Published Online November 2, 2020 https://doi.org/10.1016/S1473-3099(20)30861-6

For more on **SafeGraph** see https://www.safegraph.com

See **Online** for appendix

Limitations of using mobile phone data to model COVID-19 transmission in the USA

Mobile phone data provide a unique means to capture individual-level and population-level movement patterns, which have become heavily relied upon to inform COVID-19 responses—specifically, for evaluating the impact of, and compliance with, non-pharmaceutical interventions (NPIs), as well as modelling the spatiotemporal variability of transmission dynamics. In the Article by Hamada S Badr and colleagues,[1] we revealed the strong correlation between population-level mobility patterns and severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) transmission patterns for the 25 most affected counties in the USA in the early stages of the COVID-19 pandemic. We have since extended the analysis to include all affected counties in the USA, and a longer time period spanning from March 16 to September 16, during which mobility and local outbreaks exhibited much more complex growth and decline patterns. Furthermore, we applied the analysis to subgroups of counties clustered spatially and temporally according to both the magnitude of their outbreaks and growth (or decline) rates during specified periods, in efforts to distinguish the role of mobility patterns in SARS-CoV-2 transmission as a function of these characteristic outbreak dynamics. Critically, results from our more comprehensive analysis reveal that the strong linear association between mobility and case growth rates previously observed is absent after April.

We used county-level epidemiological data from the Johns Hopkins University Center for Systems Science and Engineering[2] to compute the COVID-19 growth rate ratio and aggregated anonymised location data from SafeGraph to estimate the time-varying mobility ratio. The methodology from Badr and colleagues was used to compute each metric and the lagged correlations. The correlation distribution for all counties over different time periods is illustrated in the appendix, with counties grouped by outbreak magnitude (low, medium, or high) or outbreak phase (growth rate ratio is increasing, decreasing, or neither increasing or decreasing). Both sets of analysis confirm a uniquely strong association between mobility patterns and SARS-CoV-2 transmission in March–April, whereas the clustering analysis reveals the relationship is strongest for those counties with larger outbreaks that were experiencing a decline in case growth (which aligns with the 25 counties evaluated in our previous study[1]). However, after April, there is no consistent, generalisable relationship between mobility patterns and SARS-CoV-2 transmission across counties, or for any subgroups.

Our findings, consistent with those of Gatalo and colleagues,[3] suggest that mobility has a less significant role in the transmission of SARS-CoV-2 than do other adopted behavioural changes and NPIs, such as wearing face masks, handwashing, maintaining physical distance, avoiding large gatherings, and closing schools. While it is possible that transmission during the initial phase of the pandemic in the USA was more sensitive to mobility patterns, the stronger correlation revealed in March–April is more likely due to the initial adoption of many NPIs in parallel, whereas erratic policies and highly variable individual-level behaviours after the initial shutdown period confound the role of mobility. Additionally, after the initial phase of the pandemic, complex inter-county movement patterns, coupled with variable epidemic seeding and establishment patterns, might have further affected the contribution of mobility to growth rate.

While mobility patterns can serve as a critical tool for assessing COVID-19 intervention impacts, there exists various challenges and limitations to their use.[4] Based on our most recent findings, parameterising SARS-CoV-2 transmission models using mobility data alone is likely to result in poorly performing models and inaccurate forecasts. The absence of a significant effect of mobility on SARS-CoV-2 transmission across all counties after April, even when accounting for outbreak magnitude and phase, suggests there are probably more critical factors than mobility alone for controlling COVID-19. Further research is needed to quantify the impact of each NPI and their interactions; however, this analysis requires data that are currently unavailable, specifically high-resolution data on compliance rates for each NPI over time.

We declare no competing interests.

*Hamada S Badr, *Lauren M Gardner*
l.gardner@jhu.edu

Department of Earth and Planetary Sciences (HSB) and Department of Civil and Systems Engineering (LMG), Johns Hopkins University, Baltimore, MD 21218, USA

1 Badr HS, Du H, Marshall M, Dong E, Squire MM, Gardner LM. Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. *Lancet Infect Dis* 2020; **20:** 1274–54.
2 Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. *Lancet Infect Dis* 2020; **20:** 533–34.
3 Gatalo O, Tseng K, Hamilton A, Lin G, Klein E. Associations between phone mobility data and COVID-19 cases. *Lancet Infect Dis* 2020; published online Sept 15. https://doi.org/10.1016/S1473-3099(20)30725-8.
4 Grantz KH, Meredith HR, Cummings DAT, et al. The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology. *Nat Commun* 2020; **11:** 4961.