**Social Distancing as a Health Behavior: County-level Movement in the United States
During the COVID-19 Pandemic is Associated with Conventional Health Behaviors**

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Note: Aggregated mobility data were provided by three companies: Cuebiq, Streetlight, and Citymapper (Citymapper.com/cmi). Cuebiq is a location intelligence and measurement platform. Through its Data for Good program, Cuebiq provides access to aggregated mobility data for academic research and humanitarian initiatives. These data are collected from anonymized users who have opted-in to provide access to their location data anonymously, through a GDPR-compliant framework. It is aggregated to the county level to provide insights on changes in human mobility over time. Streetlight made data available for the purpose of nonprofit, public benefit research in response to the COVID-19 pandemic. State- and county-level demographic, socioeconomic, and health behavior data were made available from the County Health Rankings & Roadmaps (<https://www.countyhealthrankings.org/>).

Abstract

Background: Social distancing—when people reduce their physical movement and limit social contacts beyond their immediate household—is a primary intervention available to combat the COVID-19 pandemic. The importance of social distancing is unlikely to change until effective treatments or vaccines become widely available. However, relatively little is known about how best to promote social distancing. Applying knowledge from social and behavioral research on conventional health behaviors (e.g., smoking, physical activity) to support social distancing public health efforts and research is promising, but empirical evidence supporting this approach is needed. **Purpose:** We examined whether one type of social distancing behavior—reductions in movement outside the home—was associated with conventional health behaviors. **Method:** We examined the association between GPS-derived movement behavior in 2,858 counties in United States from March 1st to April 7th, 2020 and the prevalence of county-level indicators influenced by residents' conventional health behaviors. **Results:** Changes in movement were associated with conventional health behaviors, and the magnitude of these associations were similar to the associations among the conventional health behaviors. Counties with healthier behaviors—particularly less obesity and greater physical activity—evidenced greater decreases in movement outside the home during the initial phases of the pandemic in the United States. **Conclusions:** Social distancing, in the form of reduced movement outside the home, is associated with conventional health behaviors. Existing scientific literature on health behavior and health behavior change can be more confidently used to promote social distancing during the COVID-19 pandemic.

Keywords: COVID-19; social distancing; health behaviors; smoking; physical activity; counties

Social Distancing as a Health Behavior: County-level Movement in the United States During the COVID-19 Pandemic is Associated with Conventional Health Behaviors

The SARS-CoV-2 coronavirus originated in Wuhan, China in late 2019 [1] and spread globally over the first 3 months of 2020. Human-to-human transmission of SARS-CoV-2 was confirmed in January, 2020 [2], and the first case in the United States was confirmed on January 24th. The outbreak of the disease resulting from SARS-CoV-2 (COVID-19) [3] was declared a pandemic by the World Health organization on March 11th [4]. By mid-May of 2020, the CDC recorded 1.4 million cases and 82,000 deaths due to COVID-19 in the United States [5], contributing to 4 million infections and almost 300,000 confirmed deaths worldwide [6].

In March of 2020, U.S. public health and government officials began an unprecedented effort to limit the spread of SARS-CoV-2. Owed largely to the lack of effective pharmacological interventions and vaccines, social distancing—the behavior of reducing person-to-person contact by increasing physical distancing and limiting movement among social groups [7,8]—emerged as the primary mitigation strategy for limiting the spread of the virus. Multiple levels of government enacted limitations on business and movement (e.g., closing schools and non-essential businesses, and stay-at-home orders [9]) as a behavioral intervention to stymie the spread of the virus based on the belief that the less people traveled outside their home, the less physical contact between infected and uninfected individuals that could spread the virus. Preliminary research found government actions restricting movement reduced SARS-CoV-2 infection rates [8,10], though peer-reviewed evidence in the United States is more limited.

Social distancing (also known as physical distancing) is a complex set of human behaviors that will benefit from multidisciplinary study to guide public health implementation [11-13]. The current pandemic is unique in terms of its impact on social and economic activities in the modern United States. Previous viral outbreaks, such as H1N1 [14], did not result in the level of mass behavioral change

observed in response to COVID-19. Calls for Americans to limit their movement outside the home is a novel—and in many ways unprecedented—public health effort in the modern United States. In light of the limited empirical research related focused on such efforts, lessons learned from more comprehensively-studied behaviors may be useful in understanding how to best promote social distancing behaviors. Health behaviors like smoking, physical activity, and vaccination rates have been studied by the scientific community for decades, presenting an opportunity to apply relevant theory to promote social distancing [12,15].

It is tempting to apply social and behavioral research on health behaviors to social distancing based purely on theoretical grounds, but the value of this opportunity is limited by whether social distancing behavior is associated with conventional health behaviors. Empirical evidence to this end would support the application of health behavior models to social distancing [15,16], particularly given the way health-relevant behaviors tend to correlate [17,18]. To the extent that social distancing is associated with more conventional health behaviors, stakeholders could more confidently draw on the broad literature of health behavior change [12,15,16,19,20] when studying and promoting social distancing.

Present Study

The present study used objectively-measured movement data aggregated at the county level to examine social distancing behavior in the United States during the COVID-19 pandemic from March 1st to April 7th, 2020. We hypothesized that counties whose residents evidenced healthier behaviors prior to the pandemic would also show greater decreases in movement during the pandemic. In addition, we predicted this association would remain when controlling for relevant state- and county-level characteristics.

