Title:
Impact of mitigating interventions and temperature on the instantaneous reproduction number in the COVID-19 epidemic among 30 US metropolitan areas

Author:
Xinhua Yu

Affiliation:
Division of Epidemiology, Biostatistics and Environmental Health
School of Public Health
University of Memphis

Email: xyu2@memphis.edu
Phone: 1-901-678-3433

Running title:
intervention & temperature on reproduction number

Keywords: virus transmissibility, reproduction number, mitigating intervention, temperature, epidemic, COVID-19
Impact of mitigating interventions and temperature on the instantaneous reproduction number in the COVID-19 epidemic among 30 US metropolitan areas

Abstract

Background: After more than three months into the coronavirus disease (COVID-19) epidemic, over 170,000 people had died worldwide. The current study aims to evaluate how mitigating interventions affected the epidemic process in the 30 largest metropolitan areas in the US and whether temperature played a role in the epidemic process.

Methods: Publicly available COVID-19 cases and deaths data and weather data were analyzed at the metropolitan level. The time-varying reproductive numbers were used to explore the trends.

Results: We found that virus transmissibility, measured by instantaneous reproduction number ($R_t$), had declined significantly since the end of March for all areas and almost all of them reached a $R_t$ of 1 or below by April 15, 2020. Cities with warm temperature tended to have a lower peak $R_t$ than that of cities with cold temperature. However, large geographic variations exist.

Conclusions: Though the end of epidemic of COVID-19 is near, temperature may have some weak effects on the virus transmission, and the return of the coronavirus outbreak is still possible.
Introduction

The coronavirus disease (COVID-19) epidemic caused by the novel severe acute respiratory syndrome (SARS) associated coronavirus (SARS-CoV 2) infection [1] has not only affected more than 2 million people and caused over 170,000 deaths worldwide [https://coronavirus.jhu.edu/map.html, accessed April 20, 2020], but also induced significant anxiety among the public [2]. Many people raised concerns about whether the stringent interventions were over-reacted, and whether a second wave of outbreak was possible. In the 2003 SARS epidemic, the virus went away after June 2003 and never came back[3]. Will this happen to SARS-CoV2?

There are several major differences between 2003 SARS coronavirus and 2019 SARS CoV2 [3, 4]. The 2003 coronavirus had much higher virulence, resulting in higher hospitalization and mortality rates than the 2019 coronavirus. The transmission of the 2003 coronavirus almost exclusively occurred among symptomatic cases[5], while the 2019 coronavirus can cause a large percent of asymptomatic cases who can also transmit virus [6, 7]. Furthermore, the 2019 coronavirus is also circulating in the southern hemisphere where the current temperature is warmer than that of northern hemisphere. By late 2020, it is possible the coronavirus may circulate back to the northern hemisphere, leading to a second wave of epidemic[8]. Therefore, it is important to evaluate the effects of mitigating interventions and examine whether temperature may affect the virus transmissibility and virulence.

One key measure of virus transmissibility during an epidemic is effective reproduction number (R), the average number of secondary cases infected by a primary case [9-11]. Based on the susceptible-infectious-removed (SIR) model, the reproduction number can be conceptualized as (number of contacts)*(infectivity per contact)*(generation interval), where generation interval...
refers to the average duration between the time when a primary case becoming infectious and the
time when secondary cases being infected[10]. Clearly, interventions such as social distancing,
stay home rule, school or office closures, and prohibiting large gatherings will reduce the number
of contacts, thus reducing R. On the other hand, a lower virus infectivity can also reduce R,
assuming the number of contacts remains unchanged. Therefore, exploring the changes of R over
time and across different regions can shed new lights on the impact of interventions and
environmental factors during the epidemic.

A few studies have used time varying R_t to explore the effects of intervention on the epidemic
process[12-16]. For example, one recent study found significant effects of nonpharmaceutical
interventions on the transmissibility of SARS-CoV2, measured by R_t, in Hongkong[16].
However, few studies examined the impact of environmental factors on the COVID-19 epidemic.
A few unpublished manuscripts have examined the association between temperature and
COVID-19 case counts and found no or a negative but weak association[17-19]. However, their
studies were based on case counts among different countries, which subjects to myriads of
confounding effects due to different diagnostic criteria, availability of detection kits and
reporting biases.

