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RESEARCH ARTICLE

County-Level Socioeconomic and Political Predictors of Distancing for COVID-19

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Introduction: In response to the COVID-19 pandemic, governments have implemented social distancing measures to slow viral transmission. This work aims to determine the extent to which socioeconomic and political conditions have shaped community-level distancing behaviors during the COVID-19 pandemic, especially how these dynamics have evolved over time.

Methods: This study used daily data on physical distancing from 15−17 million cell phone users in 3,037 U.S. counties. County-level changes in the average distance traveled per person were estimated relative to prepandemic weeks as a proxy for physical distancing. Pooled ordinary least squares regressions estimated the association between physical distancing and a variety of county-level demographic, socioeconomic, and political characteristics by week from March 9, 2020 to January 17, 2021. Data were collected until January 2021, at which point the analyses were finalized.

Results: Lower per capita income and greater Republican orientation were associated with significantly reduced physical distancing throughout nearly all the study period. These associations persisted after adjusting for a variety of county-level demographic and socioeconomic characteristics. Other county-level characteristics, such as the shares of Black and Hispanic residents, were associated with reduced distancing at various points during the study period.

Conclusions: These results highlight the importance of dynamic socioeconomic and political gradients in preventive behavior and imply the need for nimble policy responses.
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INTRODUCTION

The U.S. is the epicenter of the coronavirus disease 2019 (COVID-19) pandemic.[1] At the time of writing, there were >25 million cases and 418,000 reported deaths. Early modeling studies suggested that without mitigation efforts, rising numbers of COVID-19 cases could overwhelm the health system's capacity and cause millions of deaths.[2] In response, federal, state, and local governments implemented a patchwork of public health measures to slow transmission through social distancing. These included orders to stay at home and close schools and nonessential businesses. Similar policies have been implemented for previous pandemics.[3,4]

Recent findings suggest that physical distancing and shelter-in-place orders have been effective at reducing the growth rates for COVID-19[5,6] and that proxy measures of social distancing, including decreases in physical movement, have been associated with reductions in case growth across U.S. counties.[7,8] Such policy and behavioral interventions have been especially important in the absence of vaccines and effective treatments. However, the effectiveness of social distancing policies requires significant engagement by communities, which may face barriers to successful adherence depending on prevailing socioeconomic conditions and political beliefs.[9] Indeed, several studies have shown that low-income areas as well as areas that supported then-presidential candidate

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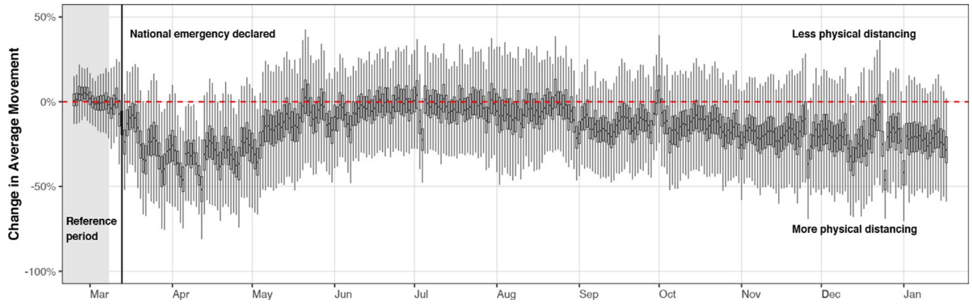

Figure 1. The trajectory of county-level physical distancing.

Note: Physical distancing was operationalized as the percentage change in county-level average distance traveled from March 1, 2020 to January 17, 2021, relative to that in pre–COVID-19 reference weeks (average of matched days from February 10, 2020 to March 8, 2020). Negative values indicate greater physical distancing. Data are represented as notched boxplots; notches indicate 95% CIs of the median. Based on 15−17 million anonymized cell phone users per day. N=3,037 U.S. counties per day. Data were obtained from Unacast.

Apr, April; Aug, August; Dec, December; Jan, January; Jul, July; Jun, June; Mar, March; Nov, November; Oct, October; Sep, September.

