Policy and weather influences on mobility during the early U.S. COVID-19 pandemic

Yihan Wu (yihanwu@college.harvard.edu)
Harvard University

Todd Mooring
Harvard University https://orcid.org/0000-0002-2293-8118

Marianna Linz
Harvard University https://orcid.org/0000-0002-3241-5062

Research Article

Keywords: COVID-19, weather, policy, mobility, United States

Posted Date: May 14th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-57737/v3

Version of Record: A version of this preprint was published on June 1st, 2021. See the published version at https://doi.org/10.1073/pnas.2018185118.

Policy and weather influences on mobility during the early U.S. COVID-19 pandemic

Yihan Wu,[1*] Todd A. Mooring,[2] and Marianna Linz[1,2]

[1]*School of Engineering and Applied Sciences, Harvard University*

[2]*Department of Earth and Planetary Sciences, Harvard University*

* Corresponding Author

Email: yihanwu@college.harvard.edu

https://orcid.org/0000-0002-2293-8118

https://orcid.org/0000-0002-3241-5062

Author Contributions

Author contributions: Y.W. and M.L. conceived the study; Y.W. analyzed data; T.A.M. and M.L. provided guidance on analysis methods; T.A.M. processed the weather data; and Y.W., T.A.M., and M.L. wrote the paper.

Published in PNAS: https://www.pnas.org/content/118/22/e2018185118

Abstract

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.

Significance Statement

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.

Main Text

Mobility Changes and Policy Timing

On March 13, 2020, U.S. President Donald Trump announced a state of emergency and a ban on travel from 26 European countries.[4] Soon thereafter, a national stay-at-home guideline was issued on March 16.[5] Every state announced school closures between March 16 and March 23,[6] rendering March 21-22 the first weekend within this school and workplace closure period. Since response to the virus in the U.S. has been widely politicized,[7,8] we examine how human behavior, reflected through mobility changes, in response to policies. Figure 1a 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, encounter rate is a mobility metric, measuring the number of devices that come within 50 m of each other[9] (see more discussion in Methods). We compute the mobility changes by identifying change points in the 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 Methods). The grocery visitation

maxima (Fig. 1, 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. 1a, yellow). Following a national stay-at-home guideline and school closures, almost all states achieved their maximum decrease in mobility (Fig. 1a, 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. 1a, 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 national stay-at-home guidelines expired,[12] but schools and many workplaces remained closed.[6] Nevertheless, there is nationally coherent timing of encounter increases (Fig. 1a, pink), in contrast to the varied timings of state stay-at-home order expirations (Fig. 1a, cyan) and of state reopening plan implementations (Fig. 1a, green). To further examine the national coherence of the encounter decrease (red) and encounter increase (pink), we use Unacast encounter rate on the county level. Out of 3054 counties for which Unacast had data, 1880 counties had March 21 as the beginning of quarantine behavior, and a total of 2559 counties had its beginning in the three-day span of March 21-23, comprising 84% of the total number of counties. 1431 counties had May 2 as the end of quarantine behavior, and a total of 2553 counties had April 30-May 2, a span of 3 days, 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, 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 777 counties. In the three-day span June 28-30, only 35% 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 three-day span.

These findings are illustrated in Figure 1b, showing that the state-level coherence of quarantine start and stop demonstrated in Figure 1a 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 pre-pandemic values (Fig. 1a, orange) before quarantine behaviors ceased (Fig. 1a, pink), suggesting variability in people's behaviors

and encounters across states 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 pre-pandemic 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 in time, and as part of this analysis, we examine how the average distance traveled (as a percent change from pre-pandemic baseline) and the encounter rates (as a percent 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 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:

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

where a is a proportionality constant and b is a growth rate (see Methods). The exponential relationship is supported by high R^2 values across the states (see Supplementary Figure 1 for examples of the exponential fit and Supplementary Figure 2 for R^2). In Figure 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 Supplementary Figure 3 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 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 standard deviation (SD) of 0.56 (County-level: mean 3.10, SD 0.71). b has a significant but 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 through June 6, incorporating data through July 15 shows that the exponential relationship holds well. The exponential relationship may have significant 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 encounters) 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 stay-at-home conditions (March 23 - 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[27,29] and others suggesting decreased transmission at warmer temperatures.[30–32] 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.[33] 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-May 1). On days with rainfall, mobility and encounter rates are clearly suppressed (not shown), consistent with previous studies.[19,34] Therefore, we omit rain days from our correlation calculation. We high-pass filtered the weather and mobility time series to remove seasonal trends (see Methods). Figure 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,[16,34] 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 years of weather data (see 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 likely due to temperatures becoming more favorable in the northern states, but too hot (or perhaps humid) for outdoor activities in the southern ones. 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.[35] In Figure 3c, 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 (Supplementary Figure 4). 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/km^2, Supplementary Figure 4).

To further show that the statistically significant temperature-mobility correlations are not by chance, we compute the number of states with significant temperature-mobility correlations using

each of the 70 pre-pandemic years of weather data, with significance again assessed against the state-specific null distributions (see Methods for details). At the 95% significance level, the number of states with a significant temperature-park visitation correlation for 2020 (17) is substantially larger than the number of falsely "significant" correlations found for any previous year (Figure 3b), while the apparent detection of a significant temperature-encounters correlation in a single state is well within the range of what can happen by chance in the absence of any causal effect (Figure 3d). We thus conclude that our analyses provide strong evidence for a real effect of temperature on park visitation, but no evidence for an effect of temperature on encounters.

The correlation between temperature and park visitation suggests that in most 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 national policy guidelines in the early part of the pandemic, human behavior was influenced by weather conditions, but people still maintained compliance with social distancing guidelines.

Conclusion

In this study, we have demonstrated that changes in human mobility during the onset of the U.S. COVID-19 pandemic were consistent nationally despite large variations in state policies. Potential person-to-person encounter rates are an exponentially increasing function of distance traveled in most states and counties. The exit from quarantine was almost uniformly seen within one day of the expiration of the national stay-at-home guidelines, and the timing for changes in mobility had almost no relation with the timing of changes to local policy. The knowledge that people changed their behavior more as a national unit than in response to regional policies should be useful to policymakers. 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 is likely to 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 not a significant relationship between the 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.

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 crosschecked.[36–40] Generally, stay-at-home orders shut down non-essential businesses, permit non-essential 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 of such orders. 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 15-17 million identifiers each day in the U.S., aggregated data from Unacast have provided important insights into understanding mobility patterns.[11] Human mobility is measured by using three proxies compared to a pre-pandemic period: change in average distance traveled, rate of potential encounters, and change in non-essential visitation. (This last metric is used only as a consistency check on Google Community Mobility Report data, see next subsection.) The baselines for calculating the percent change in average distance traveled and non-essential visitation are day-of-week-dependent averages of a pre-pandemic period (February 10- 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 m).[41] 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.[41]

Unacast expresses its potential encounter rate data as a percent change relative to a single (i.e., day-of-week-independent) pre-pandemic national average (February 10 - March 8). Therefore a densely populated place like Washington, D.C. reaches encounter rates of up to 300 in the pre-pandemic 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.[41]

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.[10] Numerical values are expressed as percentage changes from pre-pandemic baselines. 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 - February 6, 2020 period.

