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Title

- High temperature and high humidity reduce the transmission of COVID-19

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ABSTRACT

Objectives Temperature and relative humidity may affect the transmission of COVID-19. We aim to quantify the impact of temperature and relative humidity on the transmission of COVID-19.

Design Retrospective regression analysis.

Setting We used COVID-19 daily symptom-onset cases for 100 Chinese cities and daily confirmed cases for 1,005 U.S. counties.

Participants A total of 69,498 cases in China and 740,843 cases in the U.S. were included in the final analysis after application of inclusion and exclusion criteria.

Primary outcome measures The impact of temperature and relative humidity on effective reproductive number (*R* value).

Results We find a similar influence of the temperature and relative humidity on effective reproductive number (R values) for both China and the U.S. before the lockdown: 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.).

Conclusions Higher temperature and higher relative humidity in summer may potentially reduce the transmission of COVID-19, but not enough to stop the pandemic. Assuming a 30 degree and 25 percent increase in temperature and relative humidity from winter to summer, the R value will decline by 0.89, or about one third of R0 (2.5 to 3), thus, weather cannot make the R values below 1. In addition, in some areas of the northern hemisphere where the epidemic maintains a fragile balance, it is necessary to cautiously prevent possible secondary outbreak in autumn and/or winter.

Strengths and limitations of this study

This study determines statistically significant and similar regression results for both China and the U.S. data.

A "trade space for time" strategy is used, i.e. a Fama-Macbeth regression framework with Newey-West adjustment is used to address both cross-sectional and time-series autocorrelation.

Large sample size for both China and the U.S. data and demographics, social-economic statuses, geographical, healthcare and human mobility status factors are included as control variables.

The study gets robust impact of temperature and relative humidity on transmission of COVID-19 under different settings.
The R^2 of the regressions are relatively small, which may indicate more complicated factors or model have not been considered; the temperature and relative humidity range in this study does not contain extreme conditions.

MAIN TEXT

Introduction

The coronavirus disease 2019 (COVID-19) pandemic, caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has infected more than 13 million people with 580 000 dead until July 16, 2020 [1] since its first reported case in Wuhan, China in December 2019 [2,3]. Understanding factors that affect the transmission of SARS-CoV-2 is very important for predicting the transmission dynamics of the virus and for planning future control efforts. Recently there are studies analyzing the effects of anthropogenic factors to contain COVID-19, such as travel restrictions [4–6], non-pharmacological interventions [7], population flow [8], anti-contagion policies [9], contact patterns [10] e*tc.* Climate conditions (such as temperature and humidity) are important natural factors that affect the transmission of infectious diseases. Previous studies have shown that the transmission of influenza is seasonal and effected by humidity [11,12], wintertime climate and host behavior can facilitate the transmission of influenza [13–15]. Studies also show that the transmissions of other human coronaviruses that cause mild respiratory symptoms, such as OC43 (HCoV-OC43) and HCoV-HKU1, are seasonal [16,17]. The seasonality of these viruses has been borrowed to conduct an indirect long-term simulation of the transmission of SARS-CoV-2 [18,19]. However, there are not consensus on the effect of weather and humidity on the transmissibility of COVID-19. The goal of this paper is to accurately 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. In the several months' observations, R values normally have a trend, so is temperature and humidity as summer in north hemisphere is coming. Since the COVID-19 outbroke just for several months, we do not have many years data to estimate a stable time-series cointegration relationship between R and temperature and humidity. We thus use a strategy of "space for time", i.e. first estimate the cross-sectional relationship between humidity/temperature and *R* values across different cities for each time, and then use the Newey-West methodology [20] to adjust the time-series autocorrelation of these estimates. This is a Fama-Macbeth regression with Newey-West adjusted standard errors, which is widely used and verified in finance [21–23]. Furthermore, we also preform many sets of robustness checks, which are all consistent with the negative relationship between R value and temperature and humidity.

Materials and 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 S1 in supplementary materials provides summary statistics of the Chinese variables with pairwise correlation shown in Table S2.

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 S1 in supplementary materials provides summary statistics of the U.S. variables with pairwise correlation shown in Table S3.

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. Specifically, as shown in Figure S1, 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 (Supplementary Materials p2-3) [24]. 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.

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. [25]. 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 [26] 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 S4 Panel A and Panel B in supplementary materials show the panel unit root test [27] 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 [28], 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 [29] with Newey-West adjustment, 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 with Newey–West Estimation.

Fama-Macbeth regression is a two steps procedure (Supplementary Materials p4-5). 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, since these estimates might have autocorrelations, we hence adjust the error of the average with a Newey-West approach.

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:

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

We use the Newey-West approach [20] to adjust the time-series autocorrelation and heteroscedasticity in calculating standard errors in the second step. Specifically, the Newey-West estimators give adjustment of covariance matrix of errors when the residuals are autocorrelated (and/or heteroscedastic), which can be expressed as

$$S = \frac{1}{T}\left(\sum_{t=1}^{T} e_t^2 + \sum_{l=1}^{L} \sum_{t=l+1}^{T} w_l e_t e_{t-l}\right),$$

where $w_l = 1 - \frac{l}{1+L}$, e represents residuals and L is the lag (Supplementary Materials p4-5).

The Fama-Macbeth regression with Newey-West has two advantages: 1) It avoids the spurious regression problem of non-stationary series, as normally the first-step estimates, $\beta_{k,t}$, have much milder autocorrelation than the autocorrelation (time trends) in the observations. It, therefore, can be adjusted with the Newey-West method. 2) Only cross-sectional estimates in the first step are used but not their standard errors, hence, any heteroskedasticity issues in the first step will not change the final results, because the heteroskedasticity (including the one caused by spatial correlation) does not alter the unbiasedness of the ordinary least square (OLS) estimation. Table S5 in supplementary materials shows the detailed coefficients of temperature and relative humidity in the first step of Fama-Macbeth regression.

Note that Fama-Macbeth regression with Newey-West adjustment is commonly used in estimating parameters for finance and economic models that are valid in the presence of the cross-sectional correlation and time series autocorrelation [21–23]. 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.

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 [29]) 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, considering the transmission during pre-symptomatic periods [26], 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 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 [25]. 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 [30]. The results shown in Table 3 are only partly consistent with this notion [30]. 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 four 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 [31]. 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) [3] with a Weibull distribution to estimate *R* values of various cities/counties for robustness checks.

(3) **Social distancing dummy variables for the U.S. counties.** States in the U.S. announced stay-at-home orders at different times. We add a dummy variable which is set to one if the stay-at-home order is imposed, and zero otherwise.

(4) **Spatial random effect.** We also introduce a spatial model into the Fama-Macbeth regression first step to account for spatial correlation and redo the analysis.

The results of the above-mentioned four robustness checks are shown in Table S6 to Table S11 in supplementary materials. 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 2.

Discussion

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 [30], 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 [32]. Second, cold and dry weather can also weaken the hosts' immunity and make them more susceptible to the virus [33]. Our result is also consistent with the evidence that high temperature and high relative humidity reduce the viability of SARS coronavirus [34].

Outwardly, our study suggests that the summer and rainy season can potentially reduce the transmissibility of the COVID-19, but it is unlikely that the COVID-19 pandemic will "automatically" diminish in summer, 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 [35]. 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. Obviously, this is not possible for the earth's climate system.

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.

Limitations

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.

References

1 WHO. Coronavirus disease (COVID-19) pandemic. 2020.https://www.who.int/emergencies/diseases/novel-coronavirus-2019
2 Zhu N, Zhang D, Wang W, *et al.* A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med* 2020.
3 Li Q, Guan X, Wu P, *et al.* Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *N Engl J Med* 2020.
4 Kraemer MU, Yang C-H, Gutierrez B, *et al.* The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* 2020;**368**:493–497.
5 Tian H, Liu Y, Li Y, *et al.* An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science* 2020;**368**:638–642.
6 Chinazzi M, Davis JT, Ajelli M, *et al.* The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* 2020;**368**:395–400.
7 Lai S, Ruktanonchai NW, Zhou L, *et al.* Effect of non-pharmaceutical interventions to contain COVID-19 in China. *Nature* 2020.
8 Jia JS, Lu X, Yuan Y, *et al.* Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 2020;:1–5.
9 Hsiang S, Allen D, Annan-Phan S, *et al.* The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature* 2020;:1–9.
10 Zhang J, Litvinova M, Liang Y, *et al.* Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China. *Science* 2020.
11 Hemmes J, Winkler K, Kool S. Virus survival as a seasonal factor in influenza and poliomyelitis. *Nature* 1960;**188**:430–431.
12 Dalziel BD, Kissler S, Gog JR, *et al.* Urbanization and humidity shape the intensity of influenza epidemics in US cities. *Science* 2018;**362**:75–79.
13 Shaman J, Pitzer VE, Viboud C, *et al.* Absolute humidity and the seasonal onset of influenza in the continental United States. *PLoS Biol* 2010;**8**:e1000316.
14 Shaman J, Goldstein E, Lipsitch M. Absolute humidity and pandemic versus epidemic influenza. *Am J Epidemiol* 2011;**173**:127–135.
15 Chattopadhyay I, Kiciman E, Elliott JW, *et al.* Conjunction of factors triggering waves of seasonal influenza. *Elife* 2018;**7**:e30756.
16 Killerby ME, Biggs HM, Haynes A, *et al.* Human coronavirus circulation in the United States 2014–2017. *J Clin Virol* 2018;**101**:52–56.
17 Neher RA, Dyrdak R, Druelle V, *et al.* Potential impact of seasonal forcing on a SARS-CoV-2 pandemic. *Swiss Med Wkly* 2020;**150**.
18 Kissler SM, Tedijanto C, Goldstein E, *et al.* Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* 2020.

