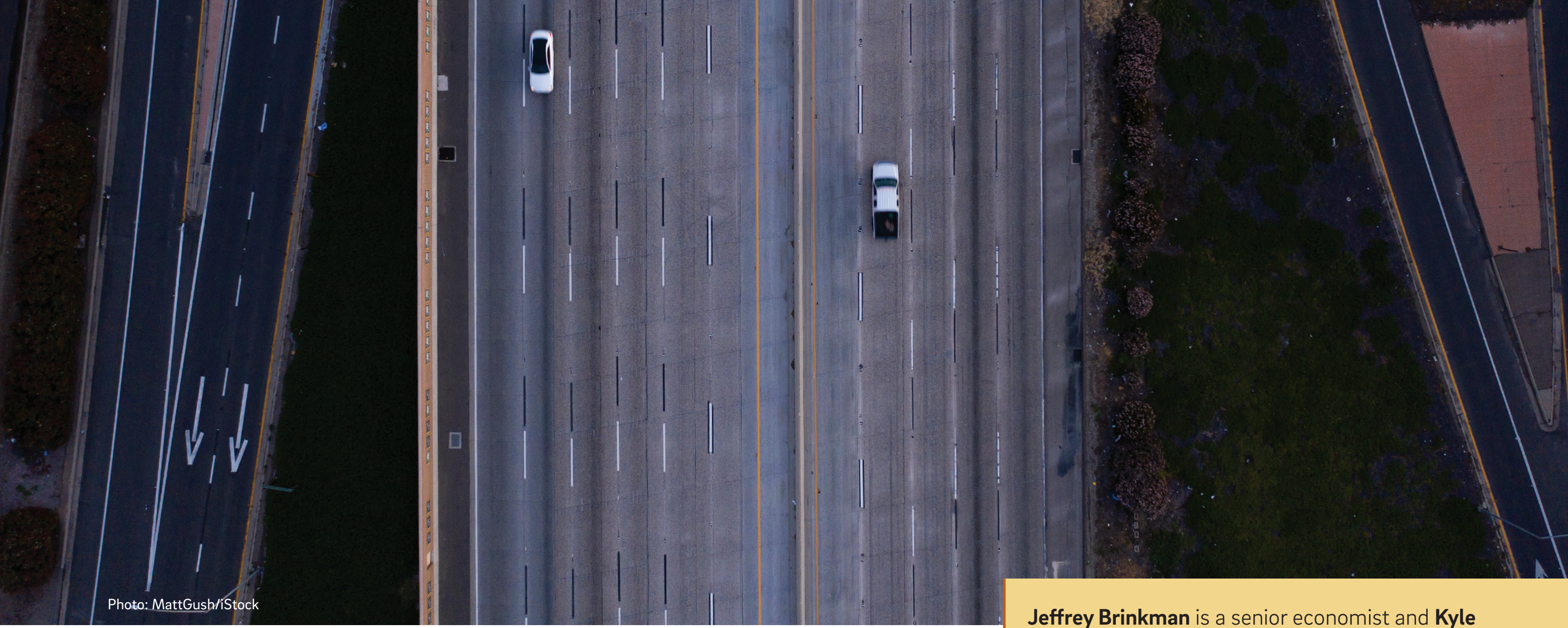

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Travel Behavior and the Coronavirus Outbreak

Cellphone location data open a window into Americans' changing travel patterns, and how well they slowed the spread of COVID-19.

BY JEFFREY BRINKMAN AND KYLE MANGUM

As COVID-19 swept the nation, policymakers sought to limit its spread by restricting mobility. State and local governments issued stay-at-home orders, closed nonessential businesses, and limited mass gatherings. How effective were these policies at limiting mobility and, by extension, slowing the spread of the virus? To find out, we examined the aggregate movement of cellphones over the course of the outbreak. We then analyzed how travel patterns changed in terms of both how much and where people traveled.

Unsurprisingly, overall travel declined significantly as the number of cases grew. By comparing counties, we found that overall travel declined in response not just to government orders but also to the number of cases locally and in nearby counties. Moreover, people's travel patterns changed in ways that limited their exposure. They reduced mobility overall as cases rose locally, but they also traveled less to locations with a high number of cases. Our measures indicate that this limited people's overall exposure and reduced the spread of the coronavirus. We conclude that providing clear and timely information about the geography of the outbreak should be a policy priority.