We cross-check corresponding metrics from Google and Unacast. Visitation to retail and recreation is a form of non-essential 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 non-essential destinations, their visitation rates were more variable compared to other non-essential visitation categories perhaps because other non-essential activities were more strongly restricted. However, park visitation also exhibits a linear relationship with average distance traveled from Unacast, 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 is 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. This first-party data is collected from anonymized users who have opted-in to provide access to their location data anonymously, through a GDPR-compliant framework. It is then aggregated to the census-block group level to provide insights on changes in human mobility over time. Of its mobility 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 starts mobility changes (Fig. 1a, red) with the Cuebiq Mobility Index; out of 3,142 counties in the U.S., 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 further gives us 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. 1a, 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. 1a, red) and stops (Fig. 1a, 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.[43] 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).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 the same exact quarantine starts. 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 affected the output of the findchangepts function for the quarantine stops, and even then, the diagnosed change points only provide the starting point for the algorithm to select the start of the quarantine period. Therefore, the exact outputs of findchangepts are not as important, and the analysis is robust to any extensions in the time series.

The mobility 30% pre-pandemic 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 pre-pandemic 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% pre-pandemic 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% pre-pandemic metric.

Exponential Relationship:

The exponential fit is

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

where *Distance* is average distance traveled and *Rate* is a normalized encounter rate defined as the number of encounters (km^{-2}) divided by the national pre-pandemic 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, a quadratic fit of the form

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

was also considered, limiting the number of parameters to only two. This polynomial model yields slightly worse, but similar, R^2 values as 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.[44-46] This dataset is available on a 0.25° horizontal grid with a time resolution of 1 hour. 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[47] 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 U.S. Census,[48] and weather conditions at the centroids were estimated as means over the four ERA5 gridboxes 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-day 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 multi-week 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-day 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-day running means that underlie the high-pass filtering. For the purpose of computing the 7-day 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 non-rainy days.

As is evident in Figures 3a and c, the observed correlations between temperature and mobility metrics are generally not equal to zero. But to credibly interpret non-zero 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 the 70 pre-pandemic 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 pre-pandemic 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 pre-pandemic year, we also exclude dates on which it was raining in that particular pre-pandemic 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 pre-pandemic years.

We quantitatively compare each state's true 2020 correlation values to the null distribution of pre-pandemic values as follows: first, we apply Fisher's Z-transform to the 70 pre-pandemic 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 non-zero—but non-causal—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 2.5th or 97.5th 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 D.C.) 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 pre-pandemic years. For each of the pre-pandemic 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.

References

1. S. Lai, *et al.*, Effect of non-pharmaceutical interventions to contain COVID-19 in China. *Nature* **585**, 410–413 (2020).
2. E. Pepe, *et al.*, COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown. *Scientific Data* **7**, 230 (2020).
3. COVID-19 Will Be 'Constant Threat' Until Vaccine Found, WHO Envoy Says | Voice of America – English https://web.archive.org/web/20200605203201/https://www.voanews.com/covid-19-pandemic/covid-19-will-be-constant-threat-until-vaccine-found-who-envoy-says. Accessed 29 July, 2020.
4. Trump's virus travel ban on Europe comes into force. *BBC News* (2020) https://web.archive.org/web/20200728173100/https://www.bbc.com/news/world-us-canada-51883728 Accessed 29 July, 2020.
5. 30 Days to Slow the Spread *coronavirus.gov* (2020) https://web.archive.org/web/20200729112720/https://www.whitehouse.gov/wp-content/uploads/2020/03/03.16.20_coronavirus-guidance_8.5x11_315PM.pdf Accessed 29, July, 2020.

6. Map: Coronavirus and School Closures - Education Week. *Education Week* (2020) https://web.archive.org/web/20200729003506/https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html Accessed 19 July, 2020.
7. H. Rothgerber, *et al.*, "Politicizing the COVID-19 Pandemic: Ideological Differences in Adherence to Social Distancing" (PsyArXiv, 2020) https:/doi.org/10.31234/osf.io/k23cv (July 29, 2020).
8. A. H. Abbas, Politicizing the Pandemic: A Schemata Analysis of COVID-19 News in Two Selected Newspapers. *Int. J. Semiot. Law - Rev. Int. Sémiot. Jurid.* (2020) https:/doi.org/10.1007/s11196-020-09745-2 (July 29, 2020).
9. The Unacast Social Distancing Scoreboard. *Unacast* (2020) https://web.archive.org/web/20200706203445/https://www.unacast.com/post/the-unacast-social-distancing-scoreboard Accessed 29 July, 2020.
10. COVID-19 Community Mobility Reports. *Google* (July 29, 2020).
11. Data for Good. *Unacast* (2020). https://web.archive.org/web/20200706193958/https://www.unacast.com/data-for-good Accessed 27 July, 2020.
12. Trump Says Federal Guidelines on Social Distancing Set to Expire. *US News World Rep.* (July 29, 2020). https://www.usnews.com/news/health-news/articles/2020-04-30/trump-says-federal-guidelines-on-social-distancing-set-to-expire.
13. Cuebiq's COVID-19 Mobility Insights. *Cuebiq* (August 5, 2020).
14. Trump Falsely Claims Much of U.S. Is 'Corona-Free.' *N. Y. Times* (2020) https://web.archive.org/web/20200804052152/https://www.nytimes.com/2020/07/28/world/coronavirus-covid-19.html Accessed 4 August, 2020).
15. S. Basu, Numerical Analysis of Disastrous Effect of Reopening Too Soon in Georgia, USA. *medRxiv*, 2020.07.01.20144667 (2020).
16. T. D. Nguyen, *et al.*, "Impacts of State Reopening Policy on Human Mobility" (National Bureau of Economic Research, 2020) https:/doi.org/10.3386/w27235 (July 29, 2020).
17. L. de Montigny, R. Ling, J. Zacharias, The Effects of Weather on Walking Rates in Nine Cities: *Environ. Behav.* **44**, 821–840 (2011).
18. S. Saneinejad, M. J. Roorda, C. Kennedy, Modelling the impact of weather conditions on active transportation travel behaviour. *Transp. Res. Part Transp. Environ.* **17**, 129–137 (2012).
19. M. Cools, E. Moons, L. Creemers, G. Wets, Changes in Travel Behavior in Response to Weather Conditions: Do Type of Weather and Trip Purpose Matter? *Transp. Res. Rec.* **2157**, 22–28 (2010).
20. C. R. de Freitas, Weather and place-based human behavior: recreational preferences and sensitivity. *Int. J. Biometeorol.* **59**, 55–63 (2015).
21. V. N. Petrova, C. A. Russell, The evolution of seasonal influenza viruses. *Nat. Rev. Microbiol.* **16**, 47–60 (2018).
22. S. F. Dowell, M. S. Ho, Seasonality of infectious diseases and severe acute respiratory syndrome–what we don't know can hurt us. *Lancet Infect. Dis.* **4**, 704–708 (2004).
23. H. M. Biggs, *et al.*, Human Coronavirus Circulation in the USA, 2014–2017. *Open Forum Infect. Dis.* **4**, S311–S312 (2017).
24. A. I. Barreca, J. P. Shimshack, Absolute humidity, temperature, and influenza mortality: 30 years of county-level evidence from the United States. *Am. J. Epidemiol.* **176 Suppl 7**, S114-122 (2012).
25. J. Shaman, E. Goldstein, M. Lipsitch, Absolute Humidity and Pandemic Versus Epidemic Influenza. *Am. J. Epidemiol.* **173**, 127–135 (2011).
26. R. E. Baker, W. Yang, G. A. Vecchi, C. J. E. Metcalf, B. T. Grenfell, Susceptible supply limits the role of climate in the early SARS-CoV-2 pandemic. *Science* **369**, 315–319 (2020).
27. S. M. Kissler, C. Tedijanto, E. Goldstein, Y. H. Grad, M. Lipsitch, Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* **368**, 860–868 (2020).
28. R. A. Neher, R. Dyrdak, V. Druelle, E. B. Hodcroft, J. Albert, Potential impact of seasonal forcing on a SARS-CoV-2 pandemic. *Swiss Med. Wkly.* **150** (2020).