19 Baker RE, Yang W, Vecchi GA, *et al.* Susceptible supply limits the role of climate in the early SARS-CoV-2 pandemic. *Science* 2020.
20 Newey WK, West KD. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 1987;**55**:703–8.
21 Lewellen J. The cross section of expected stock returns. *Forthcom Crit Finance Rev* 2014.
22 Kang W, Rouwenhorst KG, Tang K. A tale of two premiums: The role of hedgers and speculators in commodity futures markets. *J Finance* 2020;**75**:377–417.
23 Petersen MA. Estimating standard errors in finance panel data sets: Comparing approaches. *Rev Financ Stud* 2009;**22**:435–480.
24 Wallinga J, Teunis P. Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am J Epidemiol* 2004;**160**:509–516.
25 NYTimes. See Which States Are Reopening and Which Are Still Shut Down. 2020.https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html
26 Johns Hopkins University. Coronavirus symptoms start about five days after exposure, Johns Hopkins study finds. 2020.https://hub.jhu.edu/2020/03/09/coronavirus-incubation-period/
27 Hadri K. Testing for stationarity in heterogeneous panel data. *Econom J* 2000;**3**:148–161.
28 Kao C. Spurious regression and residual-based tests for cointegration in panel data. *J Econom* 1999;**90**:1–44.
29 Fama EF, MacBeth JD. Risk, return, and equilibrium: Empirical tests. *J Polit Econ* 1973;**81**:607–636.
30 Shaman J, Kohn M. Absolute humidity modulates influenza survival, transmission, and seasonality. *Proc Natl Acad Sci* 2009;**106**:3243–3248.
31 Nanfangzhoumo. What's the Difficulty of Wuhan's "All Receivable." 2020.https://www.infzm.com/contents/177054
32 Lowen AC, Steel J. Roles of humidity and temperature in shaping influenza seasonality. *J Virol* 2014;**88**:7692–7695.
33 Kudo E, Song E, Yockey LJ, *et al.* Low ambient humidity impairs barrier function and innate resistance against influenza infection. *Proc Natl Acad Sci* 2019;**116**:10905–10910.
34 Chan K, Peiris J, Lam S, *et al.* The effects of temperature and relative humidity on the viability of the SARS coronavirus. *Adv Virol* 2011;**2011**.
35 Pan A, Liu L, Wang C, *et al.* Association of public health interventions with the epidemiology of the COVID-19 outbreak in Wuhan, China. *Jama* 2020.

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Data availability statement Temperature, humidity, R values calculated from confirmed cases and all control variables except home-stay minutes used in this study will be included in the published version of this article for release online. Home-stay minutes data provided by Safegraph (https://www.safegraph.com/) cannot be disclosed since this would compromise the agreement with the data provider, nevertheless, this data can be obtained by applying for permission from the provider. R values calculated from symptom onset data are available upon request from Dr Jingyuan Wang (jywang@buaa.edu.cn).

Figure Legends

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).

Tables

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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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
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

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
p-value	0.003	0.00001	0.133
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

	Temperature	Relative Humidity	Absolute Humidity
p-value	0.020	0.019	0.014
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

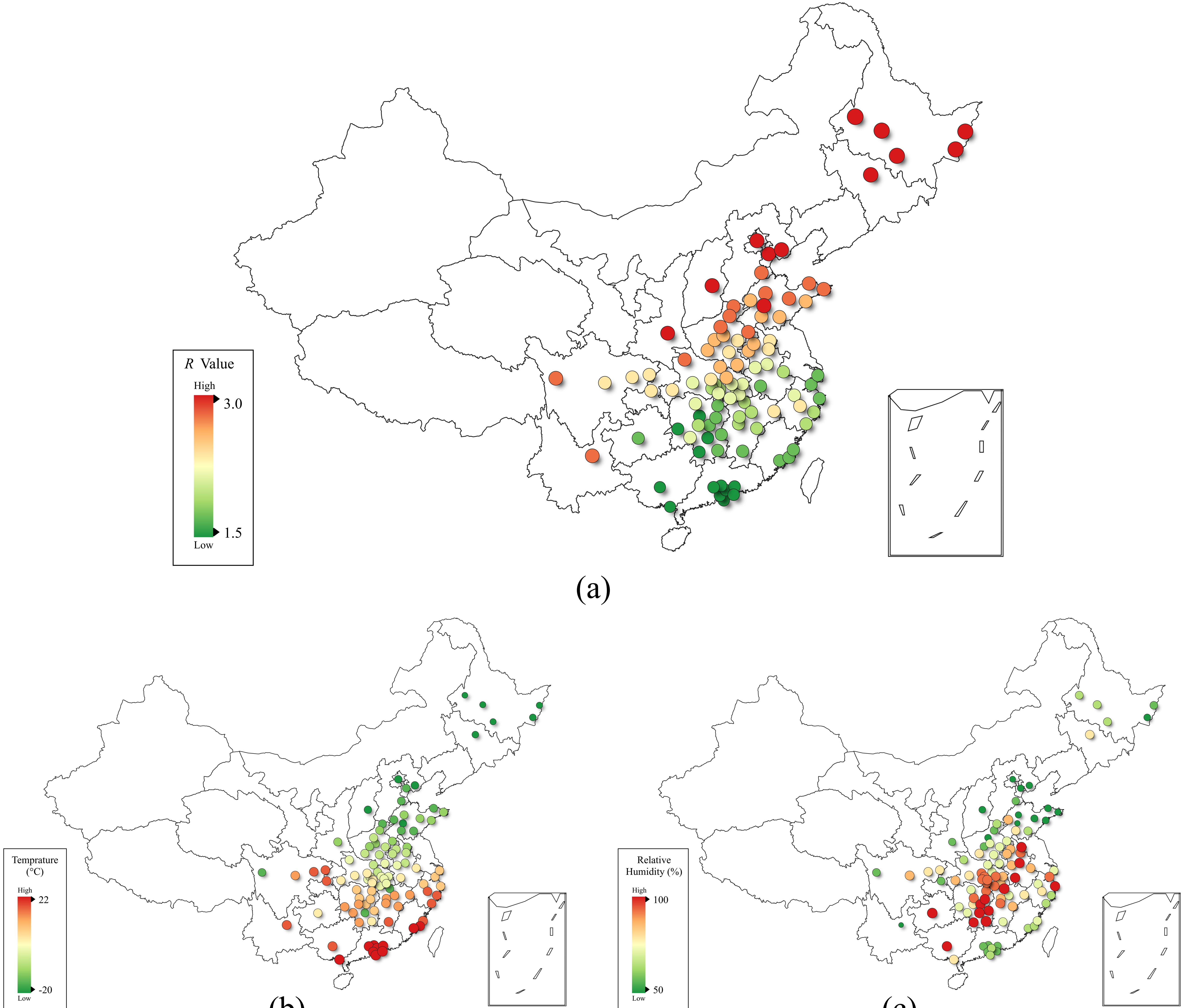
Panel B: Regression for the U.S. Counties

	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

Supplementary Materials

Supplementary Materials are included in a separate file.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1.5
Low
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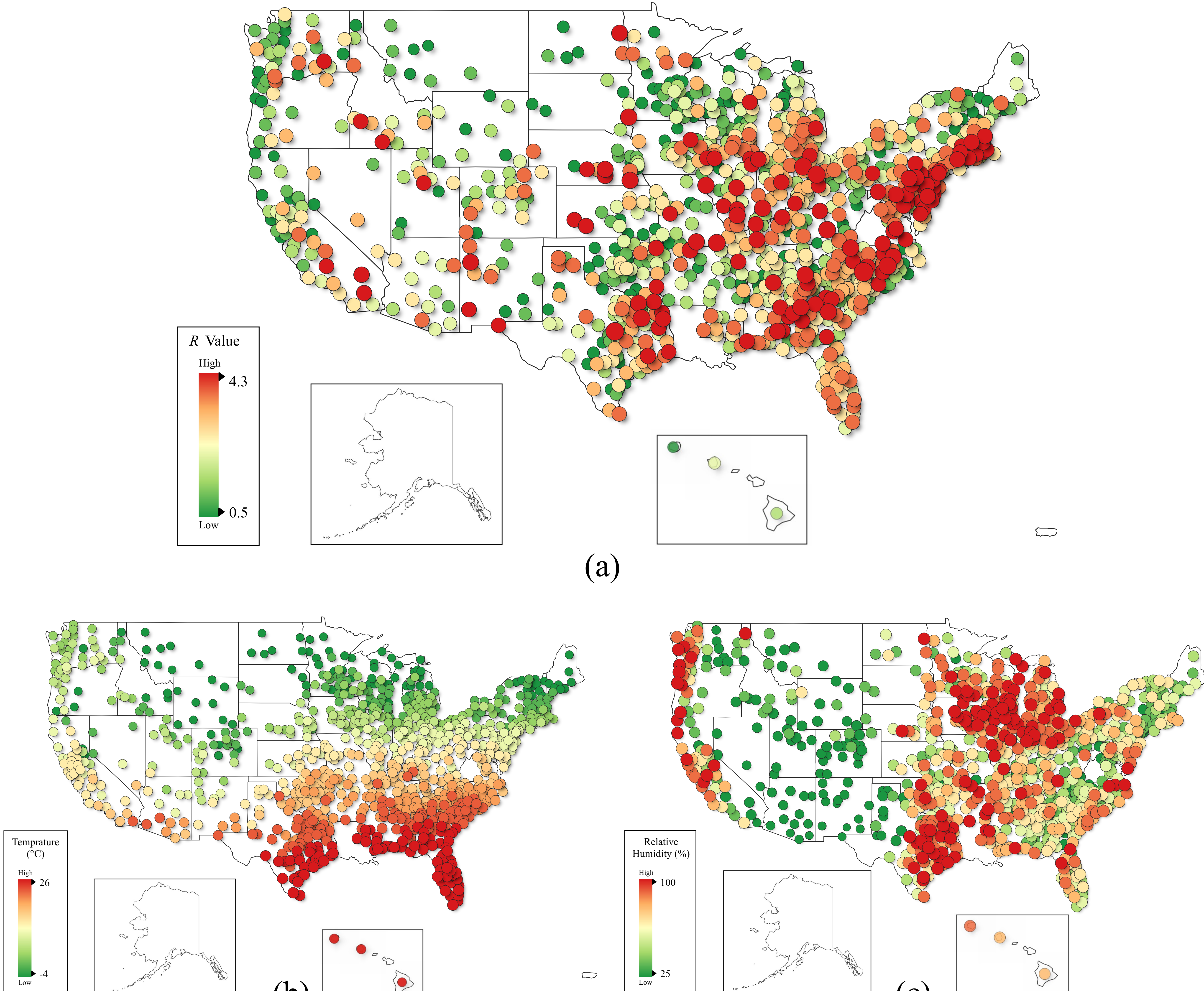
High
22
-20
Low
(b)
Relative Humidity (%)
High
100
50
Low
(c)


R Value
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4.3
0.5
Low
(a)
Temprature
(°C)
High
26
-4
Low
(b)
Relative
Humidity (%)
High
100
25
Low
(c)

Supplementary Materials for

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

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This PDF file includes:

Materials and Methods
Figs. S1
Tables S1 to S11

Materials and Methods

Estimating effective reproduction number

The basic reproduction number $R_{0,}$ which characterizes the transmission ability of an epidemic, is defined as the average number of people who will contract the contagious disease from a typical infected case in a population where everyone is susceptible. When epidemic is spreading through a population, the time-varying effective reproduction number R_t is more concerned. The effective reproduction number R_t, the R value at the time step t, is defined as the actual average number of secondary cases per primary cases cause[1].