Donald J. Trump were less likely to engage in social distancing.[5,10,11]

However, most of these studies were conducted early in the COVID-19 pandemic. The associations between physical distancing and socioeconomic and political characteristics may have evolved owing to the changing geographic nature of the pandemic, the implementation of new mitigation strategies, and the politicization of these strategies.[12] Evaluating the dynamics of physical distancing is critical for updating public health and social policy responses to respond to new patterns of transmission. Such analyses may also provide insight into how risk mitigation behaviors have shifted across population groups as the pandemic has drawn on. Therefore, this study examines the demographic, socioeconomic, and political determinants of physical distancing for the COVID-19 pandemic among U.S. counties from March 2020 through January 2021.

METHODS

Study Sample and Measures

Data for the main outcome (i.e., physical distancing) were obtained from Unacast.[13] County-level averages of distance traveled per person were estimated using location data from 15 to 17 million anonymized cell phone users per day. A device was assigned to a county on a given day if a greater part of the day was spent in that county. Distance traveled was then summed and averaged across the total number of devices assigned to that county. Physical distancing was conceptualized as the percentage change in the average movement each day relative to the average movement for 4 pre–COVID-19 reference weeks. The *reference period* was defined as the average of 4 matched days between February 10, 2020 and March 8, 2020. For example, the distance traveled per device in Philadelphia County on Tuesday, April 7 was compared with the average movement in Philadelphia County across February 11, 2020; February 18, 2020; February 25, 2020; and March 3, 2020 (all Tuesdays). Similar physical distancing measures based on average movement have been used in other studies[14,15] and been shown to predict case growth in the U.S.[7,8] The validity of the measure is also supported by the sharp decline in movement after the declaration of a national emergency for COVID-19 on March 13, 2020 (Figure 1).

Data on the main exposures of county-level SES (operationalized as income per capita) and political orientation (operationalized as the 2016 vote share for President Trump) were obtained from the American Community Survey (5-year averages from 2014 to 2018) and MIT Election Data and Science Lab, respectively. Data on most county-level covariates (percentages of male, Black, Hispanic, and foreign-born residents; share of residents aged ≥65 years; and shares of the workforce in industries most affected by COVID-19 [i.e., retail; transportation; and health, educational, or social services]) were also obtained from the American Community Survey (5-year averages). Data on the county-level share of residential plots in rural areas were obtained from the 2010 Census. These county-level characteristics were chosen a priori on the basis of their expected contribution to a community's ability to physically distance. Contemporaneous media reports suggested that structural barriers, work-related barriers (especially in specific industries), and political attitudes were shaping how communities responded to the pandemic.[16−18] As such, covariates that reflected these barriers and attitudes at the county level were included in the models (Appendix Table 1, available online). Correlations between the county-level characteristics are shown in Appendix Figure 1 (available online).

Statistical Analysis

First, for each calendar day, bivariable associations between physical distancing and each county-level demographic, socioeconomic, and political characteristic were estimated using Pearson correlations with Bonferroni correction for multiple comparisons. Then, using data from the entire study period, a pooled multivariable ordinary least squares regression estimated the association between changes in average movement and each county-level characteristic, allowing the association to vary by week. For this model, distancing was averaged by week at the county level to produce 136,665 county-weeks. The aforementioned county-level characteristics were standardized using the equivalent of a z-score with their median and IQR to compare the relative strengths of the associations. The model was adjusted by all county-level characteristics (to estimate the association of each with distancing, having adjusted for all others) as well as state fixed effects (to account for state-level differences in the degree of preparation and mitigation measures for COVID-19). The estimating equation was as follows:

$$y_i = \alpha_0 + \sum_{(j=1)}^{(j=45)} \beta_j (male\,\%)_i + \sum_{(j=1)}^{(j=45)} \gamma_j (Black\,\%)_i + \sum_{(j=1)}^{(j=45)} \delta_j (Hispanic\,\%)_i + \sum_{(j=1)}^{(j=45)} \zeta_j (elderly\,\%)_i + \sum_{(j=1)}^{(j=45)} \eta_j (f.born\,\%)_i + \sum_{(j=1)}^{(j=45)} \theta_j (income)_i + \sum_{(j=1)}^{(j=45)} \iota_j (rural\,\%)_i + \sum_{(j=1)}^{(j=45)} \kappa_j (Trump\,\%)_i + \sum_{(j=1)}^{(j=45)} \lambda_j (retail\,\%)_i + \sum_{(j=1)}^{(j=45)} \mu_j (transport.\,\%)_i + \sum_{(j=1)}^{(j=45)} \nu_j (health\,\%)_i + \sum_{(j=1)}^{(j=45)} \sum_{(s=1)}^{(s=51)} \xi_{j,s} + \varepsilon_i.,$$

