Policy and weather influences on mobility during the early US COVID-19 pandemic

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As the novel coronavirus severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) continues to proliferate across the globe, it is a struggle to predict and prevent its spread. The successes of mobility interventions demonstrate how policies can help limit the person-to-person interactions that are essential to infection. With significant community spread, experts predict this virus will continue to be a threat until safe and effective vaccines have been developed and widely deployed. We aim to understand mobility changes during the first major quarantine period in the United States, measured via mobile device tracking, by assessing how people changed their behavior in response to policies and to weather. Here, we show that consistent national messaging was associated with consistent national behavioral change, regardless of local policy. Furthermore, although human behavior did vary with outdoor air temperature, these variations were not associated with variations in a proxy for the rate of encounters between people. The independence of encounters and temperatures suggests that weather-related behavioral changes will, in many cases, be of limited relevance for SARS-CoV-2 transmission dynamics. Both of these results are encouraging for the potential of clear national messaging to help contain any future pandemics, and possibly to help contain COVID-19.

COVID-19 | United States | policy | weather | mobility

On March 13, 2020, US President Donald Trump announced a state of emergency and a ban on travel from 26 European countries (1). Soon thereafter, a national stay-at-home guideline was issued on March 16 (2). Every state announced school closures between March 16 and March 23 (3), rendering March 21–22 the first weekend within this school and workplace closure period. Since response to the virus in the United States has been widely politicized (4, 5), we examine how human behavior, reflected through mobility changes, responded to policies that aimed to limit person-to-person interactions (6). Because COVID-19 will remain dangerous until safe and effective vaccines are widely distributed (7), mobility interventions are crucial and have been successful in other countries (8). Fig. 1*A* shows the timing of statewide policies and of a variety of mobility changes. As a proxy for the number of people who may have come face to face, potential encounter rate is a mobility metric, measuring the number of devices that come within 50 m of each other (9) (see more discussion in *Materials and Methods*). We compute the mobility changes by identifying change points in the potential encounter rate time series from February 24 (the start of data availability) to May 22. Change points are identified by locating the times of greatest change and finding the nearest local minima (see *Materials and Methods*). The grocery visitation maxima (Fig. 1*A*, yellow) are derived from the grocery and pharmacy visits of the Google Community Mobility Reports (10), while all other mobility metrics are calculated from Unacast (11) potential person-to-person encounter rates.

Within a few days of the March 13 presidential announcement, every state in the nation had a peak in trips to the grocery store and pharmacy (Fig. 1*A*, yellow). Following the issuance of a national stay-at-home guideline and school closures, almost all states achieved their maximum decrease in mobility (Fig. 1*A*, red) on Saturday March 21, marking the effective beginning of a stay-at-home period nationwide. Although many states delayed implementing stay-at-home orders, there was near uniformity in the beginning and ending of quarantine behavior across states. The distinction between the nationally coherent timing of the grocery peak (yellow) and encounter decrease (red) and the scattershot timing of when state policies were put into place (Fig. 1*A*, blue) is striking. Again, we note that there were numerous factors at play at this time, with school closings being particularly important. Therefore, this consistency in timing of the quarantine start does not necessarily relate directly to the national guidance. Indeed, inspection of mobility time series for individual states suggests that, in many states, mobility was beginning to decline prior to the national state of emergency and stay-at-home guidelines.

On May 1, US national stay-at-home guidelines expired (12), but schools and many workplaces remained closed (3). Nevertheless, there was nationally coherent timing of potential encounter increases (Fig. 1*A*, pink), in contrast to the varied timings of state stay-at-home order expirations (Fig. 1*A*, cyan) and of state reopening plan implementations (Fig. 1*A*, green). To further examine the national coherence of the potential encounter decrease (red) and potential encounter increase (pink), we use county-level Unacast potential encounter data. Out of 3,054 counties for which Unacast had data, 1,881 counties had March 21 as the beginning of quarantine behavior, and a total of 2,536 counties had its beginning in the 3-d span of March 21–23, comprising 83% of the total number of counties; 1,431 counties had May 2 as the end of

Significance

This study investigates mobility changes during the first major quarantine period in response to the COVID-19 pandemic in the United States, assessing how human behavior changed in response to policies and to weather. Through mobility metrics based on tracking mobile devices, we show that consistent national behavioral change was associated with clear national messaging and independent of local policy. While the number of park visitations changed with weather conditions, generally, the changes apparently did not increase potential encounters between people. The independence of encounters and temperatures suggests that, if these results hold in the future, behavioral responses to short-term temperature variations may have, at most, a limited impact relative to any direct physical modulation of transmission by weather as the virus becomes endemic.