Using Cellphone Data to Measure Changes in Mobility

Mobility declined significantly with the onset of the pandemic in the U.S. To analyze this decline, we relied on county-level location exposure (LEX) indices.[1] These indices are constructed by calculating the percentage of cellphones in a county on a particular day that were in another county in the previous two weeks.[2] These data measure the connectedness of counties by describing a network of bilateral travel flows between all U.S. counties.

For example, on Wednesday, February 8—several weeks before cases spiked in the U.S.—over 90 percent of phones in Philadelphia had also been in the city in the previous two weeks (Figure 1, top panel). Forty-three percent of phones located in Philadelphia on that day had also been in Montgomery County, a suburb to the immediate northwest of Philadelphia, at some point in the previous two weeks.

By Wednesday, April 8, the LEX data had changed (Figure 1, bottom panel). Phones located in Philadelphia on April 8 were much less likely to have been in other counties in the previous two weeks. Montgomery County saw the largest decline: 10 percentage points, from 43 percent to 33 percent. This represents a 23 percent decline in travel between these two counties.

Predicting Declining Mobility

Coronavirus cases rose rapidly in the U.S. beginning in early March, but the severity of the outbreak varied by location. Of the central counties of five large metro areas (New York, Los Angeles, Chicago, Houston, and Philadelphia), New York experienced by far the most severe coronavirus outbreak.[3]

There were also clear differences in the timing of the outbreak across counties. In New York City's five counties there were 100 total cases on March 13, while Harris County (home of Houston, Texas) did not reach that threshold until March 24.

To further investigate how travel behavior changed after the onset of the pandemic, we used the LEX data to construct a county-level measure that captures how much people travel into and out of a county. Specifically, we counted the total number of cellphones located in a county on a particular day that were also located in a different county in the previous two weeks.

We plotted this measure of mobility as a seven-day moving average for the same central counties, indexed to the average over the last two weeks of January (Figure 2). The index declined in all counties with the onset of the pandemic. Notably, the timing and magnitude of the decline varied by county. For example, mobility in New York, where the outbreak was especially pronounced, had declined sharply by mid-March. Houston's decline in mobility was later and less pronounced. In both counties, the decline in mobility corresponded with the increase in coronavirus cases locally.

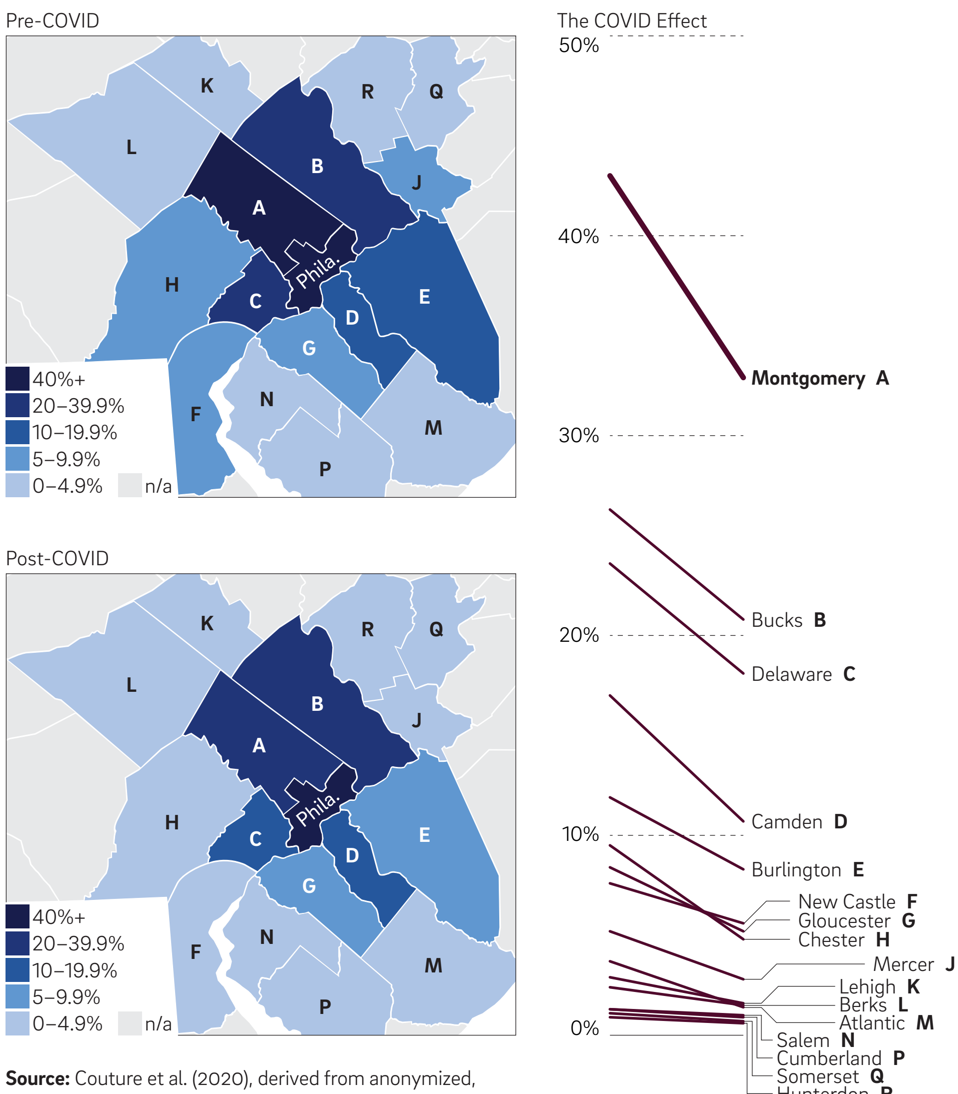
We tested the correlations between changes in mobility and the number of observed new cases over the previous two weeks using the data for more than 2,000 U.S. counties.[4] We also accounted for government orders that limited gatherings, closed businesses, or required people to stay home. We found that people did limit mobility in response to government orders, but the prevalence of cases independently explains much of the observed mobility reduction. Failure to account for this behavioral response overestimates the effectiveness of government orders.