where j denotes the week, i denotes the county, and s denotes the state (including the District of Columbia) for a given county. SEs were clustered at the county level to account for temporal dependence in physical distancing.[19] Analyses were not weighted by county population. All analyses were performed in R, version 3.6.3. Replication code is available at github.com/nolankav/social-distancing.

To test the possibility that any observed associations merely reflected rational responses to the local risk of infection, county COVID-19 case rates were added to the model as a sensitivity check. County-level cases per million residents reported over the previous week were obtained from *The New York Times*, standardized by week, and included as a proxy for the perceived local severity of the pandemic, relative to that of the rest of the country. The observed associations between the county-level characteristics and distancing were robust to their inclusion (Appendix Figure 3, available online). To ensure that the results were robust to alternative assumptions about independence between observations, SEs were clustered at the state level to account for any spatial dependence in physical distancing (e.g., state policy environments may have led to correlations in the main outcome). The alternative specification also provided support for the main findings (Appendix Figure 4, available online).

RESULTS

Descriptive analyses showed a sharp reduction in average movement among U.S. counties corresponding to the start of the COVID-19 pandemic and the declaration of a national emergency on March 13, 2020 (Figure 1). Physical distancing was most pronounced from late March to early June and returned close to pre−COVID-19 baseline levels by July 2020. Engagement in distancing then began to increase again in early September. However, even as the national trend evolved, there was substantial variability in physical distancing across counties.

Bivariable analyses showed that greater county-level income per capita was highly correlated with more physical distancing (i.e., decreased movement relative to that in other counties), whereas the county-level share of votes for President Trump in 2016 was highly correlated with less physical distancing (i.e., increased movement) (Appendix Figure 2, available online). Other county-level characteristics, including the shares of racial and ethnic minorities (Black and Hispanic), immigrants, rurality, and employment in transportation, were also correlated with changes in average movement on many days. Figure 2 plots the monthly trajectory of physical distancing by quintile of county income per capita (Figure 2A) and Republican political orientation (Figure 2B). Gradients in distancing by income and political orientation persisted throughout the study period.

A multivariable regression analysis emphasized the degree to which SES and political orientation were associated with physical distancing. The model adjusted for all specified county-level demographic, socioeconomic, and political characteristics. Figure 3 shows the adjusted estimates for the association between each county-level characteristic and physical distancing over time. All estimates were standardized on the basis of IQR to allow for meaningful comparisons of their magnitudes. Full summary statistics for the covariates are provided in Appendix Table 1 (available online). In line with the bivariable analyses, per capita income was the most consistent predictor of engagement in distancing over the study period, whereas support for President Trump was the most consistent predictor of a lack of engagement. For example, in May, increasing per capita income by the IQR (from \$22,700 to \$29,918) resulted in a 3.8−4.5 percentage-point decrease in average movement, depending on the week (p<0.001 for all weeks). During the same month, an IQR increase in support for Trump (from 54.3% to 74.6% support) resulted in a 4.8−6.7 percentage-point increase in average movement (p<0.001 for all weeks).

Other county-level characteristics varied over time in their degree of association with physical distancing. During the early months of the study period, counties with greater shares of Black and Hispanic residents were less likely to engage in distancing. These adjusted racial and ethnic differences closed during the summer months before reemerging in the fall. Similarly, rural counties were less likely to engage in distancing early on. This trend reversed during June and July, yet, by the end of the