In this study, we will compare the magnitude and changes of time-varying (instantaneous)
effective reproduction numbers (R_t) among 30 largest metropolitan areas in the US. We
hypothesize that stringent interventions are effective in curbing the epidemic, but temperature
may also facilitate the decline of the epidemic in some regions.

Methods

Data source
We obtained daily COVID-19 cases and deaths at the US county level from the data repository provided by New York Times (https://github.com/nytimes/covid-19-data, accessed on April 17, 2020). We further limited those counties to the 30 largest metropolitan areas (Table 1). All cases and deaths were summarized at the metropolitan level. The sizes of total population and people aged 65 or above for each metropolitan area were obtained from census bureau website. Information about stay-home rule for each state was scraped from popular news media. The historical daily average temperature was obtained from national climate data online (https://www7.ncdc.noaa.gov/CDO), mostly based on temperature collected from stations at each metropolitan’s main airport.

**Reproduction number and serial interval**

The time varying reproduction number (R<sub>t</sub>) was proposed by Cori A. et al. [11, 20]. This approach assumes the occurrence of secondary cases follows a Poisson distribution, conditioning on the time position in the whole infectious period of the primary case. The overall R<sub>t</sub> at time t of the epidemic is the average number of secondary cases for all prior infected cases who are still infectious at a time window (t-s, t). The estimate is based on current secondary cases, not the future infections. Therefore, it can be viewed as instantaneous R<sub>t</sub>. To smooth the estimates, a weighted average of R<sub>t</sub> over a sliding window is used (e.g., one week window). Consequently, we used a 7-day moving average of prior temperature when assessing the association between R<sub>t</sub> and temperature.

The estimation of R<sub>t</sub> also depends on the estimation of virus infectivity profile that is approximated from the distribution of generation interval. Since it is difficult to accurately estimate generation interval, serial interval is often used in calculating R<sub>t</sub> [11]. The serial interval refers to the average duration between symptom onset of a primary case and symptom onset of
secondary cases. In this study, we assumed the serial interval has a gamma distribution with
mean=4.7 days and standard deviation = 2.9 days [21, 22], similar to that of recent studies[15].
This serial interval was applied to all regions throughout the whole study period to ensure the
compatibility of $R_t$ across regions. However, different regions at different time might have
different serial intervals due to interventions and other environmental and social factors. We
also performed sensitivity analysis with a shorter serial interval (mean = 3.95, standard
devation=4.75 [23] and a longer interval (mean = 7.5, standard deviation = 3.4) [4]. The patterns
of $R_t$ were similar, except for different estimated $R_t$ values (average peak $R_t$ 1-4 for shorter
duration, and 2-9 for longer duration).

**Statistical analysis**

We adopted two time scales in the analysis. The first was calendar date to present the trends of
reproduction numbers for all metropolitan areas, starting from the date with at least 10 total
reported cases. Staggered entries into the outbreak were preserved. The second scale was the
time since the beginning of the outbreak, regardless what calendar date the outbreak happened.
This was to compare the declining patterns of $R_t$ among metropolitan areas. We also realigned
the time scale from the peak of the outbreak. The first two weeks of $R_t$ estimates were excluded,
as the first week $R_t$ were zeros, and second week estimates were too variable due to small
number of cases.

Descriptive statistics and bivariate associations were reported. Pearson correlation coefficients
and student t-tests were used for comparisons. The sizes of total population and people aged 65
or older, and the percent of positive tests at each date were used for adjustment. R package
EpiEstim was used [11] to estimate the instantaneous reproduction numbers.
There were many statistical comparisons involved. Although we did not adjust for multiple comparisons, we were cautious about over interpretations and conducted statistical tests only between prior selected pairs (e.g., southern versus northern metropolitan areas).

In this study, the author has no financial and conflict of interest to disclose. The ethics approval was exempted for this study, as no human subjects were involved, and all data were publicly available. The statistical codes and data will be available online (github address after blind review).

**Results**

The basic characteristics of metropolitan areas were presented in Table 1. All metropolitan areas had at least 1.5 million people in 2019 and over 1,000 confirmed cases. The case-fatality rates varied from 0.89 per 100 people in Salt Lake City to 7.28 per 100 people in Detroit. However, since there were large variations in case ascertainment criteria and availability of detection kits among different regions, comparing case-fatality rates was unreliable. Meanwhile, since majority of deaths occurred among elderly people, we compared the ratios of deaths to the size of elderly population among metropolitan areas. The ratios were generally lower in areas with warm weather (mean 0.026, range 0.01 to 0.09 per 100 elderly), and higher in areas with cold temperature (mean: 0.065, range 0.01 to 0.26 per 100 elderly) (p for difference = 0.046).

