Association of Cell Phone Location Data and Trends in COVID-19 Infections During Loosening of Stay-At-Home Restrictions

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Teaser: We report that during the loosening of stay-at-home mandates, U.S. counties with more county level workplace cell phone activity had a more rapid increase in incidence of COVID-19. Though these results are not applicable at an individual level, they improve estimation of areas at higher risk of COVID-19 surge.

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In December of 2019, a cluster of pneumonia cases of unknown etiology was reported in Wuhan, China.[1] Since then, the causative organism has been identified to be a novel Coronavirus, SARS-CoV-2. Mitigation attempts of the transmission of this highly contagious virus[2] proved unsuccessful[3] leading to a global pandemic. Initial outbreaks of COVID-19, the clinical syndrome caused by the SARS-CoV-2, were curbed with stay-at-home measures in in the United States.[4] We previously demonstrated that greater cell phone activity in the workplace and lower activity in residential spaces was associated with higher case rates during the time immediately after the stay-at-home orders were initiated.[5]

Another study has evaluated the potential for domestic dissemination of SARS-CoV-2 from a particular US state, again using cell phone location data.[6] Here, we aimed to determine whether greater workplace activity over 30-days was associated with increase in cases in the subsequent 2-week period during a surge in cases in June in the U.S.

This study utilized publicly available county-level data from Google over a 30-day period from May 13-June 12.[7] The primary exposure was cell phone activity at the workplace relative to the baseline period for that county by quartile. Baseline activity was defined by Google as the activity between January 3-February 6. The primary outcome was the slope of change in the 7-day rolling average for new cases over the 14-day period of June 13-June 27 (the most recent 2-weeks of available data at the time of the analysis). COVID-19 cases in each U.S. county were obtained from the "Coronavirus COVID-19 Global Cases dashboard" hosted by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.[8] We adjusted for county level factors including the prior 14-day rolling average of new cases, total population, the population density, and whether the county was considered urban or rural.[9,10] The models included squared-terms to account for strong non-linear relationships between these variables and the outcome. Because of significant skew and kurtosis in the outcome, we also categorized slopes by quartile and utilized ordinal regression to model the outcome.

For mapping, the outcome utilized was the observed minus the expected slope of change in new cases (per 100,000-residents) for each county. This was determined by first predicting the outcome based on linear regression models. The residual between observed and expected slope of change in cases was then determined by calculating the difference between the observed slope of change and the expected slope from the regression model. Cell phone activity and the observed-expected slope of change in new cases were illustrated graphically in order to demonstrate the overlap between cell phone activity and subsequent change in rates of change in new cases. Production of maps was conducted using ArcMap 10.6.1 (Esri, Redlands, CA).

We noted a greater increase in the slope of cases per-day per-unit population in counties with higher workplace activity. Counties with the lowest workplace activity had an average slope of change in new cases of 5.64 (4.60, 6.68) per 100,000 population as compared to 7.88 (6.92, 8.84) in the counties with the highest workplace activity ($p<0.001$). Those counties in with the greatest workplace activity had a higher odds of being in a higher quartile of slope [OR 2.27 (1.45, 3.58) $p<0.001$] (Table 1).

Geographic variation in workplace activity and the observed-expected slope of new COVID-19 cases per capita are shown in Figure 1. While the visual correlation between workplace activity and the difference in cases compared to expected is modest, workplace activity does appear to have been greater in key areas where the epidemic worsened more than expected (e.g. Southeast) while it remained low in areas that remained stable or improved (e.g Northeast).

We previously reported that cell phone location data from the stay-at-home phase of the pandemic had the potential to predict the future trends of the COVID-19 pandemic.[5] Higher activity at the workplace was associated with a higher rate of increase in new cases per day. This previous study was however unable to assess the impact of reopening. In the setting of loosening of these stay-at-home mandates, and a surge in COVID-19 diagnosis in certain states, the current study provides evidence that cell phone activity at the workplace correlates with worsening of the epidemic. We thus noted an association between anonymized county level cell phone location data and COVID-19 incidence – both while stay-at-home mandates were in effect and with loosening of such mandates. This lends further credibility to the fact that anonymized county level cell phone location data offers the opportunity to help predict COVID-19 trends. Using this information may help identify regions at greater risk of rapid growth and regions that may need to alter which phase of reopening is appropriate.

