High Temperature and High Humidity Reduce the Transmission of COVID-19

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Abstract

With the ongoing global pandemic of COVID-19, a question is whether the coming summer in the northern hemisphere will reduce the transmission intensity of COVID-19 with increased humidity and temperature. In this paper, we investigate this problem using the data from the cases with symptom-onset dates from January 19 to February 10, 2020 for 100 Chinese cities, and cases with confirmed dates from March 15 to April 25 for 1,005 U.S. counties. Statistical analysis is performed to assess the relationship between the transmissibility of COVID-19 and the temperature/humidity, by controlling for various demographic, socio-economic, geographic, healthcare and policy factors and correcting for cross-sectional correlation. We find a similar influence of the temperature and relative humidity on effective reproductive number (*R* values) of COVID-19 for both China and the U.S. before lockdown in both countries: one-degree Celsius increase in temperature reduces *R* value by about 0.023 (0.026 (95% CI [-0.0395,-0.0125]) in China and 0.020 (95% CI [-0.0311, -0.0096]) in the U.S.), and one percent relative humidity rise reduces *R* value by 0.0078 (0.0076 (95% CI [-0.0108,-0.0045]) in China and 0.0080 (95% CI [-0.0150,-0.0010]) in the U.S.). If assuming a 30 degree and 25 percent increase in temperature and relative humidity from winter to summer in the northern hemisphere, we expect the *R* values to decline about 0.89 (0.69 by temperature and 0.20 by humidity). Moreover, after the lockdowns in China and the U.S., temperature and relative humidity still play an important role in reducing the *R* values but to a less extent. Given the notion that the non-intervened *R* values are around 2.5 to 3, only weather factors cannot make the *R* values below their critical condition of $R<1$, under which the epidemic diminishes gradually. Therefore, public health intervention such as social distancing is crucial to block the transmission of COVID-19 even in summer.

Introduction

The novel coronavirus 2019 (COVID-19) disease has become a global pandemic with more than 4.7 million confirmed cases worldwide until May 18, 2020 [1] since its first reported case in Wuhan, China in December 2019 [2]. Compared with the epidemic of the severe acute respiratory syndrome (SARS) in 2003 [3], the geographic range of the COVID-19 outbreak is much wider. The transmission of coronavirus can be affected by a number of factors, including climate conditions (such as temperature and humidity), population density, medical care quality *etc.*[4,5]. Previous studies have shown that wintertime climate and host behavior can facilitate the transmission of influenza [6–8] and other human coronaviruses [9,10]. Recently there have also been studies analyzing the effectiveness of government policies (*e.g.*, city lockdown) to the transmission of the disease [11,12]. With the arrival of summer in the northern hemisphere, people are wondering whether hot and humid weather can slow down the COVID-19 pandemic [13,14]. Existing studies find that temperature and humidity have a significant influence on the number of confirmed cases for a certain location[15]. On the other hand, indirect evidence shows the transmission of COVID-19 in the local community among tropical areas, which indicates that the impact of meteorological conditions on COVID-19 may not be as big as those on flu and colds.[16] Therefore, the accurate measurement of the influence of weather conditions on the transmissibility of COVID-19 is important for the knowledge of the general public. However, until now, there is no direct evidence demonstrating the influence of temperature and humidity on the transmissibility directly measured by the effective reproductive number (*R* value) of COVID-19.

Furthermore, during a pandemic, getting timely and accurate research insights is essential for taking effective countermeasures and reducing economic losses. However, the duration of the COVID-19 pandemic is not yet sufficient to support a thorough study of the impact of meteorological factors on the transmission of the SARS-CoV-2 virus at any fixed location. Since the transmission of other human coronaviruses that cause mild respiratory symptoms is seasonal, recently the seasonality of these viruses has been borrowed to conduct a long-term simulation of the transmission of COVID-19 [17].

The goal of this paper is to quantify the influences of temperature and humidity on the transmissibility of COVID-19 measured by *R* values, through analyzing COVID-19 data from both China and the U.S. with rigorous statistical analysis. Specifically, we adapt the strategy of "trading space for time", that is, in a relatively short time range, linking the transmission intensity in different locations to their associated meteorological conditions. Our analysis shows that this strategy allows us to recognize the meteorological trend of the pandemic even in its early stage.

Results

COVID-19 has spread widely in both China and the U.S. The transmissibility and weather conditions in the major cities of these two countries vary largely (Figures 1 and 2). We analyze the relationship between the COVID-19 transmissibility and the weather factors, controlling for various demographic, socio-economic, geographic, healthcare and policy factors, and correcting for cross-sectional correlation. Overall, we find robust negative associations between temperature as well as humidity and COVID-19 transmission before the large-scale public-health interventions in China and the U.S. Moreover, the temperature has a consistent influence on the effective reproductive number, *R* values, for both Chinese cities and U.S. counties; relative humidity also has consistent effects across the two countries. Both of them remain to have a negative influence even after the public-health intervention (lockdown), but with smaller magnitudes since more and more people stay at home and hence expose less to the outdoor weather. More details are presented below.

Temperature, Relative Humidity, and Effective Reproductive Numbers. For either China and the U.S., we conduct a series of cross-sectional regressions (Fama-Macbeth approach [18]) of the daily effective reproductive numbers (*R* values), which measure the transmissibility of COVID-19, on the six-day average temperature and relative humidity up to and including the day when the *R* value is measured [19] and other control factors, for the before lockdown period, the after lockdown period, and the overall period. Figure 1 shows the average *R* values from January 19 to 23 (before the public health intervention) for different Chinese cities geographically, and Figure 2 shows the average *R* values from March 15 to April 6 (before the majority of states declared a stay-at-home order) for different U.S. counties.

Before the lockdown, the results for Chinese cities (Table 1) demonstrate that the six-day average temperature and relative humidity have a strong influence on *R* values, with p values smaller than or around 0.01 for all three time period specifications. One-degree Celsius increase in temperature and one percent increase in relative humidity reduce the *R* value by 0.026 (95% CI [-0.0395, -0.0125]) and 0.0076 (95% CI [-0.0108, -0.0045]), respectively. Analysis for U. S. counties (Table 2) shows that six-day average temperature and relative humidity have statistically significant associations on *R* values with *p* values lower than 0.05 before April 7, the time when most states declared state-wise stay-at-home orders [20]. One-degree Celsius increase in temperature and one percent increase in relative humidity reduce the *R* value by 0.020 (95% CI [-0.0311, -0.0096]) and 0.0080 (95% CI [-0.0150, -0.0010]) respectively.

Overall, the influence of the temperature and relative humidity on *R* values are quite similar before lockdown in China and the U.S.: one-degree Celsius increase in temperature reduces *R* value by about 0.023 (0.026 (95% CI [-0.0395,-0.0125]) in China and 0.020 (95% CI [-0.0311, -0.0096]) in the U.S.), and one percent relative humidity rise reduces *R* value by about 0.0078 (0.0076 (95% CI [-0.0108,-0.0045]) in China and 0.0080 (95% CI [-0.0150,-0.0010]) in the U.S.

After lockdown, the temperature and relative humidity also present negative relationships with *R* values for both countries. For China, it's statistically significant (with p values lower than 0.05), and one-degree Celsius increase in temperature and one percent increase in relative humidity reduce *R* values by 0.0209 (95% CI [-0.0378, -0.0041]) and 0.0054 (95% CI [-0.0104, -0.0004]), respectively. For the U.S. the estimated effects of the temperature and relative humidity on *R* values are still negative but no longer statistically significant (with p values 0.141 and 0.073, respectively). The less influence from weather conditions is very likely caused by the stay-at-home policy during the lockdown periods, and hence people expose less to the outdoor weather. Therefore, we rely more on the estimates of the weather-transmissibility relationship before the lockdowns in both countries.