The trends of $R_t$ for 30 metropolitan areas were shown in Figure 1a-1d, grouped by geographic locations and temperature conditions. Overall, the instantaneous $R_t$s in all areas reached peaks or some stable points after two to three weeks, decreased significantly since the end March, and most areas reached a $R_t$ of 1 or less by April 15. It is of note that around the week of March 25, many schools were closed and many companies started offering employees working from home.
The US government has issued COVID-19 coping guideline to all US citizens, and many states also issued stay-home rule.

Figure 1a compared $R_t$ trends between typical northeastern cities and southern cities. Boston, Chicago, New York and Philadelphia started the epidemic earlier, had higher peak $R_t$s than that of Miami, Orlando, Houston, and Los Angeles. After some initial increases (though peaked at different dates), all northern cities declined sharply after the mid-March. In addition, the trajectories of Houston and Los Angeles were similar with initial peaks at around March 18, somewhat decreased and then were stable around March 25. For Miami and Orland, the $R_t$s were quite stable during the week of March 25, and declined sharply after about March 28. However, the slopes of decline, when aligned by the time since the peak $R_t$, were similar except a few spikes in Houston and Los Angeles (appendix Figure 1a).

On the other hand, the $R_t$ curves were indistinguishable between upper midwestern cities and other southern cities (Figure 1b). Upper midwestern cities except Pittsburg all had earlier interventions in the mid-March (appendix Table 1 for dates stay-home rule issued). In addition, the west coastal cities had an early start of the epidemic, and $R_t$ curves were less volatile than that of other cities during the study period (Figure 1c). The unusually high $R_t$ in Salt Lake City in the early epidemic may be due to small number of cases during that period (Figure 1d).

Furthermore, after realigning the starting time from their respective outbreak peaks for all metropolitan areas, the overall declining patterns were similar among all regions (Appendix Figure 1a-d).

To evaluate the association between $R_t$ and temperature across regions, we compared the highest $R_t$ (occurred after the first two weeks) among them (Figure 2), most cities had a peak $R_t$ between
1 and 5. At the low temperature, peak $R_t$s varied significantly. Cities with cold average temperature generally had higher $R_t$s than those with warm temperature. However, upper midwestern cities such as Minneapolis-St. Paul, Milwaukee, and Columbus had much lower peak $R_t$s than the rest of cities. The average peak of $R_t$s in Boston, Chicago, New York, and Philadelphia were marginally higher than that of Houston, Los Angeles, Orlando and Miami ($p = 0.07$). In addition, we also arbitrarily examined the $R_t$ patterns on the 15th day after the outbreak and on March 24, 2020 when most interventions had not fully executed (Appendix Figure 2a and 2b). These cross-sectional analyses demonstrated similar patterns to that of peak $R_t$.

**Discussion**

Overall, since the end of March, the instantaneous reproduction number ($R_t$) declined over time significantly and also similarly in 30 largest metropolitan areas, and by April 15, $R_t$s in almost all areas reached 1 or below, suggesting stringent interventions were effective in halting the epidemic. However, there were large geographic variations in $R_t$ patterns, partly due to different levels of interventions, and partly maybe due to temperature variations.

Without effective interventions, the reproduction number will not decline until a large proportion of susceptible people are infected. For example, during the week of March 25, $R_t$s in Houston, Miami, and Orlando were relatively stable (Figure 1a). After the end of March, due to national effort in mitigating the epidemic, all $R_t$ curves started declining. The state of Florida, however, did not officially issue the stay-home rule until April 3, 2020, where the curves already declined significantly. This posed some difficulties in assessing the intervention effects precisely. On the other hand, a few cities demonstrated some significant impact of interventions on mitigating the epidemic. For example, some upper midwestern cities (e.g., Minneapolis-St. Paul and Milwaukee) implemented interventions earlier, had lower peak $R_t$s, and their $R_t$s started
declining early, while cities like Pittsburg and Detroit had much higher \( R_t \) at the beginning, and \( R_t \) declined later. Even for cities like Chicago and New York, the intervention effects were evident based on the sharp decline of \( R_t \) since the mid-March, despite they had much higher \( R_{ts} \) in the beginning of epidemic.