Method

Study Design

The current study used county-level movement data from March 1st to April 7th of 2020 collected by two private companies—Cuebiq (cuebiq.com) and Streetlight (<https://www.streetlightdata.com>). Cuebiq collects movement data from mobile GPS-enabled devices from individuals who consented to have their data collected. These data were then processed and aggregated at the county level to produce daily estimates of movement behavior. Streetlight also used GPS mobility data and a proprietary algorithm to produce an estimate of daily vehicle miles traveled, which were aggregated at the county level. Data from Streetlight were made available starting March 1st, which was why this was defined as the start of the study period. Additional data provided by Citymapper (citymapper.com) were used for validation purposes. Movement data were combined with county-level health behavior data from the County Health Rankings & Roadmaps (<https://www.countyhealthrankings.org/>). In the current study, we included all counties in the United States that had movement data from both Cuebiq and Streetlight during the period of interest ($N = 2,858$), which included 48 states and the District of Columbia. Streetlight did not include movement data on any counties in Alaska ($n = 29$) and Hawaii ($n = 5$), or 248 additional counties in the continental United States. Cuebiq did not provide data for 2 additional counties. Supplemental Data 1 provides the 5-digit county identifier, state, and name for all counties excluded from the current study ($n = 284$). We did not have access to any individual-level data for this study.

Measures

Movement behavior. Movement behavior was assessed using data from Cuebiq and Streetlight. These two companies provided county-level data for the primary outcome variables: *daily percentage of people staying within 1 mile of home* and *daily vehicle miles traveled*. Supplemental Analysis 1 provides an analysis of validity for these measures. For each outcome, we calculated initial change in movement in response to the pandemic by taking the difference between averages over the first 7 days of March and April.

Daily percentage of people staying within 1 mile of home. Cuebiq movement data use GPS-enabled devices to determine the greatest distance people travel from their homes on any given day (less than 300 feet, between 330 feet and 1 mile, between 1 and 10 miles, and more than 10 miles). Daily data are aggregated at the county level, resulting in a percentage for each category. We calculated the total daily percentage of people who remained within 1 mile of home for the relevant periods. Increases in the percentage of people staying within 1 mile of home indexed relatively more social distancing behavior.

Daily vehicle miles traveled. Streetlight data estimate the daily vehicle miles traveled by residents of each U.S. county in the continental United States. Streetlight uses the Cuebiq Mobility Index (continuous movement data calculated separately from the distance people travel from home) and a proprietary algorithm to produce a daily estimate of vehicle miles traveled, which is aggregated by county. We calculated a percentage of daily miles traveled. The average of the first 7 days of March was used as the reference period, and decreases in vehicle miles traveled indexed relatively more social distancing behavior.

Conventional county-level health behaviors. We used data from the 2019 County Health Rankings & Roadmaps report to measure a variety of county-level indicators influenced by residents' health behavior, including rates of smoking, obesity, physical activity, flu vaccination, and mammography screenings. Smoking measured the percentage of the adult population who smoke. Obesity measured the percentage of adults with a body mass greater than 30¹. Physical activity measured the percentage of adults over 20 reporting no leisure time physical activity. Flu vaccination rates measured the percentage of fee-for-service Medicare enrollees that had an annual flu vaccine.

¹ Strictly speaking, obesity is a physiological risk marker for the development of chronic disease [25] and reflects the cumulative effects of multiple health behaviors, including sedentary and physical activity time as well as diet. We include obesity here as a proxy for these behaviors and other lifestyle factors that give rise to adiposity.

Mammography screening rate measured the percentage of female Medicare enrollees aged 65-74 that received an annual mammography screening. These data were collected from the Behavioral Risk Factor Surveillance System, the CDC Diabetes Interactive Atlas, and Mapping Medical Disparities Tool (see the County Health Rankings & Roadmaps website for additional information on data sources and methodology). All measures were recoded so that higher values reflected a greater percentage of health-protective behaviors. We also averaged these health behavior indicators to form a single health behavior composite. The composite evidenced adequate internal reliability ($\alpha = 0.68$).

Demographic and socioeconomic characteristics. The 2019 County Health Rankings & Roadmaps report included demographic and socioeconomic characteristics at the state and county level. Variables used in the current study included county-level population, median household income, and rurality, as well percentages of people who were women, non-Hispanic white, older than 65, and had some college education. State level population and rurality were also included. These data were collected from the American Community Survey, Small Area Income and Poverty Estimates, and Census Population Estimates.

Data Analysis

To test our hypotheses, we first examined the correlations between county-level indicators influenced by residents' health behavior—smoking, obesity, physical activity, flu vaccination rate, mammography screening rate, and the overall health behavior composite—and changes in the two measures of movement behavior. Second, we used mixed effect linear models to test the association between these health behaviors and change in movement. These models nested counties within states and controlled for a variety of potentially-relevant state- and county-level demographic and socioeconomic characteristics. State factors were modeled as level-1 variables and county factors were modeled as level-2 variables in these mixed effect models. Analyses were conducted in MPLUS version 8.3 [26].