Control Variables. Several control variables also have significant influences on the transmissibility of COVID-19. In China, before the lockdowns, in cities with higher levels of population density, the virus spreads faster than that in less crowded cities due to more possible contacts among people. One thousand people per square kilometer rise in population density is associated with a 0.1188 (95% CI [0.0573, 0.1803]) increase in the *R* value before lockdown. Cities in China with more doctors have a smaller transmission intensity, since the infected are treated in hospitals and hence unable to transmit to others. Particularly, one thousand more doctors are associated with a 0.0058 [-0.0090, -0.0025] decrease in the *R* value during the overall time period; the influence of doctor number is greater before lockdown with a coefficient of 0.0109 (95% CI [-0.0163, -0.0056])). Similarly, more developed cities (with higher GDP per capita) normally have better medical conditions, hence, patients are more likely to be taken care and thus unlikely transmitting to others. Ten thousand Chinese Yuan GDP per capita increase lowers the *R* value by 0.0145 (95% CI [-0.0249, -0.0040]) before the lockdown. In the U.S., there's a strong relationship between *R* value and the number of ICU beds per capita after lockdown, with a p value at 0.001; every unit increase in ICU bed per 10,000 population decreases the *R* value by 0.0110 (95% CI [-0.0171, -0.0049]). What's more, counties with more people over 65 years old have lower *R* values, but the magnitude is small, *i.e.* one percent increase in fraction of aged over 65 is associated with a 0.0092 (95% CI [-0.0135, -0.00498]) decrease in *R* value in the overall time period.

Absolute Humidity. Absolute humidity, the mass of water vapor per cubic meter of air, relates to both temperature and relative humidity. Previous work shows that absolute humidity is a good solo variable explaining the seasonality of influenza [21]. The results shown in Table 3 are only partly consistent with this notion[21]. Particularly, for the U.S. counties, relative humidity and absolute humidity are almost equivalent in explaining the variation of the *R* value (12.57% vs. 12.55%), while absolute humidity does achieve a higher significance level (p-value of 0.00001) compared to relative humidity (p-value of 0.019) before lockdown. However, the coefficient of absolute humidity is not statistically significant for Chinese cities (p-value of 0.312).

Lockdown and Mobility. Intensive health emergency and lockdown policies have taken place since the outbreak of COVID-19 in both the U.S. and China. In the regression analysis, we use cross-sectional centralized (with sample mean extracted) explanatory variables, and thus the intercepts in the regression models estimate the average *R* value of different time periods. In China, the health emergency policies on January 24, 2020 lowered the average *R* value from 2.1174 (95% CI [1.5699,2.6649]) to 0.8084 (95% CI [0.5334,1.0833]), which corresponds to a more than 60% drop. In the U.S., the regression results of the data as of April 25 show that although the *R* value has not decreased to less than 1, the lockdown policies have reduced the average *R* value by nearly half, from 2.1970 (95% CI [1.6631,2.7309]) to 1.1837 (95% CI [1.1687,1.1985])

We use the Baidu Mobility Index (BMI) drop as the proxy for intra-city mobility change (compared to the normal time) in China. Regression results show that before the lockdown, 1% decrease of BMI drop is associated with a decrease of *R* value by 0.004093 (95% CI [-0.00683, -0.001356]). After the lockdown, the BMI drop does not significantly affect *R* value. A possible reason is that the BMI variations across cities are quite small (all in quite low levels) after the lockdown, as the paces of intervention in different Chinese cities are quite similar. Overall, the negative relationship before lockdown may also imply that the rapid response to infectious disease risks is crucial. For the U.S., we use the M50 index, the fraction of daily median of maximum moving distance over that in the normal time (workdays between February 17 and March 7), as the proxy of mobility. It has a positive relationship with *R* value for both overall and after lockdown time period with p-values lower than 0.01, which demonstrates that counties with more social movements would have higher *R* values than others.

Robustness Checks. We check the robustness of influences of temperature/humidity on *R* values over two conditions:

(1) **Wuhan city.** Among these 100 cities in China, Wuhan is a special case with the earliest outbreak COVID-19. There was an increase of more than 13,000 cases in a single day (February 12, 2020) due to the unification of testing standards with other regions of China [22]. Therefore, as a robustness check, we remove Wuhan city in our sample and redo the regression analysis.

(2) **Different measurement of serial intervals.** We also use serial intervals in previous work (mean 7.5 days, std 3.4 days based on 10 cases) [23] with a Weibull distribution to estimate *R* values of various cities/counties for robustness checks.

The results of the above-mentioned two robustness checks are shown in Table A5 to A7. All of them show that temperature and relative humidity have a strong influence on *R* values with strong statistical significance, which are consistent with the reported results in Table 1 and Table 2.

Discussions

We have identified robust negative associations between temperature/humidity and COVID-19 transmission using samples of the daily transmissibility of COVID-19, temperature and humidity for 100 Chinese cities and 1,005 U.S. counties. Although we use different datasets (symptom-onset data for Chinese cities and confirmed cases data for the U.S. counties) for different countries, we obtain consistent estimates. This result also aligns with the evidence that high temperature and high humidity can reduce the transmission of influenza [21,24–27], which can be explained by two potential reasons. First, the influenza virus is more stable in cold environments, and respiratory droplets, as containers of viruses, remain airborne longer in dry air [28,29]. Second, cold and dry weather can also weaken the hosts' immunity and make them more susceptible to the virus [30,31]. Our result is also consistent with the evidence that high temperature and high relative humidity reduce the viability of SARS coronavirus [32,33].

Our study suggests that the arrival of summer and rainy season in the northern hemisphere can potentially reduce the transmissibility of the COVID-19, but it is unlikely that the COVID-19 pandemic will "automatically" diminish when summer comes, because temperature and humidity alone are not sufficient to make the *R* value less than the critical value of 1 based on their effect estimates. An increase of roughly 30°C in temperature and 25% in relative humidity from winter to summer reduce the *R* value by 0.69 and 0.20 respectively, which would altogether lower down *R* value by 0.89. If all other conditions are held fixed, it is impossible to lower down the *R* value to 1 by just temperature and relative humidity, based on the fact that the initial *R0* value is about 2.5 to 3 [34]. Thus, from winter to summer, the *R* values decline one third at most. According to the results of both the U.S. and China, in order to lower down the *R* value to 1 from the *R* value of 3, the temperature would have to increase by 87°C or the relative humidity would have to increase by 256 percent, if all other conditions are held fixed.

Therefore, public health intervention is still necessary to block the transmission of COVID-19 even in summer. Particularly, as shown in this paper, lockdowns, constraints on human mobility, increase in hospital beds, *etc.* can effectively reduce the transmissibility of COVID-19.

Limitation. The R^2 of our regression is about 30% in China and 12% in the U.S., which means that about 70% to 88% of cross-city *R* value fluctuations cannot be explained by temperature and relative humidity (and controls). Moreover, the temperatures and relative humidity in our Chinese samples range from -21°C to 20°C and from 49% to 100%, in the U.S. the temperature and humidity range from -10°C to 29°C and from 16% to 99%; thus it is still unknown yet whether these negative relationships still hold in extremely hot and cold areas. The slight differences between the estimates on the U.S. and Chinese cities might come from the different ranges of temperature and relative humidity.

Methods

Data. Records of 69,498 patients with symptom-onset days up to February 10, 2020 for 325 cities, are extracted from the Chinese National Notifiable Disease Reporting System. Each patient's records contain the area code of his/her current residence, the area code of the reporting institution, the date of symptoms onset and the date of confirmation. In our paper, with symptom-onset data, we are able to estimate the precise *R* values for various Chinese cities. Note that in this work, in order to protect the patients' privacy, no identifiable personal information was extracted. For the U.S. data, daily confirmed cases for 1,005 counties with more than 20,000 population are collected from COVID-19 database of JHU CSSE available at https://github.com/CSSEGISandData/COVID-19/. We obtain data from March 15 to April 25 for the 1,005 counties, and there are total 740,843 confirmed cases for these counties as of April 25. Note that due to the unavailability of onset date in U.S. data, we estimate *R* values from daily confirmed cases for U.S. counties, which may be less precise than that of Chinese cities.

We collect 4,711 cases from the epidemiological surveys available online published by the Center for Disease Control and Prevention of 11 provinces and municipalities including Beijing, Shanghai, Jilin, Sichuan, Hebei, Henan, Hunan, Guizhou, Chongqing, Hainan and Tianjin. By analyzing the records of each patient's contact history with other patients, we match close contacts and screened out 105 pairs of clear virus carriers and the infected, which are used to estimate the serial intervals of COVID-19.

Temperature and relative humidity data are obtained from 699 meteorological stations in China from http://data.cma.cn/. Population density, GDP per capita, the fraction of the population aged 65 and above, the number of doctors in 2018 for each city are obtained from https://data.cnki.net. The indices representing the number of migrants from Wuhan to other cities over the period of January 7 to February 10 and Baidu Mobility Indexes are obtained from https://qianxi.baidu.com/. Panel A of Table A1 in supplementary materials provides summary statistics of the Chinese variables with pairwise correlation shown in Table A2.