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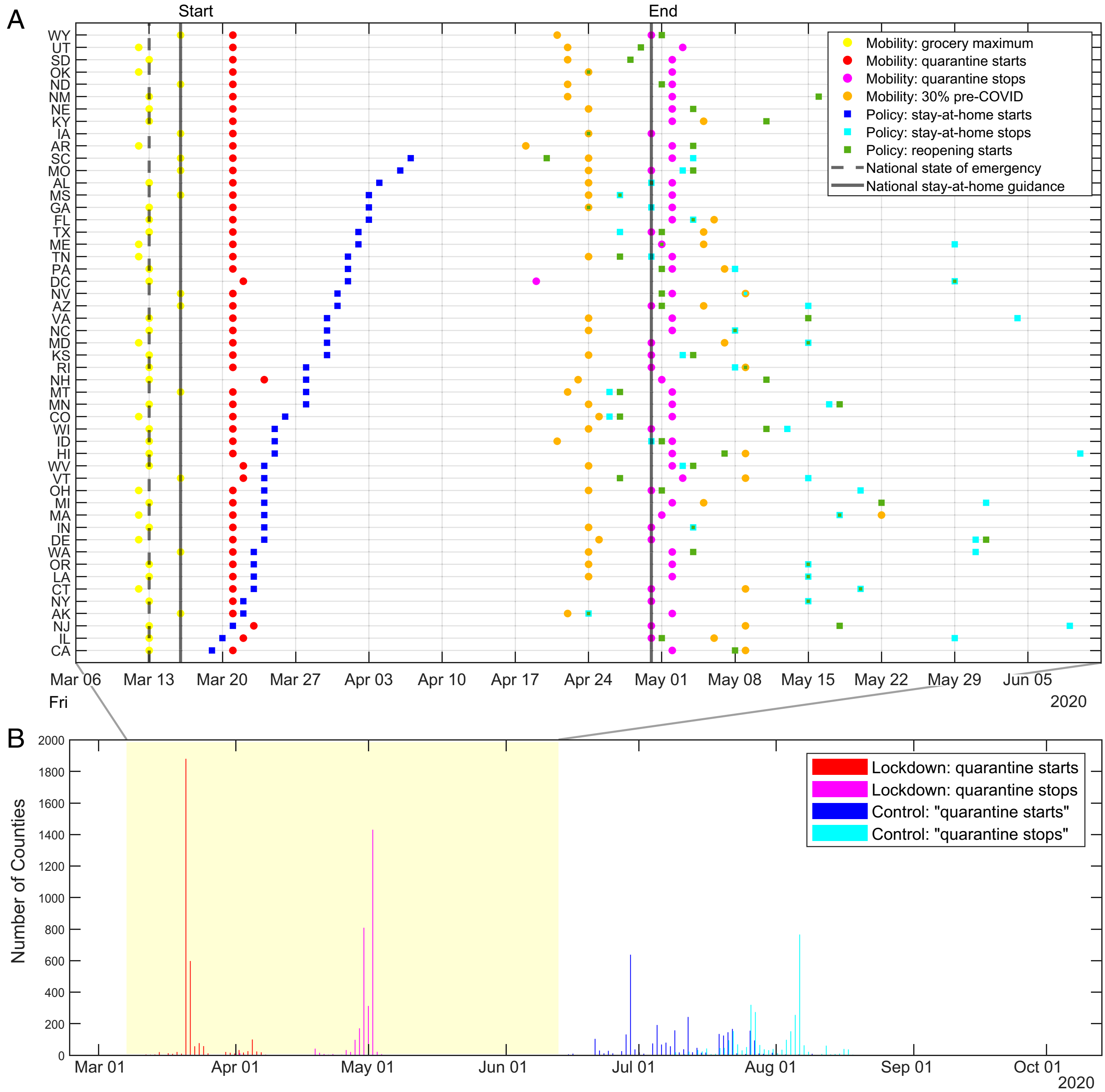

Fig. 1. (*A*) Implementation of state policies and changes in mobility behavior, ordered by date of stay-at-home orders. Warm-colored circles are metrics based on mobility: peaks in grocery visitation (yellow), beginning of quarantine based on mobility (red), timing when mobility reaches 30% of prepandemic values (orange), and the end of quarantine based on mobility (pink). Cool-colored squares are policy implementations: date of implementation of stay-at-home for each state (blue), date of expiration of stay-at-home (cyan), and date of implementation of reopening plans (green). Black lines are national declarations: the announcement of a national state of emergency (dashed), and the start and end of national stay-at-home guidelines (solid). For details about mobility metrics, see *Materials and Methods*. (*B*) Bar graph of county-level changes in mobility behavior, using real quarantine time series (red, pink) and control time series (blue, cyan).

quarantine behavior, and a total of 2,553 counties had April 30 to May 2, a span of 3 d, also comprising 84% of total counties. As a consistency check, similar results were obtained using the county-level Cuebiq Mobility Index (13), a metric of distance traveled by mobile devices.