Results

Do Pre-Pandemic Health Behaviors Predict Movement Behavior During the Pandemic?

U.S. counties with lower rates of smoking and obesity, as well as higher rates of physical activity, flu vaccinations, and mammography screenings, had greater decreases in movement from the first week of March to the first week of April in the form of more people staying within 1 mile of home and people driving fewer vehicle miles per day. The bivariate associations among the conventional health behaviors were similar in magnitude to the associations between those health behaviors and change in the movement behaviors, which were moderate to large in size (Table 1). The health behavior composite was also associated with changes in both percentage of people staying within 1 mile ($r = 0.55$) and vehicle miles people traveled per day ($r = 0.59$). When controlling for baseline levels of movement during the first week of March, the health behavior composite explained 30.7% additional variance in the percentage of people staying within 1 mile of home and 28.5% additional variance in the vehicle miles people traveled.

Predicting Change in Movement While Controlling for State- and County-level Covariates

We next tested whether health behavior predicted change in movement when accounting for state- and county-level demographic and socioeconomic characteristics that could be associated with both health behavior and changes in movement behavior. To do so, we used mixed linear models nesting counties within states. Control variables at the state level included population, rurality, and the presence of a state-wide stay-at-home order. Control variables at the county level included population, rurality, household income, education, gender, race/ethnicity, and age. When accounting for these variables, the health behavior composite significantly predicted increases in people remaining within 1 mile of home and decreases in the vehicle miles people traveled (Table 2).

Certain individual health behaviors may be more predictive of changes in movement behavior than others. To test this possibility, we used the mixed linear model specification and tested whether

each of the individual health behaviors predicted change in movement behavior. Obesity and physical activity were significantly associated with changes in both movement outcomes (Table 3). Flu vaccination rate was significantly associated with decreases in vehicle miles driven, but not with increase in people remaining within 1 mile of home (Table 3). Smoking and mammography screening rates were not significantly associated with either movement outcome when accounting for state- and county-level covariates (Table 3). These results suggest obesity and physical activity were the strongest individual health behavior predictors of which counties reduced their movement.

Demographic and Socioeconomic Covariates Associated With Changes in Movement

When examining the results of the health behavior composite mixed effect model (Table 2), there were several associations of note at the county level of analysis. First, in terms of socioeconomic status, counties that were wealthier and more educated were more likely to reduce their movement. More urban counties were similarly more likely to reduce their movement outside the home. In terms of demographic factors, counties with a lower percentage of non-Hispanic whites and a higher percentage of adults over the age of 65 were more likely to reduce their movement outside the home, though the size of these effects was smaller than those for counties' socioeconomic characteristics. At the state-level of analysis, counties in states that enacted stay-at-home orders reduced their movement more when compared to counties without such an order.

Discussion

The current study examined whether county-level indicators of residents' health behavior were associated with social distancing in response to the COVID-19 pandemic from March 1st to April 7th, 2020. Social distancing was assessed using objectively measured movement data collected from GPS-enabled devices that were aggregated at the county level ($N = 2,858$) in the United States. People in counties with more health-protective behaviors prior to the pandemic reduced their movement to a greater degree during the pandemic than people in counties with fewer health-protective behaviors.

This association remained when controlling for a variety of relevant demographic and socioeconomic covariates at the state and county level. Although there have been calls to apply social and behavior research [11] to the current crisis on theoretical grounds [12,14], few studies have provided empirical evidence to buttress these claims. The findings reported here provide this evidence, which in turn supports application of the wealth of scientific knowledge regarding conventional health behaviors and health behavior change [16,19,20] to promote social distancing behaviors.

Given the strong associations between conventional health behaviors and changes in movement behavior, a number of theoretical perspectives could have relevance to social distancing. For example, individual models of health behavior could inform our understanding of social distancing [28]. The Health Belief Model highlights how people's perception of threat related to a disease or condition—arising in part from the chance of getting a disease and severity of the disease—helps determine whether people engage in health-protective behavior [28]. Ecological models of behavior change [19] also present a number of principles that could be applied to social distancing behaviors. These models emphasize that people's behavior results from a combination of their individual decision-making and context of their family, neighborhood, and community. For example, perceptions of social norms play a powerful role in people's health behaviors, based in part on which behaviors they perceive as normative [29]. The formal and informal groups people identify with (e.g., religious groups, political party identification, neighborhoods) likely impact their perception of social distancing and resulting behavioral choices. Outlining each model of health behavior and how it might apply to social distancing from a theoretical perspective is beyond the scope of this study, but the existing literature presents ample opportunity to make use of accumulated empirical and theoretical knowledge to promote social distancing [12,15] during the current pandemic.

Beyond the overall associations between health behavior and changes in movement behavior, there were relevant individual predictors of changes in movement. In terms of conventional health

behaviors, rates of obesity and physical activity were particularly robust individual predictors of changes in movement behavior. Demographic and socioeconomic characteristics were also predictive of changes in movement behavior. Wealthier, more urban, and more educated counties reduced their movement outside the home the most. These variables could potentially be used to predict the areas least likely to change their behavior in response to future public health interventions designed to limit movement outside the home.