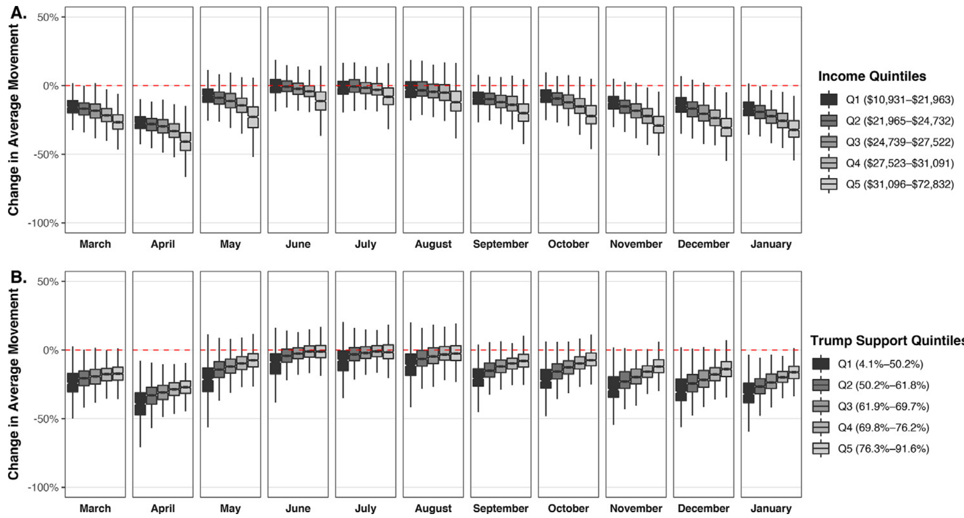

Figure 2. County-level income per capita and political orientation were associated with physical distancing.
Note: County-level distance traveled was normalized relative to that of the pre–COVID-19 baseline, averaged by month, and represented with notched boxplots, which were stratified into Qs on the basis of (A) per capita income and (B) percentage support for President Trump in 2016. Dates range from March 9, 2020 (the first day after the reference period) to January 17, 2021; as a result, the March 2020 and January 2021 averages do not represent full months. Negative values represent greater physical distancing. Notches indicate 95% CIs of the median; outliers are not shown. N=3,037 U.S. counties per month. Physical distancing data were based on 15–17 million anonymized cell phone records per day from Unacast. County-level characteristics were obtained from the American Community Survey and MIT Election Data and Science Lab.
Q, quintile.

summer, rurality became the strongest negative predictor of physical distancing. Some characteristics, such as the share of male residents and the share of employment in retail business, had little predictive value of physical distancing in the adjusted models. The observed associations were also robust to the inclusion of perceived pandemic severity, as measured by weekly COVID-19 cases per million county residents (Appendix Figure 3, available online).

DISCUSSION

In this national study using county-level data, lower SES and greater Republican orientation were strongly associated with reduced physical distancing throughout the COVID-19 pandemic to date. These patterns persisted over a period during which geographic patterns in transmission risk and policy responses shifted rapidly. County-level shares of racial and ethnic minorities as well as that of rurality were also associated with reduced physical distancing at various times, although these associations did not persist throughout the study period.

These findings suggest that income-related barriers could lead to significant socioeconomic gradients in COVID-19, similar to those for other health conditions.[20] The associations may implicate a number of potential underlying factors. For example, lower-income or gig jobs may necessitate continued work and be incompatible with working from home, raising the movement profile of a low-income community. Moreover, lower-income households may not have the necessary liquidity or savings to purchase essential goods in bulk, requiring more trips to businesses and other vendors.[21] These factors are consistent with previous studies showing that lower-income communities often struggle to engage in social distancing. A study of the 2009 H1N1 influenza epidemic using TV ratings data suggested that higher-SES groups were better able to engage in behavioral responses (i.e., home TV viewing) that were associated with social distancing.[22] Studies of COVID-19 have demonstrated that social distancing responses to emergency declarations were strongly differentiated by income[14] and that differences in mobility between low- and high-income neighborhoods have been driven by work-related needs.[11]

In addition to work-related barriers, communities of lower SES have also faced less access to health care during the pandemic. A recent study showed extreme disparities in access to critical care services, with 49% of the lowest-income communities having no available intensive care unit beds—compared with only 3% of the highest-income communities.[23] Such areas are acutely vulnerable to COVID-19. Lower-income communities also have a greater burden of comorbidities that predispose to severe disease.[24] In these ways, structural barriers have led to inequitable burdens in COVID-19 mortality, and the inability of lower-income communities to fully