To determine whether this degree of spatial coherence in mobility changes is unusual for the United States, we employ the same algorithm on a subsequent encounter rate time series of equal length (June 1 to August 28) to test whether a similar consistency is observed for any other dates. We find that the most common date selected from these control series as the "beginning of quarantine behavior" was June 29, with a frequency of only 638 counties. In the 3-d span June 28–30, only 26% of counties "began quarantine," substantially fewer than during the actual quarantine beginning on March 21–22. Similarly, the most common date designated as "end of quarantine behavior" was August 6, with a frequency of only 766 counties and with 38% of counties included in the surrounding 3-d span.

These findings are illustrated in Fig. 1*B*, showing that the state-level coherence of quarantine start and stop demonstrated in Fig. 1*A* is visible even at the county level. The distributions of the quarantine start and stop points in the spring do not overlap and are quite sharply peaked, while the mobility change point distributions computed from the summer control series are broader and overlap.

While the timings of the dramatic encounter decreases and increases are consistent, many states had already reached encounter rates that were 30% of their prepandemic values (Fig. 1*A*, orange) before quarantine behaviors ceased (Fig. 1*A*, pink), suggesting variability across states in people's behaviors and encounters during the quarantine period. Most of these states experienced a new surge in COVID-19 cases in July (14), consistent with studies that argue that an early reopening led to this new wave (15, 16). Dates of reaching 30% of prepandemic potential encounter rate are not correlated with implementation dates of reopening plans ($R^2 = 0.062$) or with expirations of stay-at-home orders ($R^2 = 0.049$), which is further evidence that mobility behaviors are substantially independent of state policies. The consistency across mobility measures suggests the primacy of national awareness and national guidelines over state policies in determining human behavior.

How Did Mobility Change?

We explore how mobility changed over time in the United States during spring 2020, and, as part of this analysis, we examine how the average distance traveled (as a fractional change from a location-specific baseline) and the encounter rates (as a change from a national baseline) changed over time.

Encounter rates are computed based on the number of times mobile devices approach each other to within a distance of 50 m (see *Materials and Methods*). Although this range is substantially larger than that over which the close personal contact believed to be most relevant to COVID-19 spread takes place, we expect even this coarse-resolution encounters metric to be more relevant to disease spread than distance traveled—hence our interest in discovering any functional relationship between these two quantities.

We identify a compact, nonlinear relationship between the distance traveled and the encounter rate, which is fitted to an exponential curve,

$$Rate = a \cdot exp(b \cdot Distance),$$

where a is a proportionality constant and b is a growth rate (see *Materials and Methods*). The exponential relationship is supported by high R^2 values across the states (see *SI Appendix*, Fig. S1 for examples of the exponential fit, and see *SI Appendix*, Fig. S2 for R^2). In Fig. 2, we show the spatial distribution of these two coefficients on the state level and their relationships with population density on the county level (see *SI Appendix*, Fig. S3 for county coefficient maps and state population density scatterplots). There is a high correlation between a and the population density, which follows naturally from the definition of encounter rates (see *Materials and Methods* for details); the places that are densely populated naturally have higher encounter rate values compared to the national baseline, resulting in a higher coefficient a ($R^2 = 0.84$).

In contrast, the coefficient b is fairly consistent across states, with a mean of 3.40 and SD of 0.56 (county level: mean 3.10, SD 0.71); b has a significantly weaker correlation with population density ($R^2 = 0.15$ at the county level and 0.21 at the state level). While this part of our analysis was conducted with data starting on February 24 and ending on June 6, incorporating data through July 15 shows that the exponential relationship holds well. The exponential relationship may have implications for the choice of functional form for any investigations of links between the more commonly available distance traveled and disease spread. This nonlinear relationship suggests that the initial decrease in distance traveled (and associated strong drop in encounter rate) was due to a preferential reduction in visits to places associated with relatively high encounter rates.

Effects of Weather on Mobility

Having demonstrated the consistency of mobility behavior with national policy and the spatial coherence of mobility changes with time, we explore the impact of weather on mobility under

