Reshaping a nation: Mobility, commuting, and contact patterns during the COVID-19 outbreak

Brennan Klein[*1,2], Timothy LaRock[*1], Stefan McCabe[*1], Leo Torres[*1], Lisa Friedland[1], Filippo Privitera[4], Brennan Lake[4], Moritz U. G. Kraemer[5,6,7], John S. Brownstein[6,7], David Lazer[1], Tina Eliassi-Rad[1], Samuel V. Scarpino[1,3], Alessandro Vespignani[1,2,3], and Matteo Chinazzi[§1,2,3]

[1]Network Science Institute, Northeastern University, Boston, USA
[2]Laboratory for the Modeling of Biological and Socio-technical Systems, Northeastern University, Boston, USA
[3]ISI Foundation, Turin, Italy
[4]Cuebiq Inc.
[5]Department of Zoology, University of Oxford, Oxford, UK
[6]Boston Children's Hospital, Boston, USA
[7]Harvard Medical School, Boston, USA

May 11, 2020

Abstract

In March 2020, many state and local governments in the United States enacted stay-at-home policies banning mass gatherings, closing schools, and promoting remote working. By analyzing anonymized location data from millions of mobile devices, we quantify how much people have reduced their daily mobility and physical contacts in accordance with these guidelines. At the regional level, we measure declines in daily commute volume as well as transit between major urban areas. We also measure changes in the average user's daily range of mobility, the number of co-location events within a region, and number of users with at least one contact in a given region. According to these five measures, we estimate that the average person in the United States had reduced their daily mobility by between 45-55% as of late April, 2020 and had reduced their daily contacts between 65-75%. The United States' physical distancing guidelines expired on April 30, 2020 and are not set to be renewed; as of early May, 2020, we report increases in mobility and contact patterns across most states (up to 10-14%, compared to the last week of April), though we do not observe a commensurate increase in commute volume. The response to the COVID-19 pandemic has amounted to one of the largest disruptions of economic, social, and mobility behavior in history, and quantifying these disruptions is vital for forecasting the further spread of this pandemic and crafting our collective response.

---

[*]Equal contribution.
[§]Correspondence: m.chinazzi@northeastern.edu

Introduction

Faced with a rapidly spreading disease and no vaccine, governments around the world have turned to non-pharmaceutical interventions (NPIs) in their efforts to fight COVID-19. Some countries that were heavily impacted early on, including China, have now succeeded in limiting local transmission through a variety of restrictions on travel and mobility, along with massive testing regimens [1, 2, 3, 4]. Italy, which experienced the earliest large-scale outbreak of COVID-19 in Europe, imposed mobility restrictions on March 8, 2020 [5], and by March 22, 2020, it had begun to show a drop in the reported number of new infections [6]. These mobility restrictions, most stringent at the epicenters of the epidemic, are thought to have dramatically changed the trajectory of the pandemic in Italy [7, 8], as they did in China [9, 10, 4]. In contrast, South Korea's prompt strategy of large-scale testing, unified public messaging encouraging social distancing and the use of face masks, along with contact tracing and early isolation of infectious individuals appears to have achieved a similar effect without the top-down mobility restrictions enforced in Italy and China [11, 12]. While most European countries now have population-wide mobility restrictions similar to those in Italy [13], the heterogeneous nature of the responses, combined with difficulties in assessing disease prevalence, makes it challenging to measure their effects.

On March 16, 2020, the United States government issued guidelines promoting NPIs to reduce the spread of the COVID-19 in the country [14]. By April 7, 95% of people in the United States were being urged by their states' governors to stay home due to the pandemic [15]. These NPIs are aimed at minimizing the number of contacts that a given person might have in a day, which will in turn reduce the number of new cases of COVID-19 in the United States. Such interventions included school closures designed to restrict rapid transmission among children, state of emergency declarations requiring non-essential businesses to close and restaurants to be take-out only, and shelter-in-place orders to minimize person-to-person contacts. As of May 1, several states have begun to "reopen" to varying degrees [16].

During this period of encouraged physical distancing, many employers have temporarily eliminated in-person meetings, although many jobs in the United States cannot easily transition to remote work. In 2018, the U.S. Bureau of Labor Statistics estimated that almost 25% of workers could work from home [17], a number that varies widely by race, education level, and industry. Despite widespread video-conferencing/teleworking software, we have not yet been able to quantify the ubiquity of these practices across the United States, though major Internet Service Providers have reported traffic increases between 20% and 30% [18]. Additionally, the typical commuting patterns of millions of people in the United States have been impacted by an unprecedented spike in joblessness; over 30 million unemployment claims were filed in the United States between March 16 and April 25 [19].

While there have been several policies and guidelines introduced that aim to mitigate the spread of the disease, a major challenge for policymakers is still the question of compliance: are people in fact reducing their daily interactions with others? If so, by how much? And what are the implications of this change in behavior both on the trajectory of the COVID-19 pandemic and on our projections of its spread?