Cell phone location data also serves as a surrogate for social distancing. Thus, the results of this study further demonstrates that social distancing is an effective method of helping slow the rate of COVID-19 infections.

While use of anonymized publicly available data to help predict the course of the epidemic is enticing, there are limitations to these data including the opt-in nature of the data and the lack of available data in all counties. Further, modeling is needed to disentangle the effects of mobility data independent of factors that contribute to changes in behaviors such as the prior severity of the epidemic. Also, the results of this analysis cannot be used at an individual level.

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Conflicts of Interest

The authors have nothing to disclose.

Tables

Table 1: Workplace Quartiles and Slope of cases per-day per-100 000 population

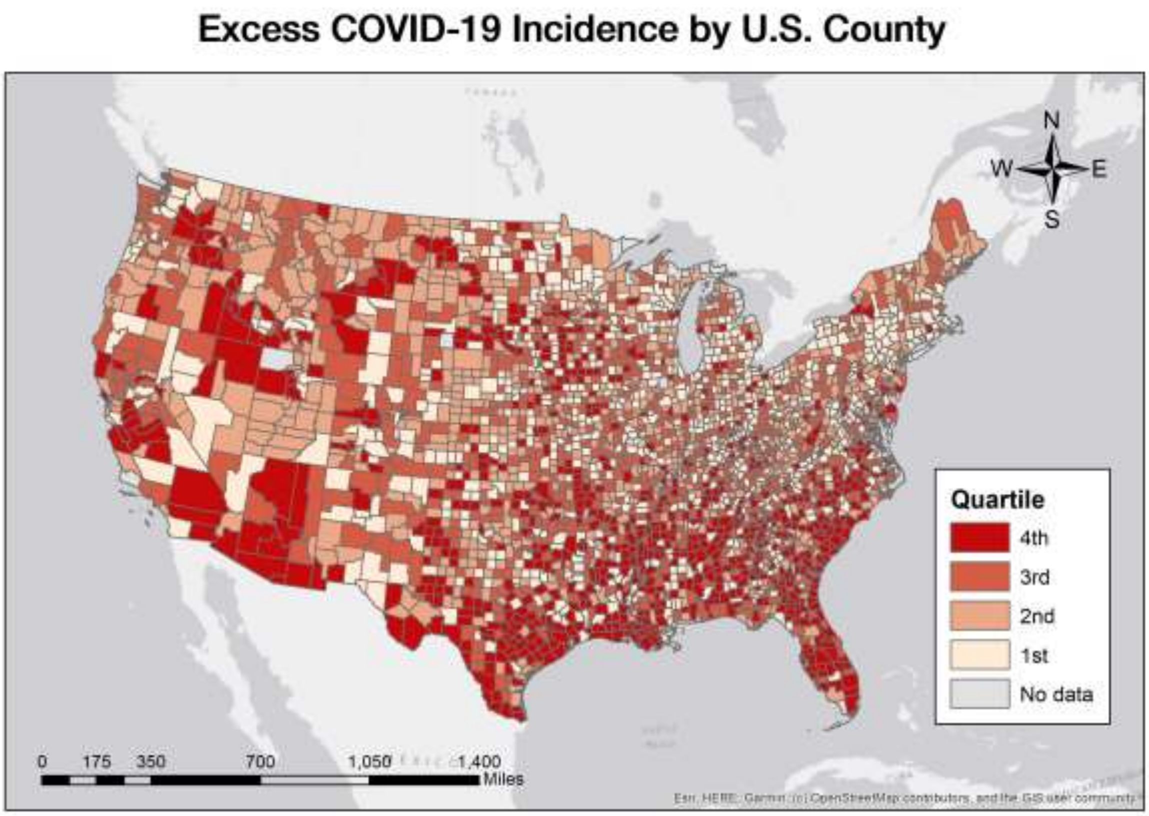
	Slope per 100k		Quartile Slope	
Workplace Quartile	β (95% CI)	p	OR (95% CI)	p
1	--		1	--
2	+1.42 (0.37-2.48)	0.009	1.46 (1.11, 1.92)	0.006
3	+2.21 (1.25, 3.16)	<0.001	2.04 (1.50, 2.78)	<0.001
4	+2.25 (1.21, 3.28)	<0.001	2.27 (1.45, 3.58)	<0.001