29. C. Poirier, *et al.*, The role of environmental factors on transmission rates of the COVID-19 outbreak: an initial assessment in two spatial scales. *Scientific Reports* **10**, 17002 (2020).Y. Yao, *et al.*, No association of COVID-19 transmission with temperature or UV radiation in Chinese cities. *Eur. Respir. J.* **55** (2020).
30. B. Oliveiros, L. Caramelo, N. C. Ferreira, F. Caramelo, Role of temperature and humidity in the modulation of the doubling time of COVID-19 cases. *medRxiv*, 2020.03.05.20031872 (2020).
31. J. Wang, *et al.*, "High Temperature and High Humidity Reduce the Transmission of COVID-19" (Social Science Research Network, 2020) https:/doi.org/10.2139/ssrn.3551767 (July 30, 2020).
32. Y. Ma, *et al.*, Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. *Sci. Total Environ.* **724**, 138226 (2020).
33. M. M. Menebo, Temperature and precipitation associate with Covid-19 new daily cases: A correlation study between weather and Covid-19 pandemic in Oslo, Norway. *Sci. Total Environ.* **737**, 139659 (2020).
34. H. A. Aaheim, K. E. Hauge, Impacts of climate change on travel habits: A national assessment based on individual choices. *CICERO Reports*(2005) (July 30, 2020).
35. Federal Reserve Bank of San Francisco, D. J. Wilson, Weather, Social Distancing, and the Spread of COVID-19. *Fed. Reserve Bank San Franc. Work. Pap. Ser.*, 01–64 (2020).
36. Chart: Each State's COVID-19 Reopening and Reclosing Plans and Mask Requirements. The National Academy for State Health Policy (2020). https://web.archive.org/web/20200716221229/https://www.nashp.org/governors-prioritize-health-for-all/ Accessed 3 August, 2020.
37. Stay on Top of "Stay At Home" – A List of Statewide Orders. *Littler Mendelson PC* (2020) https://web.archive.org/web/20200706062423/https://www.littler.com/publication-press/publication/stay-top-stay-home-list-statewide Accessed 3 August, 2020.
38. Where states reopened and cases spiked after the U.S. shutdown. *Wash. Post* https://web.archive.org/web/20200803003837if_/https://www.washingtonpost.com/graphics/2020/national/states-reopening-coronavirus-map/ Accessed 3 August, 2020.
39. Raifman J, Nocka K, Jones D, Bor J, Lipson S, Jay J, and Chan P. (2020). "COVID-19 US state policy database." Available at: www.tinyurl.com/statepolicies
40. University of Washington: Nancy Fullman, Bree Bang-Jensen, Grace Reinke, Beatrice Magistro, Rachel Castellano, Megan Erickson, Kenya Amano, John Wilkerson, and Christopher Adolph. "State-level social distancing policies in response to COVID-19 in the US". Version 1.101, November 19, 2020. http://www.covid19statepolicy.org
41. M. Génois, A. Barrat, Can co-location be used as a proxy for face-to-face contacts? *EPJ Data Sci.* **7**, 1–18 (2018).
42. U. C. Bureau, USA Counties: 2011. *U. S. Census Bur.* (August 6, 2020).
43. Find abrupt changes in signal - MATLAB findchangepts (August 6, 2020). https://www.mathworks.com/help/signal/ref/findchangepts.html. Accessed 6, August, 2020.
44. B. Bell, *et al.*, (2020): ERA5 hourly data on single levels from 1950 to 1978 (preliminary version). Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on 13-Nov-2020), https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-preliminary-back-extension?tab=overview
45. H. Hersbach, *et al.*, (2018): ERA5 hourly data on single levels from 1979 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on 28-Oct-2020), https://dx.doi.org/10.24381/cds.adbb2d47
46. H. Hersbach, *et al.*, Global reanalysis: goodbye ERA-Interim, hello ERA5. 17–24 (2019).
47. Center for International Earth Science Information Network - CIESIN - Columbia University, Gridded Population of the World, Version 4 (GPWv4): Population Count Adjusted to Match 2015 Revision of UN WPP Country Totals, Revision 11 (2018) (March 12, 2020).
48. Baruch College GIS Lab (2014). US Census Population Centroids. Retrieved from: https://www.baruch.cuny.edu/confluence/display/geoportal/US+Census+Population+Centroids

Figures and Tables

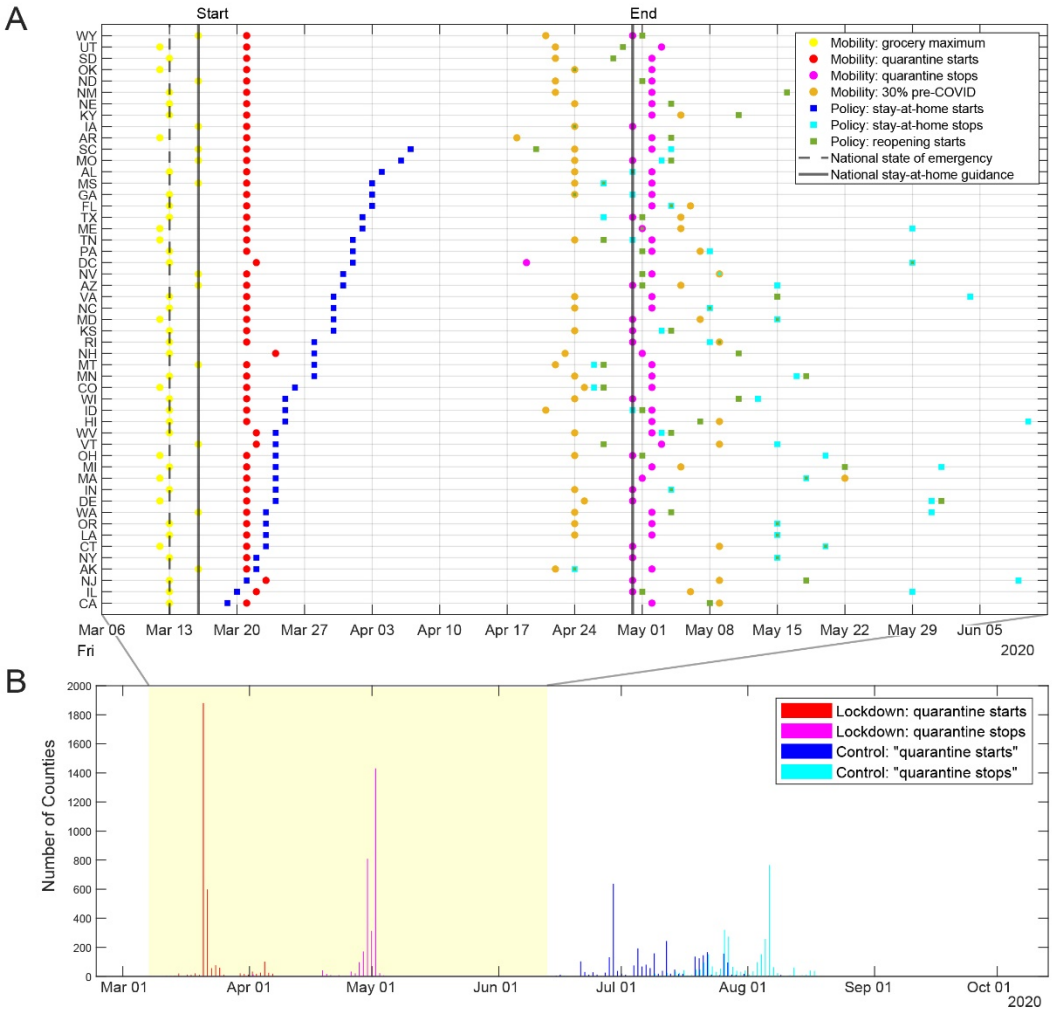

Figure 1. (a) Implementation of state policies and changes in mobility behavior, ordered by date of stay-at-home orders. Warm colored circles are metrics based on mobility: peaks in grocery visitation (yellow), beginning of quarantine based on mobility (red), timing when mobility reaches 30% of pre-pandemic 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. For details about mobility metrics, see Methods. (b) Bar graph of county-level changes in mobility behavior, using real quarantine time series (red, pink) and control time series (blue, cyan).