It has been suggested that like many other respiratory virus infections, a seasonal pattern may exist for SARS like coronavirus [24, 25]. However, as demonstrated in this study, the association between reproduction number and temperature was deeply confounded by interventions and other external factors. In this study, we found the peak \( R_{ts} \) in warm cities were lower on average than those in cold cities, suggesting that the virus transmissibility might be lower in warm temperature than cold temperature.

However, our analysis warned readers about interpreting selective findings. For emerging epidemic like COVID-19, many things had been happening simultaneously. Effective interventions such as travelling restriction, social distancing and stay-home rules will change the epidemic process [26-28]. The availability of testing, diverse case ascertainment criteria, the delay of diagnosis and case isolation, incomplete contact tracing, the percent of asymptomatic cases, and the infectivity of asymptomatic cases will profoundly affect our ability to understand the epidemic. In this study, we observed a possible negative association between temperature and virus transmissibility (Figure 1a and 2). However, there were large variations in the peak \( R_{ts} \) among regions with lower temperature, partly due to different intervention effects and also may be due to cultural and social differences. It is also likely that other environmental factors such as living conditions may affect virus transmission. For example, under cold weather, most people will stay indoors and have close and more frequent contacts with other people. The indoor environment such as air conditioning may be conducive for virus transmission.
Furthermore, the concurrent decline of $R_t$ and increase of temperature over time are also confounded by the epidemic process itself. As suggested before, a significant reduction of susceptible people will lead to a decline of $R_t$. Longitudinally comparing the trend of $R_t$ and temperature is difficult if the epidemic evolves rapidly, as in the current COVID-19 epidemic. For instance, from March to April, the epidemic had a sharp decline, while the temperature in the whole US was still suitable for virus transmission.

There were some limitations in our study. The most important limitation was the inability to account for the diverse detection capacities across regions (Appendix Table 1). In regions with lower detection capacity, not only were there fewer cases detected (especially missing those with no or mild symptoms), but also the eligibilities for detection were more stringent. Only those with symptoms might be offered for virus detection. Thus, a sudden increase in case counts might not be due to an actual increase of infected people, rather it reflected the increased availability of detection kits. This was the main reason we had highly variable estimates of $R_t$ in the beginning of epidemic. Additionally, with more detection kits available, we will observe more asymptomatic or mild symptomatic cases. Our methods assumed the same virus infectivity between symptomatic and asymptomatic cases, which is likely not true.

Our estimation of $R_t$ relied on many assumptions. $R_t$ is determined by both the growth rate of new cases and the distribution of generation interval or serial interval [10]. We assumed a universal distribution of serial interval for all regions and over the whole time period. Serial interval may change due to interventions, regional characteristics, and the stage of epidemic. More stringent interventions and stay-home rule may result in shorter serial interval because the transmission will likely occur inside the families.
We were also not able to rigorously evaluate the virulence of SARS-CoV 2. Although we briefly compared death rates across regions, due to large and unknown delays between virus infection and death in the US, most deaths would be diagnosed several weeks before. Additionally, most died cases were elderly people or those with existing chronic conditions. Therefore, assessing the virulence should untangle the confounding effects by health care resource capacities, evolving treatments, and patient’s characteristics. A possible measure of virulence is the pattern of hospitalizations, as they are less likely affected by the availability of detection. After more hospitalization data are available and more asymptomatic and mild symptomatic cases are diagnosed, future research should focus on the impact of epidemic on the severity of disease and health care resources instead of the magnitude of epidemic.

In addition, as mentioned before, secondary data analysis based on existing aggregated data suffer many types of unmeasured confounding. Therefore, our analyses were mostly descriptive and deliberately avoided over-interpretations through numerous comparisons between regions. A careful exploration of individual level data may shed some lights on these issues.