The current findings are important at both a theoretical and a practical level. At a theoretical level, future interventions attempting to reduce people's movement to limit the transmission of the SARS-CoV-2 coronavirus would benefit from drawing on evidence from past public health interventions that targeted health behaviors [16]. Intervening on many levels (e.g., individual, neighborhood, societal) would likely be more successful than attempts to address only the individual or state level [19]. Similarly, mechanisms of action with evidence from previous studies of health behavior changes (e.g., threat perception, social norms), could be useful starting places for promoting social distancing behaviors (e.g., NIH-funded Science of Behavior Change, <https://commonfund.nih.gov/behaviorchange>).

At a practical level, this work suggests that counties in which people are at greater medical risk of hospitalization and death as a result of COVID-19 are also the counties that reduced their movement outside the home the least in response to the pandemic. The health behaviors associated with *less of a decrease* in movement, particularly obesity and physical activity, are also associated with increased risk of chronic diseases, including lung diseases [30], diabetes [31], and cardiovascular diseases [32]. These chronic conditions also predict poorer COVID-19 prognosis [32]. Targeting people living in counties with unhealthier behaviors—particularly high levels of obesity and physical inactivity—using more intensive public health interventions could be a cost-effective method to promote social distancing and reduce morbidity and mortality from COVID-19. In addition, hospitals serving catchment areas that include counties with unhealthier behaviors—and likely more people with associated chronic diseases—might

expect an outsized proportion of future hospitalizations due to COVID-19 compared to counties with healthier behaviors.

The results of this study should be understood in terms of its limitations. First, the study examined objectively measured movement, but did not examine the specific number of close-proximity contacts people had outside their homes. It is possible for people to travel in a car or further than a mile from their home and limit such contacts. Although we expect such measures to be highly correlated, future work linking movement to viral transmission vectors would benefit our understanding of how movement is tied to risk of infection. Second, the current study was correlational. Although we tested the association between change in movement and health behaviors, these methods do not allow us to draw causal conclusions about such associations.

Conclusions

The current study used objective movement data to assess the association between conventional health behavior indicators and social distancing during the COVID-19 pandemic. The results of this study provide empirical evidence that social distancing behavior—in the form of decreased movement outside the home—is associated with conventional health behaviors. Public health efforts promoting social distancing would benefit from applying theoretical models of health behavior and health behavior change during the current pandemic.

References

1. Zhou F, Yu T, Du R, et al. Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. *Lancet*. 2020; 395: 1054-1062
2. Lai CC, Shih TP, Ko WC, Tang HJ, Hsueh PR. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and corona virus disease-2019 (COVID-19): the epidemic and the challenges. *Int J Antimicrob Agents*. 2020; 55: 105924. <https://doi.org/10.1016/j.ijantimicag.2020.105924>
3. World Health Organization. Naming the coronavirus disease (COVID-19) and the virus that causes it. [https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-\(covid-2019\)-and-the-virus-that-causes-it/](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it/). Accessibility verified May 14th, 2020.
4. World Health Organization. Coronavirus pandemic. <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/>. Accessibility verified May 14th, 2020.
5. Center for Disease Control and Prevention. Coronavirus Disease 2019 (COVID-19): Cases in the U.S. <https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html/>. Accessibility verified May 14th, 2020.
6. Roser M, Ritchie H, Ortiz-Ospina E, Hasell J. Our World in Data. Coronavirus pandemic (COVID-19). <https://ourworldindata.org/coronavirus/>. Accessibility verified May 14th, 2020.
7. Glass RJ, Glass LM, Beyeler WE, Min HJ. Targeted social distancing designs for pandemic influenza. *Emerg Infect Dis*. 2006; 12: 1671-1681. <http://dx.doi.org/10.3201/eid1211.060255>
8. Koo JR, Cook AR, Park M, Sun Y, Sun H, Lim JT, Tam C, Dickens BL. Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a modelling study. *Lancet Infect Dis*. 2020. Advanced online publication. [https://doi.org/10.1016/S1473-3099\(20\)30162-6](https://doi.org/10.1016/S1473-3099(20)30162-6)