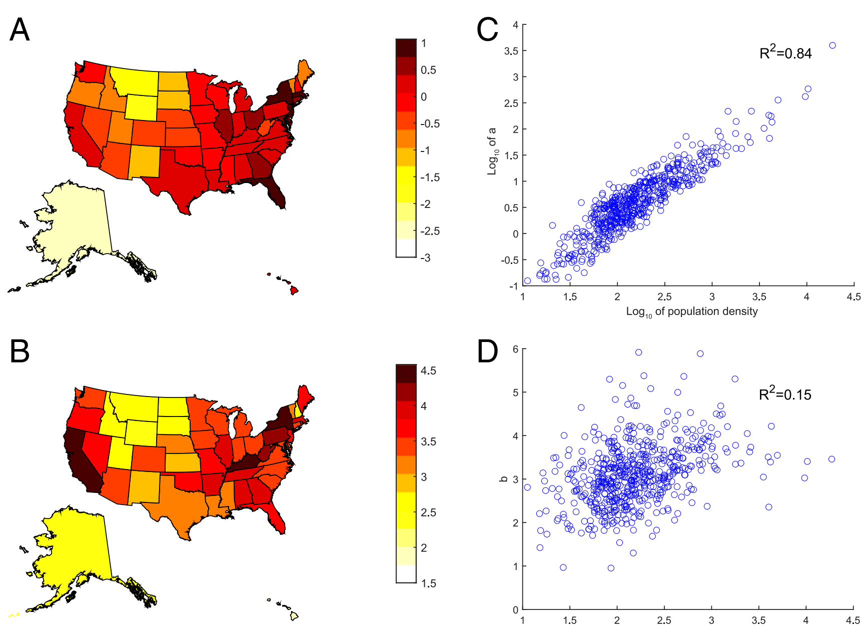

Fig. 2. (*A*) Map of $\log_{10}$ of leading coefficient a and (*B*) map of coefficient b on the state level. In *A*, the value for Washington, DC ($\log_{10} a = 2.26$) is not shown. Scatter plots of coefficients at the county level are shown against the $\log_{10}$ of population density for $\log_{10} a$ in *C* and for b in *D*.

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stay-at-home conditions (March 23 to May 1). Since it is intuitively reasonable to think that people tend to engage in more activities away from home in nicer weather, we want to understand whether people maintain low encounter rates and continue respecting policy under such conditions. Past work has shown a weak effect of temperature on human mobility and behavior (17, 18), but other types of weather (e.g., rain) are more important (19, 20). We aim to understand whether human mobility is correlated with temperature under the COVID-19 stay-at-home conditions.

For many respiratory illnesses, such as influenza (21) and the endemic coronaviruses (22, 23), transmission has a strong seasonal component, with a clear link to atmospheric conditions in the case of influenza (24, 25). Although the wide range of weather conditions in locations of COVID-19 outbreaks belies the possibility of strong modulation of this initial occurrence of the disease, such modulation is likely to impact recurrence if the susceptible population is decreased (26–28). Investigations of possible temperature and humidity effects on COVID-19 transmission have produced conflicting results, with some studies showing no apparent relationship (29, 30) and others suggesting decreased transmission at warmer temperatures (31–33). Furthermore, a single-city study found warmer temperatures and low precipitation to be positively correlated with COVID-19 incidence, perhaps due to disregard of stay-at-home orders in good weather (34). By studying the relationship between weather conditions and mobility, we find no evidence for the hypothesized disregard of policy in good weather.

We analyze the correlation of weather with park visitation and encounter rate at the state level under stay-at-home conditions (March 23 to May 1). Previous studies show that mobility and encounter rates are suppressed on days with rainfall (19, 35). Therefore, we omit rain days from our correlation calculation. We high-pass filtered the weather and mobility time series to remove seasonal trends (see *Materials and Methods*). Fig. 3 shows a weakly positive correlation between temperature and park visitation but a lack of correlation between temperature and encounter rate. In other words, while people in some states change their behavior to visit parks more when temperatures are higher, in line with previous work (16, 35), their potential encounter rates do not significantly increase. Note that, because this analysis was performed only for the quarantine time period and during a limited season, the specific correlations cannot be easily extrapolated to other times of year or social conditions. The significance of the correlations is evaluated based on comparing the correlations with state-specific null distributions of correlation values constructed from the previous 70 y of weather data (see *Materials and Methods* for details).

There are spatial variations in temperature correlation with park visitation, which is positive in the northeast and central plains states and negative in Alabama, Louisiana, and Florida, though these correlations were not significant at the 90% level. The spatial differences are plausibly due to warmer days being more suitable for outdoor activity in the northern states but less suitable in the southern states because warm days in the latter region are excessively hot (or perhaps humid). While a parabolic fit could, in principle, capture a threshold above which temperature is hot enough to suppress outdoor activity, in practice, no region had a temperature range large enough to reliably estimate this threshold (36). In Fig. 3*C*, Florida exhibits a negative correlation between temperature and encounters. Similar trends for correlations between temperature and encounters are observed on the county level, which adds nuance to the overall picture of weak correlations between temperature and encounters (*SI Appendix*, Fig. S4). Note, however, that the magnitude of these correlations is typically quite low and rarely above 0.5 (the total variance explained is up to 25%), and areas with a correlation above 0.5 are not densely populated (population density less than 100 people per km^2; *SI Appendix*, Fig. S4).

It is reasonable to wonder whether the identification of many states with significant temperature–mobility correlations is simply an artifact of the large number of tests conducted and the existence of spatial and temporal autocorrelations in the weather data. To address this multiple comparison problem, we also analyze each of the 70 prepandemic years of weather data to determine the number of states typically detected as showing "significant" correlations between these earlier weather time series and the 2020 mobility data. These "significant" correlations are necessarily coincidental, and the numbers of states with such correlations in the prepandemic years therefore provide a baseline against which the number of states with significant 2020 correlations can be assessed.