For U.S., temperature and relative humidity data are from National Oceanic and Atmospheric Administration at https://www.ncdc.noaa.gov/. Population data and the fraction of over 65 for each county are obtained from https://www.census.gov/. GDP and person income in 2018 for each county are obtained from https://www.bea.gov/. Data describing mobility changes, including the fraction of maximum moving distance over normal time, and home-stay minutes for each county are obtained from https://github.com/descarteslabs/DL-COVID-19 and https://www.safegraph.com/, respectively. Gini index, fraction of population below poverty level, fraction of not in labor force (16 years or over), fraction of total household more than $200,000, fraction of food stamp/SNAP benefits are obtained from American Community Survey data at https://www.census.gov/. The number of ICU beds for each county is obtained from https://www.kaggle.com/jaimeblasco/icu-beds-by-county-in-the-us/data. Panel B of Table A1 in supplementary materials provides summary statistics of the U.S. variables with pairwise correlation shown in Table A3.

Construction of Effective Reproductive Numbers. We use the effective reproductive numbers, the *R* value, to quantify the transmission of COVID-19 in different cities and counties. The calculation of *R* values contains two steps. First, we estimate the serial interval, which is the time between successive cases in a chain of transmission, of COVID-19 using the 105 pairs of virus carriers and the infected. We fit 105 samples of serial intervals with the Weibull distribution (a distribution commonly used to fit the serial interval of influenza) [35]. Specifically, as shown in Figure A1, we fit the Weibull distribution using the Maximum Likelihood Estimation (MLE) method by Python package 'Scipy' and R package 'MASS' (Python version 3.7.4, 'Scipy' version 1.3.1 and R version 3.6.2, 'MASS' version 7.3_51.4). The two results are consistent with each other. The mean and standard deviation of the serial intervals are 7.4 and 5.2 days, respectively. Note that cities with a small number of confirmed cases normally have a highly wiggled *R* value curve due to inaccurate *R* value estimation, therefore, we select 100 cities with more than 40 cases in our sample from the 325 Chines cities. We then calculate the effective reproductive number, *R* value, for each of the 100 Chinese cities from the date of the first-case to February 10 through a time-dependent method based on Maximum Likelihood Estimation (MLE) [36]. The inputs to the method are epidemic curves, *i.e.* the historical numbers of patients of each day, for a certain city. For estimation of *R* values in U.S. counties, the settings of serial intervals remain the same as China, *i.e.* with 7.4 days mean and 5.2 days standard deviation. We use the same methods of estimating *R* values of all 1,005 U.S. counties from the date when the first confirmed case occurred in the county to April 25. The main difference remains that the epidemic curves of U.S. counties are arranged by the date of confirmation due to lack of symptom-onset data; whereas Chinese curves are based on symptom-onset dates. The *R* values are calculated with the Package 'R0' developed by Boelle & Obadia with the R version 3.6.2 and 'R0' version 1.2_6.[37]

Study Period. We aim to study the influences of various factors on *R* value under the outdoor environment, therefore if people stay at home for most of their time under the restrictions of the isolation policy, weather conditions are unlikely to influence the virus transmission due to no chance of contact among people. We, therefore, perform separate analyses before and after the large-scale stay-at-home policy for both China (January 24) and the U.S. (April 7), respectively. Note that the first-level response to major public health emergencies in many major Chinese cities and provinces including Beijing and Shanghai were announced on 24 January. Moreover, the number of cases in most cities was too small before January 18 to estimate the *R* value accurately. Thus, we take the daily *R* values from January 19 to January 23 for each city as the before lockdown period. Although Wuhan City imposed a travel restriction at 10 a.m. on January 23, a large number of people still left Wuhan before 10 a.m. on that day, so our sample still includes January 23. We take January 24 to February 10 as the period after lockdown for China. As reported by The New York Times, most states had announced state-wise stay-at-home orders from April 7 for the U.S. [20]. Moreover, the number of cases in most counties before March 15 is too small for estimating *R* value. Thus, we take daily *R* values from March 15 to April 6 for each county as values during the before-lockdown period and daily *R* values from April 7 to April 25 as values during the after-lockdown period.

Statistical Analysis. We use six-day average temperature and relative humidity *up to and including* the day when the *R* value is measured, which is inspired by the five-day incubation period estimated from Johns Hopkins University [19] plus one-day onset. In the data of this work, the series of the 6-days average temperature, the 6-days average relative humidity, and the daily effective reproduction number *R* are mostly non-stationary. We find declining trends of *R* values for nearly all China cities and the U.S. counties, which may be due to the nature of the disease and due to people's raised awareness and increased self-protection measures even before the lockdown orders from the government. Table A4 Panel A and Panel B in supplementary materials show the panel unit root test results for China and U.S. data, respectively. As such, direct time-series regression cannot be applied, since it will lead to the so-called spurious regression[38], that is, a regression that provides misleading statistical evidence of a linear relationship between non-stationary time series variables. We, hence, adopt the Fama-Macbeth methodology[18], which consists of a series of cross-sectional regressions and has been proved effective in various disciplines including finance and economics. The details are illustrated as follows.

Fama-Macbeth Regression [18]. Fama-Macbeth regression is a two steps procedure. In the first step, it runs cross-sectional regression at each point of time; the second step estimates the coefficient as the average of the cross-sectional regression estimates:

Step 1: Denote the time length as T, the number of controls as m. For each time t, we run a cross-sectional regression:

$$R_{i,t} = c_t + \beta_{temp,t} * temp_{i,t} + \beta_{humi,t} * humi_{i,t} + \sum_{j=1}^{M} \beta_{control_j,t} * control_{j,i,t} + \epsilon_{i,t}$$

Step 2: Estimate the average of the first step regression coefficient estimates:

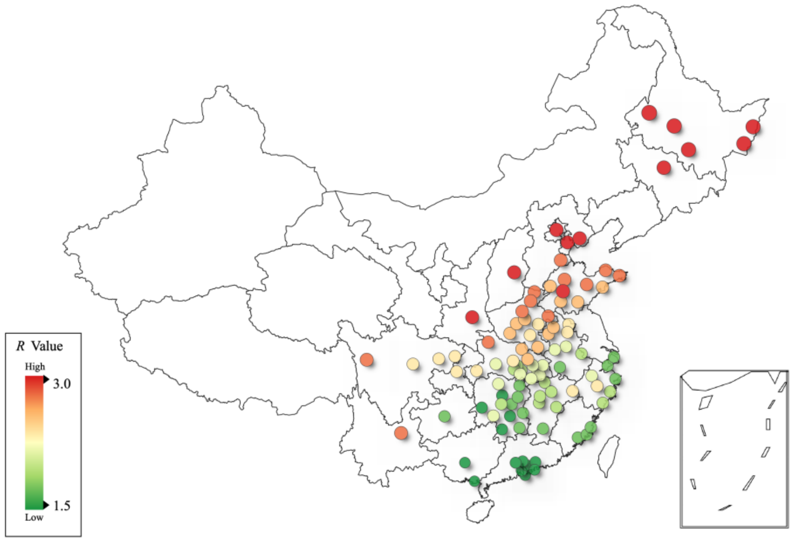
$$\widehat{\beta}_k = \frac{1}{T} \sum_{t=1}^{T} \beta_{k,t}$$

We use the Newey-West approach[39] to adjust the time-series autocorrelation and heteroscedasticity in calculating standard errors in the second step. Note that Fama-MacBeth regression is commonly used in estimating parameters for finance and economic models that are valid even in the presence of the cross-sectional correlation. To the best of our knowledge, our study is a novel application of the Fama-Macbeth method in urgent public health and epidemiological problems.