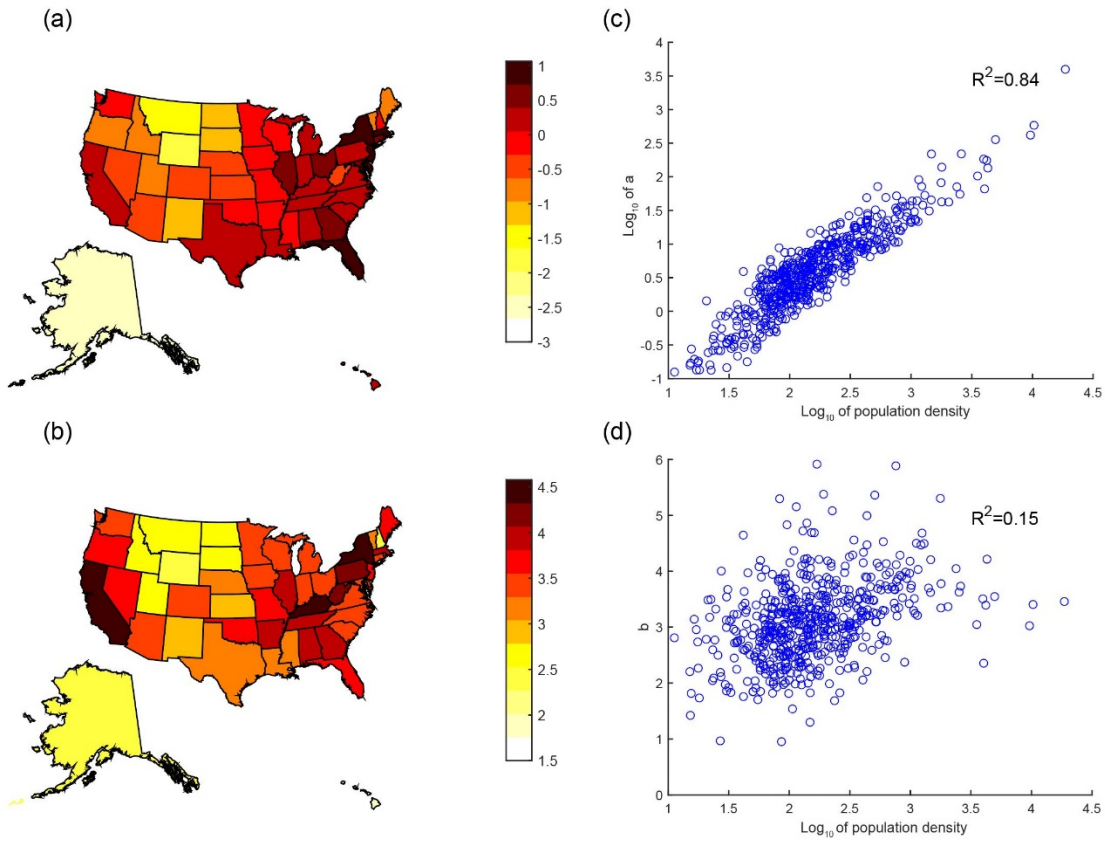

Figure 2. Map of $\log_{10}$ of leading coefficient a (a) and map of coefficient b (b) on the state level. In (a), the value for Washington D.C. ($\log_{10} a = 2.26$) is not shown. Scatter plots of coefficients at the county level are shown against the $\log_{10}$ of population density for $\log_{10}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

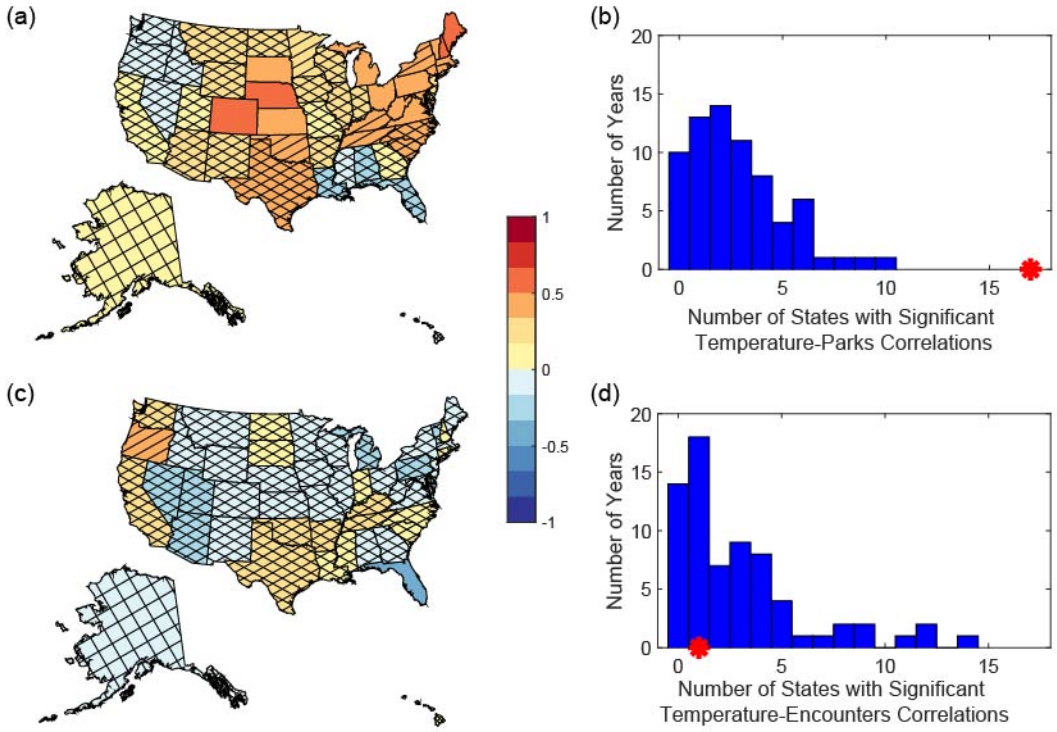

Figure 3. State-level observed correlation coefficients of temperature and park visitation (a). Both the temperature and the park visitation time series are high-pass filtered before computing the correlations, and the significance of the observed correlations is determined via comparisons to null distributions of correlations computed using pre-pandemic (1950-2019) weather data (see 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 ($p<0.05$). Information about the number of states likely to exhibit spurious "significant" correlations in the absence of any causal effect of temperature on park visitation is provided in (b). Red star indicates the number of states with significant observed (2020) correlations. Each blue bar indicates the number of pre-pandemic years (1950-2019) in which the given number of states is (necessarily incorrectly) identified as having a significant correlation between the pre-pandemic year's temperature and 2020 park visitation (see Methods for details). (c,d) as (a,b) but for temperature-encounters correlation.