Park visitation was significantly correlated with actual 2020 temperatures in 17 states, but its correlations with any previous year of temperature data are significant in, at most, 10 states and typically 5 or fewer (Fig. 3*B*). In contrast, the number of states in which the correlation between 2020 temperature and potential encounters is significant (one) is well within the range of what could have happened by chance in the absence of any causal effect. Correlations with previous years of weather data often yield two or more "significant" states (Fig. 3*D*). We thus conclude that our analyses provide evidence for a real effect of temperature on park visitation, but no evidence for an effect of temperature on potential encounters. (An additional statistical analysis yielding the same qualitative conclusion is discussed in *SI Appendix*.)

The correlation between temperature and park visitation suggests that, in many states, people visited parks more on relatively warm days, but the lack of correlation between temperature and encounter rates shows that this change does not result in more potential encounters, perhaps because interactions in parks constitute a relatively small fraction of all human encounters. Therefore, under US national policy guidelines in the early part of the pandemic, human behavior was influenced by weather conditions but apparently not in ways that limited adherence to social distancing recommendations.

Conclusion

In this study, we have demonstrated that changes in human mobility during the onset of the US COVID-19 pandemic were consistent nationally despite large variations in state policies. Potential person-to-person encounter rates were an exponentially increasing function of distance traveled in most states and counties. The exit from quarantine was almost uniformly seen within 1 d of the expiration of the national stay-at-home guidelines, and the timing for changes in mobility had almost no relation to the timing of changes to local policy. The knowledge that people changed their behavior more as a national unit than in response to state policies should be useful to policy makers. Although a more tailored, local approach might be preferred when different regions have significant differences in community spread, these results suggest that a uniform national guideline may be more effective in altering behaviors.

In addition, we saw that, although temperature did impact behaviors (temperature and park visitation are correlated), it did not impact risky behaviors (temperature and potential encounters are not correlated). Despite anecdotes of people flocking to beaches on unseasonably warm spring days and the concerns this brought for the spread of COVID-19, our results show that there was no detectable significant relationship between temperature and potential encounters. Our weather results specifically apply to the early period of the pandemic, and the correlations should not be extrapolated more generally. The combination of weather results implies that people did change their behaviors with the weather, but not in an especially risky way. This is an encouraging sign for adherence to future policies.

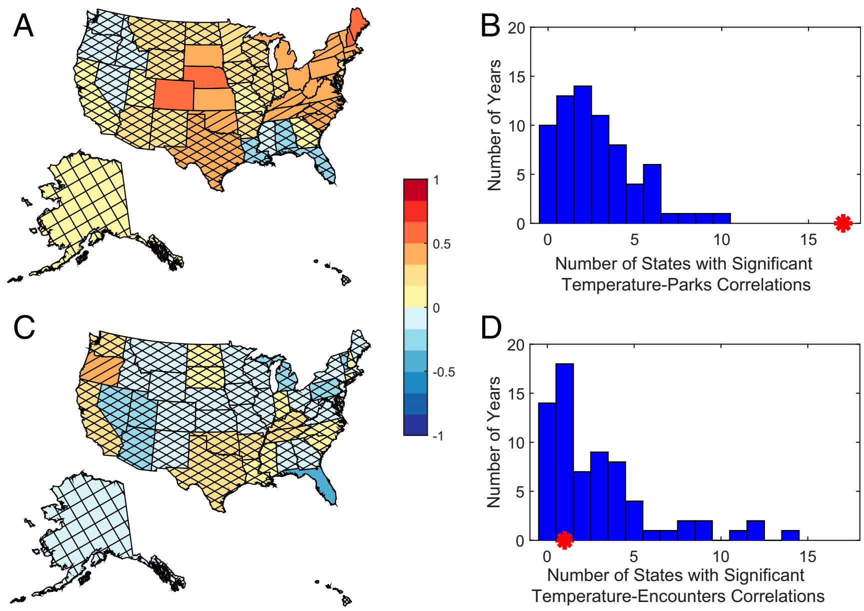

Fig. 3. (*A*) State-level observed correlation coefficients of temperature and park visitation. Both the temperature and the park visitation time series are high-pass filtered before computing the correlations, and the significance of the observed correlations is determined via comparisons to null distributions of correlations computed using prepandemic (1950–2019) weather data (see *Materials and Methods* for details). Single hatching is used to mark states for which the correlations are significant at the 90% level ($P < 0.1$), while no hatching indicates significance at the 95% level ($P < 0.05$). (Cross hatching marks states that are not significant at the 90% level [$P > 0.1$].) (*B*) Information about the number of states likely to exhibit spurious "significant" correlations in the absence of any causal effect of temperature on park visitation. Red star indicates the number of states with significant observed (2020) correlations. Each blue bar indicates the number of prepandemic years (1950–2019) in which the given number of states is (necessarily incorrectly) identified as having a significant correlation between the prepandemic year's temperature and 2020 park visitation (see *Materials and Methods* for details). (*C* and *D*) As in *A* and *B* but for temperature–potential encounter rate correlations.