The near ubiquity of mobile phone usage—coupled with state-of-the-art techniques for anonymizing data and enhancing user privacy [20, 21]—has led to many insights about humanity's response to the COVID-19 pandemic [22, 7, 23, 24, 25, 26, 27, 28, 29]. These
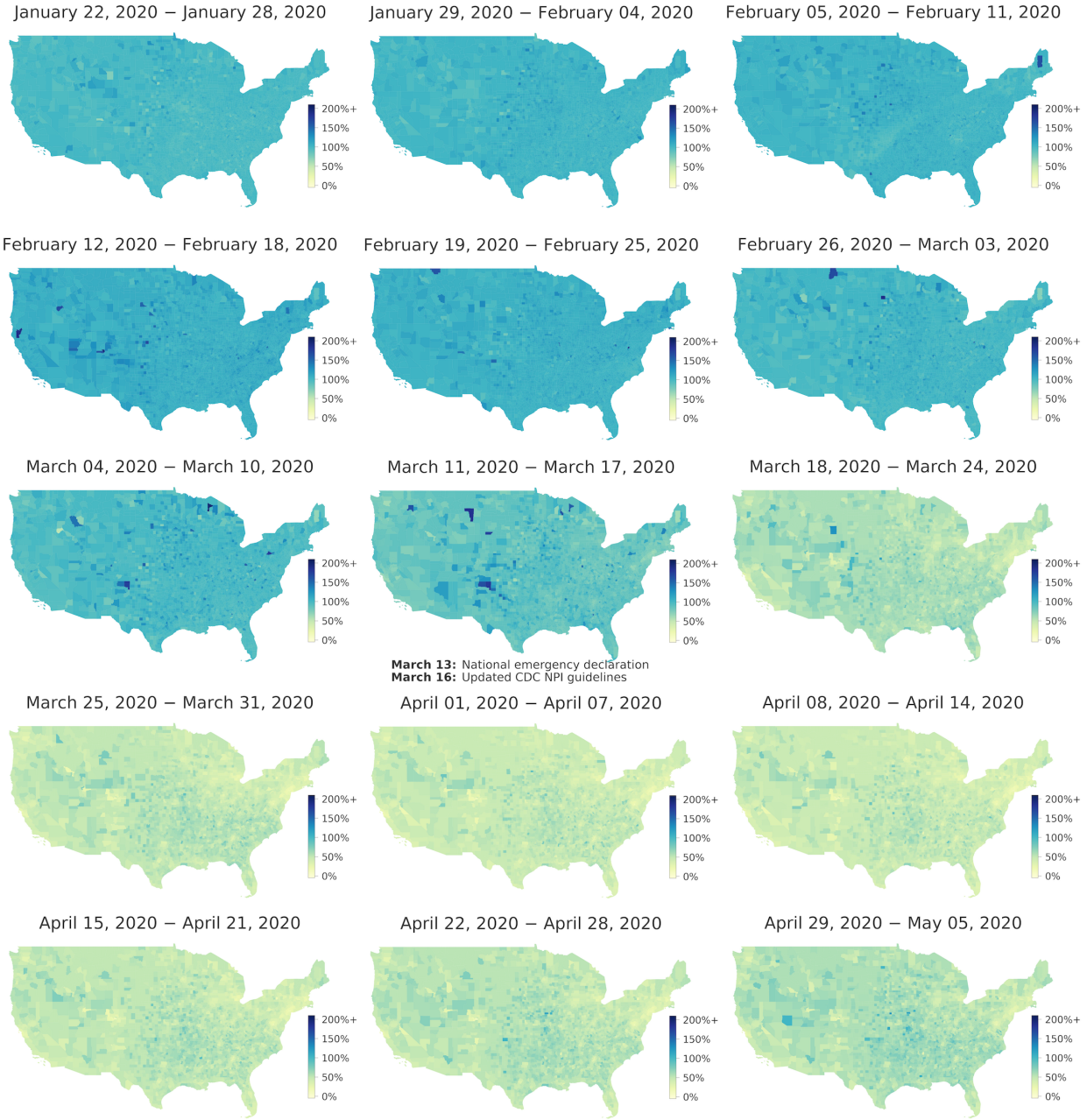
Figure 1: **Visual timeline of physical distancing in the United States.** To highlight the nationwide disruptions in everyday activity, we color each county by a composite measure, simply calculated as the average of its typical daily commute volume, individual mobility, co-location events outside of work/home, and number of users with at least one contact outside of work/home (here, "typical" refers to the average activity between January 16 and February 29, 2020, excluding holidays; see Results section for more details). We report each of these measures separately in Figure 3 and define them in the Materials & Methods section.

types of data are also useful for quantifying reductions in mobility or changes in consumer behavior (e.g., spending less on retail [30] or visiting parks more often [28]).

Here, we quantify changes in day-to-day mobility, commuting, and interaction behavior in the United States at the micro- and macroscopic levels. Using anonymized, aggregated location data from more than 37 million mobile devices between January 1, 2020 and May 9, 2020, we observe dramatic reductions in individual mobility and commuting patterns across the United States. In most counties across the United States, these reductions began between Wednesday, March 11 and Monday, March 16. At the individual level, we estimate the changes in daily range of mobility, number of co-location events outside of home and work, as well as the unique number of users with at least one contact outside of home and work. At the macroscopic level, we calculate changes in commuting volume between census tracts in the United States as well as changes in inter-city travel.

Together, these five measures provide an assessment of the extent to which people in the United States are reducing mobility and physical proximity during the COVID-19 pandemic. As of May 9, 2020, we estimate decreases along each of these measures, ranging from about 45% to 80% nationally. This means that people are commuting less (both short and long distance commutes), moving around less, and interacting with fewer people outside their home and work. We cannot distinguish the extent to which these patterns are driven by the adoption of remote-working practices versus increases in unemployment. Nor can we identify any single cause of these changes in behavior. However, quantifying these reductions in commuting, mobility, and person-to-person contact patterns will help to fine-tune predictive models of the spread of COVID-19, and these in turn will help us proactively respond to the trajectory of this pandemic.

An interactive version of the analyses outlined in this manuscript is available at the following online dashboard: `https://covid19.gleamproject.org/mobility`.

Results

Among the many analyses possible with these datasets, we selected a set of measures that could be directly used by researchers to inform their epidemic models by accounting for realistic changes in nationwide mobility and contact patterns. Indeed, the following results are already being used as key benchmarks for calibrating large-scale metapopulation models of disease transmission such as the Global Epidemic and Mobility Model (GLEAM) [31, 32, 22, 33, 34, 2]. We measure mobility behavior mainly at two scales: changes in the behavior of individuals (micro-scale) and changes in activity within geographic regions (macro-scale). Figures 1 and 2 summarize the main results, showing that by early May 2020, mobility and person-to-person contact events have decreased by more than 55% on average in the United States.

In order to measure behavior over a consistent sample of users, we selected a subset (i.e., a "panel") of users in the Cuebiq data who were active during a baseline period. The panel used here consists of users who were active on at least 21 days between January 15 and February 29, 2020, with at least 11 of those days occurring between February 12 and 29. We defined an active day as one in which more than 50 observations were collected (i.e., 50 location pings from the mobile device). This subset includes almost 11.7 million anonymous users nationally.

In Figures 2 and 3, we report the percent of *typical* activity in each plot (and in Figure 4,

we report differences in this percentage). Here, typical refers to the average activity for each day of the week, within a given date range; in this case, we select days between January 16 and February 28, 2020, excluding holidays, as typical. For each measure, we divide its daily value by the average value of its corresponding day of the week (i.e., Mondays are compared to the average Monday). In Figures 2 and 3, values of 100% denote typical behavior, which is why most days throughout February hover at 100%.

Micro-scale: Individual mobility and contact patterns

Changes in individual mobility patterns

In order to capture how individual range of mobility has decreased during the COVID-19 pandemic, we calculate the *radius of gyration* [35] for each (anonymized) mobile device in the panel of users selected for this study (See Materials & Methods for a formal definition of the radius of gyration). This measure tells us how far an individual is traveling from their average daily position. In other words, it is a proxy for the distance that a person travels during the day.

By early May 2020, the average radius of gyration of users in our panel decreased between 45-55% relative to a typical weekday, as shown in Figure 3a. Similar results have been found for New York City [23]. The radius of gyration typically increases on the weekends (i.e., users take longer trips during these days), but this trend began to disappear nationally following the updated CDC NPI guidelines on March 16, suggesting that individuals began to stay home rather than taking trips.