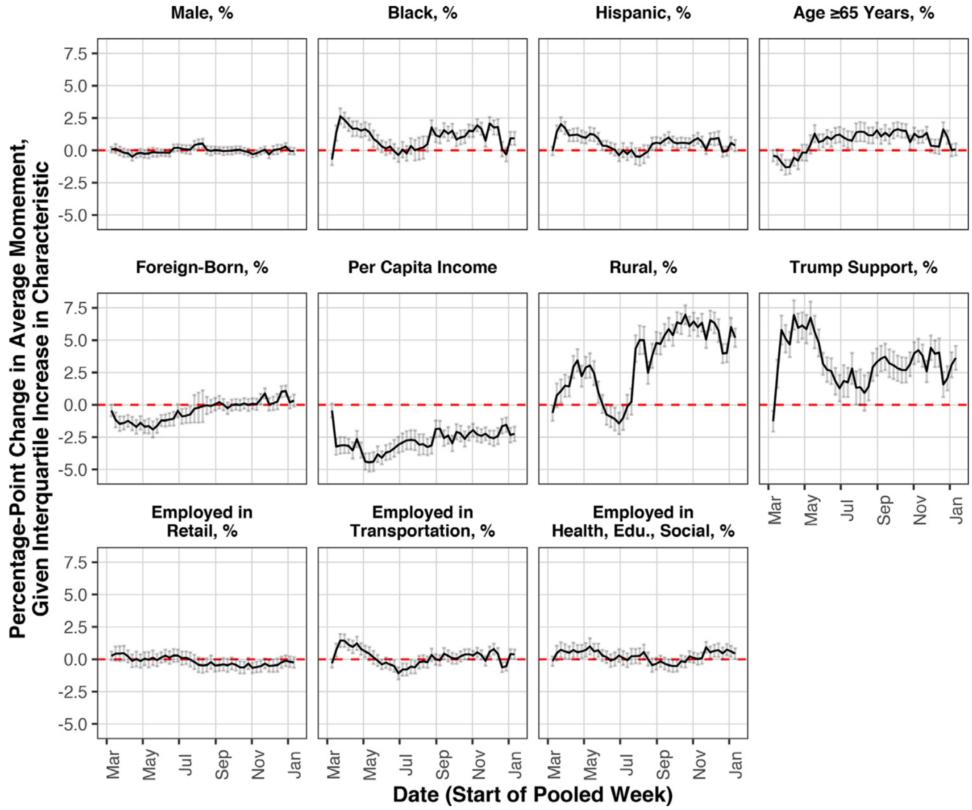

Figure 3. County-level characteristics predicted physical distancing over time.
Note: Each point along the lines represents the percentage-point change in average county movement during that week, given an interquartile change in the indicated county-level characteristic. Negative values represent greater physical distancing. For example, a coefficient of −3.0 for income per capita implies that increasing income by the IQR among U.S. counties was associated with 3.0 percentage points less movement during that week. Changes in county-level distance traveled were averaged by week for N=136,665 county-weeks. Coefficients were estimated using a pooled OLS regression, constructed by interacting all state fixed effects and county-level characteristics with each week throughout the study period. Coefficients are aligned with the start of the pooled week. 95% CIs based on cluster-robust errors at the county level are provided.
Edu., education; Jan, January; Jul, July; Mar, March; Nov, November; OLS, ordinary least square; Sep, September.

engage in physical distancing may deepen the existing inequities affecting these populations.

At various points during the study period, communities with greater shares of Black and Hispanic residents were less likely to engage in physical distancing. In the U.S., race and ethnicity intersect with many structural barriers, including income, access to health care, and the burden of chronic health conditions.[24,25] These barriers are then compounded by racial bias within governmental and healthcare institutions.[26,27] As a result, racial and ethnic minorities have experienced inequitably higher rates of cases, hospitalizations, and deaths owing to COVID-19.[28,29] In the context of this study, it is likely that the county-level associations between race, ethnicity, and physical distancing primarily reflect the uncontrolled confounding of structural barriers and the influence of racial bias rather than any cultural differences between racial and ethnic groups.