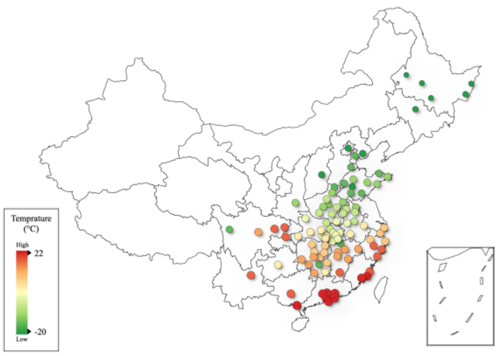
Specifically, on each day during a study period, we perform a cross-sectional regression of the daily R values of various cities or counties on their 6-day average temperature and relative humidity, and several categories of control variables as follows:

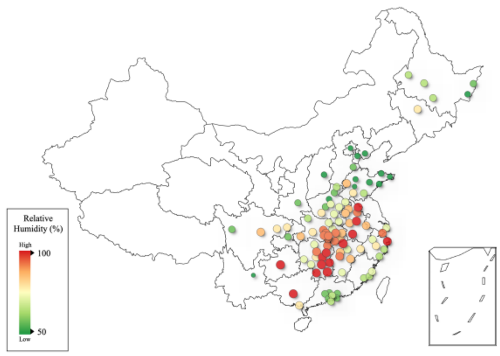
(1) *Demographics.* Population density and fraction of people aged 65 and older for both China and the U.S.
(2) *Socio-economic statuses.* GDP per capita for Chinese cities. For the U.S. counties, Gini index and the first PCA factor derived from several factors including GDP per capita, personal income, the fraction of population below poverty level, the fraction of population not in labor force (16 years or over), the fraction of population with total household more than $200,000, the fraction of food stamp/SNAP benefits.
(3) *Geographical variables.* Latitude and longitude for both China and the U.S.
(4) *Healthcare.* The number of doctors for Chinese cities and the number of ICU beds per capita for U.S. counties.
(5) *Human mobility status.* For Chinese cities, the number of people migrated from Wuhan in the 14 days prior to the R measurement, and the drop rate of BMI compared to the same day in the first week of Jan 2020. For U.S. counties, the fraction of maximum moving distance over the median of normal time (weekdays from Feb 17 to March 7), and home-stay minutes are used as mobility proxies. All human mobility controls are averaged over a 6-day period in the regression.

All analyses are conducted in the software Stata version 16.0.



(a)





(b) (c)

Figure 1: A city-level visualization of the COVID-19 transmission (a), temperature (b) and relative humidity (c).

Average *R* values from January 19 to 23, 2020 for 100 Chinese cities are used in subplot (a). The average temperature and relative humidity for the same period are plotted in (b) and (c).

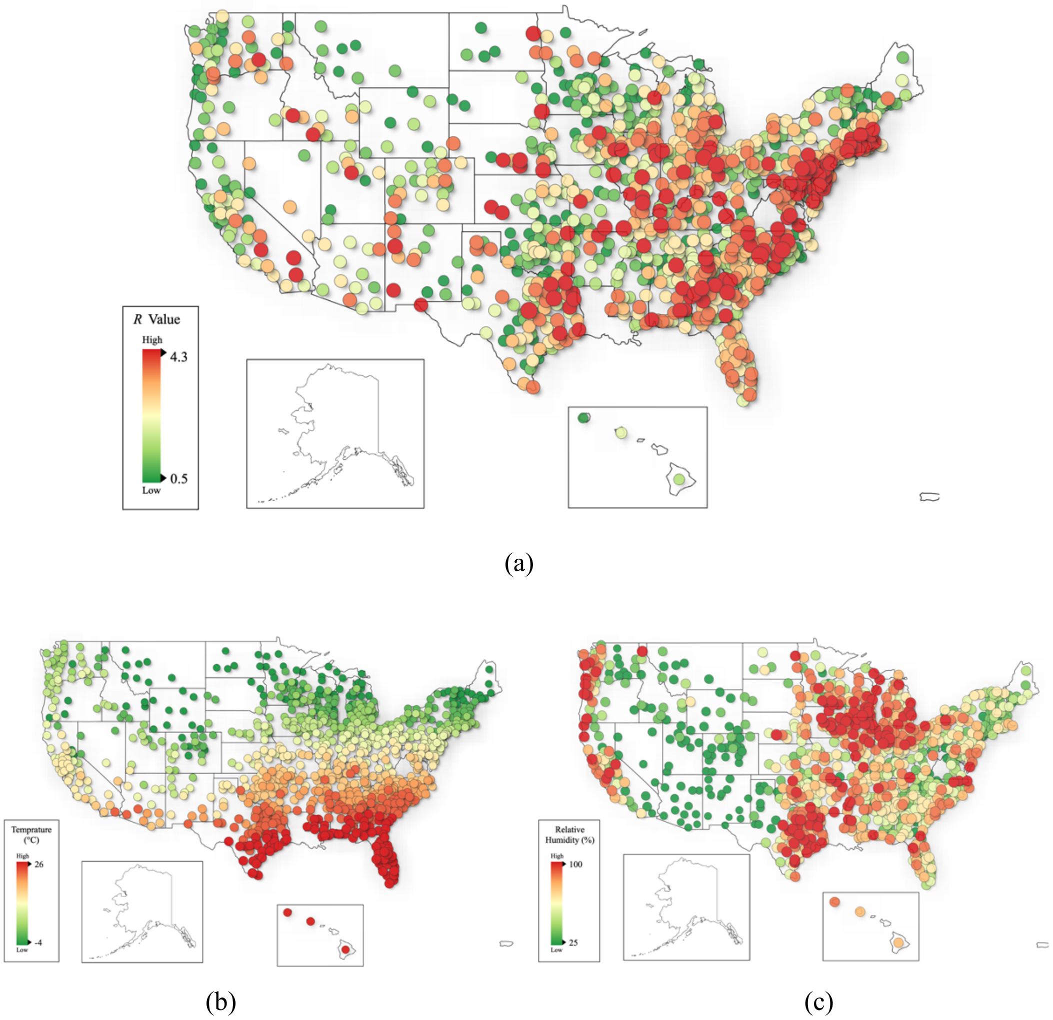


Figure 2: A county-level visualization of the COVID-19 transmission (a), temperature (b) and relative humidity (c) in the U.S.

Average *R* values from March 15 to April 6, 2020 for 1,005 U.S. counties are used in subplot (a). The average temperature and relative humidity for the same period are plotted in (b) and (c).

Table 1: Fama-Macbeth Regression for Chinese Cities

Daily R values from January 19 to February 10 and averaged temperature and relative humidity over 6 days up to and including the day when R value is measured, are used in the regression for 100 Chinese cities with more than 40 cases. The regression is estimated by the Fama-MacBeth approach.

	Overall	**Before Lockdown (Jan 24)**	**After Lockdown (Jan 24)**
R2	0.3013	0.1895	0.3323
Temperature			
coef	-0.0220	-0.0260	-0.0209
95%CI	[-0.0356,-0.0085]	[-0.0395,-0.0125]	[-0.0378,-0.0041]
std.err	0.0065	0.0049	0.0080
t-stat	-3.38	-5.35	-2.62
p-value	0.003	0.006	0.018
Relative Humidity			
coef	-0.0059	-0.0076	-0.0054
95%CI	[-0.0098,-0.0019]	[-0.0108,-0.0045]	[-0.0104,-0.0004]
std.err	0.0019	0.0011	0.0024
t-stat	-3.08	-6.70	-2.29
p-value	0.005	0.003	0.035
Population Density			
coef	0.0259	0.1188	0.0001
95%CI	[-0.0292,0.0810]	[0.0573,0.1803]	[-0.0359,0.0362]
std.err	0.0266	0.0222	0.0171
t-stat	0.98	5.36	0.01
p-value	0.340	0.006	0.993
Percentage over 65			
coef	0.1255	0.3230	0.0707
95%CI	[-1.7524,2.0034]	[-1.1797,1.8256]	[-2.3231,2.4644]
std.err	0.9055	0.5412	1.1346
t-stat	0.14	0.60	0.06
p-value	0.891	0.583	0.951
GDP per capita			
coef	0.0045	-0.0145	0.0098
95%CI	[-0.0157,0.0248]	[-0.0249,-0.0040]	[-0.0105,0.0301]
std.err	0.0098	0.0038	0.0096
t-stat	0.46	-3.85	1.02
p-value	0.647	0.018	0.322
No. of doctors			
coef	-0.0058	-0.0109	-0.0043
95%CI	[-0.0090,-0.0025]	[-0.0163,-0.0056]	[-0.0064,-0.0022]
std.err	0.0015	0.0019	0.0010
t-stat	-3.71	-5.69	-4.41
p-value	0.001	0.005	0.0004