Figures

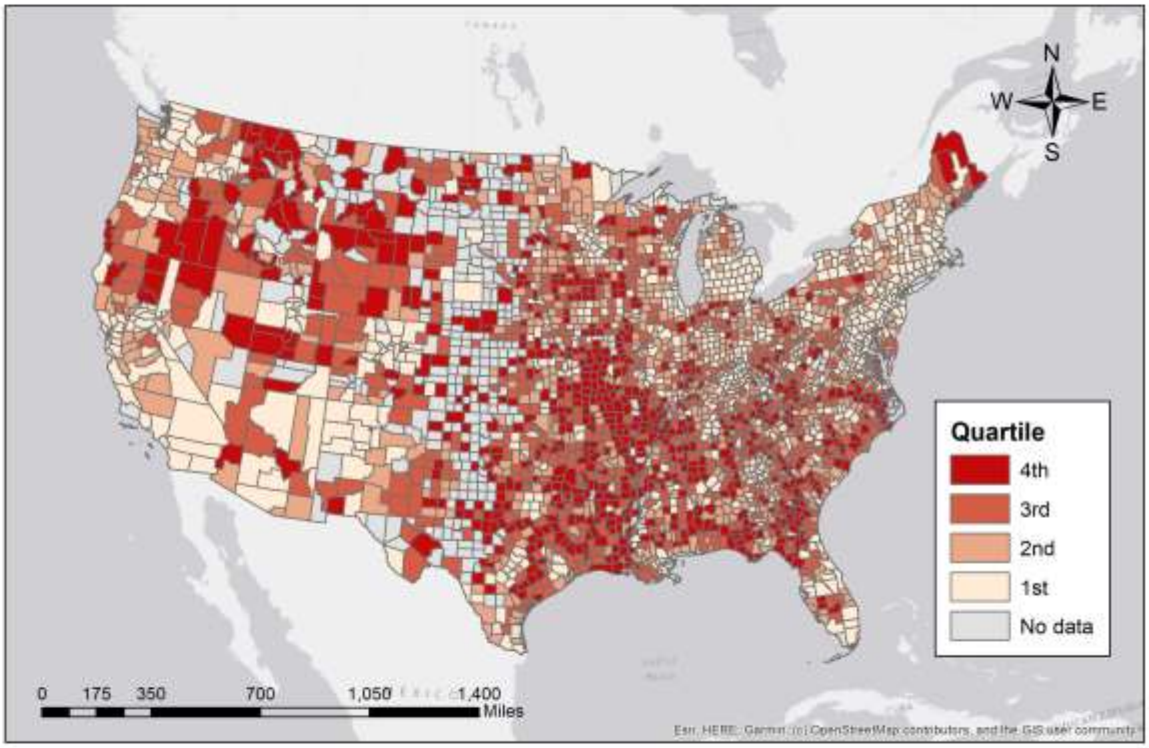
Figure 1

Figure 1A: Graphical representation of U.S. county map showing work place activity divided by quartile.

Figure 1B: New cases of COVID-19 (June 13-June 27) of U.S. county map divided into quartiles.



Workplace Cell Phone Activity by U.S. County



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