Throughout the majority of the study period, greater Republican orientation was associated with reduced engagement in physical distancing. Partisanship has dramatically shaped the government and public's responses to COVID-19 in the U.S. Political leaders have been polarized in their handling of the pandemic,[12] and some have even spread misinformation about the virus, treatments, and policy responses.[30−32] Public polls have shown divergent attitudes about the severity of the pandemic on the basis of political affiliation,[9] and political messaging appears to partly explain variation in prevention behaviors, cases, and deaths.[10,33] For example, a recent study suggested that Democratic-leaning counties were more likely to reduce their mobility in response to governors' recommendations to stay home.[10] Another study showed that partisan differences in distancing partly explain the disparities in case and fatality growth across U.S. counties.[34]

Building on these findings, this study shows that political differences have continued to shape physical distancing behavior, months into the pandemic. Early on, largely Democratic cities were most burdened by

COVID-19 and consequently engaged in more distancing. However, even as cases and deaths have risen in rural Republican areas, support for Trump has continued to predict less distancing, albeit at a lower magnitude. These partisan influences have persisted beyond the 2020 general election and were robust to the inclusion of local COVID-19 case rates in the model. Such differences are concerning during a pandemic that requires a coordinated public health response. That they persist even in the face of a rapidly evolving pandemic is more concerning still. Other health conditions disparately impact Republican communities,[35,36] and gradients in social distancing could result in the same for COVID-19.

Limitations

This study has several limitations. First, even though physical movement predicts case growth at the community level,[7,8] it is one of many social distancing behaviors that also include limiting visits to nonessential businesses, maintaining physical space from other people, and working from home. Moreover, the risk of transmission due to mobility may depend on local social and geographic contexts; that is, a given percentage-point change in distance traveled in 1 county may not translate to the same risk of transmission as in another county. Thus, the proxy metric used in this study may not fully capture the degree of the risk faced by different demographic, socioeconomic, and political groups. Second, physical distancing may have been measured with error, given that the data did not sample all cell phone users and did not reflect nonusers. Third, this study has the potential for omitted-variable and ecologic biases owing to aggregated, cross-sectional data. Finally, although a pooled regression with errors clustered at the county level accounts for some temporal dependence in the measurement of physical distancing,[19] some dependence may remain and bias the inferences in the analysis. The literature on confidence bands may offer more advanced corrections for multiple comparisons and temporal dependence in future studies.[37,38]

CONCLUSIONS

This study underscores the heterogeneity of communities' engagement in public health responses to COVID-19. It documents gradients by socioeconomic and political conditions that may partly explain the inequities in COVID-19 cases and mortality. These patterns may also help policymakers and health professionals to identify the communities that are most vulnerable to transmission and to direct resources and communications accordingly.

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2021.01.040.