Person-to-person contact activity

We use two proxy measures to approximate the extent to which people in the United States are engaging in physical social distancing behavior. The first is the number of *co-location events* that a user has in a given day, outside their workplace or home. These could include passing another person on the street, waiting in line at a grocery store, interacting at a park, and so on. The second, related measure is the number of *unique* users with at least one contact within a state in a given day. To highlight the difference between these two measures, consider them in a disease transmission context: every co-location event can be thought of as an opportunity for a virus to spread (assuming infectious individuals and close enough co-location), while the number of unique users merely refers to the total number of people who experienced at least one contact event in a given day.

To estimate these two measures, we first define a co-location event as two devices being inside the same *geohash* within a five minute time window. A geohash is a sequence of letters that maps each longitude-latitude coordinate to a unique identifier at a pre-specified spatial resolution. In this study, we used an 8-character geohash, which corresponds to approximately 60-foot^2 grids (see Materials & Methods). This analysis excludes users' personal areas (i.e. home and work locations). For more details about the privacy measures taken to preserve users' identities we refer the reader to the Materials & Methods section.
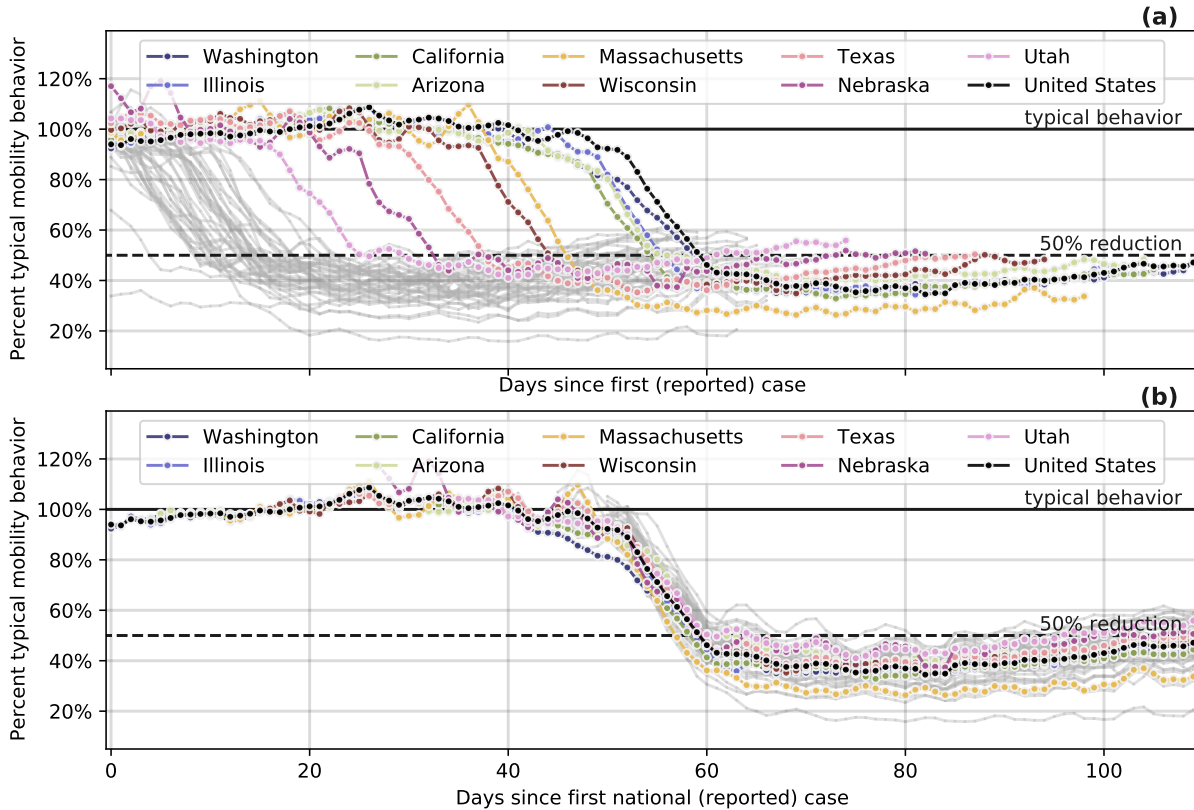
Figure 2: **Aggregated mobility reductions at the state level over time.** Averaging our five proxy indicators of physical distancing (combined reductions of typical daily commute volume, inter-CSA transit, individual mobility, co-location events outside of work and home, and unique number of users with at least one contact outside of home and work), we report the percent of typical behavior by **(a)** days since the first reported case and **(b)** days since the first national reported case. We highlight the nine states with the earliest reported case and plot the rest in grey.

Co-location events outside home and work. On average, there has been a dramatic decline in the number of co-location events that users experience in a day (Figure 3a), with the onset of this decline around March 11. While normally users experience more co-location events during the weekends (Fridays, Saturdays especially, and Sundays), by early May, the number of co-location events was roughly 75% less than their typical behavior before social distancing measures took effect. This is up from the minimum of approximately 80% reduction in early April.

Number of unique users with one contact outside home and work. Similar to the observed decrease in the number of co-location events per day, the number of *unique* users in our panel that experience at least one contact in a day is also decreasing (Figure 3a). In most states there are approximately 25% fewer unique users with contacts per day by May 9, 2020.