9. Blavatnik School of Government at the University of Oxford. Coronavirus Government Response Tracker. <https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>. Accessibility verified May 14th, 2020.
10. Soucy JR, Sturrock SL, Berry I, et al. Estimating effects of physical distancing on the COVID-19 pandemic using an urban mobility index. Preprint; <https://doi.org/10.1101/2020.04.05.20054288>
11. Holmes EA, O'Connor RC, Perry VH, et al. Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science. *Lancet Psychiat*. 2020. Advance online publication [https://doi.org/10.1016/S2215-0366\(20\)30168-1](https://doi.org/10.1016/S2215-0366(20)30168-1)
12. West R, Michie S, Rubin GJ, Amlôt R. Applying principles of behaviour change to reduce SARS-CoV-2 transmission. *Nature Human Behaviour*. 2020;1-9. <https://doi.org/10.1038/s41562-020-0887-9>
13. Bedford J, Enria D, Giesecke J, et al. COVID-19: Towards controlling of a pandemic. *The Lancet*. 2020; 395: 1015-8. [https://doi.org/10.1016/S0140-6736\(20\)30673-5](https://doi.org/10.1016/S0140-6736(20)30673-5)
14. Shrestha SS, Swerdlow DL, Borse RH, et al. Estimating the burden of 2009 pandemic influenza A (H1N1) in the United States (April 2009-April 2010). *Clin Infect Dis*. 2011; 52(suppl 1): S75–S82.
15. Bavel, J.J.V., Baicker, K., Boggio, P.S. et al. Using social and behavioural science to support COVID-19 pandemic response. *Nat Hum Behav*. 2020. Advanced online publication <https://doi.org/10.1038/s41562-020-0884-z>
16. Glanz K, Bishop DB. The role of behavioral science theory in development and implementation of public health interventions. *Ann Rev Public Health*. 2010; 31: 399-418. <https://doi.org/10.1146/annurev.publhealth.012809.103604>
17. Berrigan D, Dodd K, Troiano RP, Krebs-Smith SM, Barbash RB. Patterns of health behavior in US adults. *Prevent Med*. 2003; 36: 615-23. [https://doi.org/10.1016/S0091-7435\(02\)00067-1](https://doi.org/10.1016/S0091-7435(02)00067-1)
18. De Vries H, van't Riet J, Spijt M, Metsemakers J, et al. Clusters of lifestyle behaviors: results from the Dutch SMILE study. *Prevent Med*. 2008; 46: 203-208. <https://doi.org/10.1016/j.ypmed.2007.08.005>

19. Sallis JF, Owen N, Fisher E. Ecological models of health behavior. *Health Behavior: Theory, Research, and Practice*. Eds. Glanz K et al. 2015; 5: 43-64. San Francisco: Josey-Bass.
20. Richard L, Gauvin L, Raine K. Ecological models revisited: Their uses and evolution in health promotion over two decades. *Ann Rev Public Health*. 2011; 32: 307-326.
<https://doi.org/10.1146/annurev-publhealth-031210-101141>
21. Lupton JR, Townsend JL. A systematic review and meta-analysis of the acceptability and effectiveness of university smoke-free policies. *J Am Coll Health*. 2015; 19; 63: 238-247.
<https://doi.org/10.1080/07448481.2015.1015029>
22. Daughton DM, Andrews CE, Orona CP, Patil KD, Rennard SI. Total indoor smoking ban and smoker behavior. *Prevent Med*. 1992; 21: 670-676. [https://doi.org/10.1016/0091-7435\(92\)90073-Q](https://doi.org/10.1016/0091-7435(92)90073-Q)
23. Diabetes Prevention Program Research Group. 10-year follow-up of diabetes incidence and weight loss in the Diabetes Prevention Program Outcomes Study. *Lancet*. 2009; 374: 1677-1686.
[https://doi.org/10.1016/S0140-6736\(09\)61457-4](https://doi.org/10.1016/S0140-6736(09)61457-4)
24. Conn VS, Hafdahl AR, Mehr DR. Interventions to increase physical activity among healthy adults: meta-analysis of outcomes. *Am J Public Health*. 2011; 101:751-758.
<https://doi.org/10.2105/AJPH.2010.194381>
25. Kelly MP, Barker M. Why is changing health-related behaviour so difficult?. *Public Health*. 2016; 136: 109-116. <https://doi.org/10.1016/j.puhe.2016.03.030>
26. Nimptsch, K., Konigorski, S., & Pischon, T. (2019). Diagnosis of obesity and use of obesity biomarkers in science and clinical medicine. *Metabolism*; 92: 61-70.
<https://doi.org/10.1016/j.metabol.2018.12.006>
27. Muthén LK, and Muthén BO. *Mplus User's Guide*. Seventh Edition. Los Angeles, CA: Muthén & Muthén; 1998-2012.

28. Glanz K, Rimer BK, Viswanath K. *Health Behavior and Health Education*. 2008. San Francisco, Josey Bass.
29. Reid AE, Cialdini RB, Aiken LS. Social Norms and Health Behavior. *Handbook of Behavioral Medicine*. Ed., Steptoe A. 2010. Springer, New York, NY.
30. Aubry MC, Wright JL, Myers JL. The pathology of smoking-related lung diseases. *Clinics Chest Med*. 2000; 21: 11-35. [https://doi.org/10.1016/S0272-5231\(05\)70005-8](https://doi.org/10.1016/S0272-5231(05)70005-8)
31. Wilmot, E.G., Edwardson, C.L., Achana, F.A., et al. Sedentary time in adults and the association with diabetes, cardiovascular disease and death: systematic review and meta-analysis. *Diabetologia*. 2012; 55: 2895-2905. <https://doi.org/10.1007/s00125-012-2677-z>
32. Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China. *JAMA*. 2020; 323: 1239-1242. <https://doi.org/10.1001/jama.2020.2648>

Table 1. *Bivariate Associations of Movement with Health Behaviors*

<i>N</i> = 2,858	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Increase in staying < 1 mile from home (1)	1.0							
Decrease in vehicle miles traveled (2)	.73	1.0						
Smoking status (3)	.50	.36	1.0					
Obesity (4)	.47	.41	.59	1.0				
Physical activity (5)	.58	.47	.68	.70	1.0			
Flu vaccination rate (6)	.34	.44	.20	.11	.29	1.0		
Mammography screening rate (7)	.29	.25	.27	.17	.27	.46	1.0	
Health behavior composite (8)	.59	.55	.65	.61	.74	.70	.74	1.0

Note: All health behaviors are coded such that greater values represent more health-protective behaviors. The health behavior composite was an average of the individual health behaviors. All *ps* < .001.