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
Drop of BMI			
coef	0.3051	-0.4093	0.5036
95%CI	[-0.3352,0.9454]	[-0.6830,-0.1356]	[-0.1133,1.1205]
std.err	0.3087	0.0986	0.2924
t-stat	0.99	-4.15	1.72
p-value	0.334	0.014	0.103
Inflow population from Wuhan			
coef	-0.0052	-0.0006	-0.0065
95%CI	[-0.0106,0.0002]	[-0.0010,-0.0001]	[-0.0127,-0.0003]
std.err	0.0026	0.0002	0.0029
t-stat	-2.00	-3.58	-2.21
p-value	0.058	0.023	0.041
Latitude			
coef	0.0046	0.0096	0.0032
95%CI	[-0.0145,0.0236]	[-0.0133,0.0325]	[-0.0211,0.0274]
std.err	0.0092	0.0083	0.0115
t-stat	0.50	1.16	0.28
p-value	0.625	0.311	0.786
Longitude			
coef	-0.011	-0.0270	-0.0065
95%CI	[-0.0199,-0.0021]	[-0.0528,-0.0013]	[-0.0137,0.0007]
std.err	0.0043	0.0093	0.0034
t-stat	-2.56	-2.92	-1.91
p-value	0.018	0.043	0.074
const			
coef	1.0929	2.1174	0.8084
95%CI	[0.5078,1.6781]	[1.5699,2.6649]	[0.5334,1.0833]
std.err	0.2821	0.1972	0.1303
t-stat	3.87	10.74	6.20
p-value	0.001	0.0004	0

Table 2: Fama-Macbeth Regression for the U.S. Counties

Daily R values from March 15 to April 25 and temperature and relative humidity over 6 days up to and including the day when R value is measured, are used in the regression for 1,005 U.S. counties with more than 20,000 population. The regression is estimated by the Fama-MacBeth approach.

	Overall	**Before Lockdown (April 7)**	**After Lockdown (April 7)**
R2	0.1155	0.1344	0.0925
Temperature			
coef	-0.0165	-0.0204	-0.0118
95%CI	[-0.0257,-0.0073]	[-0.0311,-0.0096]	[-0.0279,0.0043]
std.err	0.0045	0.0052	0.0077
t-stat	-3.62	-3.93	-1.54
p-value	0.001	0.001	0.141
Relative Humidity			
coef	-0.0049	-0.0080	-0.0013
95%CI	[-.0.0103,0.0005]	[-0.0150,-0.0010]	[-0.0027,0.0001]
std.err	0.0027	0.0034	0.0007
t-stat	-1.84	-2.36	-1.90
p-value	0.073	0.028	0.073
Population Density			
coef	4.39E-6	7.00E-6	1.23E-6
95%CI	[-0.00001,0.00002]	[-0.00003,0.00004]	[9.84E-7,3.45E-6]
std.err	8.44E-6	0.00002	1.05E-6
t-stat	0.52	0.44	1.17
p-value	0.606	0.666	0.258
Percentage over 65			
coef	-0.9243	-1.1084	-0.7014
95%CI	[-1.3510,-0.4976]	[-1.8119,-0.4050]	[-1.0696,-0.3332]
std.err	0.2113	0.3392	0.1752
t-stat	-4.37	-3.27	-4.00
p-value	0.0001	0.004	0.001
Gini			
coef	-1.8428	-1.9255	-1.7426
95%CI	[-3.5058,-0.1797]	[-4.4539,0.6028]	[-2.4697,-1.0154]
std.err	0.8235	1.2191	0.3461
t-stat	-2.24	-1.58	-5.03
p-value	0.031	0.129	0.0001
Socio-economic factor			
coef	0.0916	0.1406	0.0324
95%CI	[0.0338,0.1495]	[0.0886,0.1925]	[-0.0108,0.0756]
std.err	0.0287	0.0250	0.0206
t-stat	3.20	5.61	1.58
p-value	0.003	0.00001	0.133

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
No. of ICU beds per capita			
coef	-0.0097	-0.0086	-0.0110
95%CI	[-0.0233,0.0039]	[-0.0299,0.0126]	[-0.0171,-0.0049]
std.err	0.0067	0.0102	0.0029
t-stat	-1.44	-0.84	-3.81
p-value	0.156	0.408	0.001
Fraction of maximum moving distance over normal time			
coef	0.0038	0.0022	0.0057
95%CI	[0.0014,0.0062]	[-0.0008,0.0053]	[0.0048,0.0066]
std.err	0.0012	0.0015	0.0004
t-stat	3.23	1.50	13.71
p-value	0.002	0.147	0
Home stay minutes			
coef	0.0003	0.0008	-0.0002
95%CI	[-0.0002,0.0008]	[0.0004,0.0011]	[-0.0004, -0.00003]
std.err	0.0002	0.0002	0.0001
t-stat	1.32	4.46	-2.40
p-value	0.194	0.0002	0.027
Latitude			
coef	-0.0174	-0.0333	0.0018
95%CI	[-0.0357,0.0009]	[-0.0492,-0.0173]	[-0.0189,0.0224]
std.err	0.0091	0.0077	0.0098
t-stat	-1.92	-4.33	0.18
p-value	0.061	0.0003	0.861
Longitude			
coef	0.0068	0.0102	0.0027
95%CI	[0.0031,0.0105]	[0.0082,0.0122]	[0.0004,0.0049]
std.err	0.0018	0.0010	0.0011
t-stat	3.71	10.51	2.49
p-value	0.001	0	0.023
const			
coef	1.7386	2.1970	1.1837
95%CI	[1.1784,2.2988]	[1.6631,2.7309]	[1.1687,1.1985]
std.err	0.2774	0.2574	0.0071
t-stat	6.27	8.53	166.63
p-value	0	0	0

Table 3: Absolute Humidity

Table 3 shows the explanatory power of the absolute humidity in the pre-lockdown period for Chinese cities from January 19 to 23 (Panel A) and the U.S. counties from March 15 to April 6 (Panel B).

Panel A: Regression for Chinese Cities

	Temperature	Relative Humidity	Absolute Humidity
R2	0.1817	0.1783	0.1799
Temperature			
coef	-0.0151		
95%CI	[-0.0262, -0.0040]		
std.err	0.0040		
t-stat	-3.78		
p-value	0.019		
Relative Humidity			
coef		-0.0038	
95%CI		[-0.0060, -0.0016]	
std.err		0.0008	
t-stat		-4.83	
p-value		0.008	
Absolute Humidity			
coef			-0.0159
95%CI			[-0.0545, 0.0227]
std.err			0.0139
t-stat			-1.15
p-value			0.316
Population Density			
coef	0.1222	0.1062	0.1190
95%CI	[0.0500, 0.1943]	[0.0441, 0.1684]	[0.0371, 0.2010]
std.err	0.0260	0.0224	0.0295
t-stat	4.70	4.74	4.03
p-value	0.009	0.009	0.016
Percentage over 65			
coef	-0.3769	-0.5738	-0.8898
95%CI	[-1.6135, 0.8597]	[-1.6715, 0.5239]	[-1.9335, 0.1538]
std.err	0.4454	0.3954	0.3759
t-stat	-0.85	-1.45	-2.37
p-value	0.445	0.220	0.077
GDP per capita			
coef	-0.0174	-0.0190	-0.0205
95%CI	[-0.0303, -0.0046]	[-0.0328, -0.0052]	[-0.0340, -0.0069]
std.err	0.0046	0.0050	0.0049
t-stat	-3.76	-3.81	-4.20
p-value	0.020	0.019	0.014

	Temperature	Relative Humidity	Absolute Humidity
No. of doctors			
coef	-0.0109	-0.0111	-0.0111
95%CI	[-0.0167, -0.0051]	[-0.0167, -0.0054]	[-0.0168, -0.0053]
std.err	0.0021	0.0020	0.0021
t-stat	-5.21	-5.45	-5.37
p-value	0.006	0.006	0.006
Drop of BMI			
coef	-0.5174	-0.4236	-0.5370
95%CI	[-0.8038, -0.2309]	[-0.6320, -0.2152]	[-0.8650, -0.2090]
std.err	0.1032	0.0751	0.1181
t-stat	-5.01	-5.64	-4.55
p-value	0.007	0.005	0.010
Inflow population from Wuhan			
coef	-0.0006	-0.0004	-0.0005
95%CI	[-0.0010,-0.0001]	[-0.0009, 0.00003]	[-0.0010, -8.04E-6]
std.err	0.0001	0.0002	0.0002
t-stat	-3.70	-2.57	-2.82
p-value	0.021	0.062	0.048
Latitude			
coef	0.0283	0.0422	0.0396
95%CI	[0.0104, 0.0461]	[0.0331, 0.0512]	[0.0267, 0.0525]
std.err	0.0064	0.0032	0.0046
t-stat	4.40	12.98	8.53
p-value	0.012	0.0002	0.001
Longitude			
coef	-0.0299	-0.0273	-0.0289
95%CI	[-0.0559, -0.0039]	[-0.0523, -0.0023]	[-0.0543, -0.0034]
std.err	0.0094	0.0090	0.0092
t-stat	-3.19	-3.03	-3.15
p-value	0.033	0.039	0.035
const			
coef	2.1182	2.1184	2.1176
95%CI	[1.5681, 2.6684]	[1.5667, 2.6700]	[1.5682, 2.6670]
std.err	0.1981	0.1987	0.1979
t-stat	10.69	10.66	10.70
p-value	0.0004	0.0004	0.0004