Our results suggest that coherent national guidance could dramatically change people's behavior again in the future, with the potential to help contain virus transmission. This may not apply to COVID-19, given the current highly politicized climate, but we nevertheless expect this result will be useful to future pandemic planning.

Materials and Methods

Policy Timing. Dates were collected for three types of state-level policy changes: implementation and expiration of a stay-at-home order and implementation of a reopening plan (Fig. 1). Multiple sources that gather information from states' executive orders and press releases were cross-checked (37–41). Generally, stay-at-home orders shut down nonessential businesses, permit nonessential employees to work from home, and encourage citizens to stay at home at all times except for certain essential activities; some states mandate staying at home, while others advise this action. The implementation date of a stay-at-home order is defined to be its first effective date. The expiration date of a stay-at-home order is the date on which it legally expired or was lifted, inclusive of any continuous extension of such an order past its originally announced expiration date. However, any reimplementations of stay-at-home orders in response to COVID-19 surges in July are not considered.

The date of implementation of a reopening plan is the first day on which certain categories of nonessential businesses were permitted to reopen. For states that explicitly announced a phased reopening plan, the implementation date is the starting date of phase 1 of the plan. For states that do not have an explicit reopening plan, the implementation date is generally the first day on which nonessential businesses, such as restaurants and retail, were allowed to operate at below-average capacity. Note that (by these definitions) some states began reopening before their stay-at-home orders expired.

Unacast Mobility Data. With three measures based on data for 15 to 17 million identifiers each day in the United States, aggregated data from Unacast have provided important insights into understanding mobility patterns (11). Human mobility is measured by using three proxies compared to a prepandemic period: change in average distance traveled, change in rate of potential encounters, and change in nonessential visitation. (This last metric is used only as a consistency check on Google Community Mobility Report data; see the next subsection.) The baselines for calculating the change in average distance traveled and nonessential visitation are day-of-week–dependent averages of a prepandemic period (February 10 to March 8) specific to the state or county.

We expect potential encounter rate to be a better metric of disease transmission efficiency than distance traveled, because COVID-19 is believed to spread mainly via close contact with infected individuals. Potential encounter rate is calculated by observing the dwell locations of a sample of mobile devices and counting the number of other devices that come within 50 m of each sample device during a period of an hour (9). Dwell locations are defined as places where the device is traveling below a certain velocity threshold, so as to remove potential encounters of people in separate vehicles where they would not come into direct contact. Other situations like traffic jams are also filtered to ensure only direct contacts are accounted for. Since walkers do not pass the velocity threshold, potential encounters of walkers are included. People coming into contact multiple times in a day are only counted once.

The use of a rather large 50-m range to define an encounter suggests that the Unacast potential encounter rate represents an upper bound on the rate of genuinely disease transmission-relevant contact events. There is also some evidence that contact rates measured at finer spatial resolutions (~1.5 m) are increasing functions of the numbers of people present in areas of larger spatial extent (tens of meters) (42). This is consistent with the idea that the Unacast potential encounter rates are informative about shorter-distance contact events, although the extent to which transmission-relevant contact patterns can be usefully inferred from data about colocation within tens of meters remains a subject of research (42).

Unacast expresses its potential encounter rate data as a change relative to a single (i.e., day-of-week–independent) prepandemic national average (February 10 to March 8). Therefore a densely populated place like Washington, DC, reaches encounter rates of up to 300 in the prepandemic period, while some states exhibit a very small range of encounter rates.

Unacast also provides population data on the state and county level, which was used to calculate population density in conjunction with land area data (43).

Google Community Mobility Report. Google's Community Mobility Report dataset documents volume of visits to six different categories of places: grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces

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(10). Numerical values are expressed as fractional changes from a prepandemic baseline. The baseline varies by day of week, and, for each day of the week, is defined as the median of the five realizations of that day that occurred in the January 3 to February 6, 2020 period.

We cross-check corresponding metrics from Google and Unacast. Visitation to retail and recreation is a form of nonessential visitation, and Unacast's nonessential visitation metric exhibits a tight linear relationship with Google's retail and recreation visitation metric, observed on the state level. While parks were also nonessential destinations, their visitation rates were more variable compared to other nonessential visitation categories, perhaps because other nonessential activities were more strongly restricted. However, park visitation also exhibits a linear relationship with Unacast average distance traveled, suggesting that travel to parks may be a major driver of day-to-day variations in travel under quarantine.