Table 2. *Mixed Effect Model Results Predicting Change in Movement Behaviors*

<i>N</i> = 2,858	Increase in % of people staying < 1 mile from home		Decrease in vehicle miles traveled	
	β	95% CI	β	95% CI
County-level predictors				
Health behavior composite	0.11*	[0.02, 0.21]	0.16**	[0.09, 0.24]
March baseline	-0.32**	[-0.38, -0.26]	0.05	[-0.02, 0.12]
Population size	0.10*	[0.02, 0.19]	-0.01	[-0.07, 0.05]
Rurality	-0.10**	[-0.16, -0.06]	-0.28**	[-0.33, -0.24]
Household income	0.46**	[0.39, 0.54]	0.16**	[0.11, 0.22]
Education	0.23**	[0.18, 0.27]	0.37**	[0.31, 0.43]
Age	0.08**	[0.03, 0.14]	0.07*	[0.02, 0.13]
Ethnicity	-0.17**	[-0.27, -0.07]	-0.08*	[-0.15, -0.01]
Gender	0.01	[-0.02, 0.03]	-0.00	[-0.04, 0.04]
State-level predictors				
Stay-at-home order issued	0.50**	[0.31, 0.69]	0.30*	[0.06, 0.54]
Population size	-0.01	[-0.18, 0.17]	-0.00	[0.22, 0.21]
Rurality	0.11	[-0.21, 0.44]	0.18	[-0.21, 0.57]

Note: Models nested counties within states. "March baseline" represents the average of the outcomes over the first week of March. Rurality is coded as percent of the county or state that is rural. Ethnicity is coded as percentage non-Hispanic whites. Education is coded as percent with some college education. Gender is coded as percentage women. Stay-at-home order assessed whether the state issued a stay-at-home order.

* $p \leq .05$. ** $p \leq .01$.

Table 3. *Associations of Movement with Individual Health Behaviors in Mixed Effect Models*

<i>N</i> = 2,858	Increase in % of people staying < 1 mile from home		Decrease in vehicle miles traveled	
	β	95% CI	β	95% CI
Smoking status	0.00	[-0.08, 0.09]	0.05	[-0.03, 0.12]
Obesity	0.20**	[0.13, 0.26]	0.18**	[0.13, 0.23]
Physical activity	0.16**	[0.08, 0.25]	0.21**	[0.15, 0.27]
Flu vaccination rate	0.05	[-0.01, 0.11]	0.05*	[0.00, 0.10]
Mammography screening rate	-0.03	[-0.09, 0.02]	0.02	[-0.05, 0.08]

Note: All health behaviors are coded such that greater values represent more health-protective behaviors.

* $p \leq .05$. ** $p \leq .01$.

Figure 1. Change in movement behavior from the first week of March to the first week of April. Counties were categorized by the health behavior composite, which was z-scored. *Best* were 1.0 SD or more above the mean ($n = 473$, 16.6%), *Very good* = between 0.5 and 1 SD ($n = 398$, 13.9%), *Good* = between the mean and 0.5 SD ($n = 532$, 18.6%), *Fair* = the mean and -0.5 SD ($n = 544$, 19.0%), *Poor* = between -0.5 and -1 SD below the mean ($n = 486$, 17.0%), *Very poor* less than 1 SD below the mean ($n = 425$, 14.9%). Error bars represent 95% confidence intervals.

Supplemental Materials

Social Distancing as a Health Behavior: County-level Movement in the United States

During the COVID-19 Pandemic is Associated with Conventional Health Behaviors

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Supplemental Data 1. Excluded Counties