Panel B: Regression for the U.S. Counties

	Temperature	Relative Humidity	Absolute Humidity
R2	0.1210	0.1257	0.1255
Temperature			
coef	-0.0138		
95%CI	[-0.0267,-0.0009]		
std.err	0.0062		
t-stat	-2.21		
p-value	0.038		
Relative Humidity			
coef		-0.0078	
95%CI		[-0.0140, -0.0014]	
std.err		0.0031	
t-stat		-2.53	
p-value		0.019	
Absolute Humidity			
coef			-0.0496
95%CI			[-0.0664, -0.0327]
std.err			0.0081
t-stat			-6.11
p-value			0
Population Density			
coef	6.51E-6	6.25E-6	5.50E-6
95%CI	[-0.00002, 0.00004]	[-0.00003,0.00004]	[-0.00002, 0.00004]
std.err	0.00002	0.00002	0.00001
t-stat	0.43	0.40	0.38
p-value	0.671	0.689	0.711
Percentage over 65			
coef	-0.9306	-1.0137	-0.9071
95%CI	[-1.5574, -0.3038]	[-1.7090, -0.3183]	[-1.6107, -0.2034]
std.err	0.3022	0.3353	0.339
t-stat	-3.08	-3.02	-2.67
p-value	0.005	0.006	0.014
Gini			
coef	-1.6920	-1.8024	-1.7177
95%CI	[-4.4260, 1.0420]	[-4.3390, 0.7342]	[-4.3598, 0.9263]
std.err	-1.3183	-1.2231	1.2744
t-stat	-1.28	-1.47	-1.35
p-value	0.213	0.155	0.192
Socio-economic factor			
coef	0.1371	0.1265	0.1363
95%CI	[0.0842,0.1900]	[0.0783, 0.1747]	[0.0914, 0.1812]
std.err	0.0255	0.0232	0.0217

	Temperature	Relative Humidity	Absolute Humidity
t-stat	5.38	5.44	6.30
p-value	0.00002	0.00002	0
No. of ICU beds per capita			
coef	-0.0122	-0.0097	-0.0127
95%CI	[-0.0359,0.0114]	[-0.0294,0.0100]	[-0.0351,-0.0097]
std.err	0.0114	0.0095	0.0108
t-stat	-1.07	-1.02	-1.17
p-value	0.294	0.317	0.253
Fraction of maximum moving distance over normal time			
coef	0.0005	0.0014	0.0011
95%CI	[-0.0038,0.0048]	[-0.0015, 0.0043]	[-0.0023,0.0045]
std.err	0.0021	0.0014	0.0016
t-stat	0.24	0.98	0.65
p-value	0.815	0.338	0.520
Home stay minutes			
coef	0.0006	0.0006	0.0006
95%CI	[0.0003, 0.0009]	[0.0003,0.0010]	[0.0003, 0.0010]
std.err	0.0001	0.0002	0.0002
t-stat	3.94	3.91	3.88
p-value	0.001	0.001	0.001
Latitude			
coef	-0.0201	-0.0097	-0.0361
95%CI	[-0.0367, -0.0036]	[-0.0174, -0.0020]	[-0.0511, -0.0211]
std.err	0.0080	0.0037	0.0072
t-stat	-2.53	-2.61	-4.98
p-value	0.019	0.016	0.00006
Longitude			
coef	0.0104	0.0098	0.0107
95%CI	[0.0084, 0.0123]	[0.0079, 0.0117]	[0.0086,0.0128]
std.err	0.0009	0.0009	0.0010
t-stat	11.02	10.66	10.52
p-value	0	0	0
const			
coef	2.2121	2.1911	2.2137
95%CI	[1.6662, 2.7580]	[1.6600, 2.7222]	[1.6659, 2.7616]
std.err	0.2632	0.2561	0.2641
t-stat	8.40	8.56	8.38
p-value	0	0	0

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Supplementary Materials for

High Temperature and High Humidity Reduce the Transmission of COVID-19

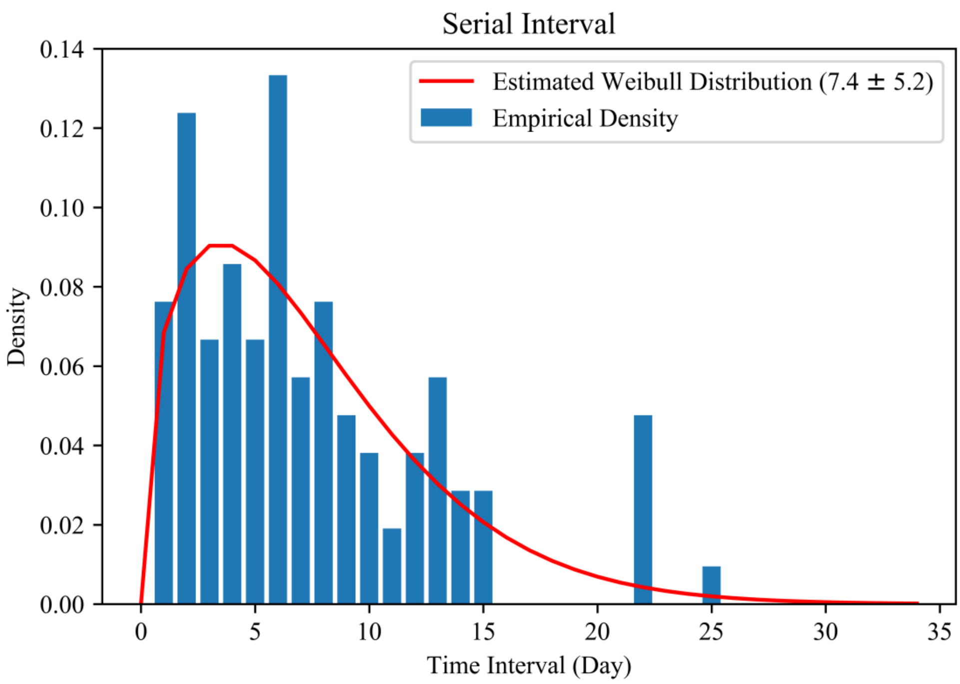

Figure A1: Estimation of the serial interval with the Weibull distribution

Bars denote the probability of occurrences in specified bins, and the red curve is the density function of the estimated Weibull distribution.

Table A1: Data Summary

This table summarizes the variables used in this paper. Panel A and B summarizes the data of Chinese cites and the U.S. counties.

Panel A: Data Summary for the Chinese Cities

	Mean	Std	Min	Max
R	1.072	0.707	0.131	4.609
6-Day Average Temperature (Celsius)	4.468	6.842	-21.100	19.733
6-Day Average Relative Humidity (%)	77.147	9.589	48.667	99.833
GDP per Capita (RMB 10k)	6.800	3·716	2.159	18.957
Population Density (k/km^2)	0.692	0.812	0.00800	6.522
No· Doctors (k)	16.020	11.488	1.972	68.549
Proxy for Inflow population from Wuhan (10 k)	5.096	14.833	0.000	138.154
Fraction over 65	0.121	0.0186	0.0826	0.152
Drop of BMI compared to first week 2020	-0.413	0.347	-0.886	0.759

Panel B: Data Summary for the U.S. Counties

	Mean	Std	Min	Max
R	1.517	0.836	0.040	4.997
6-Day Average Temperature (Celsius)	10.738	6.503	-10.192	28.826
6-Day Average Relative Humidity (%)	67.815	11.932	16.388	99.096
Population Density (/mile^2)	374.275	1678.13	2.562	48229.375
Fraction over 65	0.167	0.0423	0.0633	0.374
Gini index	0.449	0.0309	0.357	0.597
GDP per capita (k Dollar)	45.599	24.417	13.006	378.762
Fraction below poverty level	15.970	5.604	4.000	38.100
Personal income (Dollar)	46923.2	14586.7	26407	251728
Fraction of not in labor force, 16 years or over	38.842	6.737	19.600	62.000
Fraction of total household more than $200,000	3.564	2.948	0.400	23.100
Fraction of food stamp/SNAP benefits	13.854	5.355	1.400	38.800
No. ICU beds per 10000 capita	2.182	1.945	0.000	17.357
Fraction of maximum moving distance over normal time	33.286	25.918	0.000	478.000
Home-stay minutes	749.064	145.883	206.585	1275.341

Table A2: Pairwise Correlation Analysis for Chinese Cities

Pairwise correlation coefficients are obtained by averaging all correlation coefficients from each time step in the Fama-Macbeth approach.