Crucially, both of these measures above do not include interactions within the home or
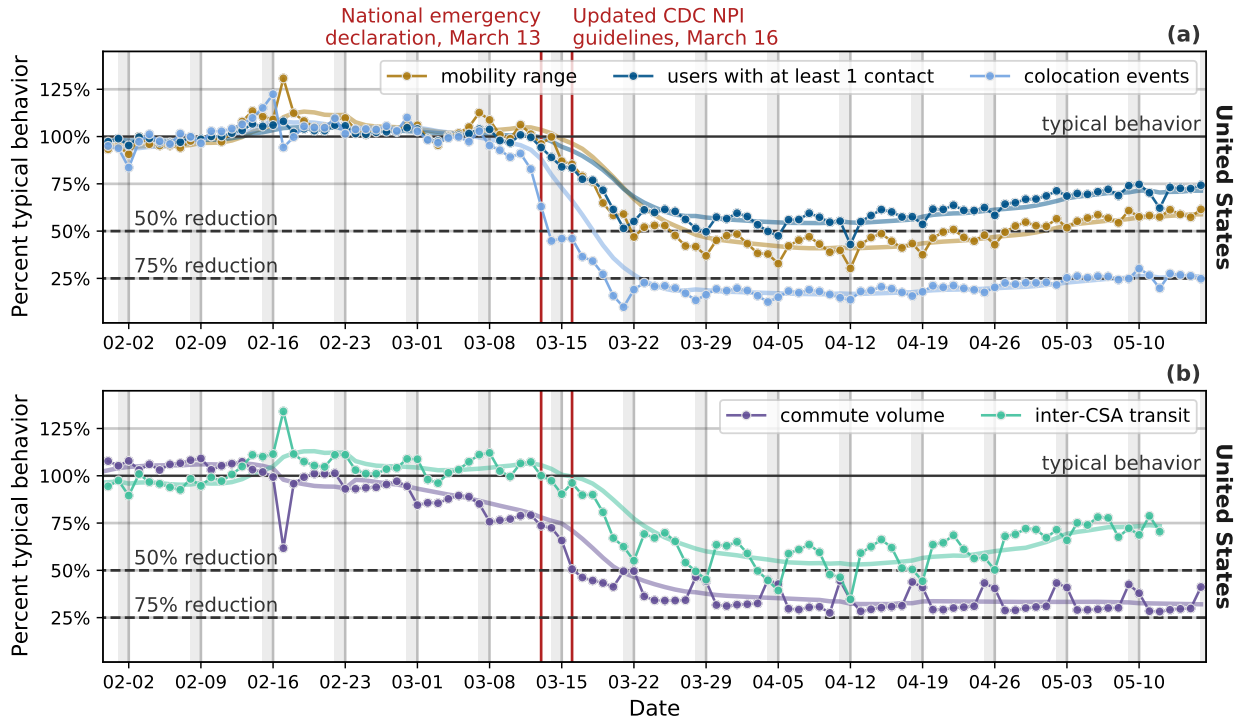
Figure 3: **Change in proxies for mobility and person-to-person contact over time.**
Here we show the percent deviation from typical individual-level behavior and macro-scale
mobility patterns over time in the United States. **(a)** Micro-scale: changes in typical daily
individual mobility, co-location events outside of work and home, and number of unique users
with at least one contact outside of home and work. **(b)** Macro-scale: changes in typical
daily commute volume and inter-CSA transit. By the national declaration of emergency
(March 13), reductions in every measure had begun, reaching at least 45% by April 1. A
7-day rolling average is shown alongside each measure. Shaded areas denote weekends.

the workplace, as the dataset used in this study up-levels these locations in order to preserve
privacy. This means that a user's "home" is assigned to the centroid of the census tract
block group that they reside in, as is their "work" location.

Macro-scale: Changes in commuting volume and inter-city travel

We measure two indicators of macro-scale mobility during the COVID-19 pandemic in the
United States: *commuting volume* between census tracts in the United States, and *inter-
city travel*, defined by the number of users who visit two U.S. Census Bureau Combined
Statistical Areas (CSAs) [36] within 24 hours.

Changes in commuting volume

In general, by May 9, 2020, the average commuting volume—the total number of commutes
within 24 hours in a given county—across United States has been reduced by approximately
65% of the typical daily values (Figure 3b), with the biggest differences observed in early

to mid-April. Every point in Figure 3 corresponds to the fraction of commutes observed that day divided by the average for the same day of the week in earlier weeks before any restrictions were put in place. For example, on federal holidays such as Presidents Day (February 17, 2020), we see a typical drop in commutes corresponding to city wide closures of schools, businesses, and governments in cities where the holiday is officially recognized. Importantly, by March 20, the total number of daily commutes is less than Presidents' Day across all cities included in this analysis.

There are slight individual differences between the reductions in commuting volume in different cities across the country, which can be viewed in the interactive dashboard accompanying this report (`https://covid19.gleamproject.org/mobility`). Quantifying local commuting patterns during the peak of physical distancing in the United States will continue to be useful for understanding the effect that the federal and local governments' guidelines have on reducing mobility. This is especially important as states begin to "reopen" and send employees back to work despite the persistent and heterogeneous growth rates of the number of new COVID-19 cases across the United States.

Changes in inter-city mobility

In order to study the reduction in inter-city travel, we calculated the number of anonymous users who visited at least two separate CSAs in a single day (e.g. a user starts the day in San Francisco and ends the day in Denver), which offers a coarse estimate of long-range travel between major metropolitan areas including, for example, flights, train trips, and long-range road trips. Across all cities included in this report, we observe typical weekday/weekend patterns of mobility between other CSAs, showing more inter-CSA mobility on Fridays, Saturdays, and Sundays. In every CSA included in these analyses, we observe a sharp decline in the number of users traveling between CSAs (Figure 3b). At its peak, the amount of inter-CSA transit among the users in our panel had decreased by almost 50%, on average. These findings are encouraging for modeling and ultimately curtailing the spread of COVID-19, as they indicate a reduced likelihood of inter-city transmission of the virus.

Early May 2020: Signs of fatigue in social distancing

Using our proxy measures for physical distancing and reductions in daily mobility, we see up to 75% reductions in typical mobility and person-to-person interaction patterns. This, broadly speaking, suggests that people across the United States are complying with federal, state, and local guidelines encouraging reduced mobility and contact with others. Based on the panel of users studied in this work, we estimate that the peak of physical distancing behavior took place throughout the middle of April 2020 (based on the seven-day rolling averages plotted in Figure 3).