FIGURE 1

Travel In and Out of Philadelphia Plummets in Response to COVID

Travel to and from Montgomery County sees the biggest drop.

County-level location exposure (LEX) indices, Philadelphia metropolitan statistical area, February 8 & April 8, 2020



Source: Couture et al. (2020), derived from anonymized, aggregated smartphone movement data provided by PlaceIQ.

Mobility, Exposure, and Travel Behavior

Overall travel declined, but did people also change where they travelled to? If the goal of reduced mobility is to reduce exposure to the virus, policymakers would want people to travel less but also to avoid locations with a high number of cases.

To study exposure, we measured how many people in each county traveled to other counties where there were already confirmed cases. Specifically, for each county we multiplied the number of cellphones that appeared in another county in the previous two weeks by the number of cases in that county. We then summed across all destination counties to calculate an exposure measure. This exposure measure will decline if people travel less, but also if they avoid counties with a high number of virus cases.

Figure 3 shows an example of this exposure measure for the Philadelphia metropolitan area.[5] The actual exposure measure is plotted in burgundy. By "exposure" we mean contact with counties outside of Philadelphia. It starts at zero before cases appear and gradually rises throughout the sample, despite the decline in travel.

We then computed what the exposure would have been had travel behavior remained unchanged during the outbreak. First, the blue line shows what the exposure would have been had people not changed their travel behavior at all. This assumes that people continued to travel as they did before March 1, even as the number of coronavirus cases rose. This counterfactual suggests that the exposure measure would have been twice as high on May 1 had there been no change in mobility.

The second counterfactual, plotted in pink, shows what the exposure measure would have been if people reduced travel overall but did not change the locations they traveled to. In other words, we assume that total travel to other counties was reduced, but the share of travel to each county did not change. In this case, exposure declined, but not to the extent actually observed. This is evidence that people avoided locations where cases had grown, and this significantly reduced overall exposure.

Exposure and Case Growth

How did the reduction in mobility and exposure affect the spread of the coronavirus? It can be difficult for policymakers to answer this important question because of reverse causality: A decline in mobility can cause a reduction in the spread of the virus, but the spread of the virus can also cause a reduction in mobility.

To resolve this dilemma, we disentangled these effects by separately using as explanatory variables a measure of generic mobility and a measure of virus exposure. The former varies with the level of travel while the latter varies with travel to destinations with relatively higher case counts. We found that mobility alone–that is, detached from destination case counts–is not correlated with the spread of the virus. When we used our measure of case exposure–that is, mobility to areas with more cases–we found a positive correlation between exposure and new cases.[6] We estimate that a 1 percent increase in the exposure measure is associated with a 0.1 to 0.2 percent increase in new daily cases. In other words, movement between counties increased the spread of the coronavirus. However, reductions in mobility likely resulted in significantly slower spread, given that overall exposure in the U.S. at the end of April was half as high as it would have been if people hadn't traveled less often to locations with fewer cases.[7]