2013	AK	Aleutians East Borough	8113	CO	San Miguel County
2016	AK	Aleutians West Census Area	8115	CO	Sedgwick County
2020	AK	Anchorage Borough	13007	GA	Baker County
2050	AK	Bethel Census Area	13061	GA	Clay County
2060	AK	Bristol Bay Borough	13239	GA	Quitman County
2068	AK	Denali Borough	13265	GA	Taliaferro County
2070	AK	Dillingham Census Area	13307	GA	Webster County
2090	AK	Fairbanks North Star	15001	HI	Hawaii County
2100	AK	Haines Borough	15003	HI	Honolulu County
2105	AK	Hoonah-Angoon Census	15005	HI	Kalawao County
2110	AK	Juneau Borough	15007	HI	Kauai County
2122	AK	Kenai Peninsula Borough	15009	HI	Maui County
2130	AK	Ketchikan Gateway Bo	16003	ID	Adams County
2150	AK	Kodiak Island Borough	16015	ID	Boise County
2158	AK	Kusilvak Census Area	16023	ID	Butte County
2164	AK	Lake and Peninsula B	16025	ID	Camas County
2170	AK	Matanuska-Susitna Bo	16033	ID	Clark County
2180	AK	Nome Census Area	16035	ID	Clearwater County
2185	AK	North Slope Borough	16037	ID	Custer County
2188	AK	Northwest Arctic Borough	16061	ID	Lewis County
2195	AK	Petersburg Census Area	20017	KS	Chase County
2198	AK	Prince of Wales-Hyde	20019	KS	Chautauqua County
2220	AK	Sitka Borough	20025	KS	Clark County
2230	AK	Skagway Municipality	20033	KS	Comanche County
2240	AK	Southeast Fairbanks	20039	KS	Decatur County
2261	AK	Valdez-Cordova Census Area	20049	KS	Elk County
2275	AK	Wrangell City	20071	KS	Greeley County
2282	AK	Yakutat Borough	20083	KS	Hodgeman County
2290	AK	Yukon-Koyukuk Census	20097	KS	Kiowa County
6003	CA	Alpine County	20101	KS	Lane County
6091	CA	Sierra County	20105	KS	Lincoln County
8009	CO	Baca County	20109	KS	Logan County
8017	CO	Cheyenne County	20153	KS	Rawlins County
8023	CO	Costilla County	20187	KS	Stanton County
8025	CO	Crowley County	20199	KS	Wallace County
8027	CO	Custer County	20203	KS	Wichita County
8033	CO	Dolores County	21189	KY	Owsley County
8047	CO	Gilpin County	21201	KY	Robertson County
8053	CO	Hinsdale County	22059	LA	La Salle Parish
8057	CO	Jackson County	25019	MA	Nantucket County
8061	CO	Kiowa County	26003	MI	Alger County
8065	CO	Lake County	26083	MI	Keweenaw County
8079	CO	Mineral County	26095	MI	Luce County
8091	CO	Ouray County	26131	MI	Ontonagon County
8109	CO	Saguache County	26153	MI	Schoolcraft County
8111	CO	San Juan County	27031	MN	Cook County

27069	MN	Kittson County	31087	NE	Hitchcock County
27077	MN	Lake of the Woods Co	31091	NE	Hooker County
27087	MN	Mahnomen County	31103	NE	Keya Paha County
27125	MN	Red Lake County	31113	NE	Logan County
27155	MN	Traverse County	31115	NE	Loup County
28055	MS	Issaquena County	31117	NE	McPherson County
29129	MO	Mercer County	31133	NE	Pawnee County
29227	MO	Worth County	31149	NE	Rock County
30005	MT	Blaine County	31165	NE	Sioux County
30011	MT	Carter County	31171	NE	Thomas County
30015	MT	Chouteau County	31173	NE	Thurston County
30019	MT	Daniels County	31183	NE	Wheeler County
30025	MT	Fallon County	32009	NV	Esmeralda County
30033	MT	Garfield County	32011	NV	Eureka County
30037	MT	Golden Valley County	32015	NV	Lander County
30039	MT	Granite County	32017	NV	Lincoln County
30045	MT	Judith Basin County	32021	NV	Mineral County
30051	MT	Liberty County	32027	NV	Pershing County
30055	MT	McCone County	35003	NM	Catron County
30057	MT	Madison County	35011	NM	DeBaca County
30059	MT	Meagher County	35013	NM	Dona Ana County
30065	MT	Musselshell County	35019	NM	Guadalupe County
30069	MT	Petroleum County	35021	NM	Harding County
30071	MT	Phillips County	35023	NM	Hidalgo County
30073	MT	Pondera County	35033	NM	Mora County
30075	MT	Powder River County	35059	NM	Union County
30077	MT	Powell County	36041	NY	Hamilton County
30079	MT	Prairie County	37177	NC	Tyrrell County
30091	MT	Sheridan County	38001	ND	Adams County
30097	MT	Sweet Grass County	38005	ND	Benson County
30099	MT	Teton County	38007	ND	Billings County
30101	MT	Toole County	38011	ND	Bowman County
30103	MT	Treasure County	38013	ND	Burke County
30107	MT	Wheatland County	38019	ND	Cavalier County
30109	MT	Wibaux County	38023	ND	Divide County
31005	NE	Arthur County	38027	ND	Eddy County
31007	NE	Banner County	38029	ND	Emmons County
31009	NE	Blaine County	38031	ND	Foster County
31015	NE	Boyd County	38033	ND	Golden Valley County
31017	NE	Brown County	38037	ND	Grant County
31049	NE	Deuel County	38039	ND	Griggs County
31057	NE	Dundy County	38041	ND	Hettinger County
31069	NE	Garden County	38043	ND	Kidder County
31071	NE	Garfield County	38045	ND	LaMoure County
31073	NE	Gosper County	38047	ND	Logan County
31075	NE	Grant County	38051	ND	McIntosh County
31077	NE	Greeley County	38063	ND	Nelson County
31085	NE	Hayes County	38065	ND	Oliver County