REFERENCES

1. Arentz M, Yim E, Klaff L, et al. Characteristics and outcomes of 21 critically ill patients with COVID-19 in Washington State. *JAMA.* 2020;323(16):1612–1614. https://doi.org/10.1001/jama.2020.4326.
2. Davies NG, Kucharski AJ, Eggo RM, Gimma A, Edmunds WJ, Centre for the Mathematical Modelling of Infectious Diseases COVID-19 working group. Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. *Lancet Public Health.* 2020;5(7):e375–e385. https://doi.org/10.1016/S2468-2667(20)30133-X.
3. Bootsma MCJ, Ferguson NM. The effect of public health measures on the 1918 influenza pandemic in U.S. cities. *Proc Natl Acad Sci U S A.* 2007;104(18):7588–7593. https://doi.org/10.1073/pnas.0611071104.
4. Markel H, Lipman HB, Navarro JA, et al. Nonpharmaceutical interventions implemented by U.S. cities during the 1918–1919 influenza pandemic [published correction appears in *JAMA.* 2007;298(19):2264]. *JAMA.* 2007;298(6):644–654. https://doi.org/10.1001/jama.298.6.644.
5. Courtemanche C, Garuccio J, Le A, Pinkston J, Yelowitz A. Strong social distancing measures in the United States reduced the COVID-19 growth rate. *Health Aff (Millwood).* 2020;39(7):1237–1246. https://doi.org/10.1377/hlthaff.2020.00608.
6. Siedner MJ, Harling G, Reynolds Z, et al. Social distancing to slow the U.S. COVID-19 epidemic: longitudinal pretest−posttest comparison group study [published correction appears in *PLoS Med.* 2020;17(10):e1003376]. *PLoS Med.* 2020;17(8):e1003244. https://doi.org/10.1371/journal.pmed.1003244.
7. Gao S, Rao J, Kang Y, et al. Association of mobile phone location data indications of travel and stay-at-home mandates with COVID-19 infection rates in the U.S. *JAMA Netw Open.* 2020;3(9):e2020485. https://doi.org/10.1001/jamanetworkopen.2020.20485.
8. Sehra ST, George M, Wiebe DJ, Fundin S, Baker JF. Cell phone activity in categories of places and associations with growth in cases of COVID-19 in the U.S. *JAMA Intern Med.* 2020;180(12):1614–1620. https://doi.org/10.1001/jamainternmed.2020.4288.
9. Butchireddygari L. How concerned are Americans about coronavirus so far? *FiveThirtyEight.* March 13, 2020. https://fivethirtyeight.com/features/how-concerned-are-americans-about-coronavirus-so-far/. Accessed March 29, 2020.
10. Grossman G, Kim S, Rexer JM, Thirumurthy H. Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States. *Proc Natl Acad Sci U S A.* 2020;117(39):24144–24153. https://doi.org/10.1073/pnas.2007835117.
11. Jay J, Bor J, Nsoesie EO, et al. Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nat Hum Behav.* 2020;4(12):1294–1302. https://doi.org/10.1038/s41562-020-00998-2.