Physical distancing policies across the United States are broadly popular according to public polling [37]. However as of April 30, several states began to officially "reopen" to varying degrees [16]. Additionally, by late April, there have been anecdotal stories of (relatively) large gatherings of people, social media posts documenting such gatherings, as well as local and national news articles reporting on such gatherings [38]. These types of gatherings range
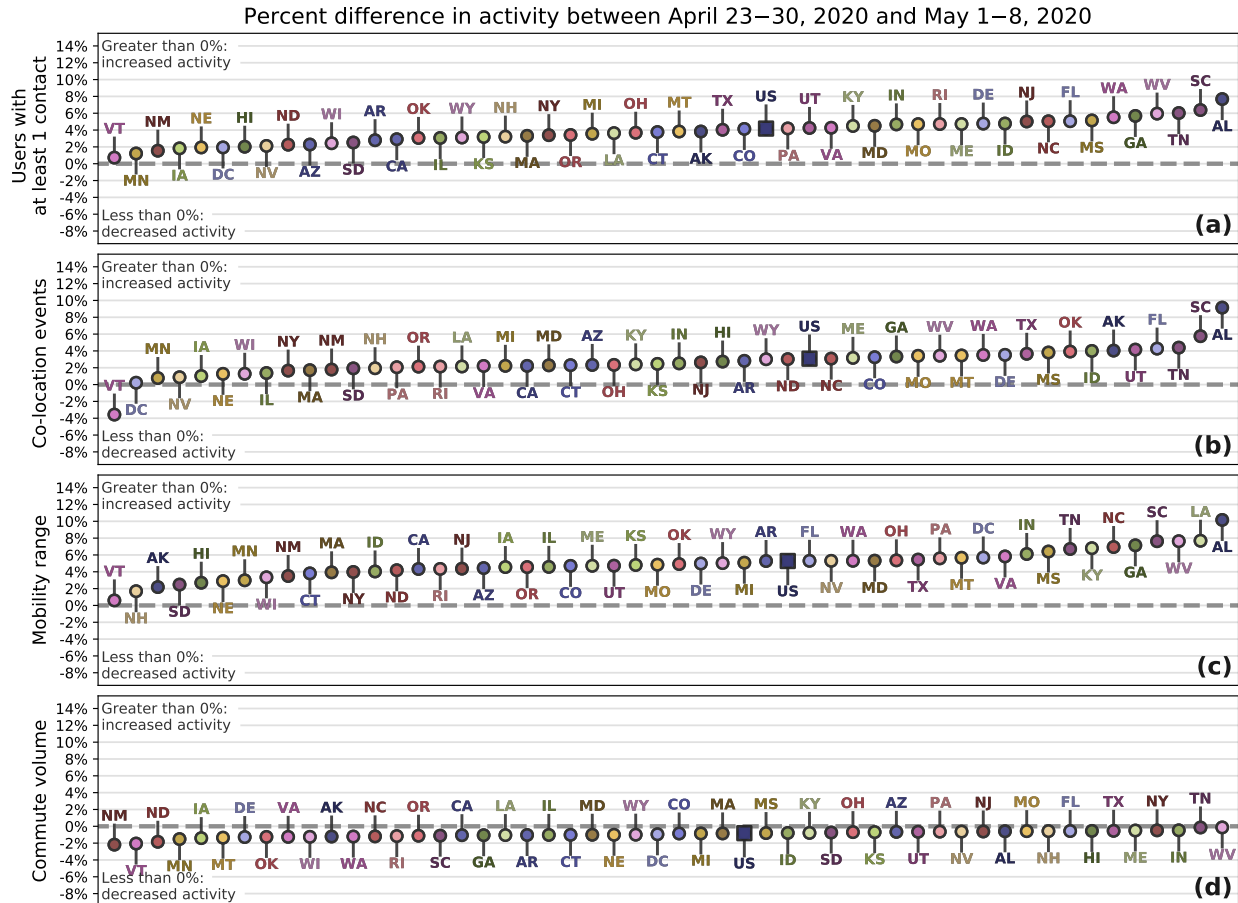
Figure 4: **As of early May 2020, many states show a dampening of physical distancing behavior.** Here we report the differences between behavior between April 23-30 and May 1-8, 2020, by comparing the seven-day rolling averages of four proxies for mobility and physical distancing behavior: **(a)** daily co-location events, **(b)** daily unique users with co-locations, **(c)** daily mobility range, and **(d)** daily commute volume. In these plots, 0% indicates that there was no change between late April and early May; that is, if there was a 50% reductions in mobility statewide as of April 29, then there would still be 50% reductions in early May. In each subplot, the average change for the United States is depicted by a square marker. See Figure 3 for nationwide trends. See Table 1 to access the data that comprise each of these plots.

from gatherings in public spaces such as parks or beaches to gatherings of people protesting physical distancing policies in certain states [39].

As of early May 2020, every state in the United States remains at a fraction of its typical activity across our proxy measures for mobility and physical distancing patterns. However, by comparing the seven-day rolling averages of these proxy measures, we see that people in many states across the United States are beginning show *fatigue* in following physical distancing behaviors (Figure 4). That is, many states are beginning to get closer to their typical mobility patterns, though as of May 9, no state has increased by more than 14% from

late April. The largest increases are seen in the average number of daily co-location events (Figure 4b) and average mobility range (Figure 4c), with the majority of states showing a positive (i.e., closer to typical) change in activity.

Across most states, commute volume continues to either decrease relative to typical patterns or stay the same, with only a few states showing increased commuting volume between May 1 and May 8 (Figure 4d). We cannot assess whether the continued reduction in commuting volume is due to more businesses temporarily or permanently closing, more people losing their jobs or becoming furloughed, or more people remote-working, though we suspect it is a combination of all of these. Further work can be done to better understand the timeline and the effect the federal and local governments' guidelines for both reducing mobility as well as reversing the reductions observed in early May 2020.

Discussion

It is vital to quantify the effect of any major policy intervention, especially in matters of public health. In order to accurately calibrate epidemic models of the COVID-19 pandemic in the United States, we must understand the large-scale, population-wide changes in mobility that have occurred across the United States starting in early and mid-March 2020. In this manuscript, we have taken a step towards estimating these changes. Using high-resolution, anonymized location data from millions of mobile devices, we augment our growing understanding of the effect of work-from-home policies, mobility restrictions, job loss, and shelter-in-place orders on urban and inter-urban mobility.

In short, we quantify physical distancing in the United States. By studying the daily mobility patterns of millions of anonymous mobile phone users, we show that people are limiting their daily interactions with others, possibly also reducing their chances of becoming infected with COVID-19. This is done through a combination of nationwide reductions in commuting volume to/from work as well as heavily reduced inter-urban transit. People's daily social routines have changed dramatically as well, with people's daily mobility being reduced by up to 60%, along with approximately 80% fewer daily co-location events at the peak of physical distancing.

As of early May 2020, we observe slight increases in our proxy measures for physical distancing and mobility patterns, with most states showing an increase in daily co-location events, number of users with at least a contact, and individual range of mobility compared to the last week in April. In states that have partially reopened [16], we see greater increases in these proxy measures for physical distancing, though the true extent and impact of reopening is yet to be determined and it is left for future work. Commuting volume in most states either remains the same or has further decreased from late April to early May. Because we do not see a commensurate increase in commute volume in early May, we hesitate to make strong claims about the nature of the reopening period in the United States. The increases in contacts and mobility could be partially due to a public that has been showing fatigue in maintaining strict social distancing behaviors. Other mobile phone analyses seem to corroborate this finding, as visits to local parks has been increasing since the beginning of April [28]. However, additional work is needed to fully characterize the effect of this uptick in mobility.

These massive efforts to comply with the CDC's physical distancing guidelines have come at a substantial cost to the economic and social health of people in the United States. Additionally, despite these large-scale physical distancing measures and reductions in mobility, the United States nonetheless has reported over one million cases of COVID-19 and, as of May 11, 2020, has over 80,000 reported deaths (with estimates of the true number being much higher [40]). This suggests that mere physical distancing is insufficient without a vigorous testing and contact tracing regimen [41], as seen in countries like South Korea, Taiwan, and China.

