principles that may apply to a pandemic include, but are not limited to the following:

1. **The Data Quality Principle.** Personal health information (PHI) relevant to SARS-CoV-2 is collected at county, state and national levels in epidemiological surveillance. On public release, these data should be de-identified, accurate, timely, and complete.

2. **The Purpose Specification Principle.** As a reportable infectious disease, states and territories require timely data reporting for COVID-19 cases, hospitalizations, and deaths. Confidential PHI data from various sources (e.g., health care providers, labs, hospitals, medical examiners) are reported to county and state health departments for the purpose of disease prevention and control. Health departments de-identify the data when reporting to CDC, and all data are used for the purpose of pandemic surveillance to inform prevention and control strategies.

3. **The Use Limitation Principle.** Consistent with HIPAA regulations, PHI data are de-identified and analyzed for epidemiological surveillance.

4. **The Security Safeguards Principle.** Infectious disease reporting methods are consistent with HIPAA regulations. Only de-identified public health data are released to the public.

5. **The Collection Limitation Principle.** Personal health information collected for the purposes of monitoring and compliance with reportable infectious disease laws should have direct identifiers removed in accordance with HIPAA regulations.
6. **The Openness Principle.** Practices and policies relevant to personal health information should be guided by an openness policy that includes clear definitions of personal data, explains the purpose of data collection, provides information about how and where data are stored and personnel who control the data.

c) What are best practices for properly cabining emergency authorities that supersede extant data protections?

d) What data should organizations be collecting?

In order to protect the public's health, accurate and complete epidemiological data must be regularly and quickly reported. Data are already collected for the following categories: new cases with method of diagnosis, population testing, deaths, hospitalizations, ICU admissions, Multisystem Inflammatory Syndrome in Children (MIS-C) cases, and exposure information. All data categories can be improved with more complete demographic data, non-suppression, and age disaggregation. Given the rise in cases with late effects of SARS-CoV-2 infection as we observe the natural history of COVID-19 in different populations, data pertaining to the long term effects of infection should also be collected and be complete with accurate demographic information. Data standardization in reporting is essential for comparability across populations.

e) What rules are all right to override to advance public health, and what should remain in force?

f) What data rights may be contracted away, and what should remain inalienable?

g) What level of identification of data is appropriate for which purposes?

De-identification of direct identifiers is already in place and is appropriate for informing public health prevention and control strategies. Improvements to demographic reporting and completeness are needed, some of which include limited identifiable data per HIPAA designation.

h) When is there a need for identifiable data?

The majority of PHI is restricted to laboratory and clinical settings. The only HIPAA-designated limited identifiers that are essential for public release and surveillance purposes are specific dates associated with measures such as date of hospitalization, date of death, date of testing, and county-level data to discern regional patterns. Because sample sizes are large, limited identifiers cannot be linked at the individual level. PHI should be retained by local, state, and federal agencies to facilitate dataset linkages to answer specific research questions. Linked datasets can then be de-identified prior to public release.

i) When is aggregate data more appropriate?

Data that are restricted to limited identifiers within a large sample population are appropriate for epidemiological surveillance. Demographic data should include disaggregated age.

j) Is case-level data without identifiers an adequate compromise?

For epidemiological surveillance purposes, case-level data is absolutely essential, but alone is insufficient since testing information is needed for all persons, independent of the test result. At a minimum, case-level data must include race/ethnicity and age in accordance with our suggested specified categories. In keeping with HIPAA rules about age, aggregation of age data after age 89 is sufficient.

k) How do standards differ at the local / state / federal levels?

Some states and territories classify COVID-19 as an immediately reportable disease, whereas others list it as a reportable communicable disease, both requiring timely reporting. Data reported to federal levels are de-identified. Patient confidentiality and HIPAA regulations apply in all case reports from clinical and laboratory settings.