Conclusion

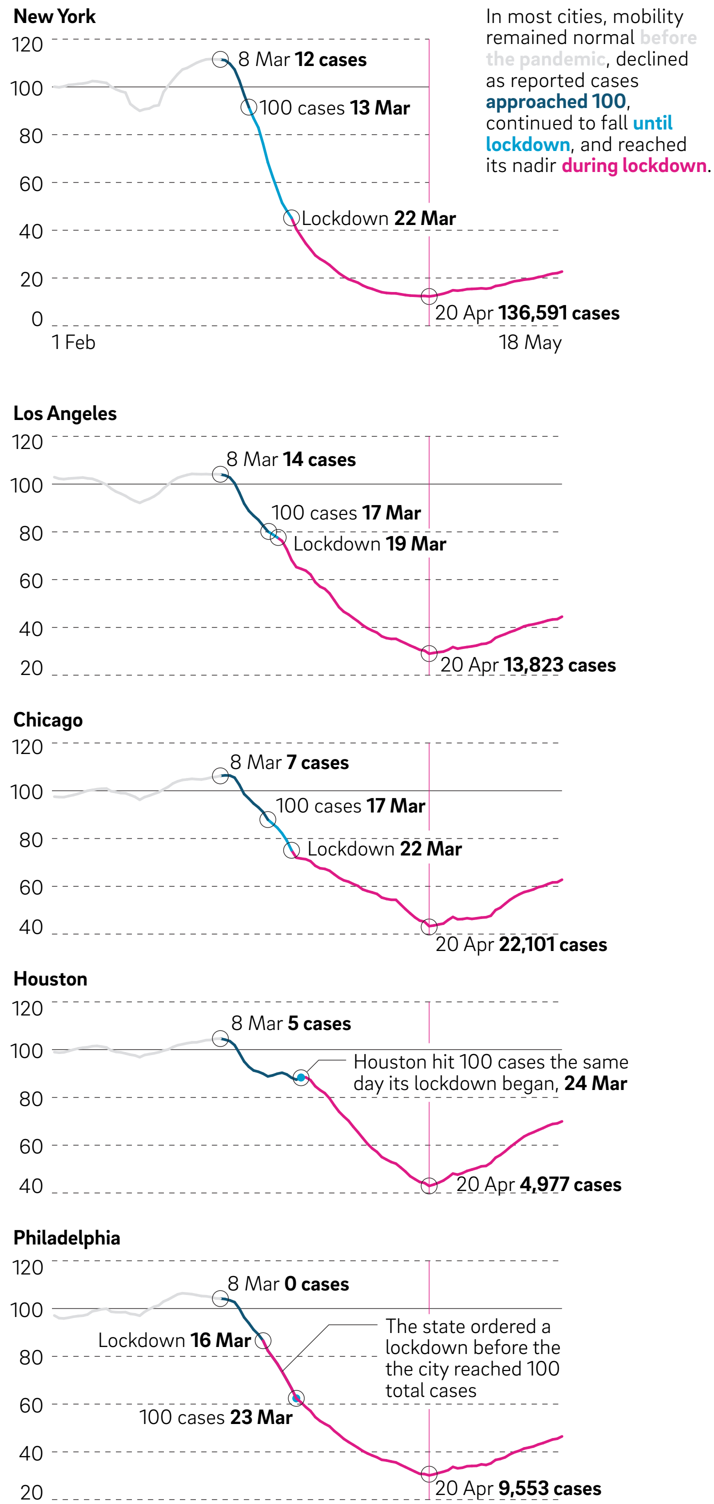
Travel patterns changed in the U.S. during the coronavirus outbreak. People adjusted their travel patterns based on available information about the number of cases locally. Not only did people reduce overall travel but they avoided locations with a prevalence of cases. This significantly decreased exposure to and, in turn, reduced the spread of the virus.

If travel outside of localities affects the spread of the virus, and if travel patterns change in response to outbreaks, there are two related implications for policymakers. First, accurate and timely information about cases and deaths should be a priority. Second, multiregional coordination and information sharing could be important policy tools in the fight against the coronavirus. EI

FIGURE 2

Mobility Declined in All Counties

LEX indices, plotted as a 7-day moving average indexed to the average over the last two weeks of January; central counties of five largest metros, Feb 1 to May 18, 2020



Note: We define "lockdown" as the period during which there is a government-mandated stay-at-home order. When a municipality and a state both issued stay-at-home orders, we chose whichever date came first.

Source: Couture et al. (2020), derived from anonymized, aggregated smartphone movement data provided by PlaceIQ.

Our Methodology

For each home county, we calculate the total number of cellphones that appear in that county on a given day and also appeared in another county in the previous two weeks. We denote this value as the number of trips.