Recent work has shown that a more nuanced understanding of typical human mixing patterns can have dramatic effects on the spread of a disease and our models of the spread of a disease; it is particularly useful to understand age-based, setting-specific contact patterns within a population [42, 4]. That is, if a common cold is spreading among youngsters in a school setting, their parents are more likely to become infected with the virus; in cultures where grandparents commonly reside with *their* children, we might expect the virus to have a relatively higher effect. In the context of COVID-19, understanding these age-based contact patterns within households, workplaces, schools, and within the community is especially important, given the fact that the virus appears to be particularly deadly for older adults [43]. The current study is limited by the absence of this data, and in many ways traditional surveying methods can offer more robust estimates (see [4]).

In addition, in this study we are currently not linking socio-demographic characteristics to the users we monitor, and therefore we are not controlling for features such as age distribution or socio-economic status. This constitutes a limitation of the current approach since it precludes us from exploring the correlations that exist between the aggregate behavior of individuals and their characteristics. Indeed, we do not know individual socio-demographic information about the users in our sample, and this is by design to ensure protection of user privacy. Lastly, vulnerable populations are excluded from this data (in particular, children and incarcerated individuals). For this reason, we are leaving for future work to explore ways to link our user base to aggregate US Census Tract statistics.

Materials & Methods

Mobility data are provided by Cuebiq, a location intelligence and measurement platform. Through its Data for Good program (`https://www.cuebiq.com/about/data-for-good/`), Cuebiq provides access to aggregated and privacy-enhanced mobility data for academic research and humanitarian initiatives. These first-party data are collected from users who have opted in to provide access to their GPS location data anonymously, through a GDPR-compliant framework. Additionally, Cuebiq provides an estimate of home and work census areas for each user. In order to preserve privacy, noise is added to these "personal areas", by upleveling these areas to the Census block group level [36]. This allows for demographic analysis while obfuscating the true home location of anonymous users and preventing misuse of data.

The method of data collection is dependent on the operating system of the device. In this report, we do not systematically distinguish between users based on the operating system of their mobile device; however, we observe that the proportions of users of each operating

system are relatively even, and this distribution is similar across cities. Most of the aggregate behavioral measures that we report do not exhibit major discrepancies when limited to operating system; though there remain under-explored correlations between operating system and aggregated socio-demographic characteristics of the users that could impact people's ability to comply with the CDC's physical distancing guidelines.

Calculating individual-level changes in mobility in the U.S.

Estimating the change in individual mobility using the radius of gyration

As defined in [35], the radius of gyration characterizes the extent of a given user's trajectory in a single day. It measures the mean square distance from the trajectory's center of mass to the locations reached that day. Formally,

$$r = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \|\vec{r}_i - \vec{r}_{cm}\|^2}, \tag{1}$$

where n is the user's number of observations on that day, $\vec{r}_i$ is the ith observed position of the user, $i = 1, 2, ..., n$, and $\vec{r}_{cm} = \sum_i \vec{r}_i / n$ is the center of mass of the trajectory. A larger radius of gyration corresponds to a trajectory with positions that are far away from the trajectory's average position. In the current context, a smaller radius of gyration indicates that a user travels less distance away from their daily average position in a city. In order to compute typical mobility within a given region, we sum the total daily radius of gyration that by users in that region within 24-hour periods of time.

Estimating the change in daily contact events outside home and work

The method for constructing the co-location events is as follows. First, we split each day into five minute time windows, resulting in 288 time bins per day. For every location event, we use its timestamp to assign it to a time bin, then assign the longitude-latitude coordinate of the observation to an 8-character string known as a *geohash*. A geohash defines an approximate grid covering the earth, the area of which varies with latitude. The largest dimensions of an 8-character geohash are 38m x 19m, at the equator [44]. If a user does not have an observation for a given time bin, we carry the last observation forward until there is another observation. We finally define two users to be co-located if they are observed in the same geohash in the same time bin. Note that users may be observed at multiple locations per time bin and will be considered co-located with other users in each unique location they visit in the five minute window, regardless of the exact timing or sequence of those visits. The general approach is described through an example in Figure 5. We compute the *total* co-location events and the total number of unique users with at least one co-location event, summing within states, then nationally.

Estimating the change in the daily commute volume

In order to quantify the changes in commuting behavior to and from work, we first filter our panel of users to include only those who have at least two (privacy-preserving) "personal

Figure content:

Device A: Location data

Time	Location
11:09:55	Home
11:12:04	Sidewalk
11:14:23	Café
11:31:20	Sidewalk
11:35:13	Sidewalk
11:38:12	Gym
12:02:45	Gym
12:03:55	Sidewalk
12:07:55	Lunch
12:11:12	Lunch
12:14:51	Sidewalk
12:18:01	Work

* Note: "Gym" and "Gym" are the same location, but they occupy different geohash locations.

Device A: Time-binned data | | | **Device B: Time-binned data**

Device A bin	Device A loc	Colocation	Device B loc	Device B bin
11:05 - 11:09	Home X		X Home	11:05 - 11:09
11:10 - 11:14	Sidewalk, Café		X Home	11:10 - 11:14
11:15 - 11:19	Café		~~Home~~, Sidewalk	11:15 - 11:19 *
11:20 - 11:24	Café	Colocation	Café	11:20 - 11:24
11:25 - 11:29	Café	Colocation	Café	11:25 - 11:29
11:30 - 11:34	Sidewalk	Colocation	Café, Sidewalk	11:30 - 11:34
11:35 - 11:39	Sidewalk, Gym		Café	11:35 - 11:39
11:40 - 11:44	Gym		Café	11:40 - 11:44
11:45 - 11:49	Gym		Café, Sidewalk	11:45 - 11:49
11:50 - 11:54	Gym		X Home	11:50 - 11:54
11:55 - 11:59	Gym		X Home	11:55 - 11:59
* 12:00 - 12:04	Gym, Sidewalk		X Home	12:00 - 12:04
12:05 - 12:09	Lunch		X Home	12:05 - 12:09
12:10 - 12:14	Lunch, Sidewalk		X Home	12:10 - 12:14
12:15 - 12:19	Work X		Sidewalk, ~~Work~~	12:15 - 12:19 *
12:20 - 12:24	Work X		X Work	12:20 - 12:24

Device B: Location data

Time	Location
11:15:09	Home
11:18:04	Sidewalk
11:23:04	Café
11:45:04	Café
11:48:30	Sidewalk
11:52:09	Home
12:12:36	Home
12:15:30	Sidewalk
12:18:32	Work

* Note: "Home" & "Work" are not used for estimating colocation. But if another location is listed in the same time bin, it is used for estimating colocation.