38069	ND	Pierce County	46137	SD	Ziebach County
38075	ND	Renville County	48011	TX	Armstrong County
38081	ND	Sargent County	48033	TX	Borden County
38083	ND	Sheridan County	48045	TX	Briscoe County
38085	ND	Sioux County	48095	TX	Concho County
38087	ND	Slope County	48101	TX	Cottle County
38091	ND	Steele County	48125	TX	Dickens County
38095	ND	Towner County	48137	TX	Edwards County
38103	ND	Wells County	48155	TX	Foard County
40025	OK	Cimarron County	48229	TX	Hudspeth County
41021	OR	Gilliam County	48235	TX	Irion County
41037	OR	Lake County	48243	TX	Jeff Davis County
41055	OR	Sherman County	48261	TX	Kenedy County
41069	OR	Wheeler County	48263	TX	Kent County
42023	PA	Cameron County	48269	TX	King County
42053	PA	Forest County	48271	TX	Kinney County
42113	PA	Sullivan County	48301	TX	Loving County
46003	SD	Aurora County	48311	TX	McMullen County
46007	SD	Bennett County	48327	TX	Menard County
46017	SD	Buffalo County	48345	TX	Motley County
46021	SD	Campbell County	48377	TX	Presidio County
46025	SD	Clark County	48393	TX	Roberts County
46031	SD	Corson County	48413	TX	Schleicher County
46037	SD	Day County	48431	TX	Sterling County
46039	SD	Deuel County	48433	TX	Stonewall County
46041	SD	Dewey County	48443	TX	Terrell County
46043	SD	Douglas County	48447	TX	Throckmorton County
46045	SD	Edmunds County	49009	UT	Daggett County
46049	SD	Faulk County	49017	UT	Garfield County
46055	SD	Haakon County	49031	UT	Piute County
46059	SD	Hand County	49033	UT	Rich County
46063	SD	Harding County	49055	UT	Wayne County
46069	SD	Hyde County	50009	VT	Essex County
46071	SD	Jackson County	50013	VT	Grand Isle County
46073	SD	Jerauld County	51017	VA	Bath County
46075	SD	Jones County	51091	VA	Highland County
46085	SD	Lyman County	51678	VA	Lexington city
46089	SD	McPherson County	53013	WA	Columbia County
46095	SD	Mellette County	53019	WA	Ferry County
46097	SD	Miner County	53023	WA	Garfield County
46102	SD	Oglala Lakota County	53069	WA	Wahkiakum County
46105	SD	Perkins County	54013	WV	Calhoun County
46107	SD	Potter County	54071	WV	Pendleton County
46111	SD	Sanborn County	54075	WV	Pocahontas County
46117	SD	Stanley County	55037	WI	Florence County
46119	SD	Sully County	55041	WI	Forest County
46121	SD	Todd County	55078	WI	Menominee County
46129	SD	Walworth County	56027	WY	Niobrara County

Supplemental Analyses 1. Validating County-level Movement Data

Validation Analyses. The two outcome measures assessing movement—*daily percentage of people staying within 1 mile of home* and *daily vehicle miles traveled*—were provided by private companies that did not describe how their data was cleaned, calculated, or aggregated. As a result, we assessed the validity of the measures by examining the degree to which three companies' different daily measures of movement (Cuebiq, Streetlight, and Citymapper) correlated from March 2nd to March 31st. Citymapper included movement data for *daily planned trips outside the home* in eight U.S. cities (see below), which was compared to Cuebiq and Streetlight data from the county most central to those cities. Specific counties used and the correlation among the three measures are provided in Supplemental Table 1. All correlations were greater than 0.70, and 83.3% were greater than 0.90 (20 of 24 correlations). In addition, daily average Cuebiq and Streetlight county-level data correlated at $r = 0.90$ for this period. This high degree of shared variance among these measures suggests that these measures assess a similar construct and provide some evidence towards the validity of the measure

Daily Planned Trips Outside the Home. Citymapper provided daily numbers of trips outside the home planned by their users each day from March 2nd to the present. The number of trips each day was benchmarked to a "typical usage period" from January 6th to February 2nd, resulting in a percentage of daily planned trips. Lower percentages equate to fewer planned trips and represent reduced movement. Data was made available for eight U.S. cities: Boston, Chicago, Los Angeles, New York City, Philadelphia, San Francisco, Seattle, and Washington D.C. As data was not available at a county-level, percentage of planned trips for these cities was used as additional validation for the *Daily Percentage of People Staying Within 1 Mile of Home* and *Daily Vehicle Miles Traveled* movement data.

Supplemental Table 1. Correlations Among County-level Movement Data

<i>N</i> = 30 days (March 2 to March 31, 2020)	(1)	(2)	(3)
Boston (Suffolk county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.92	1.0	
Planned trips outside the home (3)	.77	-.79	1.0
Chicago (Cook county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.92	1.0	
Planned trips outside the home (3)	.95	-.97	1.0
Los Angeles (Los Angeles county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.92	1.0	
Planned trips outside the home (3)	.96	-.95	1.0
New York City (see note)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.94	1.0	
Planned trips outside the home (3)	.91	-.95	1.0
Philadelphia (Philadelphia county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.93	1.0	
Planned trips outside the home (3)	.93	-.95	1.0
San Francisco (San Francisco county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.95	1.0	
Planned trips outside the home (3)	.97	-.94	1.0
Seattle (King county)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.91	1.0	
Planned trips outside the home (3)	.95	-.94	1.0
Washington D.C. (values for the entire district were used)			
People staying within 1 mile of home (1)	1.0		
Vehicle miles traveled (2)	-.94	1.0	
Planned trips outside the home (3)	.73	-.84	1.0

Note: All correlations are significant, $p < .001$. New York City daily values were the mean of Bronx, Kings, New York, Richmond, and Queens counties.