Finally, our study has some unique strengths. First, we focus on large metropolitan areas to ensure enough cases, have comparable societal structure, individual behaviors and health care resources. Second, we explored the changes of effective reproduction number ($R_t$) over time and across regions to understand the impact of interventions and temperature on virus transmissibility. We presented and compared all regions to avoid selective reporting bias. To study the association between temperature and the epidemic process, we focus on the comparisons of $R_t$ at the peak of outbreak and before interventions, presumably less confounded by interventions and other factors.
In summary, we observed strong effects of interventions on mitigating the COVID-19 epidemic in 30 US metropolitan areas. There was a possible negative association between instantaneous reproduction number and temperature. However, whether this predicts the coronavirus will disappear in the summer and never come back, like that of 2003 SARS coronavirus, is hard to tell. Given that the virus is circulating in both northern and southern hemisphere, we need to be vigilant about a possible second wave of outbreak later of the year.
References:

1. Zhu, N., et al., A Novel Coronavirus from Patients with Pneumonia in China, 2019. N Engl J Med, 2020. 382(8): p. 727-733.

2. Pew Research Center: Most Americans Say Coronavirus Outbreak Has Impacted Their Lives. 2020, Pew Research Center.

3. Peiris, J.S., et al., The severe acute respiratory syndrome. N Engl J Med, 2003. 349(25): p. 2431-41.

4. Li, Q., et al., Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus-Infected Pneumonia. N Engl J Med, 2020. 382(13): p. 1199-1207.

5. Fraser, C., et al., Factors that make an infectious disease outbreak controllable. Proc Natl Acad Sci U S A, 2004. 101(16): p. 6146-51.

6. Li, C., et al., Asymptomatic and Human-to-Human Transmission of SARS-CoV-2 in a 2-Family Cluster, Xuzhou, China. Emerg Infect Dis, 2020. 26(7).

7. Bai, Y., et al., Presumed Asymptomatic Carrier Transmission of COVID-19. JAMA, 2020.

8. Lipsitch, M., D.L. Swerdlow, and L. Finelli, Defining the Epidemiology of Covid-19 - Studies Needed. N Engl J Med, 2020. 382(13): p. 1194-1196.

9. Hethcote, H.W., The Mathematics of Infectious Diseases. SIAM Review 2000. 42(4): p. 54.

10. Wallinga, J. and M. Lipsitch, How generation intervals shape the relationship between growth rates and reproductive numbers. Proc Biol Sci, 2007. 274(1609): p. 599-604.

11. Cori, A., et al., A new framework and software to estimate time-varying reproduction numbers during epidemics. Am J Epidemiol, 2013. 178(9): p. 1505-12.
12. Cowling, B.J., L.M. Ho, and G.M. Leung, *Effectiveness of control measures during the SARS epidemic in Beijing: a comparison of the Rt curve and the epidemic curve.* Epidemiol Infect, 2008. 136(4): p. 562-6.

13. Cauchemez, S., et al., *Unraveling the drivers of MERS-CoV transmission.* Proc Natl Acad Sci U S A, 2016. 113(32): p. 9081-6.

14. Gastanaduy, P.A., et al., *Impact of Public Health Responses During a Measles Outbreak in an Amish Community in Ohio: Modeling the Dynamics of Transmission.* Am J Epidemiol, 2018. 187(9): p. 2002-2010.

15. Zhang, J., et al., *Evolving epidemiology and transmission dynamics of coronavirus disease 2019 outside Hubei province, China: a descriptive and modelling study.* Lancet Infect Dis, 2020.

16. Cowling, B.J., et al., *Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study.* Lancet Public Health, 2020.

17. Pawar, S., et al., *Effects of temperature on COVID-19 transmission*, Y. University, Editor. 2020.

18. Bannister-Tyrrell, M., et al., *Preliminary evidence that higher temperatures are associated with lower incidence of COVID-19, for cases reported globally up to 29th February 2020.* medRxiv, 2020: p. 2020.03.18.20036731.

19. Troplett, M., *Evidence that higher temperatures are associated with lower incidence of COVID-19 in pandemic state, cumulative cases reported up to March 27, 2020.* 2020.

20. Thompson, R.N., et al., *Improved inference of time-varying reproduction numbers during infectious disease outbreaks.* Epidemics, 2019. 29: p. 100356.
21. Nishiura, H., N.M. Linton, and A.R. Akhmetzhanov, *Serial interval of novel coronavirus (COVID-19) infections*. Int J Infect Dis, 2020. 93: p. 284-286.

22. Lauer, S.A., et al., *The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application*. Ann Intern Med, 2020.

23. Du, Z., et al., *Serial Interval of COVID-19 among Publicly Reported Confirmed Cases*. Emerg Infect Dis, 2020. 26(6).