Hour of day:
00 | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 | 09 | 10 | **11** | **12** | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23

Example timeline of device location and device colocation estimation

X "Work" and "Home" used for illustration purposes only. Cuebiq data refers to these as "personal areas" and are up-leveled / differentially-private.
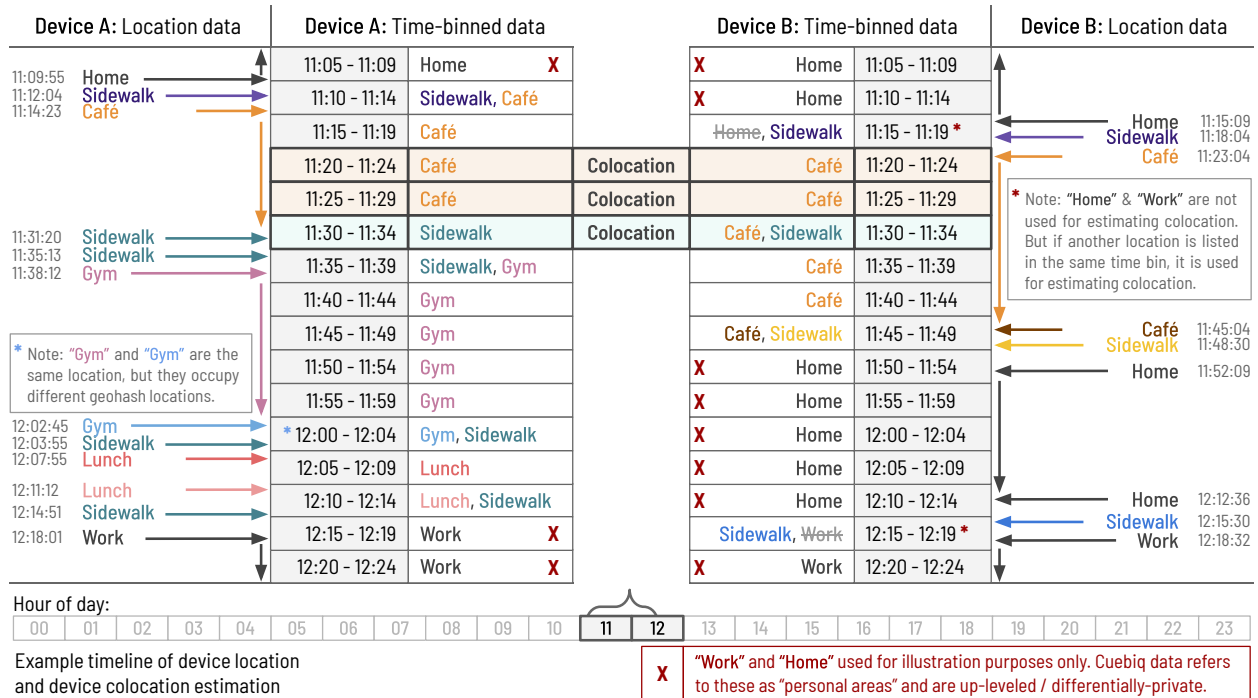
Figure 5: **Illustration of co-location estimation technique.** In this example, two users' mobile devices ping at periodic intervals, reporting their location throughout a given day. We highlight a window of time between 11:05am and 12:25pm, noting how observations are carried forward in time if a device does not ping within every five-minute time bin. Users can be listed in two locations during the same time bin. Home and Work locations are up-leveled to preserve user privacy and are therefore not included in our estimates of co-location events. Note: For expedience in this figure, we used interpretable location names instead of raw coordinates; the data does not include amenity information like "lunch" or "café".

areas", which are then defined as the most commonly-visited geohash during daytime hours (9:00am - 5:00pm, which we refer to as "work") and nighttime hours (8:00pm - 4:00am, which we refer to as "home") by users in the panel; this method is imperfect (i.e., it may obfuscate users who exclusively work night shifts), but it is based on assumptions about the typical worker in the United States. These personal areas are then up-leveled in order to preserve user privacy. That is, these coordinates are aggregated to the centroid of the census tract that each observation falls into. One *commute*, then, is defined as a user visiting their "home" and "work" in a given day.

Estimating the change in inter-CSA transit

As described previously, we estimate the change in inter-CSA transit by calculating the number of anonymous users who visited at least two separate CSAs in a single day. Such inter-CSA transit could be from long-range commutes, from travel (i.e., on federal holidays, such as Presidents' Day in February, we observe a spike in inter-CSA transit, suggesting tourism or vacation), or other miscellaneous transit including, for example, airline travel, train or bus trips, or long-range road trips.

State	Contacts	Co-locations	Mobility	Commutes
AK	7.695%	5.588%	6.673%	-0.439%
AL	10.487%	7.456%	12.536%	0.328%
AR	6.509%	3.969%	7.152%	-0.504%
AZ	3.340%	2.435%	6.353%	-0.554%
CA	4.542%	2.789%	5.349%	-0.440%
CO	7.745%	4.617%	7.248%	-0.021%
CT	7.285%	3.374%	5.023%	-0.069%
DC	2.999%	0.346%	3.346%	-0.385%
DE	6.414%	3.825%	6.370%	-0.223%
FL	7.189%	4.109%	7.936%	0.171%
GA	9.586%	5.017%	9.197%	0.092%
HI	3.260%	2.755%	4.813%	-0.024%
IA	6.036%	2.700%	6.159%	-0.866%
ID	6.644%	4.759%	5.905%	-0.322%
IL	6.190%	2.664%	7.128%	-0.392%
IN	7.569%	3.249%	7.401%	0.037%
KS	6.513%	3.746%	7.366%	-0.160%
KY	7.370%	3.414%	6.760%	-0.392%
LA	6.370%	3.320%	8.643%	-0.284%
MA	6.173%	2.495%	4.885%	0.300%
MD	5.331%	2.206%	5.507%	-0.633%
ME	4.721%	2.293%	4.469%	-0.066%
MI	11.692%	4.852%	10.380%	-0.084%
MN	6.630%	2.733%	6.470%	-0.857%
MO	8.139%	4.222%	7.571%	-0.298%
MS	8.092%	4.234%	9.299%	0.303%
MT	8.605%	6.577%	8.407%	0.252%
NC	7.327%	3.915%	7.797%	-0.605%
ND	6.099%	4.019%	6.192%	0.017%
NE	4.515%	2.256%	4.808%	-0.333%
NH	6.525%	3.215%	6.144%	-0.201%
NJ	7.413%	3.435%	5.710%	0.065%
NM	4.219%	3.163%	5.274%	-0.300%
NV	3.562%	1.355%	7.123%	-0.379%
NY	6.727%	2.382%	5.262%	0.141%
OH	7.026%	3.312%	7.406%	-0.105%
OK	8.438%	6.311%	7.644%	0.289%
OR	4.688%	2.900%	5.257%	-0.921%
PA	7.254%	2.845%	6.852%	-0.208%
RI	7.359%	3.131%	5.310%	-0.361%
SC	9.165%	6.609%	9.045%	0.008%
SD	7.072%	3.943%	7.290%	-0.342%
TN	9.787%	5.256%	9.107%	0.462%
TX	6.467%	4.400%	7.318%	0.232%
US	7.121%	3.815%	7.147%	-0.135%
UT	6.912%	5.106%	7.706%	-0.615%
VA	5.970%	2.747%	5.932%	-0.726%
VT	3.717%	-2.343%	4.782%	0.888%
WA	5.011%	2.720%	4.620%	-0.553%
WI	8.246%	3.647%	6.802%	-0.753%
WV	7.506%	3.817%	7.438%	0.365%
WY	6.520%	5.560%	7.329%	-0.022%

Table 1: **Changes in activity in early May 2020.** Data are reported as the percent difference in activity between the average of April 23-30 and May 1-8, 2020.