Supplementary Information Text

As an additional check to ensure that our results are not an artifact of multiple testing, we used the false discovery rate-controlling procedure of Benjamini and Hochberg (1995).[1-3] In our context, the false discovery rate (FDR) is the expected fraction of states incorrectly detected as having a significant temperature-mobility correlation when such a correlation does not in fact exist. The procedure[4] requires as input the p-values of the family of tests to be analyzed, which we compute from the state-specific null distributions as described in the Methods section. We chose to analyze the temperature-park visitation and temperature-potential encounters correlations as separate families of 51 tests each (50 states plus D.C.) and to control the false discovery rate at 0.05 in each family.

After applying this procedure using the (2020) p-values and our chosen false discovery rate, we identified 11 states as having significant temperature-park visitation correlations and zero states with significant temperature-potential encounters correlations. This is compared to 17 states and one state, respectively, identified as having significant correlations before applying this multiple testing correction. Although fewer states are identified as having significant temperature-park visitation correlations than in our primary analysis, our main focus is not on the significance of correlations in individual states but on whether a temperature effect on human behavior is apparent in the dataset as a whole (i.e. nationwide). Thus, at the national scale we again observe statistically significant correlations between temperature and park visitation and a lack of such correlations between temperature and potential encounter rates, further supporting our conclusions. The results of the main analysis and the FDR analysis are shown in Table S1.

We also investigated an alternative method for evaluating the significance of the individual state-level temperature and mobility correlations, by estimating whether the correlations are significantly different from zero via a bootstrapping technique. By resampling days at random with replacement from our March 23 to May 1, 2020 time series only (i.e., without using previous years of weather data), we generate 4000 additional synthetic datasets of temperature and mobility per state and then use these synthetic datasets to recompute 4000 synthetic correlation values per state. These distributions of synthetic correlation values form the basis of the correlation significance information presented in Fig. S5. Note that the observed correlations shown in this figure are necessarily independent of this resampling technique and are therefore reproduced exactly from Figure 3.

It is important to note that these results are comparable to those obtained from our primary analysis using the state-specific null distributions of correlation values. In comparing Fig. 3 with Fig. S5, we observe similar relationships between the patterns of significant temperature-park visitations correlations and significant temperature-encounters correlations. While this bootstrapping technique identifies correlations in a few more states as significant, states identified as having significant correlations in our primary analysis are also found to have significant correlations in this tertiary analysis. We have not applied any form of multiple testing correction to our bootstrapping-based results.

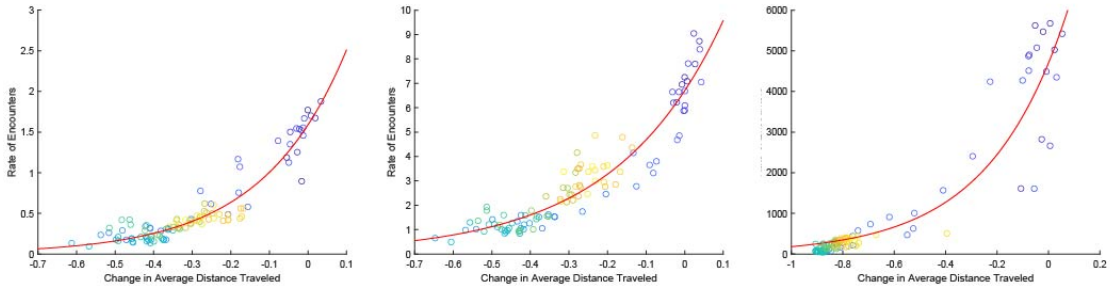

Fig. S1. Relationship between change in average distance traveled and change in rate of encounters in California (left), Florida (middle), and New York County (Manhattan), New York (right), colored by date (dark blue is February 24, light yellow is June 6). Data are expressed relative to pre-pandemic baselines. Exponential model fits are plotted in red.

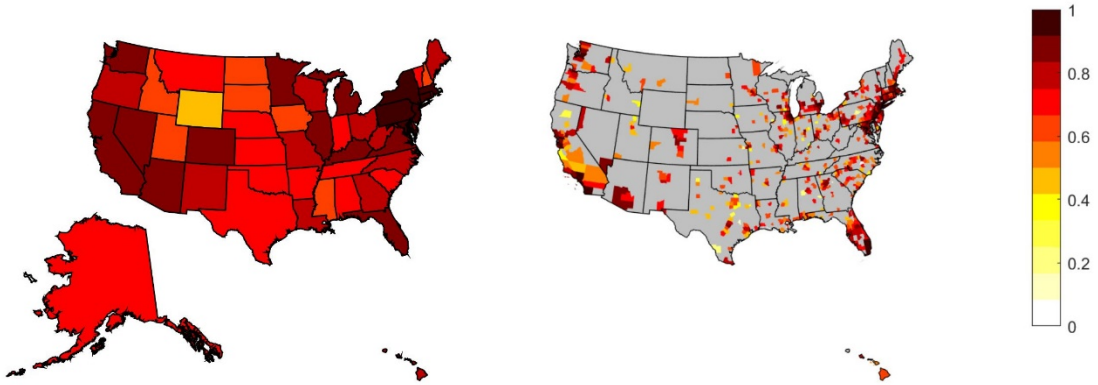

Fig. S2. Adjusted R^2 values of exponential fits on the state (left) and county (right) levels. Alaska is not shown on the county map as Anchorage Municipality is the only region available (R^2=0.68). Regions with missing data are colored in gray.