To construct an exposure measure, we multiply the number of trips to a location (N_d) by the number of cases in that location (C_d) on each day. We then sum the resulting products across all destination counties. In other words, this exposure measure, which is plotted in burgundy in Figure 3, is calculated by

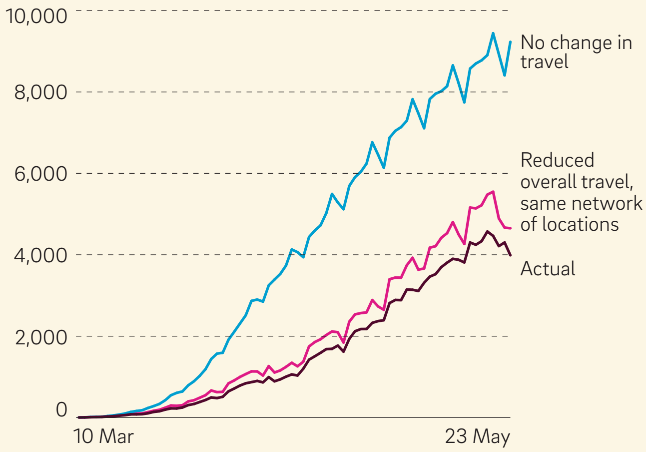
$$exposure = \sum_d N_d \times C_d$$

Our first counterfactual uses the same county case data but fixes the trips at pre-COVID-19 levels. In other words, we assume that travel behavior does not change at all (remaining at a fixed, prepandemic value of N_d), but we let cases evolve as they actually did in the data. This is the blue line in Figure 3.

FIGURE 3

Reductions in Mobility Reduced Exposure to Virus

Exposure index, Philadelphia metro area, March 10–May 23, 2020



Source: Couture et al. (2020), derived mobility data from anonymized, aggregated smartphone movement data provided by PlaceIQ; case data come from the COVID-19 Dashboard of the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, https://systems.jhu.edu/.

Note: To compute the exposure index, we multiplied the number of cellphones that appeared in another county in the previous two weeks by the number of cases in that county. We then summed across all destination counties.

Next, we decompose the trip data to better understand how travel behavior changed. The total trips to a destination from a home county is by definition the total number of trips from a home county to any location (N) multiplied by the fraction of total trips to that destination (F_d). This decomposition can be written as

$$N_d = N \times F_d$$

By decomposing the trips in this way, we can calculate the exposure measure while assuming that the total number of trips declined as in the data (that is, N declines), but that the fraction of trips to each destination remained the same as during the preperiod (that is, F_d is fixed). This is the counterfactual exposure measure plotted in pink in Figure 3.

Notes

1 These indices were created by Couture et al. (2020), derived from anonymized, aggregated smartphone movement data provided by PlaceIQ. The LEX data and a more detailed description can be found at https://github.com/COVIDExposureIndices.

2 More precisely, the data measure whether a cellphone pings in a county. Pings occur for a variety of reasons, including when a phone is turned on or is moved into the range of a different cell tower.

3 Data from the COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, https://systems.jhu.edu/. The authors downloaded the data from https://github.com/CSSEGISandData. Data visualizations can be found at https://coronavirus.jhu.edu/.

4 The correlations are apparent when measuring new cases in a variety of time windows, ranging from one- or two-week lags to the cumulative count from the start of the outbreak.

5 We calculate a weighted average of the exposure measure for all counties in the Philadelphia metropolitan area.

6 In our 2020 working paper, we also employed an instrumental variable strategy using government shutdown orders to estimate the causal effect of exposure on new cases and we found similar results.

7 Note that these estimates are based on a direct effect on new daily cases early in the pandemic and not a complete model of long-run transmission of the disease. In our 2020 working paper we used a simple model of disease transmission based on these estimates to understand how the disease may have spread differently under counterfactual mobility scenarios.

References

Brinkman, Jeffrey, and Kyle Mangum. "The Geography of Travel Behavior in the Early Phase of the COVID-19 Pandemic," Federal Reserve Bank of Philadelphia Working Paper, forthcoming.

Couture, Victor, Jonathan Dingel, Allison Green, Jessie Handbury, and Kevin Williams. "Measuring Movement and Social Contact with Smartphone Data: A Real-time Application to COVID-19" (2020).

Dong, Ensheng, Hongru Du, Lauren Gardner. "An Interactive Web-based Dashboard to Track COVID-19 in Real Time," *Lancet: Infectious Diseases*, 20:5 (2020), pp. 533–534. https://doi.org/10.1016/S1473-3099(20)30120-1.

Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), https://systems.jhu.edu/ (2020).