Cuebiq Mobility Data. Aggregated mobility data are provided by Cuebiq, 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 first-party data are collected from anonymized users who have opted in to provide access to their location data anonymously, through a general data protection regulation-compliant framework. The data are then aggregated to the census block group level to provide insights on changes in human mobility over time. Of the available Cuebiq data, we used the Cuebiq Mobility Index, defined as the $\log_{10}$ of the median distance traveled by all devices (13).

We conduct a consistency check on quarantine start mobility changes (Fig. 1*A*, red) by using Cuebiq Mobility Index time series; out of 3,142 counties in the United States, 1,965 counties had March 21 as the beginning of quarantine behavior and 715 counties had March 22, comprising 85% of the total number of counties. This gives us further confidence in the nationally coherent encounter decrease result.

Mobility Metrics. We examine mobility trends on both the state level and the county level and calculate dates of key mobility changes. The grocery visitation maxima (Fig. 1*A*, yellow) are the dates of the maxima in the grocery and pharmacy visit category of the Google dataset, while all other mobility change dates are calculated from the Unacast potential encounter rate data. Quarantine starts (Fig. 1*A*, red) and stops (Fig. 1*A*, pink) are calculated in MATLAB using the findchangepts function. For each time series of encounter rate, we use findchangepts to find two times at which the mean of the time series changes most significantly (44). For each time series, we observe a significant decrease in encounter rates and a significant increase in encounter rates, corresponding to the period of going into quarantine and reopening, respectively. Given these two change points, we then define the start of the quarantine period as the last day of a period of continuous mobility decrease that starts on or before the day of the first change point (i.e., quarantine starts on the date of minimum encounter rates at the end of this period of decrease). Similarly, the end of the quarantine period is defined to be the first day of a period of continuous mobility increase that ends on or after the day of the second change point (i.e., quarantine ends on the date of minimum encounter rates at the beginning of reopening). As stated above, we also apply the algorithm to the Cuebiq Mobility Index to cross-check results for the beginning of quarantine on the county level.

This algorithm was robust to extensions of the encounter rate time series. The same analysis on the full encounter rate time series through the end of July yields exactly the same quarantine start dates. Similarly, quarantine stops were the same for most of the states and exhibit the same consistency across states on May 2. The time series extensions only affect the output of the findchangepts function for the quarantine stops, and, even then, the diagnosed change points are only the first step of the algorithm's selection of the beginning and end of the quarantine period. Therefore, the exact outputs of findchangepts are not central to the results and the analysis is robust to any extensions in the time series.

The mobility 30% prepandemic metric (Fig. 1, orange) is defined as the first day after the beginning of quarantine for which encounter rates reached 30% of the state's prepandemic average encounter rate. While the 30% level is chosen here, the analysis is robust to other levels of mobility as well. The same analysis but using mobility 40% or 50% prepandemic metric yields similar consistencies across states. The 30% level was appropriate because it captures the significant variability of encounter rates between states during the quarantine period while avoiding excessive influence from minor mobility fluctuations, which was evident when examining a 20% prepandemic metric.

Exponential Relationship. The exponential fit is

$$Rate = a \cdot exp(b \cdot Distance),$$

where *Distance* is average distance traveled and *Rate* is a normalized encounter rate defined as the number of encounters (per square kilometer) divided by the national prepandemic baseline.

The relationship between potential encounters and average distance traveled was investigated on both the state level and the county level. While Unacast generates data for almost all counties, we analyzed the relationship only for counties with populations greater than 100,000. Counties with smaller populations have relatively few encounters, and therefore their encounter rate data are quite noisy, which makes it difficult to obtain reasonable fits.

In addition to an exponential model, we also considered a quadratic fit of the form

$$Rate = a \cdot (Distance + b)^2,$$

limiting the number of parameters to only two. This polynomial model yields slightly worse, but similar, R^2 values than those of the exponential model. The fitted parameters of the polynomial model are also highly correlated across states with those of the exponential model. Both may be plausible and capture the highly nonlinear relationship between distance traveled and encounter rate. We present the exponential model here because its parameters are more physically meaningful.

Weather Data. The near-surface temperature and precipitation data used in this study are taken from the ERA5 reanalysis product (45–47). ERA5, the fifth generation of global atmospheric reanalysis from the European Centre for Medium-Range Weather Forecasts, is available on a 0.25° horizontal grid with a time resolution of 1 h. To define state-level daily average weather conditions, we computed population-weighted spatial averages over each state using 2020 estimated populations from a 1/24°-resolution version of the Gridded Population of the World dataset (48) in a manner conceptually similar to previous work (27). For our county-level analyses, we estimated daily average weather conditions at the population centroid of each county. The centroids are based on the 2010 US Census (49), and weather conditions at the centroids were estimated as means over the four ERA5 grid boxes centered closest to each centroid.