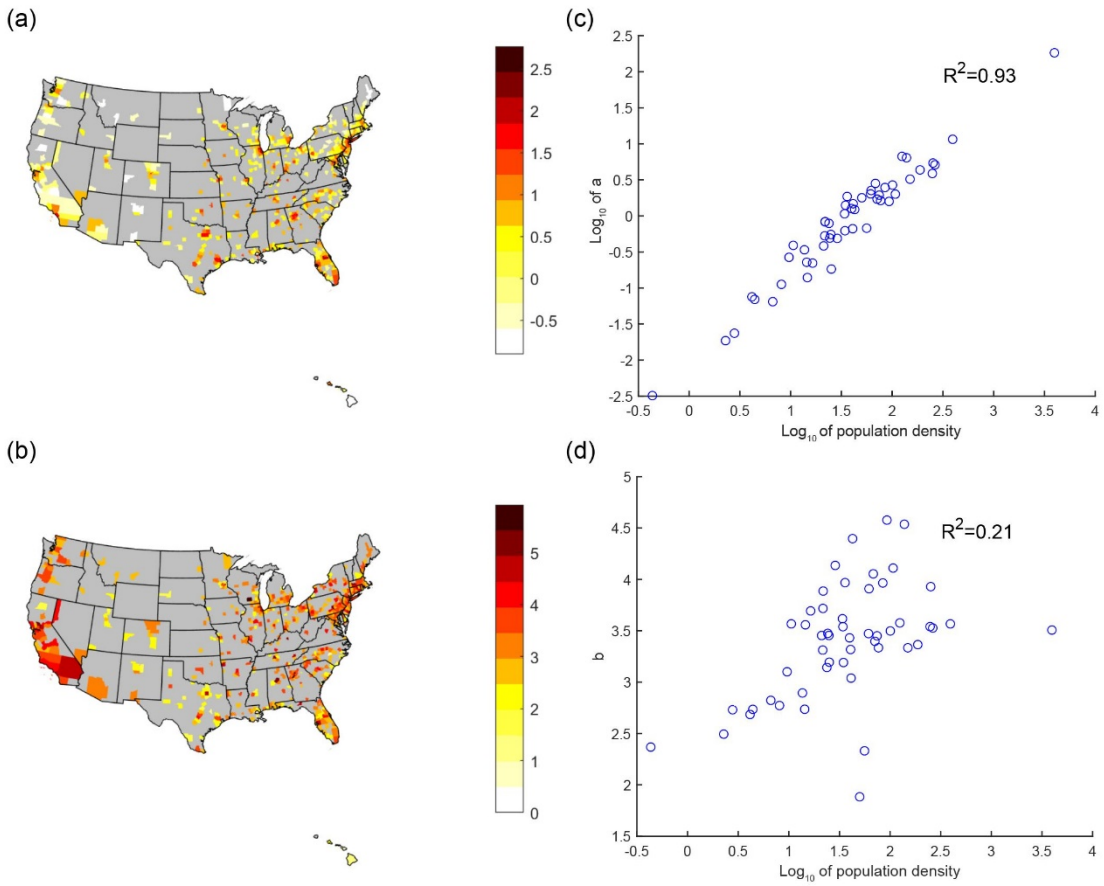

Fig. S3. Map of $\log_{10}$ of leading coefficient *a* (a) and map of growth rate coefficient *b* (b) on the county level. In (a), the value for New York County (Manhattan), New York ($\log_{10} a$ =3.60) is not shown. In (a) and (b), Alaska is not shown as Anchorage Municipality is the only region available ($\log_{10} a$=-0.213, *b*=2.28). Regions with missing data are colored in gray. Scatter plots of coefficients at the state level are shown against the $\log_{10}$ of population density for $\log_{10} a$ in (c) and for *b* in (d).

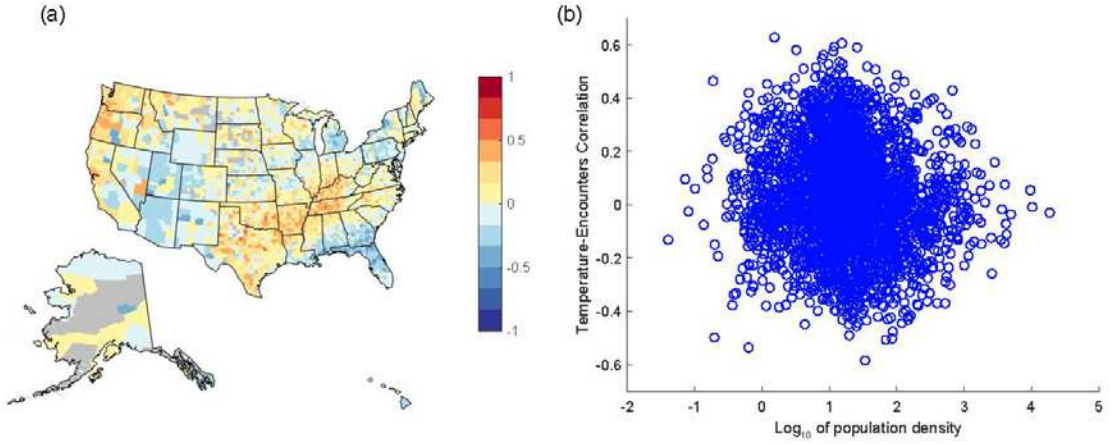

Fig. S4. (a) Observed county-level correlation coefficient of temperature and potential encounter rate. (b) Relationship between county-level correlation coefficient of temperature and potential encounter rate and $\log_{10}$ of population density.

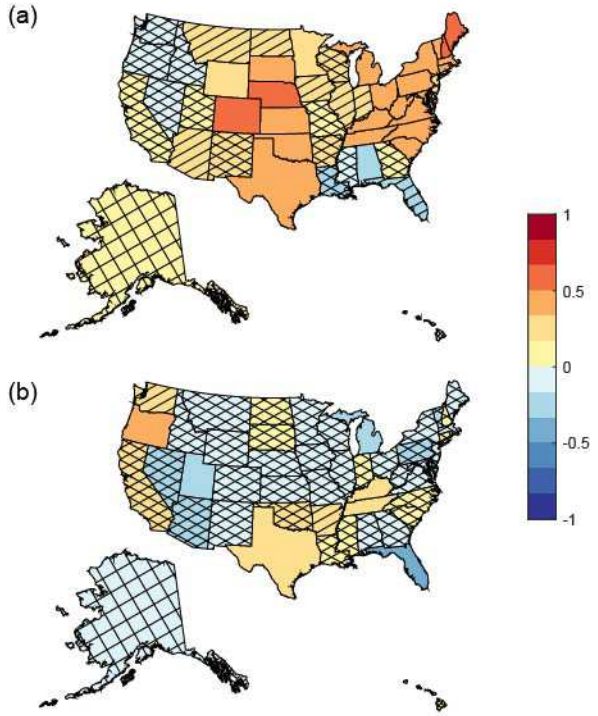

Fig. S5. State-level correlation coefficient of temperature and park visitation (a) or correlation coefficient of temperature and encounter rate (b), both reproduced from Fig. 3. Significance of the correlations was estimated using a bootstrapping technique (see Supplementary Information Text for details). Single hatching marks areas where zero is within 1.96 standard deviations of the observed correlation (i.e., significant at ~95% or less), while cross hatching shows where zero is within 1.64 standard deviations of the observed correlation (significant at ~90% or less). A lack of hatching indicates where zero is at least 1.96 standard deviations from the observed correlation (significant at ~95% or more). Rainy days have been excluded from this analysis and all time series were high-pass filtered prior to computing the correlations (see Methods for details).

Table S1. State-level temperature-mobility correlation results. Before applying the FDR procedure, 17 states exhibit significant temperature-park visitation correlations (bolded), and one state exhibits a significant temperature-potential encounters correlation (bolded). After applying the FDR procedure, 11 states exhibit significant temperature-park visitation correlations, and zero states exhibit significant temperature-potential encounters correlations as shown in the "FDR Significance" columns.

	Temperature-park visitations			Temperature-potential encounters		
State	Correlation Coefficient (2020)	p-value	FDR Significance	Correlation Coefficient (2020)	p-value	FDR Significance
AL	-0.3697	0.1467	N	-0.2041	0.5529	N
AK	0.1384	0.6961	N	-0.0080	0.9531	N
AZ	0.2753	0.1441	N	-0.2382	0.2523	N
AR	0.3099	0.3165	N	0.2333	0.2309	N
CA	0.0350	0.9412	N	0.1711	0.3305	N
CO	**0.6566**	**0.0018**	**Y**	0.0143	0.8723	N
CT	**0.3602**	**0.0250**	**N**	0.0247	0.8042	N
DE	0.0361	0.7895	N	-0.2572	0.3868	N
D.C.	**0.4150**	**0.0008**	**Y**	-0.1480	0.5412	N
FL	-0.2275	0.2240	N	**-0.4658**	**0.0245**	**N**
GA	0.1836	0.7998	N	-0.0874	0.8996	N
HI	-0.0846	0.6826	N	0.0935	0.7617	N
ID	0.0086	0.7714	N	-0.0245	0.8937	N
IL	0.2936	0.1084	N	-0.1944	0.5761	N
IN	0.3226	0.1282	N	-0.1092	0.9557	N
IA	0.2564	0.1040	N	-0.1758	0.5143	N
KS	**0.3781**	**0.0250**	**N**	-0.1247	0.5608	N
KY	0.3983	0.0823	N	0.2476	0.1824	N
LA	-0.2614	0.2690	N	0.0207	0.6278	N
ME	**0.5565**	**0.0001**	**Y**	-0.0056	0.8258	N
MD	**0.3479**	**0.0035**	**Y**	-0.0437	0.9147	N
MA	**0.3753**	**0.0068**	**Y**	-0.0112	0.7955	N
MI	**0.4656**	**0.0086**	**Y**	-0.3627	0.1405	N
MN	0.3110	0.0588	N	-0.0743	0.6386	N
MS	-0.1197	0.5993	N	0.0284	0.7167	N
MO	0.1851	0.4224	N	-0.1634	0.6676	N
MT	0.2379	0.3380	N	-0.0149	0.9648	N
NE	**0.5483**	**0.0008**	**Y**	-0.1312	0.5367	N
NV	-0.0226	0.8801	N	-0.2293	0.4560	N
NH	**0.4758**	**0.0007**	**Y**	0.0528	0.6252	N
NJ	0.2168	0.3225	N	-0.0569	0.7510	N