We then calculate the effective reproductive number R_t for each city through a time-dependent method based on Maximum Likelihood Estimation (MLE)[2]. The inputs to the method are epidemic curves, *i.e.* the historical numbers of patients of each day, for a certain city. Specifically, we denote $w(\tau|\theta)$ as the probability distribution for the serial interval, which is defined as the time between symptom onset of a case and symptom onset of her/his secondary cases. Let $p_{(i,\, j)}$ be the relative likelihood that case i has been infected by case j, given the difference in time of symptom onset $t_i - t_j$, can be expressed in terms of $w(\tau|\theta)$. That is, the relative likelihood that case i has been infected by case j can be expressed as

$$p_{ij} = \frac{w(t_i - t_j)}{\sum_{i \neq k} w(t_i - t_k)}$$

The relative likelihood of case i infecting case j is independent of the relative likelihood of case i infecting any other case k. The distribution of the effective reproduction number for case i is

$$R_i \sim \sum_j \text{Bernoulli}[p_{(j,i)}]$$

With the expected value

$$E(R_i) = \sum_j p_{(j,i)}$$

The average daily effective reproduction number R_t is estimated as the average over R_i for all cases i who develop the first symptom of onset on day t.

The above calculation is implemented with the Package ‘R0’ developed by Boelle & Obadia with the R version 3.6.2 and ‘R0’ version 1.2_6 (https://cran.r-project.org/web/packages/R0/index.html).

Fama-MacBeth Regression with Newey-West Adjustment

Fama-MacBeth regression is a way to study the relationship between the response variable and the features in the panel data setup. Particularly, Fama-MacBeth regression runs a series of cross-sectional regression and uses the average of cross-sectional regression coefficients as the second step parameter estimation. In equation form, for n response variables, m features and time series length T

$$
\begin{gathered}
R_{i,1} = \alpha_1 + \beta_{1,1}F_{1,i,1} + \beta_{2,1}F_{2,i,1} + \ldots + \beta_{m,1}F_{m,i,1} + \epsilon_{i,1}, \\
R_{i,2} = \alpha_2 + \beta_{1,2}F_{1,i,2} + \beta_{2,2}F_{2,i,2} + \ldots + \beta_{m,2}F_{m,i,2} + \epsilon_{i,2}, \\
\ldots \\
R_{i,T} = \alpha_T + \beta_{1,T}F_{1,i,T} + \beta_{2,T}F_{2,i,T} + \ldots + \beta_{m,T}F_{m,i,T} + \epsilon_{i,T}.
\end{gathered}
$$

where $R_{i,t}$, $i \in \{1, \ldots, n\}$ is the response values, $\beta_{k,t}$ are first step regression coefficients for feature k at time t, $F_{k,i,t}$ are the input features of feature k, sample i at time t. In the second step, the average of the first step regression coefficient, $\hat{\beta}_k$, can be calculated directly, or via the following regression

$$\beta_{k,t} = c_k + \epsilon_t.$$

where ϵ_t is a random noise.

Since βs might have time-series autocorrelation, in the second step, we thus use the Newey-West approach [3] to adjust the time-series autocorrelation (and heteroscedasticity) in calculating standard errors. Specifically, for the second step, we have

$E[\epsilon] = 0$ and $E[\epsilon\epsilon'] = \sigma^2\Omega$.

The covariance matrix of c_k is

$$V_{C_k} = \frac{1}{T}\left(\frac{1}{T}\mathbf{1}'\mathbf{1}\right)^{-1}\left(\frac{1}{T}\mathbf{1}'(\sigma^2\Omega)\mathbf{1}\right)\left(\frac{1}{T}\mathbf{1}'\mathbf{1}\right)^{-1},$$

Where $\mathbf{1}$ is a $T \times 1$ vector of 1, $\sigma^2\Omega$ is the covariance matrix of errors.

The middle matrix can be rewritten as

$$Q = \frac{1}{T}\mathbf{1}'(\sigma^2\Omega)\mathbf{1}$$
$$= \frac{1}{T}\sum_{i=1}^{T}\sum_{j=1}^{T}\sigma_{ij}$$

The Newey-West estimators give consistent estimation of Q when the residuals are autocorrelated and/or heteroscedastic. The Newey-West estimator can be expressed as

$$S = \frac{1}{T}\left(\sum_{t=1}^{T}e_t^2 + \sum_{l=1}^{L}\sum_{t=l+1}^{T}w_l e_t e_{t-l}\right),$$

Where $w_l = 1 - \frac{l}{1+L}$, e represents residuals and L is the lag.

We use Fama-Macbeth regressions for two reasons. Firstly, temperature and relative humidity series have trends with the arrival of summer while R values series also have downward trends. In this case, panel regression will get spurious regression results from the time-series perspective. However, the cross-sectional regression involving cities (counties) of various meteorological conditions and COVID-19 spread intensities will not have the spurious regression issues. Secondly, Fama-MacBeth regression is valid even in the presence of the cross-sectional heteroskedasticity (including complex spatial covariance), because in the second-step regression, only the value of the first step estimates βs are used, but not their standard errors. Therefore, as long as the first-step estimator is unbiased, which is the case for heteroskedasticity (including complex spatial covariance), the Fama-Macbeth estimation is correct.

Less rigorously speaking, we use the first step of Fama-MacBeth regression to find out the extent that the transmissibility of the areas of high temperature and high relative humidity are compared with that of low temperature, low relative humidity areas in each day. We then use the second step to test whether daily relationship is a common fact during a time period.

Modelling Spatial Effect

We use generalized linear mixed model (GLMM) with spatial random effects to account for spatial autocorrelation between cities or counties in each cross-sectional regression. The form of model is

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u} + \boldsymbol{\epsilon},$$

Where $\boldsymbol{y}$ is the $N \times 1$ outcome vector, $\boldsymbol{X}$ is the $N \times p$ matrix of the p explantary variables (the intercept term can be included by setting the first column of X as a vector of ones), $\boldsymbol{\beta}$ is the vector of regression coefficients, $\boldsymbol{u}$ is the vector of spatial random effects, and $\boldsymbol{\epsilon}$ is the random error vector whose entries are independent and identically distributed as $N(0, \sigma^2)$. We assume $\boldsymbol{u} \sim N(0, \boldsymbol{\sigma_s^2 G})$, $where$ $\boldsymbol{\sigma_s^2}$ is the spatial variance and $\boldsymbol{G}$ follows a Matérn correlation structure[4].

The Matérn model flexibly specifies the correlation between any two cities or counties as a function of their geographical distance; the model has two parameters, a scale parameter ρ and a "smoothness" parameter ν, and it subsumes the exponential and squared exponential models as special cases. Maximum likelihood method is used for parameter estimation[5].

We have also tried conditional autoregressive model (CAR)[6] in which the spatial correlation is described by an adjacency matrix of the cities/counties. The Matérn model performs better than the CAR model as judged by the Akaike information criterion (AIC); the average AIC value across all cross-sectional regressions is 896.9 and 936.5 for the Matérn model and the CAR model, respectively.

All computation is done in R package "spaMM" version 3.3.0[7]. We report the results from the Matérn model in Table S10 and S11.

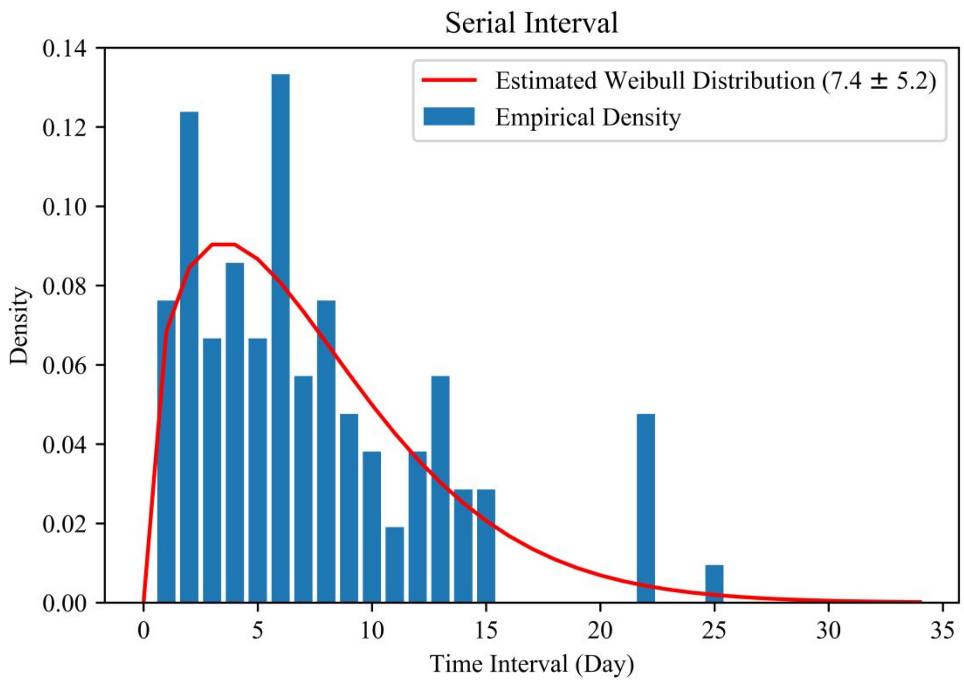

Fig. S1. Estimation of the serial interval with the Weibull distribution

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

Table S1. 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/km²)	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 (/mile²)	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 S2: 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 S3: 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 S4: Unit Root Test for R, Temperature and Relative Humidity

Panel A and B show the results of Handri LM test [8] 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 S5: Coefficients of temperature and relative humidity in first step of Fama-Macbeth Regression

Panel A and B show regression coefficients of temperature and relative humidity in the first step of Fama-Macbeth regression, for Chinese cities and the U.S. counties, respectively.