	Temperature	Relative Humidity	Population Density	Percentage over 65	GDP per capita	No. of doctors	Drop of BMI	Inflow population from Wuhan	Latitude	Longitude
Temperature	1.00	0.32	0.33	-0.37	0.33	0.13	-0.21	0.04	-0.92	-0.57
Relative Humidity	0.32	1.00	-0.08	0.01	-0.16	-0.09	0.29	0.09	-0.44	-0.32
Population Density	0.33	-0.08	1.00	-0.27	0.57	0.29	-0.40	-0.09	-0.27	-0.03
Percentage over 65	-0.37	0.01	-0.27	1.00	-0.20	0.13	0.25	0.06	0.45	0.13
GDP per capita	0.33	-0.16	0.57	-0.20	1.00	0.45	-0.76	-0.14	-0.25	0.05
No. of doctors	0.13	-0.09	0.29	0.13	0.45	1.00	-0.39	-0.12	-0.06	-0.22
Drop of BMI	-0.21	0.29	-0.40	0.25	-0.76	-0.39	1.00	0.04	0.12	-0.14
Inflow population from Wuhan	0.04	0.09	-0.09	0.06	-0.14	-0.12	0.04	1.00	-0.05	-0.12
Latitude	-0.92	-0.44	-0.27	0.45	-0.25	-0.06	0.12	-0.05	1.00	0.59
Longitude	-0.57	-0.32	-0.03	0.13	0.05	-0.22	-0.14	-0.12	0.59	1.00

Table A3: Pairwise Correlation Analysis for the U.S. Counties

Pairwise correlation coefficients are obtained by averaging all correlation coefficients from each time step in the Fama-Macbeth approach.

	Temperature	Relative Humidity	Population Density	Percentage over 65	Gini	Se-factor	No. of ICU beds per capita	M50_index	Home stay minutes	Latitude	Longitude
Temperature	1.00	0.17	0.01	-0.05	0.34	0.36	0.11	0.34	0.00	-0.90	0.04
Relative Humidity	0.17	1.00	-0.06	0.08	0.05	0.02	0.00	0.07	0.10	-0.20	0.12
Population Density	0.01	-0.06	1.00	-0.11	0.23	0.07	0.07	-0.19	0.11	0.01	0.10
Percentage over 65	-0.05	0.08	-0.11	1.00	0.02	0.14	-0.04	-0.03	-0.18	0.05	0.13
Gini	0.34	0.05	0.23	0.02	1.00	0.53	0.37	0.15	-0.17	-0.35	0.07
Socio-economic factor	0.36	0.02	0.07	0.14	0.53	1.00	0.21	0.32	-0.41	-0.34	0.00
No. of ICU beds per capita	0.11	0.00	0.07	-0.04	0.37	0.21	1.00	0.18	-0.10	-0.11	0.10
M50_index	0.34	0.07	-0.19	-0.03	0.15	0.32	0.18	1.00	-0.37	-0.37	-0.08
Home-stay minutes	0.00	0.10	0.11	-0.18	-0.17	-0.41	-0.10	-0.37	1.00	0.06	-0.08
Latitude	-0.90	-0.20	0.01	0.05	-0.35	-0.34	-0.11	-0.37	0.06	1.00	-0.06
Longitude	0.04	0.12	0.10	0.13	0.07	0.00	0.10	-0.08	-0.08	-0.06	1.00

Table A4: Unit Root Test for R, Temperature and Relative Humidity

Panel A and B show the results of Handri LM test [1] with null hypotheses of non-unit-roots, for Chinese cities and the U.S. counties, respectively.

Panel A: Test Results for Chinese Cities

	***R* value**	**Temperature**	**Relative Humidity**
z-stat	18.7472	51.1532	42.6092
p-value	0.0000	0.0000	0.0000

Panel B: Test Results for the U.S. Counties

	***R* value**	**Temperature**	**Relative Humidity**
z-stat	43.0116	61.0510	76.8665
p-value	0.0000	0.0000	0.0000

Table A5: Fama-Macbeth Regression for Chinese Cities except Wuhan

Daily *R* values from January 19 to February 10 and the averaged temperature and relative humidity over 6 days up to and including the day when *R* value is measured, are used in the regression for 99 Chinese cities (without Wuhan). The regression is estimated by the Fama-MacBeth approach.

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
R2	0.3029	0.1915	0.3339
Temperature			
coef	-0.0223	-0.0287	-0.0205
95%CI	[-0.0358, -0.0088]	[-0.0406, -0.0168]	[-0.0369, -0.0041]
std.err	0.0065	0.0043	0.0078
t-stat	-3.44	-6.69	-2.64
p-value	0.002	0.003	0.017
Relative Humidity			
coef	-0.0060	-0.0071	-0.0056
95%CI	[-0.0100, -0.0019]	[-0.0105, -0.0038]	[-0.0108, -0.0005]
std.err	0.0019	0.0012	0.0024
t-stat	-3.07	-5.86	-2.32
p-value	0.006	0.004	0.033
Population Density			
coef	0.0262	0.1198	0.0002
95%CI	[-0.0290, 0.0814]	[0.0564, 0.1832]	[-0.0352, 0.0356]
std.err	0.0266	0.0228	0.0168
t-stat	0.98	5.25	0.01
p-value	0.336	0.006	0.991
Percentage over 65			
coef	0.1316	0.3849	0.0612
95%CI	[-1.7302, 1.9933]	[-1.0386, 1.8084]	[-2.3111, 2.4335]
std.err	0.8977	0.5127	1.1244
t-stat	0.15	0.75	0.05
p-value	0.885	0.495	0.957
GDP per capita			
coef	0.0048	-0.0110	0.0092
95%CI	[-0.0148, 0.0244]	[-0.0252, 0.0033]	[-0.0114,0.0298]
std.err	0.0095	0.0051	0.0098
t-stat	0.51	-2.13	0.94
p-value	0.616	0.100	0.360
No. of doctors			
coef	-0.0057	-0.0109	-0.0043
95%CI	[-0.0089, -0.0025]	[-0.0162, -0.0056]	[-0.0064,-0.0022]
std.err	0.0015	0.0019	0.0010
t-stat	-3.73	-5.69	-4.35
p-value	0.001	0.005	0.0004

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
Drop of BMI			
coef	0.3135	-0.4107	0.5146
95%CI	[-0.3290, -0.9559]	[-0.6870, -0.1344]	[-0.0995, 1.1287]
std.err	0.3098	0.0995	0.2911
t-stat	1.01	-4.13	1.77
p-value	0.323	0.015	0.095
Inflow population from Wuhan			
coef	-0.0052	-0.0006	-0.0065
95%CI	[-0.0106, 0.0002]	[-0.0011, -0.0002]	[-0.0128, -0.0002]
std.err	0.0026	0.0002	0.0030
t-stat	-1.99	-3.93	-2.17
p-value	0.059	0.017	0.044
Latitude			
coef	0.0040	0.0082	0.0029
95%CI	[-0.0149, 0.0230]	[-0.0132, 0.0296]	[-0.0213, 0.0271]
std.err	0.0091	0.0077	0.0115
t-stat	0.44	1.06	0.25
p-value	0.663	0.347	0.804
Longitude			
coef	-0.0110	-0.0293	-0.0059
95%CI	[-0.0209, -0.0010]	[-0.0579, -0.0008]	[-0.0134, 0.0017]
std.err	0.0048	0.0103	0.0036
t-stat	-2.29	-2.85	-1.64
p-value	0.032	0.046	0.119
const			
coef	1.0925	2.1209	0.8069
95%CI	[0.5059, 1.6792]	[1.5697, 2.6721]	[0.5327, 1.0810]
std.err	0.2829	0.1985	0.1299
t-stat	3.86	10.68	6.21
p-value	0.001	0	0

Table A6: Relationship between Temperature, Relative Humidity, and *R* Values: Robustness Check with the Serial Interval of Mean 7.5 Days and Standard Deviation 3.4 days in Li et al (2020) [2] for Chinese Cities

This table utilizes estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days) [2] to construct *R* values for China. The table reports the coefficients of the effective reproductive number, *R* values, on an intercept, temperature, relative humidity and control variables in the Fama-MacBeth regressions.