24. Lin, K., et al., *Environmental factors on the SARS epidemic: air temperature, passage of time and multiplicative effect of hospital infection*. Epidemiol Infect, 2005. 134(2): p. 7.

25. Shi, P., et al., *The impact of temperature and absolute humidity on the coronavirus disease 2019 (COVID-19) outbreak - evidence from China*. medRxiv, 2020: p. 2020.03.22.20038919.

26. Chinazzi, M., et al., *The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak*. Science, 2020.

27. Hellewell, J., et al., *Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts*. Lancet Glob Health, 2020. 8(4): p. e488-e496.

28. Ferguson, N., et al., *Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand* 2020, Imperial College: UK.
### Table 1: Characteristics and death rates for 30 largest metropolitan areas

| Metropolitan area         | Total population | Age >=65 | Cumulative cases | Cumulative deaths | Deaths per 100 Cases | Deaths per 100 old people |
|---------------------------|------------------|----------|------------------|-------------------|----------------------|---------------------------|
| New York                  | 16,669,277       | 2,789,981| 103,943          | 4,358             | 4.19                 | 0.16                      |
| Los Angeles               | 10,039,107       | 1,493,190| 10,854           | 455               | 4.19                 | 0.03                      |
| Washington DC - Baltimore | 9,360,001        | 1,370,637| 13,475           | 350               | 2.60                 | 0.03                      |
| Houston                   | 7,066,141        | 865,112  | 6,097            | 102               | 1.67                 | 0.01                      |
| St. Francisco - St. Jose  | 6,463,637        | 991,147  | 5,364            | 173               | 3.23                 | 0.02                      |
| Chicago                   | 6,021,020        | 950,164  | 21,466           | 894               | 4.16                 | 0.09                      |
| St Louis                  | 5,485,267        | 797,415  | 3,936            | 140               | 3.56                 | 0.02                      |
| Atlanta                   | 5,261,067        | 741,175  | 8,165            | 274               | 3.36                 | 0.04                      |
| Dallas-Fort Worth         | 5,081,942        | 615,560  | 3,295            | 80                | 2.43                 | 0.01                      |
| Philadelphia              | 3,815,431        | 691,016  | 15,203           | 496               | 3.26                 | 0.07                      |
| Minneapolis-St. Paul      | 3,654,908        | 580,638  | 1,276            | 71                | 5.56                 | 0.01                      |
| Cleveland - Akron         | 3,149,448        | 669,206  | 2,587            | 132               | 5.10                 | 0.02                      |
| Seattle                   | 3,074,865        | 444,891  | 6,842            | 407               | 5.95                 | 0.09                      |
| Boston                    | 2,979,288        | 529,944  | 15,218           | 515               | 3.38                 | 0.10                      |
| Denver                    | 2,967,239        | 419,589  | 5,015            | 198               | 3.95                 | 0.05                      |
| Miami - Fort Lauderdale   | 2,716,940        | 467,586  | 8,325            | 183               | 2.20                 | 0.04                      |
| Charlotte                 | 2,675,243        | 424,892  | 2,067            | 44                | 2.13                 | 0.01                      |
| Orlando                   | 2,608,147        | 430,027  | 1,989            | 33                | 1.66                 | 0.01                      |
| Portland                  | 2,492,412        | 424,694  | 1,289            | 57                | 4.42                 | 0.01                      |
| City          | Population | Income 1990 | Income 1990 | Population| Income 1990 | Income 1990 |
|--------------|------------|-------------|-------------|-----------|-------------|-------------|
| Sacramento - | 2,363,730  | 419,255     | 1,169       | 47        | 4.02        | 0.01        |
| Oakland      |            |             |             |           |             |             |
| Pittsburg    | 2,317,600  | 542,666     | 1,652       | 81        | 4.90        | 0.01        |
| Las Vegas    | 2,266,715  | 358,821     | 2,625       | 121       | 4.61        | 0.03        |
| Cincinnati   | 2,198,450  | 394,794     | 1,249       | 59        | 4.72        | 0.01        |
| Kansas       | 2,157,990  | 368,576     | 1,288       | 76        | 5.90        | 0.02        |
| Columbus     | 2,122,271  | 325,706     | 1,776       | 35        | 1.97        | 0.01        |
| Detroit      | 2,116,944  | 387,897     | 13,828      | 1,006     | 7.28        | 0.26        |
| Indianapolis | 2,074,537  | 337,623     | 5,373       | 284       | 5.29        | 0.08        |
| Durham-Raleigh| 1,974,709 | 289,249     | 1,340       | 19        | 1.42        | 0.01        |
| Salt Lake City| 1,880,948 | 207,100     | 1,804       | 16        | 0.89        | 0.01        |
| Milwaukee    | 1,575,179  | 288,873     | 2,348       | 137       | 5.83        | 0.05        |
Figure 1a-1d: Time trends of instantaneous reproduction number for 30 largest metropolitan areas