12. Green J, Edgerton J, Naftel D, Shoub K, Cranmer SJ. Elusive consensus: polarization in elite communication on the COVID-19 pandemic. *Sci Adv.* 2020;6(28):eabc2717. https://doi.org/10.1126/sciadv.abc2717.
13. Ngo M. *Unacast updates social distancing scoreboard*. Unacast; March 31, 2020. https://www.unacast.com/post/unacast-updates-social-distancing-scoreboard. Accessed May 3, 2020.
14. Weill JA, Stigler M, Deschenes O, Springborn MR. Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proc Natl Acad Sci U S A.* 2020;117(33):19658–19660. https://doi.org/10.1073/pnas.2009412117.
15. Rubin D, Huang J, Fisher BT, et al. Association of social distancing, population density, and temperature with the instantaneous reproduction number of SARS-CoV-2 in counties across the United States. *JAMA Netw Open.* 2020;3(7):e2016099. https://doi.org/10.1001/jamanetworkopen.2020.16099.
16. Maheshwari S, Corkery M. Plight of retail workers: 'I'm scared to go to work. *The New York Times.* March 18, 2020. https://www.nytimes.com/2020/03/18/business/coronavirus-retail-workers.html. Accessed December 3, 2020.
17. Miller CC, Kliff S, Sanger-Katz M. Avoiding coronavirus may be a luxury some workers can't afford. *The New York Times.* March 1, 2020. https://www.nytimes.com/2020/03/01/upshot/coronavirus-sick-days-service-workers.html. Accessed December 3, 2020.
18. Healy J, Robertson C, Tavernise S. How coronavirus is already being viewed through a partisan lens. *The New York Times.* March 1, 2020. https://www.nytimes.com/2020/03/01/us/coronavirus-us-politics.html. Accessed December 4, 2020.
19. Bertrand M, Duflo E, Mullainathan S. How much should we trust differences-in-differences estimates? *Q J Econ.* 2004;119(1):249–275. https://doi.org/10.1162/003355304772839588.
20. Woolf SH, Braveman P. Where health disparities begin: the role of social and economic determinants—and why current policies may make matters worse. *Health Aff (Millwood).* 2011;30(10):1852–1859. https://doi.org/10.1377/hlthaff.2011.0685.
21. Orhun AY, Palazzolo M. Frugality is hard to afford. *J Mark Res.* 2019;56(1):1–17. https://doi.org/10.1177/0022243718821660.
22. Springborn M, Chowell G, MacLachlan M, Fenichel EP. Accounting for behavioral responses during a flu epidemic using home television viewing [published correction appears in *BMC Infect Dis.* 2016; 16:474]. *BMC Infect Dis*. 2015;15(1):21. https://doi.org/10.1186/s12879-014-0691-0.
23. Kanter GP, Segal AG, Groeneveld PW. Income disparities in access to critical care services. *Health Aff (Millwood).* 2020;39(8):1362–1367. https://doi.org/10.1377/hlthaff.2020.00581.
24. Raifman MA, Raifman JR. Disparities in the population at risk of severe illness from COVID-19 by race/ethnicity and income. *Am J Prev Med.* 2020;59(1):137–139. https://doi.org/10.1016/j.amepre.2020.04.003.
25. Tai DBG, Shah A, Doubeni CA, Sia IG, Wieland ML. The disproportionate impact of COVID-19 on racial and ethnic minorities in the United States. *Clin Infect Dis.* 2021;72(4):703–706. https://doi.org/10.1093/cid/ciaa815.
26. Egede LE, Walker RJ. Structural racism, social risk factors, and COVID-19 — a dangerous convergence for Black Americans. *N Engl J Med.* 2020;383(12):e77. https://doi.org/10.1056/NEJMp2023616.
27. Devakumar D, Shannon G, Bhopal SS, Abubakar I. Racism and discrimination in COVID-19 responses. *Lancet.* 2020;395(10231):1194. https://doi.org/10.1016/S0140-6736(20)30792-3.
28. Holmes L Jr, Enwere M, Williams J, et al. Black−White risk differentials in COVID-19 (SARS-COV2) transmission, mortality and case fatality in the United States: translational epidemiologic perspective and challenges. *Int J Environ Res Public Health.* 2020;17(12):4322. https://doi.org/10.3390/ijerph17124322.
29. Wadhera RK, Wadhera P, Gaba P, et al. Variation in COVID-19 hospitalizations and deaths across New York City boroughs. *JAMA.* 2020;323(21):2192–2195. https://doi.org/10.1001/jama.2020.7197.
30. Superville D, Seitz A. Trump defends disproved COVID-19 treatment. *AP NEWS.* July 29, 2020. https://apnews.com/80130998284858a7b73c997e76677137. Accessed August 8, 2020.
31. Broad WJ, Levin D. Trump muses about light as remedy, but also disinfectant, which is dangerous. *The New York Times.* April 24, 2020. https://www.nytimes.com/2020/04/24/health/sunlight-coronavirus-trump.html. Accessed May 18, 2020.
32. Kang C, Frenkel S. Facebook removes trump campaign's misleading coronavirus video. *The New York Times.* August 5, 2020. https://www.nytimes.com/2020/08/05/technology/trump-facebook-coronavirus-video.html. Accessed August 8, 2020.
33. Bursztyn L, Rao A, Roth C, Yanagizawa-Drott D. *Misinformation During a pandemic*. Cambridge, MA: National Bureau of Economic Research, September 1, 2020 Published. https://doi.org/10.3386/w27417.
34. Gollwitzer A, Martel C, Brady WJ, et al. Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nat Hum Behav.* 2020;4(11):1186–1197. https://doi.org/10.1038/s41562-020-00977-7.
35. Bor J. Diverging life expectancies and voting patterns in the 2016 U.S. presidential election. *Am J Public Health.* 2017;107(10):1560–1562. https://doi.org/10.2105/AJPH.2017.303945.
36. Goodwin JS, Kuo YF, Brown D, Juurlink D, Raji M. Association of chronic opioid use with presidential voting patterns in U.S. counties in 2016. *JAMA Netw Open.* 2018;1(2):e180450. https://doi.org/10.1001/jamanetworkopen.2018.0450.
37. Working H, Hotelling H. Applications of the theory of error to the interpretation of trends. *J Am Stat Assoc.* 1929;24(165A):73–85. https://doi.org/10.1080/01621459.1929.10506274.
38. Montiel Olea JL, Plagborg-Møller M. Simultaneous confidence bands: theory, implementation, and an application to SVARs. *J Appl Econ.* 2019;34(1):1–17. https://doi.org/10.1002/jae.2656.