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
R2	0.2843	0.2009	0.3074
Temperature			
coef	-0.0267	-0.0430	-0.0222
95%CI	[-0.0486,-0.0048]	[-0.0694,-0.0165]	[-0.0456,0.0012]
std.err	0.0106	0.0095	0.0111
t-stat	-2.53	-4.52	-2.00
p-value	0.019	0.011	0.061
Relative Humidity			
coef	-0.0076	-0.0104	-0.0068
95%CI	[-0.0121,-0.0031]	[-0.0166,-0.0041]	[-0.0121,-0.0015]
std.err	0.0022	0.0023	0.0025
t-stat	-3.47	-4.59	-2.69
p-value	0.002	0.010	0.015
Population Density			
coef	0.0223	0.1673	-0.0180
95%CI	[-0.0672,0.1118]	[0.0350,0.2996]	[-0.0825,0.0465]
std.err	0.0432	0.0477	0.0306
t-stat	0.52	3.51	-0.59
p-value	0.611	0.025	0.563
Percentage over 65			
coef	-0.7581	0.3976	-1.0791
95%CI	[-3.7515,2.2353]	[-2.9474,3.7426]	[-4.8094,2.6511]
std.err	1.4434	1.2048	1.7680
t-stat	-0.53	0.33	-0.61
p-value	0.605	0.758	0.550
GDP per capita			
coef	0.0058	-0.0291	0.0154
95%CI	[-0.0246,0.0361]	[-0.0390,-0.0193]	[-0.0124,0.0433]
std.err	0.0147	0.0035	0.0132
t-stat	0.39	-8.21	1.17
p-value	0.698	0.001	0.258
No. of doctors			
coef	-0.0065	-0.0135	-0.0045
95%CI	[-0.0107,-0.0023]	[-0.0205,-0.0065]	[-0.0067,-0.0024]
std.err	0.0020	0.0025	0.0010
t-stat	-3.22	-5.35	-4.47
p-value	0.004	0.006	0.0003

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
Drop of BMI			
coef	0.3287	-0.7465	0.6274
95%CI	[-0.5135,1.1709]	[-1.3448,-0.1483]	[-0.1037,1.3585]
std.err	0.4061	0.2155	0.3465
t-stat	0.81	-3.46	1.81
p-value	0.427	0.026	0.088
Inflow population from Wuhan			
coef	-0.0053	-0.0003	-0.0067
95%CI	[-0.0114,0.0008]	[-0.0009,0.0003]	[-0.0139,0.0006]
std.err	0.0029	0.0002	0.0034
t-stat	-1.79	-1.34	-1.94
p-value	0.087	0.250	0.069
Latitude			
coef	0.0026	0.0045	0.0021
95%CI	[-0.0245,0.0298]	[-0.0518,0.0608]	[-0.0302,0.0344]
std.err	0.0131	0.0203	0.0153
t-stat	0.20	0.22	0.14
p-value	0.843	0.835	0.893
Longitude			
coef	-0.0103	-0.0305	-0.0046
95%CI	[-0.0233,0.0027]	[-0.0796,0.0186]	[-0.0160,0.0067]
std.err	0.0063	0.0177	0.0054
t-stat	-1.64	-1.72	-0.86
p-value	0.116	0.16	0.399
const			
coef	1.0616	2.2036	0.7444
95%CI	[0.4353,1.6879]	[1.431,2.9762]	[0.5063,0.9826]
std.err	0.3020	0.2783	0.1129
t-stat	3.52	7.92	6.60
p-value	0.002	0.001	0

Table A7: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with the Serial Interval of Mean 7.5 Days and Standard Deviation 3.4 days in Li et al (2020) [2] for the U.S. Counties

This table utilizes estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days) [2] to construct *R* values for the U.S. counties. The table reports the coefficients of the effective reproductive number, *R* value, on an intercept, temperature, relative humidity and control variables in the Fama-MacBeth regressions.

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
R2	0.1170	0.1508	0.0760
Temperature			
coef	-0.0199	-0.0271	-0.0113
95%CI	[-0.0330,-0.0069]	[-0.0456,-0.0086]	[-0.0296,0.0071]
std.err	0.0065	0.0089	0.0087
t-stat	-3.08	-3.03	-1.29
p-value	0.004	0.006	0.214
Relative Humidity			
coef	-0.0052	-0.0086	-0.0011
95%CI	[-0.0114,0.0011]	[-0.0169,-0.0003]	[-0.0030,0.0008]
std.err	0.0031	0.0040	0.0009
t-stat	-1.68	-2.14	-1.20
p-value	0.101	0.044	0.244
Population Density			
coef	0.00002	3.00E-05	5.07E-08
95%CI	[-0.00003,0.00006]	[-0.0001,0.0001]	[-2.20e-6,2.30e-6]
std.err	0.00002	4.00E-05	1.07E-06
t-stat	0.73	0.71	0.05
p-value	0.469	0.483	0.963
Percentage over 65			
coef	-0.9733	-1.2685	-0.6159
95%CI	[-1.4465,-0.5000]	[-1.9245,-0.6124]	[-1.0408,-0.1911]
std.err	0.2343	0.3163	0.2022
t-stat	-4.15	-4.01	-3.05
p-value	0.0002	0.001	0.007
Gini			
coef	-1.9913	-2.4119	-1.4822
95%CI	[-3.6305,-0.3521]	[-4.9880,0.1643]	[-2.2360,-0.7285]
std.err	0.8117	1.2422	0.3588
t-stat	-2.45	-1.94	-4.13
p-value	0.018	0.065	0.001
Socio-economic factor			
coef	0.0906	0.1424	0.0279
95%CI	[0.0166,0.1646]	[0.0627,0.2222]	[-0.0112,0.0670]
std.err	0.0366	0.0385	0.0186
t-stat	2.47	3.70	1.50
p-value	0.018	0.001	0.152

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
No. of ICU beds per capita			
coef	-0.0113	-0.0127	-0.0096
95%CI	[-0.0263,0.0038]	[-0.0367,0.0113]	[-0.0147,-0.0044]
std.err	0.0075	0.0116	0.0025
t-stat	-1.51	-1.10	-3.91
p-value	0.138	0.285	0.001
Fraction of maximum moving distance over normal time			
coef	0.0036	0.0019	0.0056
95%CI	[0.0006,0.0066]	[-0.0023,0.0061]	[0.0043,0.0070]
std.err	0.0015	0.0020	0.0007
t-stat	2.44	0.94	8.67
p-value	0.019	0.356	0
Home-stay minutes			
coef	0.0003	0.0007	-0.0003
95%CI	[-0.0003,0.0008]	[0.0003,0.0011]	[-0.0005,-2e-05]
std.err	0.0003	0.0002	0.0001
t-stat	1.00	3.28	-2.24
p-value	0.321	0.003	0.038
Latitude			
coef	-0.0259	-0.0514	0.0049
95%CI	[-0.0551,0.0032]	[-0.0825,-0.0203]	[-0.0179,0.0277]
std.err	0.0144	0.0150	0.0109
t-stat	-1.80	-3.43	0.45
p-value	0.080	0.002	0.657
Longitude			
coef	0.0070	0.0110	0.0021
95%CI	[0.0019,0.0120]	[0.0059,0.0161]	[0.0003,0.0039]
std.err	0.0025	0.0025	0.0009
t-stat	2.79	4.45	2.50
p-value	0.008	0.0002	0.022
const			
coef	1.7601	2.2325	1.1882
95%CI	[1.1636,2.3566]	[1.6514,2.8137]	[1.1588,1.2177]
std.err	0.2954	0.2802	0.0140
t-stat	5.96	7.97	84.82
p-value	0	0	0

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2. Li, Q. *et al.* Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *N. Engl. J. Med.* **382:** 1199–207 (2020).