NM	0.1904	0.4584	N	-0.1154	0.6378	N
NY	0.3718	0.0665	N	-0.1245	0.6180	N
NC	0.3226	0.1095	N	0.0741	0.5831	N
ND	0.2566	0.2452	N	0.0343	0.9551	N
OH	**0.4970**	**0.0446**	**N**	-0.1913	0.9180	N
OK	0.4512	0.0736	N	0.1674	0.3496	N
OR	-0.0488	0.8803	N	0.3382	0.0539	N
PA	**0.4957**	**0.0107**	**Y**	-0.2853	0.3118	N
RI	**0.4587**	**0.0029**	**Y**	0.0948	0.6825	N
SC	0.3095	0.1091	N	-0.0495	0.9818	N
SD	**0.3993**	**0.0197**	**N**	0.0069	0.9309	N
TN	0.3463	0.0579	N	0.2405	0.2049	N
TX	0.3803	0.1613	N	0.1748	0.1069	N
UT	0.0574	0.9163	N	-0.3123	0.1269	N
VT	**0.5007**	**0.0022**	**Y**	-0.1210	0.3614	N
VA	**0.2930**	**0.0217**	**N**	-0.0892	0.8975	N
WA	0.0421	0.8459	N	0.3485	0.2398	N
WV	**0.4344**	**0.0350**	**N**	-0.2317	0.5929	N
WI	0.2321	0.1646	N	-0.1793	0.5066	N
WY	0.3178	0.1596	N	-0.0076	0.8520	N

Supplementary Information References

1. Y. Benjamini, Y. Hochberg, Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)* **57**, 289–300 (1995).
2. Y. Benjamini, D. Yekutieli, The Control of the False Discovery Rate in Multiple Testing under Dependency. *The Annals of Statistics* **29**, 1165–1188 (2001).
3. Y. Benjamini, Discovering the false discovery rate. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)* **72**, 405–416 (2010).
4. D. Groppe, fdr_bh. *MATLAB Central File Exchange* (February 27, 2021).

Figures

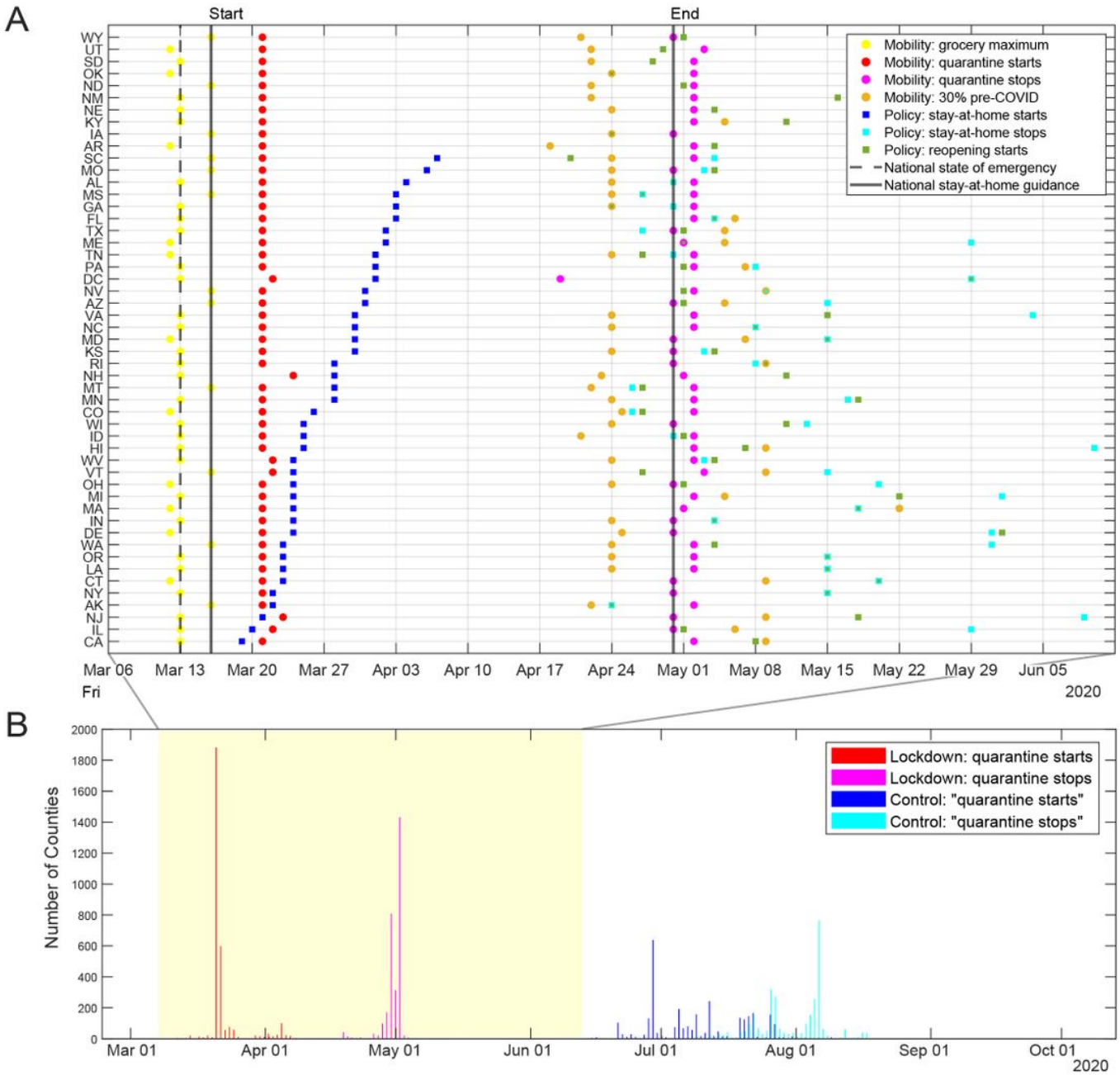

Figure 1

(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 pre-pandemic 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. For details about mobility metrics, see Methods. (b) Bar graph of

county-level changes in mobility behavior, using real quarantine time series (red, pink) and control time series (blue, cyan).