References

[1] S. Lai, *et al.*, *Nature* (2020).

[2] M. Chinazzi, *et al.*, *Science* **368** (2020).

[3] M. U. G. Kraemer, *et al.*, *Science* **368**, 493 (2020).

[4] J. Zhang, *et al.*, *Science* (2020).

[5] H. Regan, Italy announces lockdown as global coronavirus cases surpass 105,000, `https://www.cnn.com/2020/03/08/asia/coronavirus-covid-19-update-intl-hnk/index.html` (2020).

[6] Johns Hopkins Coronavirus Resource Center, New Cases of COVID-19 In World Countries, `https://coronavirus.jhu.edu/data/new-cases` (2020).

[7] E. Pepe, *et al.*, *medRxiv* (2020).

[8] D. Cereda, *et al.*, *arXiv* (2020).

[9] World Health Organization, Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19), `https://www.who.int/publications-detail/report-of-the-who-china-joint-mission-on-coronavirus-disease-2019-(covid-19)` (2020).

[10] H. Tian, *et al.*, *Science* (2020).

[11] M. Fisher, C. Sang-Hun, How South Korea Flattened the Curve, `https://nyti.ms/3aeD35c` (2020).

[12] D. Normile, Coronavirus cases have dropped sharply in South Korea. What's the secret to its success?, `https://doi.org/10.1126/science.abb7566` (2020).

[13] European Commission, Coronavirus response: Transport measures, `https://ec.europa.eu/transport/coronavirus-response_en` (2020).

[14] The White House, Coronavirus Guidelines for America, `https://www.whitehouse.gov/briefings-statements/coronavirus-guidelines-america/` (2020).

[15] S. Mervosh, D. Lu, V. Swales, See Which States and Cities Have Told Residents to Stay at Home, `https://nyti.ms/2y5j9LN` (2020).

[16] S. Mervosh, J. C. Lee, L. Gamio, N. Popovich, See Which States Are Reopening and Which Are Still Shut Down, `https://nyti.ms/2Y37Ezj` (2020).

[17] U.S. Bureau of Labor Statistics, Workers who could work at home, did work at home, and were paid for work at home, by selected characteristics, averages for the period 2017-2018, `https://www.bls.gov/news.release/flex2.t01.htm` (2019).

[18] C. Kang, D. Alba, A. Satariano, Surging Traffic Is Slowing Down Our Internet, `https://nyti.ms/3amTGeO` (2020).

[19] U.S. Department of Labor, April 30, 2020: Unemployment insurance weekly claims report, `https://www.dol.gov/sites/dolgov/files/OPA/newsreleases/ui-claims/20200774.pdf` (2020).

[20] N. Oliver, *et al.*, *Science Advances* **0764** (2020).

[21] Y. A. de Montjoye, *et al.*, *Scientific Data* **5**, 1 (2018).

[22] C. O. Buckee, *et al.*, *Science* **368**, 145 (2020).

[23] M. Bakker, A. Berke, M. Groh, A. S. Pentland, E. Moro, Social Distancing in New York City, `http://curveflattening.media.mit.edu/posts/social-distancing-new-york-city/` (2020).

[24] D. Martín-Calvo, A. Aleta, A. Pentland, Y. Moreno, E. Moro, Effectiveness of social distancing strategies for protecting a community from a pandemic with a data-driven contact network based on census and real-world mobility data, `https://covid-19-sds.github.io/` (2020).

[25] J. Glanz, *et al.*, Where America Didn't Stay Home Even as the Virus Spread, `https://nyti.ms/3aAql0E` (2020).

[26] J. Valentino-DeVries, D. Lu, G. J. Dance, Location Data Says It All: Staying at Home During Coronavirus Is a Luxury, `https://www.nytimes.com/interactive/2020/04/03/us/coronavirus-stay-home-rich-poor.html` (2020).

[27] C. Canipe, The social distancing of America, `https://graphics.reuters.com/HEALTH-CORONAVIRUS/USA/qmypmkmwpra/index.html` (2020).

[28] Google, See how your community is moving around differently due to COVID-19, `https://www.google.com/covid19/mobility/` (2020).

[29] S. Gao, *et al.*, *arXiv* (2020).

[30] United States Department of Commerce, Advance monthly sales for retail trade and food services, `https://www.census.gov/retail/marts/www/marts_current.pdf` (2020).

[31] D. Balcan, *et al.*, *Proceedings of the National Academy of Sciences* **106**, 21484 (2009).

[32] D. Balcan, *et al.*, *Journal of Computational Science* **1**, 132 (2010).

[33] M. F. Gomes, *et al.*, *PLoS Currents* **6** (2014).

[34] Q. Zhang, *et al.*, *Proceedings of the National Academy of Sciences* **114**, E4334 (2017).

[35] M. C. González, C. A. Hidalgo, A.-L. Barabási, *Nature* **453**, 779 (2008).

[36] United States Census Department, Glossary, `https : / / www . census . gov / programs-surveys/geography/about/glossary.html` (2019).

[37] D. Lazer, *et al.*, The State of the Nation: A 50-State COVID-19 Survey, `https:// covidstates.org/` (2020).

[38] J. Goldstein, C. Kilgannon, Balmy Weekend Presents a Challenge: New Yorkers Rushing to Parks, `https://nyti.ms/2YqTrwn` (2020).

[39] M. Martina, S. Herald, Hundreds protest in Michigan seeking end to governor's emergency powers, `https://reut.rs/2yT9Sqt` (2020).

[40] J. Katz, D. Lu, M. Sanger-Katz, U.S. Coronavirus Death Toll Is Far Higher Than Reported, C.D.C. Data Suggests, `https://nyti.ms/2ybWxtp` (2020).

[41] A. Aleta, *et al.*, *arXiv* pp. 1–31 (2020).

[42] D. Mistry, *et al.*, *arXiv* pp. 1–18 (2020).

[43] F. Zhou, *et al.*, *The Lancet* **395**, 1054 (2020).

[44] G. Niemeyer, Geohash, `https://en.wikipedia.org/wiki/Geohash` (2008).

Acknowledgements