Panel A: Regression Coefficients for Chinese Cities

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Jan, 19	-0.0373	-0.0109
Jan, 20	-0.0064	0.0009
Jan, 21	-0.0127	-0.0093
Jan, 22	-0.0309	-0.0121
Jan, 23	-0.0427	-0.0066
Jan, 24	-0.0249	0.0010
Jan, 25	-0.0238	-0.0062
Jan, 26	-0.0506	-0.0174
Jan, 27	-0.0526	-0.0159
Jan, 28	-0.0196	-0.0063
Jan, 29	-0.0340	-0.0101
Jan, 30	-0.0305	-0.0096
Jan, 31	-0.0391	-0.0087
Feb, 1	-0.0388	-0.0102
Feb, 2	-0.0248	-0.0097
Feb, 3	-0.0108	-0.0022
Feb, 4	-0.0091	0.0020
Feb, 5	0.0039	0.0040
Feb, 6	-0.0061	-0.0037
Feb, 7	-0.0034	0.0006
Feb, 8	0.0103	-0.0030
Feb, 9	-0.0077	-0.0067
Feb, 10	-0.0150	0.0052

Panel B: Regression Coefficients for U.S. Counties

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Mar, 15	-0.0402	-0.0190
Mar, 16	-0.0309	-0.0192
Mar, 17	-0.0052	-0.0129
Mar, 18	-0.0192	-0.0146
Mar, 19	-0.0412	-0.0237
Mar, 20	0.0224	-0.0114
Mar, 21	-0.0112	-0.0158
Mar, 22	-0.0138	-0.0169
Mar, 23	-0.0021	-0.0195
Mar, 24	-0.0107	-0.0166
Mar, 25	-0.0184	-0.0073
Mar, 26	-0.0231	-0.0095
Mar, 27	-0.0241	-0.0010
Mar, 28	-0.0468	0.0013
Mar, 29	-0.0314	0.0007
Mar, 30	-0.0533	0.0076
Mar, 31	-0.0403	0.0071
Apr, 1	-0.0386	-0.0003
Apr, 2	-0.0234	-0.0017
Apr, 3	0.0029	-0.0024
Apr, 4	0.0037	-0.0031
Apr, 5	-0.0177	-0.0010
Apr, 6	-0.0057	-0.0040
Apr, 7	-0.0041	-0.0028
Apr, 8	-0.0116	-0.0029
Apr, 9	-0.0138	-0.0032
Apr, 10	-0.0123	-0.0032
Apr, 11	-0.0211	-0.0021

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Apr, 12	-0.0297	-0.0002
Apr, 13	-0.0244	-0.0008
Apr, 14	-0.0310	-0.0016
Apr, 15	-0.0295	-0.0012
Apr, 16	-0.0271	-0.0010
Apr, 17	-0.0297	0.0022
Apr, 18	-0.0245	0.0027
Apr, 19	-0.0196	0.0020
Apr, 20	-0.0110	-0.0012
Apr, 21	0.0068	-0.0002
Apr, 22	0.0126	-0.0015
Apr, 23	0.0061	-0.0033
Apr, 24	0.0216	-0.0028
Apr, 25	0.0186	-0.0030

Table S6: Fama-Macbeth Regression for Chinese Cities except Wuhan

Daily *R* values from January 19 to February 10 and the average 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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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
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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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 S7: 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)[1] for Chinese Cities

This table utilizes estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days)[1] 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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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
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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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 S8: 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)[1] for the U.S. Counties

This table utilizes estimated serial interval in a previous paper (mean 7.5 days, std 3.4 days)[1] 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

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
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
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			

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
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

Table S9: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with social distancing dummy variable for the U.S. Counties.

U.S. states lifted stay-at-home orders, namely series of social distancing policies, at different times. This table shows the regression results for the U.S. Counties with an additional dummy explanatory variable recording whether the state where a county is located already lifted a stay-at-home order. The regression is estimated by the Fama-MacBeth approach.

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
R2	0.1201	0.1403	0.0956
Temperature			
coef	-0.0158	-0.01988	-.01092
95%CI	[-0.0246,-0.0071]	[-0.0300,-0.0097]	[-0.0265,0.0047]
std.err	0.0043	0.0049	0.0074
t-stat	-3.65	-4.07	-1.47
p-value	0.0007	0.0005	0.159
Relative Humidity			
coef	-0.0050	-0.0080	-0.0014
95%CI	[-0.0104,0.0004]	[-0.0151,-0.0010]	[-0.0026,0.0002]
std.err	0.0027	0.0034	0.0006
t-stat	-1.88	-2.37	-2.46
p-value	0.067	0.027	0.024
Population Density			
coef	4.56e-06	7.77e-06	6.89e-07
95%CI	[-1e-5,2e-2]	[-2.53e-5,4.08e-5]	[-1.10e-6,2.48e-6]
std.err	8.34e-06	1.59e-05	8.53e-07
t-stat	0.55	0.49	0.81
p-value	0.587	0.631	0.430
Percentage over 65			
coef	-0.948	-1.1645	-0.6851
95%CI	[-1.3747,-0.5205]	[-1.8362,-0.4927]	[-1.0610,-0.3092]

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
std.err	0.2115	0.3239	0.1789
t-stat	-4.48	-3.60	-3.83
p-value	6e-5	0.002	0.001
Gini			
coef	-1.8813	-1.9719	-1.7717
95%CI	[-3.5537,-0.2090]	[-4.5293,0.5855]	[-2.5073,-1.0360]
std.err	0.8281	1.2331	0.3502
t-stat	-2.27	-1.60	-5.06
p-value	0.028	0.124	8e-5
Socio-economic factor			
coef	0.0891	0.1321	0.0371
95%CI	[0.0372,0.1411]	[0.0835,0.1807]	[-0.0048,0.0790]
std.err	0.0257	0.02343	0.0200
t-stat	3.47	5.64	1.86
p-value	0.001	1e-05	0.079
No. of ICU beds per capita			
coef	-0.0096	-0.0084	-0.0111
95%CI	[-0.0235,0.0043]	[-0.0301,0.0133]	[-0.0172,-0.0050]
std.err	0.0069	0.0104	0.0029
t-stat	-1.40	-0.80	-3.83
p-value	0.169	0.430	0.001
Fraction of maximum moving distance over normal time			
coef	0.0041	0.0031	0.0054
95%CI	[0.0016,0.0066]	[-0.0004,0.0067]	[0.0043,0.0065]
std.err	0.0012	0.0017	0.0005
t-stat	3.35	1.82	10.25
p-value	0.002	0.082	0
Home-stay minutes			
coef	0.0003	0.0007	-0.0002

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
95%CI	[-0.0002,0.0007]	[0.0004,0.0010]	[-0.0004,-3e-05]
std.err	0.0002	0.0002	9e-5
t-stat	1.33	4.73	-2.42
p-value	0.191	0.0001	0.026
Latitude			
coef	-0.0182	-0.0348	0.0018
95%CI	[-0.0371,0.0007]	[-0.0510,-0.0185]	[-0.0188,0.0225]
std.err	0.0094	0.0078	0.0098
t-stat	-1.95	-4.43	0.19
p-value	0.058	0.0002	0.854
Longitude			
coef	0.0069	0.0103	0.0029
95%CI	[0.0033,0.0106]	[0.0082,0.0124]	[0.0008,0.0050]
std.err	0.0018	0.0010	0.0010
t-stat	3.82	10.13	2.85
p-value	0.0005	0	0.011
Stay-at-home order			
coef	0.0199	0.0939	-0.0695
95%CI	[-0.0651,0.1049]	[0.0199,0.1678]	[-0.13026,-0.088]
std.err	0.0421	0.0356	0.0289
t-stat	0.47	2.63	-2.40
p-value	0.638	0.015	0.027
const			
coef	1.7395	2.1976	1.1850
95%CI	[1.1800,2.2989]	[1.6645,2.7306]	[1.1695,1.2005]
std.err	0.2770	0.2570	0.0074
t-stat	6.28	8.55	160.27
p-value	0	0	0

Table S10: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with spatial random effect of Chinese cities.

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between cities.

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
Temperature			
coef	-0.0212	-0.0269	-0.0196
95%CI	[-0.0361, -0.0063]	[-0.0429, -0.0108]	[-0.0377, -0.0016]
std.err	0.0072	0.0058	0.0085
t-stat	-2.96	-4.65	-2.30
p-value	0.007	0.010	0.034
Relative Humidity			
coef	-0.0045	-0.0074	-0.0037
95%CI	[-0.0090, -0.00003]	[-0.0103, -0.0044]	[-0.0091, 0.0017]
std.err	0.0022	0.0011	0.0026
t-stat	-2.09	-6.90	-1.46
p-value	0.049	0.002	0.162
Population Density			
coef	0.0257	0.1059	0.0034
95%CI	[-0.0197, 0.0711]	[0.0208, 0.1911]	[-0.0200, 0.0268]
std.err	0.0219	0.0307	0.0111
t-stat	1.17	3.45	0.31
p-value	0.253	0.026	0.764
Percentage over 65			
coef	0.0783	0.2110	0.0415
95%CI	[-1.5748, 1.7315]	[-1.1675, 1.5894]	[-2.0603, 2.1432]
std.err	0.7971	0.4965	0.9962
t-stat	0.10	0.42	0.04