(a)

(b)
Figure 2: Association between maximal reproduction number and 7-day average temperature among 30 metropolitan areas
## Appendix:

### Appendix Table 1: Positive detection rates at various time by state

| State | Metro areas                               | % positive as of March 25, 2020 | % positive as of April 15, 2020 | Date of stay at home rule | % positive at rule mandating |
|-------|-------------------------------------------|---------------------------------|---------------------------------|---------------------------|------------------------------|
| CA    | Los Angeles, St. Francisco-St. Jose, Sacramento-Oakland | 12.9%                           | 10.6%                           | 19-Mar-20                 | 9.5%                         |
| CO    | Denver                                    | 11.8%                           | 20.4%                           | 11-Apr-20                 | 19.9%                        |
| DC    | Washington DC - Baltimore                 | 11.4%                           | 19.3%                           | 1-Apr-20                  | 15.2%                        |
| FL    | Miami-Fort Lauderdale, Orlando            | 9.9%                            | 10.4%                           | 3-Apr-20                  | 10.5%                        |
| GA    | Atlanta                                   | 20.2%                           | 23.1%                           | 2-Apr-20                  | 23.3%                        |
| IL    | Chicago                                   | 13.1%                           | 21.0%                           | 21-Mar-20                 | 12.1%                        |
| IN    | Indianapolis                              | 14.2%                           | 18.7%                           | 24-Mar-20                 | 12.5%                        |
| KS    | Kansas                                    | 5.1%                            | 9.9%                            | 30-Mar-20                 | 7.5%                         |
| MA    | Boston                                    | 9.3%                            | 22.9%                           | 24-Mar-20                 | 8.4%                         |
| MI    | Detroit                                   | 48.4%                           | 31.0%                           | 24-Mar-20                 | 52.6%                        |
| MN    | Minneapolis-St. Paul                      | 2.5%                            | 4.6%                            | 27-Mar-20                 | 2.8%                         |
| MO    | St. Louis                                 | 49.1%                           | 10.1%                           | 3-Apr-20                  | 9.8%                         |
| NC    | Durham-Raleigh, Charlotte                 | 4.8%                            | 7.7%                            | 30-Mar-20                 | 6.3%                         |
| NV    | Las Vegas                                 | 7.0%                            | 11.7%                           | 1-Apr-20                  | 10.0%                        |
| NY    | New York                                  | 29.8%                           | 40.4%                           | 22-Mar-20                 | 24.7%                        |
| OH    | Cleveland, Columbus, Cincinnati           | 4.8%                            | 11.2%                           | 22-Mar-20                 | 71.5%                        |
| OR    | Portland                                  | 4.6%                            | 5.0%                            | 23-Mar-20                 | 5.0%                         |
| PA    | Philadelphia, Pittsburg                   | 9.1%                            | 19.6%                           | 1-Apr-20                  | 12.0%                        |
| TX    | Houston, Dallas-Fort Worth                | 7.2%                            | 10.4%                           | 2-Apr-20                  | 9.2%                         |
| UT    | Salt Lake City                            | 5.1%                            | 5.4%                            | 27-Mar-20                 | 5.2%                         |
| WA    | Seattle                                   | 9.4%                            | 8.7%                            | 23-Mar-20                 | 7.8%                         |
| WI    | Milwaukee                                 | 5.5%                            | 8.6%                            | 25-Mar-20                 | 5.5%                         |
Appendix Figure 1a – d, Declining trend of instantaneous reproduction number over time after the peak of epidemic
(c) Instantaneous reproduction number vs. days since the peak of outbreak for various cities.

(d) Another view showing the same data for different cities, highlighting the temporal dynamics of the outbreak.

These graphs illustrate the progression of the disease spread in different cities, emphasizing the importance of early intervention and containment measures.
Appendix Figure 2a-b: Variations of instantaneous reproduction numbers across metropolitan areas.