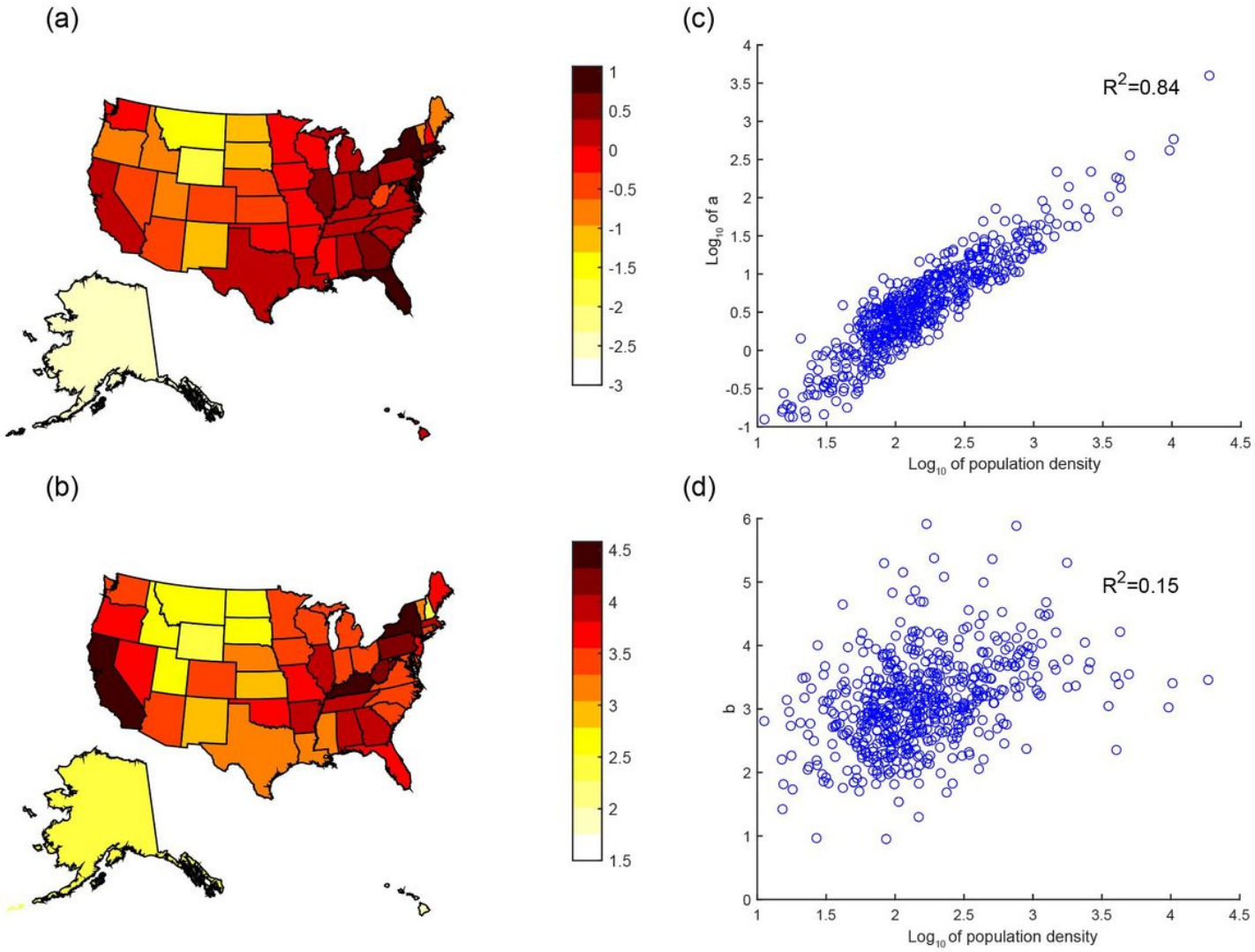

Figure 2

Map of log10 of leading coefficient a (a) and map of coefficient b (b) on the state level. In (a), the value for Washington D.C. (log10 a = 2.26) is not shown. Scatter plots of coefficients at the county level are shown against the log10 of population density for log10 a in (c) and for b in (d)

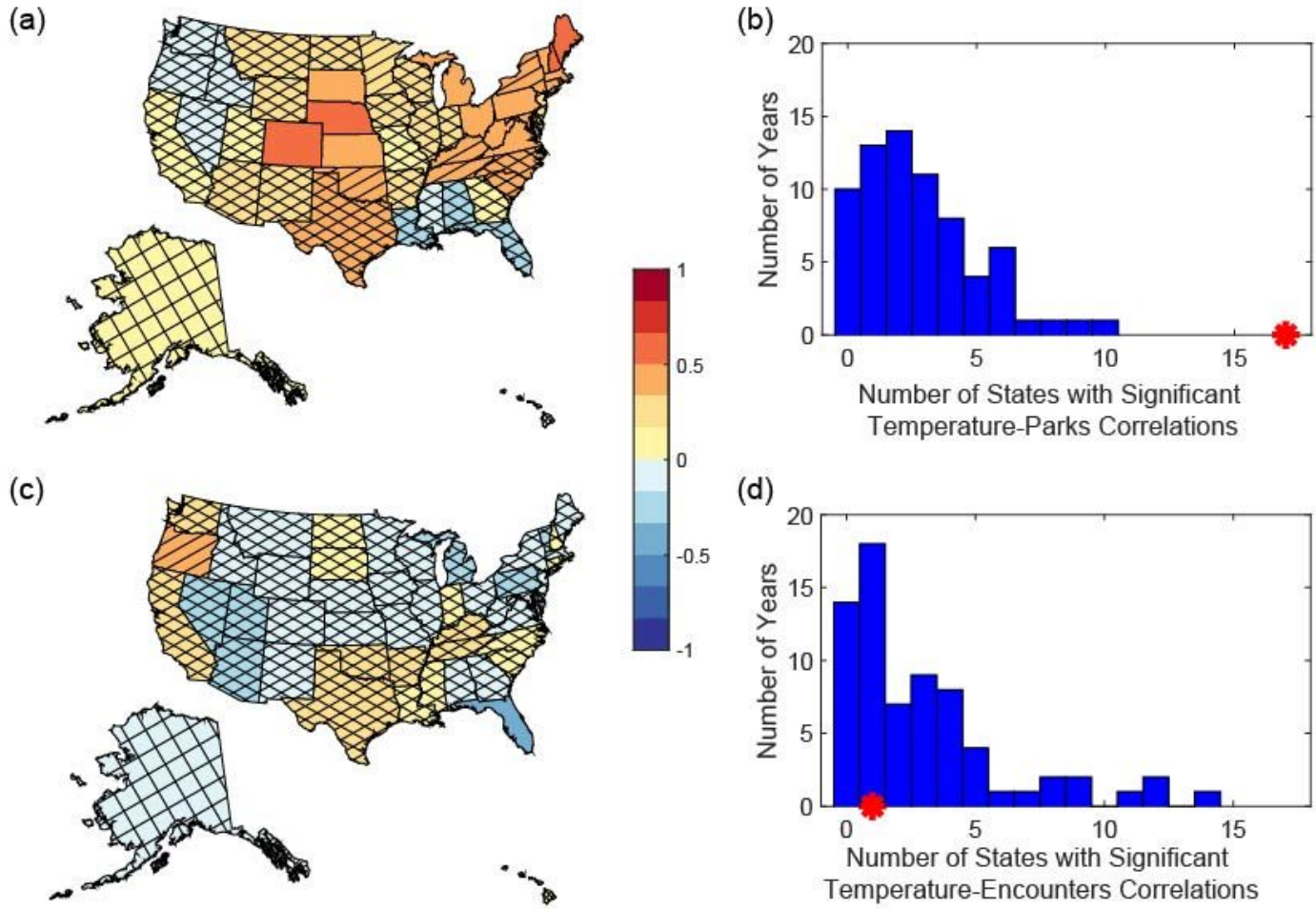

Figure 3

State-level observed correlation coefficients of temperature and park visitation (a). 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 pre-pandemic (1950-2019) weather data (see 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 ($p<0.05$). Information about the number of states likely to exhibit spurious "significant" correlations in the absence of any causal effect of temperature on park visitation is provided in (b). Red star indicates the number of states with significant observed (2020) correlations. Each blue bar indicates the number of pre-pandemic years (1950-2019) in which the given number of states is (necessarily incorrectly) identified as having a significant correlation between the pre-pandemic year's temperature and 2020 park visitation (see Methods for details). (c,d) as (a,b) but for temperature-encounters correlation.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- figs101.jpg
- FigureS2.jpg
- FigureS3.jpg
- figs4final.jpg
- figs5final01.jpg