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
p-value	0.923	0.693	0.967
GDP per capita			
coef	-0.0022	-0.0155	0.0015
95%CI	[-0.0203, 0.0159]	[-0.0262, -0.0048]	[-0.0187, 0.0218]
std.err	0.0087	0.0038	0.0096
t-stat	-0.25	-4.04	0.16
p-value	0.805	0.016	0.876
No. of doctors			
coef	-0.0056	-0.0101	-0.0044
95%CI	[-0.0083, -0.0030]	[-0.0163, -0.0039]	[-0.0059, -0.0029]
std.err	0.0013	0.0022	0.0007
t-stat	-4.40	-4.52	-6.10
p-value	0.0003	0.011	0.0002
Drop of BMI			
coef	0.2327	-0.3903	0.4057
95%CI	[-0.3638, 0.8291]	[-0.6699, -0.1106]	[-0.2111, 1.0225]
std.err	0.2876	0.1007	0.2924
t-stat	0.81	-3.87	1.39
p-value	0.427	0.018	0.183
Inflow population from Wuhan			
coef	-0.0028	-0.0001	-0.0035
95%CI	[-0.0055, -0.00004]	[-0.0011, 0.0008]	[-0.0063, -0.0007]
std.err	0.0013	0.0003	0.0013
t-stat	-2.11	-0.43	-2.62
p-value	0.047	0.688	0.018
Latitude			
coef	0.0063	0.0076	0.0059
95%CI	[-0.0161, 0.0286]	[-0.0191, 0.0343]	[-0.0221, 0.0339]
std.err	0.0108	0.0096	0.0133

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
t-stat	0.58	0.79	0.44
p-value	0.566	0.472	0.662
Longitude			
coef	-0.0100	-0.0258	-0.0056
95%CI	[-0.0195, -0.0006]	[-0.0514, -0.0003]	[-0.0141, 0.0028]
std.err	0.0046	0.0092	0.0040
t-stat	-2.20	-2.81	-1.40
p-value	0.039	0.048	0.178
const			
coef	1.1002	2.1148	0.8183
95%CI	[0.5229, 1.6774]	[1.5587, 2.6710]	[0.5551, 1.0815]
std.err	0.2784	0.2003	0.1247
t-stat	3.95	10.56	6.56
p-value	0.001	0	0.0002

Table S11: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with spatial random effect of the U.S. counties.

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between counties.

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
Temperature			
coef	-0.0136	-0.0135	-0.0136
95%CI	[-0.0215, -0.0057]	[-0.0236, -0.0034]	[-0.0280, 0.0007]
std.err	0.0039	0.0049	0.0068
t-stat	-3.46	-2.78	-2.00
p-value	0.001	0.011	0.061
Relative Humidity			
coef	-0.0052	-0.0072	-0.0029
95%CI	[-0.0095, -0.0010]	[-0.0130, -0.0014]	[-0.0042, -0.0016]
std.err	0.0021	0.0028	0.0006
t-stat	-2.51	-2.57	-4.59
p-value	0.016	0.017	0.0003
Population Density			
coef	3.26e-8	2.98e-6	-3.54e-6
95%CI	[-0.00002, 0.00002]	[-0.00003, 0.00004]	[-5.13e-6, -1.95e-6]
std.err	8.58e-6	0.00002	7.57e-7
t-stat	0.00	0.18	-4.67
p-value	0.997	0.858	0.0002
Percentage over 65			
coef	-0.7988	-1.0894	-0.4471
95%CI	[-1.4330, -0.1647]	[-2.0771, -0.1017]	[-0.7620, -0.1322]
std.err	0.3140	0.4763	0.1499
t-stat	-2.54	-2.29	-2.98

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
p-value	0.015	0.032	0.008
Gini			
coef	-1.8186	-2.2916	-1.2460
95%CI	[-3.3837, -0.2534]	[-4.5288, -0.0543]	[-2.1425, -0.3495]
std.err	0.7750	1.0788	0.4267
t-stat	-2.35	-2.12	-2.92
p-value	0.024	0.045	0.009
Socio-economic factor			
coef	0.1131	0.1480	0.0708
95%CI	[0.0682, 0.1580]	[0.0903, 0.2056]	[0.0451, 0.0965]
std.err	0.0222	0.0278	0.0122
t-stat	5.08	5.32	5.78
p-value	0.0002	0.0002	0.0002
No. of ICU beds per capita			
coef	-0.0092	-0.0127	-0.0050
95%CI	[-0.0238, 0.0054]	[-0.0359, 0.0105]	[-0.0101, 0.0002]
std.err	0.0072	0.0112	0.0025
t-stat	-1.27	-1.14	-2.01
p-value	0.210	0.267	0.059
Fraction of maximum moving distance over normal time			
coef	0.0040	0.0024	0.0059
95%CI	[0.0012, 0.0068]	[-0.0014, 0.0063]	[0.0054, 0.0064]
std.err	0.0014	0.0019	0.0002
t-stat	2.93	1.30	25.03
p-value	0.005	0.207	0
Home-stay minutes			
coef	0.0003	0.0005	0.00002
95%CI	[0.00002, 0.0006]	[0.0001, 0.0009]	[-0.0002, 0.0002]
std.err	0.0001	0.0002	0.0001

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
t-stat	2.15	2.81	0.19
p-value	0.038	0.010	0.851
Latitude			
coef	-0.0152	-0.0278	-0.00004
95%CI	[-0.0308, 0.0003]	[-0.0423, -0.0133]	[-0.0208, 0.0207]
std.err	0.0077	0.0070	0.0099
t-stat	-1.98	-3.97	-0.00
p-value	0.055	0.001	0.997
Longitude			
coef	0.0060	0.0084	0.0032
95%CI	[0.0033, 0.0088]	[0.0064, 0.0104]	[0.0015, 0.0049]
std.err	0.0014	0.0010	0.0008
t-stat	4.45	8.78	3.86
p-value	0.0003	0	0.001
const			
coef	1.7377	2.2018	1.1759
95%CI	[1.1715, 2.3039]	[1.6623, 2.7413]	[1.1594, 1.1923]
std.err	0.2803	0.2601	0.0078
t-stat	6.20	8.46	150.10
p-value	0	0	0

References

1 Li Q, Guan X, Wu P, *et al.* Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *N Engl J Med* 2020.
2 Wallinga J, Teunis P. Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am J Epidemiol* 2004;**160**:509–516.
3 Newey WK, West KD. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 1987;**55**:703–8.
4 Stein ML. *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media 2012.
5 Breslow NE, Clayton DG. Approximate inference in generalized linear mixed models. *J Am Stat Assoc* 1993;**88**:9–25.
6 Cressie N. *Statistics for spatial data*. John Wiley & Sons 2015.
7 Rousset F, Ferdy J-B. Testing environmental and genetic effects in the presence of spatial autocorrelation. *Ecography* 2014;**37**:781–790.
8 Hadri K. Testing for stationarity in heterogeneous panel data. *Econom J* 2000;**3**:148–161.

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- Impact of temperature and relative humidity on the transmission of COVID-19: A modeling study in China and the U.S.

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ABSTRACT

Objectives We aim to assess the impact of temperature and relative humidity on the transmission of COVID-19 across communities after accounting for community-level factors such as demographics, socioeconomic status, and human mobility status.

Design A retrospective cross-sectional regression analysis via the Fama-MacBeth procedure is adopted.

Setting We use the data for COVID-19 daily symptom-onset cases for 100 Chinese cities and COVID-19 daily confirmed cases for 1,005 U.S. counties.

Participants A total of 69,498 cases in China and 740,843 cases in the U.S. are used for calculating the effective reproductive numbers.

Primary outcome measures Regression analysis of the impact of temperature and relative humidity on the effective reproductive number (*R* value).

Results Statistically significant negative correlations are found between temperature/relative humidity and the effective reproductive number (*R* value) in both China and the U.S.

Conclusions Higher temperature and higher relative humidity potentially suppress the transmission of COVID-19. Specifically, an increase in temperature by 1 degree Celsius is associated with a reduction in the *R* value of COVID-19 by 0.026 (95% CI [-0.0395,-0.0125]) in China and by 0.020 (95% CI [-0.0311, -0.0096]) in the U.S.; an increase in relative humidity by 1% is associated with a reduction in the *R* value by 0.0076 (95% CI [-0.0108,-0.0045]) in China and by 0.0080 (95% CI [-0.0150,-0.0010]) in the U.S. Therefore, the potential impact of temperature/relative humidity on the effective reproductive number alone is not strong enough to stop the pandemic.

Strengths and limitations of this study

1. Cross-sectional observations from 100 Chinese cities and 1,005 U.S. counties cover a wide spectrum of meteorological conditions.

2. Demographics, socioeconomic status, geographical, healthcare, and human mobility factors are all included in the regression analysis.
3. The Fama-MacBeth regression framework allows the identification of associations between temperature/relative humidity and COVID-19 transmissibility for nonstationary short-duration data.
4. The exact mechanism of the negative association between *R* and temperature/relative humidity has not been investigated in this study.
5. The temperature and relative humidity data have range limitations and do not contain extreme conditions.

MAIN TEXT

Introduction

The coronavirus disease 2019 (COVID-19) pandemic, caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has infected more than 70 million people with 1,595,187 deaths across 220 countries and territories as of December 13, 2020 [1], since its first reported case in Wuhan, China in December 2019 [2,3]. COVID-19 has had disastrous impacts on global public health, the environment, socioeconomics, etc [4–7]. Understanding the factors that affect the transmission of SARS-CoV-2 is crucial for predicting the transmission dynamics of the virus and making appropriate intervention policies. Numerous recent studies have analyzed the effects of anthropogenic factors on COVID-19 transmission, such as travel restrictions [8–10], nonpharmacological interventions [11], population flow [12], anti-contagion policies [13], and contact patterns [14].

Meteorological factors, such as temperature and humidity, have previously been suggested to be associated with the transmissibility of certain infectious diseases. For example, prior studies have shown that the transmission of influenza is seasonal and is affected by humidity [15,16], and that wintertime climate and host behavior can facilitate the transmission of influenza [17–19]. Studies have also shown that the transmission of other human coronaviruses that cause mild respiratory symptoms, such as OC43 (HCoV-OC43) and HCoV-HKU1, is seasonal [20,21]. The seasonality of these related viruses has been leveraged in an indirect long-term simulation of the transmission of SARS-CoV-2 [22,23], and other studies have demonstrated a correlation between meteorological factors and pandemic spreading [24]. In addition, temperature and humidity have been shown to be important natural factors affecting pulmonary diseases [25], which are prevalent in COVID-19 patients.