Weather and Mobility Analysis. Since mobility analysis suggested that stay-at-home was practiced nationally from March 23 to May 1, we examine data for this 40-d period. The correlation of temperature and park visitation from Google is compared with the correlation of temperature and potential encounter rates from Unacast. While park visitation does relate to average distance traveled, park visitation best captures outdoor activities that experience the effect of weather conditions.

Several details of the correlation calculations warrant further explanation. Mobility is notably suppressed on rainy days, which we define as days with $>$0.5 mm of precipitation. To isolate the relationship between temperature and mobility, we omit these days from our correlation calculations. In addition, it is possible that the signal of any causal relationship between temperature and mobility could be masked by chance correlations between seasonal trends in weather and non−weather-related multiweek trends in mobility. In an attempt to avoid this problem, we high-pass filter the weather and mobility time series before computing their correlations. The high-pass filtering is done by subtracting 7-d running means from the time series. Although deliberately introducing rain-related gaps to our time series is acceptable (indeed, desirable) for the correlation calculations themselves, continuous time series are required to compute the 7-d running means that underlie the high-pass filtering. For the purpose of computing the 7-d running means (and this purpose only), we thus generate "filled" time series in which the true rainy day data values are replaced by values linearly interpolated from the adjacent nonrainy days.

As is evident in Fig. 3 *A* and *C*, the observed correlations between temperature and mobility metrics are generally not equal to zero. But, to credibly interpret nonzero correlations as evidence of a causal relationship, additional information is required about the range of correlation values likely to be observed in the absence of such a relationship. To address this issue, we correlate mobility data from March 23 to May 1, 2020 with ERA5 temperature data from March 23 to May 1 of each of the 70 prepandemic years (1950–2019). Clearly, there should not be a causal relationship between 2020 mobility variations and weather variations in previous years. Therefore, correlations computed using the true 2020 temperature data should be of relatively large magnitude (in comparison to their counterparts computed using pre-2020 temperatures) if they are to serve as convincing evidence of a causal effect of temperature on mobility.

More specifically, for each state, we compute 70 of these null distribution correlation values (i.e., one for each prepandemic year of ERA5 data). The correlation procedure is generally the same as used with the actual 2020 temperature data, with one slight difference related to the exclusion of rainy days. As in the 2020 correlation calculations, we exclude dates on which it was raining in 2020, because we do not want our search for temperature effects on mobility to be overwhelmed by rain effects. But, for each prepandemic year, we also exclude dates on which it was raining in that particular prepandemic year. We make this additional exclusion because the 2020 temperature distributions used in our correlation calculations are implicitly conditional on there being minimal rain (precisely because we chose to exclude the 2020 rainy days from the 2020 correlation calculations), and we thought it advisable to impose this same condition on the correlation calculations for the prepandemic years.

We quantitatively compare each state's true 2020 correlation values to the null distribution of prepandemic values as follows: First, we apply Fisher's Z transform to the 70 prepandemic correlations and then use them to compute the variance of a Gaussian probability distribution centered on zero. The lack of causal connection between 2020 mobility variations and pre-2020 weather variations makes it appropriate to assume that this parameterized form of our null distribution is centered on zero. Annually repeating changes in weather and mobility that could lead to substantially nonzero—but noncausal—correlations should already have been removed by the high-pass filtering. After generating these parametric null distributions, we use them to determine the unusualness of the (suitably Z transformed) 2020 correlation values. We consider a 2020 correlation value to be "significant" if it falls within the outermost 5% of the relevant null distribution (i.e., beyond the 2.5 or 97.5 percentiles—in other words, a two-tailed test with a significance threshold of $P = 0.05$).

Given that, for each mobility metric, we are performing 51 such significance tests (one per state and Washington, DC), we must also consider the possibility that some states might exhibit "significant" temperature−mobility correlations purely by chance. To determine whether our 2020 results are likely to be contaminated by such spurious correlations, we also use our state-specific parametric null distributions to test the significance of the correlations found for each of the 70 prepandemic years. For each of the prepandemic years, we note how many states are incorrectly identified as showing significant mobility−temperature correlations. Finally, we use the resulting distributions of numbers of false significance identifications to contextualize the actual numbers of states found to have "significant" temperature−mobility correlations in 2020 (Fig. 3 *B* and *D*).

Data Availability. Data and scripts necessary to reproduce the figures are available at https://doi.org/10.7910/DVN/XAK0DV. This archive of reduced data also includes the Unacast state level potential encounter rate metric from 24 February 2020 to 6 June 2020, the MATLAB function used to identify quarantine start and stop dates and additional information about when potential encounter rates returned to 20%, 40%, and 50% of prepandemic levels. Researchers interested in requesting the raw Unacast and Cuebiq mobility datasets should consult the companies' Websites (9, 11, 13). Unreduced forms of all other datasets used in the paper are available online (10, 37–41, 43, 45, 46, 48, 49).

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