However, there is no consensus on the impact of meteorological factors on COVID-19 transmissibility. For example, the study by Merow *et al.* shows that ultraviolet light is associated with a decreasing trend in COVID-19 case growth rates [26]. In contrast, other studies claim no association between COVID-19 transmissibility and temperature and ultraviolet light [27] or a positive association between temperature and daily confirmed cases [28,29]. Since the COVID-19 outbreak has lasted for less than a year, we do not have multiyear time-series data to estimate a stable serial cointegration between meteorological factors and certain indicators of COVID-19 transmissibility. As large-scale social intervention unfolded shortly after the outbreak in both countries, the periods without nonpharmaceutical intervention were quite short. Thus, estimation of the influences of meteorological factors on COVID-19 transmissibility is challenging.

The goal of this paper is to accurately quantify such influences, where the meteorological factors include temperature and humidity, and the COVID-19 transmissibility is measured by the effective reproductive number (*R* values). Our analysis is based on COVID-19 data from both China and the U.S. With several months of observations, the *R* values typically will have a trend, as will temperature and humidity. In this paper, we consider a strategy of “trading-space-for-time” by using Fama-MacBeth regression with Newey-West adjustment for standard errors, which is widely used in finance [30–32]. Specifically, we first estimate the cross-sectional association between temperature/relative humidity and R values across 100 cities in China from January 19 to February 15 (nationwide lockdown started from January 24) and 1,005 counties in the U.S. from March 15 to April 25 (nationwide lockdown started from April 7) and then adjust for the time-series autocorrelation of these estimates. Demographics, socioeconomic status, geographical, healthcare, and human mobility status factors are also included in our modeling process as control variables. Our framework enables analysis during the early stage of an infectious disease outbreak and thus has considerable potential for informing policymakers to consider social interventions in a timely fashion.

Materials and Methods

Data.

Records of 69,498 COVID-19 patients with symptom-onset days up to February 10, 2020 from 325 cities are extracted from the Chinese National Notifiable Disease Reporting System. Each patient's records include the area code of his/her current residence, the area code of the reporting institution, the date of symptom onset and the date of confirmation. With such symptom-onset data, we are able to estimate the precise R values for different Chinese cities. For U.S. data, daily confirmed cases for 1,005 counties with a more than 20,000 population size are collected from the COVID-19 database of the Johns Hopkins University Center for Systems Science and Engineering (which is publicly available at https://github.com/CSSEGISandData/COVID-19/). We extract the data from March 15 to April 25 for the 1,005 counties, which results in a total of 740,843 confirmed cases. Due to the unavailability of onset date information in the U.S. data, we estimate R values from the daily confirmed cases for U.S. counties, which may be less precise than the estimation for the Chinese cities.

We also collect 4,711 cases from Chinese epidemiological surveys published online by the Centers 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, we match close contacts and select 105 pairs of clear virus carriers and infections, 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/. Other factors, including population density, GDP per capita, the fraction of the population aged 65 and above, and the number of doctors for each city in 2018, are obtained from https://data.cnki.net. The indices indicating the number of migrants from Wuhan to other cities over the period of January 7 to February 10 and the Baidu Mobility Index are obtained from https://qianxi.baidu.com/. Panel A of Table S1 in the supplementary materials provides the summary statistics of the variables for analyzing the data from China with their pairwise correlations shown in supplementary Table S2.

For the U.S., temperature and relative humidity data are collected from the National Oceanic and Atmospheric Administration (https://www.ncdc.noaa.gov/). Population data and the fraction of residents over 65 years of age for each county are obtained from the American Community Survey (https://www.census.gov/). GDP and personal 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/. The Gini index, the fraction of the population below the poverty level, the fraction of residents who are not in the labor force (under 16 years old), the fraction of households with a total income greater than $200,000, and the fraction of the population with food stamp/SNAP benefits are obtained from the American Community Survey. 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 S1 in the supplementary materials provides the summary statistics of the variables for analyzing the U.S. data with their pairwise correlations shown in supplementary Table S3.

Patient and public involvement

In this study, in order to protect the patient privacy, no identifiable protected health information is extracted from the Chinese National Notifiable Disease Reporting System. The Chinese epidemiological surveys data has personal information removed before publication. Patient and/or public are not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Construction of Effective Reproductive Numbers.

We use the effective reproductive number, or the *R* value, to quantify the transmission of COVID-19 in different cities and counties. The calculation of the *R* value consists of two steps. First, we estimate the serial interval, which is the time between successive cases in a transmission chain of COVID-19 using 105 pairs of virus carriers and infections. We fit these 105 samples of serial intervals with a Weibull distribution using maximum likelihood estimation (MLE) (implemented with the 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)), as shown in Figure S1. The results of the two implementations 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 typically have a highly wiggy *R* value curve due to inaccurate *R* value estimation. Therefore, we select cities with more than 40 cases in China, 100 in total. We then calculate the *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 MLE (Supplementary Materials pages 4-5) [33]. For estimation of *R* values in U.S. counties, the settings of serial intervals are set to the same as China, *i.e.,* with a 7.4 day mean and 5.2 day standard deviation. We use the same methods of estimating the *R* values of all 1,005 U.S. counties from the date when the first confirmed case occurred in the county to April 25, 2020.

Study Period.

We aim to study the influences of various factors on the *R* value under the outdoor environment, because if people stay at home for most of their time under the restrictions of the isolation policy, weather conditions are unlikely to influence virus transmission. We thus perform separate analyses before and after the large-scale stay-at-home quarantine policies for both China (January 24) and the U.S. (April 7). The first-level response to major public health emergencies in many major Chinese cities and provinces, including Beijing and Shanghai, was announced on January 24. Moreover, the numbers of cases in most cities before January 18 are too small to accurately estimate the *R* value. Therefore, 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 for Wuhan. We take January 24 to February 10 as the period after lockdown for China. As reported by The New York Times, most states announced state-wide stay-at-home orders from April 7 for the U.S. [34]. Moreover, the number of cases in most counties before March 15 is too small to accurately estimate the *R* value, so we take March 15 to April 6 for each county as the before-lockdown period and April 7 to April 25 as the after-lockdown period.

Statistical Analysis.

We use six-day average temperature and relative humidity values up to and including the day when the *R* value is measured. Our strategy is inspired by the five-day incubation period estimated from Johns Hopkins University [35] plus a one-day onset. In the data of this work, the series of the 6-

day average temperature and relative humidity and the daily R values are mostly nonstationary. We find a declining trend of R values for nearly all Chinese cities and the U.S. counties during our study periods, which could be due to the nature of the disease and people's raised awareness and increased self-protection measures even before the lockdown. Table S4 Panel A and Panel B in the supplementary materials show the panel Handri LM unit root test [36] results for the China and U.S. data. In this case, direct time-series regression cannot be applied due to the so-called spurious regression [37] problem, which states the fact that a regression may provide misleading statistical evidence of a linear relationship between nonstationary time-series variables. We thus adopt the Fama-MacBeth methodology [38] with Newey-West adjustment, which consists of a series of cross-sectional regressions and has been proven effective in various disciplines, including finance and economics. The details are described as follows.

Fama-MacBeth Regression with the Newey–West Adjustment.

Fama-MacBeth regression is a two-step procedure (Supplementary Materials p2-3). In the first step, it runs a cross-sectional regression at each point in time; the second step estimates the coefficient as the average of the cross-sectional regression estimates. Since these estimates might have autocorrelations, we adjust the error of the average with a Newey-West approach. Mathematically, our method proceeds as follows.

Step 1: Let T be the length of the time period and M be the number of control variables. For each timestamp 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 regression coefficient estimates obtained from the first step:

$$\hat{\beta}_{\mathrm{k}} = \frac{1}{T}\sum_{t=1}^{T} \beta_{\mathrm{k},t}$$

We use the Newey-West approach [39] to adjust for the time-series autocorrelation and heteroscedasticity in calculating the standard errors in the second step. Specifically, the Newey-West estimators can be expressed as

$$S = \frac{1}{T}\left(\sum_{t=1}^{T} e_t^2 + \sum_{l=1}^{L}\sum_{t=l+1}^{T} w_l e_t e_{t-l}\right),$$

where $w_l = 1 - \frac{l}{1+L}$, where e represents residuals and L is the lag (Supplementary Materials pages 2-3).

The Fama-MacBeth regression with Newey-West adjustment has two advantages: 1) It avoids the spurious regression problem for nonstationary series, as the first-step estimates, $\{\beta_{\mathrm{k},t}\}$, have much milder autocorrelations than the autocorrelations (time trends) within the observations. Such autocorrelations can be adjusted by the Newey-West procedure. 2) Only cross-sectional coefficient estimates in the first step are used to estimate the coefficients, but not their standard errors; hence, any heteroskedasticity and residual-dependent issues in the first step will not influence the final results, because the heteroskedasticity and residual dependency (including the one caused by spatial correlation) does not alter the unbiasedness of the coefficient in the ordinary least squares (OLS) estimation. Supplementary Table S5 shows the detailed coefficients of temperature and relative humidity in the first step of the Fama-MacBeth regression.

Note that the Fama-MacBeth regression with Newey-West adjustment is commonly used in estimating parameters for finance and economic models that are valid in the presence of cross-sectional correlation and time-series autocorrelation [30–32]. To the best of our knowledge, our study is a novel application of this method in emergent public health and epidemiological problems.

In our implementation, on each day of the study period, we perform a cross-sectional regression of the daily R values of various cities or counties based on their 6-day average temperature and relative humidity values, as well as several categories of control variables, including the following:

(1) *Demographics.* The population density and the fraction of people aged 65 and older for both China and the U.S.
(2) *Socioeconomic statuses.* The GDP per capita for Chinese cities. For the U.S. counties, the Gini index and the first PCA factor derived from several factors including GDP per capita, personal income, the fraction of the population below the poverty level, the fraction of the population not in the labor force (16 years or over), the fraction of the population with a total household income more than $200,000, and the fraction of the population with food stamp/SNAP benefits.
(3) *Geographical variables.* Latitudes and longitudes.
(4) *Healthcare.* The number of doctors in 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 that migrated from Wuhan in the 14 days prior to the *R* measurement and the drop rate of the Baidu Mobility Index 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 Stata version 16.0.

Results

COVID-19 has spread widely in both China and the U.S. The transmissibility and meteorological conditions in the cities/counties of these two countries vary greatly (see Figures 1 and 2). We analyze the relationship between COVID-19 transmissibility and temperature/relative humidity, controlling for various demographics, socioeconomic statuses, geographical, healthcare, and human mobility status factors and correcting for cross-sectional correlations. Overall, we find robust negative correlations between COVID-19 transmissibility before the large-scale public health interventions (lockdown) in China and the U.S. and temperature and relative humidity. Moreover, 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 continue to have a negative influence even after the public health intervention, but with smaller magnitudes since an increasing number of people stay at home and hence are exposed less to the outdoor weather. More details are presented below.

Temperature, Relative Humidity, and Effective Reproductive Numbers

For both China and the U.S., we conduct a series of cross-sectional regressions (the Fama-MacBeth approach [38]) of the daily effective reproductive numbers (*R* values), which measure COVID-19 transmissibility, on the six-day average temperature and relative humidity up to and including the day when the *R* value is measured, considering the transmission during presymptomatic periods [35] 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 lockdown) 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.

Overall, the results for Chinese cities (Table 1) demonstrate that the six-day average temperature and relative humidity have a significant relationship with *R* values, with p-values smaller than or approximately 0.01 for all three specified time periods. The analysis of U.S. counties (Table 2) shows that six-day average temperature and relative humidity have statistically significant correlations with *R* values, with p-values lower than 0.05 before April 7, the time when most states declared state-wide stay-at-home orders [34].

The influences of the temperature and relative humidity on the *R* values are quite similar before the lockdown in China and the U.S.: a one-degree Celsius increase in temperature is associated with an approximately 0.023 decrease (-0.026 (95% CI [-0.0395,-0.0125]) in China and -0.020 (95% CI [-0.0311, -0.0096]) in the U.S.) in the *R* value, and a one percent relative humidity rise is associated with an approximately 0.0078 decrease (-0.0076 (95% CI [-0.0108,-0.0045]) in China and -0.0080 (95% CI [-0.0150,-0.0010]) in the U.S.) in the *R* value. After lockdown, the temperature and relative humidity also present negative relationships with the *R* values for both countries. For China, it is statistically significant (with p-values lower than 0.05), and a one-degree Celsius increase in temperature and a one percent increase in relative humidity are associated with a 0.0209 decrease (95% CI [-0.0378, -0.0041]) and a 0.0054 decrease (95% CI [-0.0104, -0.0004]) in the *R* value, respectively. For the U.S., the estimated effects of temperature and relative humidity on the *R* values are still negative but no longer statistically significant (with p-values of 0.141 and 0.073, respectively). The lesser influence of weather conditions is very likely caused by the stay-at-home policy during lockdown periods, when people are less exposed 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 COVID-19 transmissibility. In China, before the lockdowns, in cities with higher levels of population density, the virus spreads faster than in less crowded cities due to more possible contacts among people. A one thousand people per square kilometer increase in population density is associated with a 0.1188 increase (95% CI [0.0573, 0.1803]) in the *R* value before lockdown. Cities in China with more doctors have a smaller transmission intensity since the infections are treated in hospitals and hence are unable to be transmitted to others. In particular, one thousand more doctors are associated with a 0.0058 decrease (95% CI [-0.0090, -0.0025]) 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 cared for and thus unlikely to be transmitting the infection to others. A ten thousand Chinese Yuan GDP per capita increase is associated with a decrease in the *R* value by 0.0145 (95% CI [-0.0249, -0.0040]) before the lockdown. In the U.S., there is a strong relationship between the *R* value and the number of ICU beds per capita after lockdown, with a p-value of 0.001; every unit increase in ICU bed per 10,000 population is associated with a 0.0110 decrease (95% CI [-0.0171, -0.0049]) in the *R* value. Moreover, counties with more people over 65 years old have lower *R* values, but the magnitude is small, *i.e.,* a one percent increase in the fraction of individuals aged over 65 is associated with a 0.0092 decrease (95% CI [-0.0135, -0.00498]) in the *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. A previous work shows that absolute humidity is a good solo variable explaining the seasonality of influenza [40]. The results shown in Table 3 are only partly consistent with this notion [40]. In particular, for the U.S. counties, relative humidity and absolute humidity are almost equivalent in explaining the variation in the *R* value (12.57% vs. 12.55%), while absolute humidity does achieve a higher significance level (p-value less than 0.00001) than 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 a proxy for intracity mobility change (compared to the normal time) in China. The regression results show that before the lockdown, a 1% decrease in BMI drop is associated with a decrease in the *R* value by 0.004093 (95% CI [-0.00683, -0.001356]). After the lockdown, the BMI drop does not significantly affect the *R* value. A possible reason is that the BMI variations across cities are quite small (all at quite low levels) after the lockdown, as the paces of interventions 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 the *R* value 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 the influences of temperature/humidity on *R* values over four conditions:

(1) **Wuhan city.** Among these 100 cities in China, Wuhan is a special case with the earliest outbreak of COVID-19. There was an increase of more than 13,000 cases on a single day (February 12, 2020) due to the unification of testing standards with other regions of China [41]. Therefore, as a robustness check, we remove Wuhan city from our sample and redo the regression analysis.

(2) **Different measurements of serial intervals.** We also use serial intervals in a previous work (mean 7.5 days, std 3.4 days based on 10 cases) [3] with a Weibull distribution to estimate the *R* values of various cities/counties for robustness checks.

(3) **Social distancing dummy variables for the U.S. counties.** States in the U.S. announced stay-at-home orders at different times. We add a dummy variable that is set to one if the stay-at-home order is imposed and zero otherwise.

(4) **Spatial random effect.** We also introduce a spatial model into the first step of the Fama-MacBeth regression to account for spatial correlation and redo the analysis.

The results of the abovementioned four robustness checks are shown in supplementary Table S6 to S11. All of them show that temperature and relative humidity have a strong influence on *R* values with strong statistical significance, which is consistent with the reported results in Tables 1 and 2.

Discussion

We identify robust negative correlations between temperature/relative humidity and the COVID-19 transmissibility using samples of the daily transmission of COVID-19, temperature and relative humidity for 100 Chinese cities and 1,005 U.S. counties. Although we use different datasets (symptom-onset data for Chinese cities and confirmed case 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 [40], which can be explained by several potential reasons. The influenza virus is more stable in cold environments, and respiratory droplets, as containers of viruses, remain airborne longer in dry air [42]. Cold and dry weather can also weaken host immunity and make the hosts more susceptible to the virus [43]. Our result is also consistent with the evidence that high temperature and high relative humidity reduce the viability of SARS coronavirus [44]. High transmission in cold temperatures may also be explained by behavioral differences; for instance, people may spend more time indoors and have a greater chance of interacting with others. Further studies should be performed to disentangle these multiple explanations and change the association relationship in our study to a casual effect.

Our study has several strengths. First, we use data from vast geographical scopes in both China and the U.S. that contain a variety of meteorological conditions. Second, we employ all kinds of control variables such as demographics, socioeconomic status, geographical, healthcare and human mobility status factors as control variables to capture the effect of regional disparity. Third, we use the Fama-MacBeth regression framework to estimate associations between temperature/relative humidity and COVID-19 transmissibility when our data are nonstationary and in a short duration. Compared to the study by Merow *et al.,* which investigates the influence of meteorological conditions on COVID-19 infections with only population density and the proportion of individuals aged over 65 years considered as control variables [26], our study incorporates more categories of variables to explain the heterogeneity among different regions. Although a study by Yao *et al.* has announced no association between COVID-19 transmission and temperature, they use a 2-month averaged temperature for analysis, and the temperature trends are not considered [27]. A study by Xie *et al.* reports positive relationships between temperature and COVID-19 cases [29]. However, the demographic factors for cities are not incorporated as controls, and the effectiveness of nonstationary time series problem for the panel regression methods they use is not explicitly discussed.

We do acknowledge several limitations. Our findings cannot verify the detailed mechanisms between temperature/relative humidity and COVID-19 transmissibility. Our study is a statistical analysis but not an experiment. These findings should be considered with caution when used for prediction. The R^2 of our regression is approximately 30% in China and 12% in the U.S., which means that approximately 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%, respectively, and in the U.S., the temperature and humidity range from -10°C to 29°C and from 16% to 99%, respectively; thus, it is still unknown whether these negative relationships still hold in extremely hot and cold areas. The slight differences between the estimates on the Chinese cities and the U.S. counties might come from the different ranges of temperature and relative humidity.

Outwardly, our study suggests that the summer and rainy seasons can potentially reduce the transmissibility of COVID-19, but it is unlikely that the COVID-19 pandemic will “automatically” diminish in summer. Cold and dry seasons can potentially break the fragile transmission balance and the weaken downward trends in some areas of the Northern Hemisphere.

Therefore, public health intervention is still necessary to block the transmission of COVID-19 even in the summer. In particular, as shown in this paper, lockdowns, constraints on human mobility, increases in hospital beds, etc., can potentially reduce the transmissibility of COVID-19. Given the relationship between temperature/relative humidity and COVID-19 transmissibility, policymakers can adjust their intervention policy according to the different temperature/relative humidity conditions. When new infectious diseases emerge, our framework can also provide policymakers with fast support, although this is not expected.

Contributorship statement J.W. initiated this project. J.W., W.L. and F.W. planned and oversaw the project. K.T. and K.C. contributed econometrics methods. K.F and X.L. prepared the datatsets and conducted analysis. K.T, W.F and J.W. wrote the manuscript with input from all authors.

Competing interests The authors declare no competing interests.

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Data sharing statement Temperature, humidity, R values calculated from confirmed cases and all control variables except home-stay minutes used in this study will be included in the published version of this article for release online. Home-stay minute data provided by Safegraph (https://www.safegraph.com/) cannot be disclosed since this would compromise the agreement with the data provider, nevertheless, these data can be obtained by applying for permission from the provider. R values calculated from symptom onset data are available upon request from Dr Jingyuan Wang (jywang@buaa.edu.cn).

References

1 WHO. Coronavirus disease (COVID-19) pandemic. 2020.https://www.who.int/emergencies/diseases/novel-coronavirus-2019

2 Zhu N, Zhang D, Wang W, *et al.* A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med* 2020.

3 Li Q, Guan X, Wu P, *et al.* Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *N Engl J Med* 2020.

4 Bashir MF, Benjiang M, Shahzad L. A brief review of socio-economic and environmental impact of Covid-19. *Air Qual Atmosphere Health* 2020;:1–7.

5 Ní Ghráinne B. Covid-19, Border Closures, and International Law. *SSRN 3662218* 2020.

6 Bashir MF, Benghoul M, Numan U, *et al.* Environmental pollution and COVID-19 outbreak: insights from Germany. *Air Qual Atmosphere Health* 2020;**13**:1385–1394.

7 Collivignarelli MC, Abbà A, Bertanza G, *et al.* Lockdown for CoViD-2019 in Milan: What are the effects on air quality? *Sci Total Environ* 2020;**732**:139280.

8 Kraemer MU, Yang C-H, Gutierrez B, *et al.* The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* 2020;**368**:493–497.

9 Tian H, Liu Y, Li Y, *et al.* An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science* 2020;**368**:638–642.

10 Chinazzi M, Davis JT, Ajelli M, *et al.* The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* 2020;**368**:395–400.

11 Lai S, Ruktanonchai NW, Zhou L, *et al.* Effect of non-pharmaceutical interventions to contain COVID-19 in China. *Nature* 2020.

12 Jia JS, Lu X, Yuan Y, *et al.* Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 2020;:1–5.

13 Hsiang S, Allen D, Annan-Phan S, *et al.* The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature* 2020;:1–9.

14 Zhang J, Litvinova M, Liang Y, *et al.* Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China. *Science* 2020.

15 Hemmes J, Winkler K, Kool S. Virus survival as a seasonal factor in influenza and poliomyelitis. *Nature* 1960;**188**:430–431.

16 Dalziel BD, Kissler S, Gog JR, *et al.* Urbanization and humidity shape the intensity of influenza epidemics in US cities. *Science* 2018;**362**:75–79.

17 Shaman J, Pitzer VE, Viboud C, *et al.* Absolute humidity and the seasonal onset of influenza in the continental United States. *PLoS Biol* 2010;**8**:e1000316.

18 Shaman J, Goldstein E, Lipsitch M. Absolute humidity and pandemic versus epidemic influenza. *Am J Epidemiol* 2011;**173**:127–135.

19 Chattopadhyay I, Kiciman E, Elliott JW, *et al.* Conjunction of factors triggering waves of seasonal influenza. *Elife* 2018;**7**:e30756.
20 Killerby ME, Biggs HM, Haynes A, *et al.* Human coronavirus circulation in the United States 2014–2017. *J Clin Virol* 2018;**101**:52–56.
21 Neher RA, Dyrdak R, Druelle V, *et al.* Potential impact of seasonal forcing on a SARS-CoV-2 pandemic. *Swiss Med Wkly* 2020;**150**.
22 Kissler SM, Tedijanto C, Goldstein E, *et al.* Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* 2020.
23 Baker RE, Yang W, Vecchi GA, *et al.* Susceptible supply limits the role of climate in the early SARS-CoV-2 pandemic. *Science* 2020.
24 Bashir MF, Ma B, Komal B, *et al.* Correlation between climate indicators and COVID-19 pandemic in New York, USA. *Sci Total Environ* 2020;:138835.
25 Chen C, Liu X, Wang X, *et al.* Effect of air pollution on hospitalization for acute exacerbation of chronic obstructive pulmonary disease, stroke, and myocardial infarction. *Environ Sci Pollut Res* 2020;**27**:3384–3400.
26 Merow C, Urban MC. Seasonality and uncertainty in COVID-19 growth rates. *Proc Natl Acad Sci* 2020;**117**:27456–64.
27 Yao Y, Pan J, Liu Z, *et al.* No Association of COVID-19 transmission with temperature or UV radiation in Chinese cities. *Eur Respir J* 2020;**55**.
28 Al-Rousan N, Al-Najjar H. The correlation between the spread of COVID-19 infections and weather variables in 30 Chinese provinces and the impact of Chinese government mitigation plans. 2020.
29 Xie J, Zhu Y. Association between ambient temperature and COVID-19 infection in 122 cities from China. *Sci Total Environ* 2020;**724**:138201.
30 Lewellen J. The cross section of expected stock returns. *Forthcom Crit Finance Rev* 2014.
31 Kang W, Rouwenhorst KG, Tang K. A tale of two premiums: The role of hedgers and speculators in commodity futures markets. *J Finance* 2020;**75**:377–417.
32 Petersen MA. Estimating standard errors in finance panel data sets: Comparing approaches. *Rev Financ Stud* 2009;**22**:435–480.
33 Wallinga J, Teunis P. Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am J Epidemiol* 2004;**160**:509–516.
34 NYTimes. See Which States Are Reopening and Which Are Still Shut Down. 2020.https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html
35 Johns Hopkins University. Coronavirus symptoms start about five days after exposure, Johns Hopkins study finds. 2020.https://hub.jhu.edu/2020/03/09/coronavirus-incubation-period/
36 Hadri K. Testing for stationarity in heterogeneous panel data. *Econom J* 2000;**3**:148–161.
37 Kao C. Spurious regression and residual-based tests for cointegration in panel data. *J Econom* 1999;**90**:1–44.
38 Fama EF, MacBeth JD. Risk, return, and equilibrium: Empirical tests. *J Polit Econ* 1973;**81**:607–636.
39 Newey WK, West KD. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 1987;**55**:703–8.
40 Shaman J, Kohn M. Absolute humidity modulates influenza survival, transmission, and seasonality. *Proc Natl Acad Sci* 2009;**106**:3243–3248.
41 Nanfangzhoumo. What's the Difficulty of Wuhan's "All Receivable." 2020.https://www.infzm.com/contents/177054
42 Lowen AC, Steel J. Roles of humidity and temperature in shaping influenza seasonality. *J Virol* 2014;**88**:7692–7695.
43 Kudo E, Song E, Yockey LJ, *et al.* Low ambient humidity impairs barrier function and innate resistance against influenza infection. *Proc Natl Acad Sci* 2019;**116**:10905–10910.

44 Chan K, Peiris J, Lam S, *et al.* The effects of temperature and relative humidity on the viability of the SARS coronavirus. *Adv Virol* 2011;**2011**.

Figures and Tables

Figure 1: A city-level visualization of 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 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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
p-value	0.001	0.005	0.0004
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

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
p-value	0.003	0.00001	0.133
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

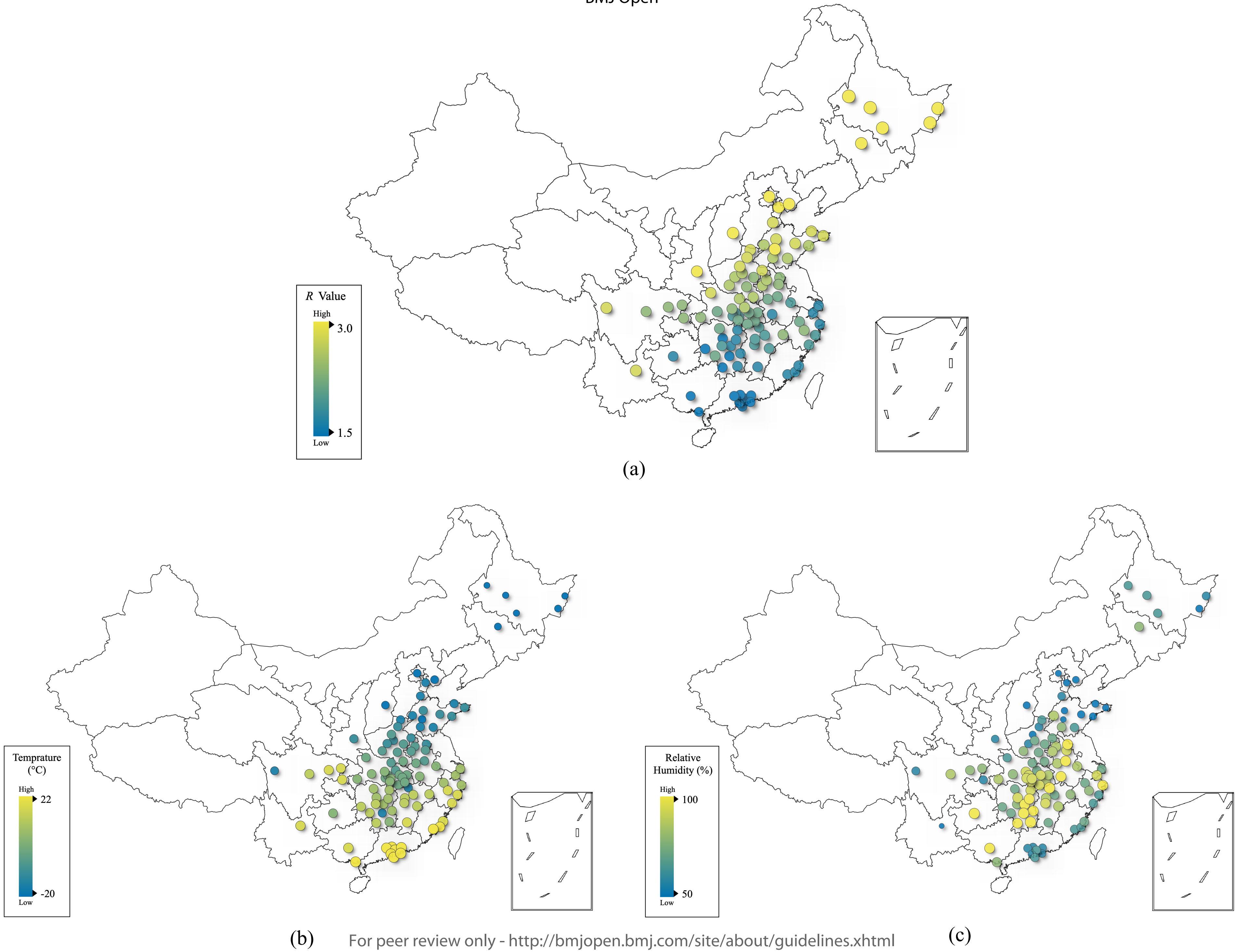
	Temperature	Relative Humidity	Absolute Humidity
p-value	0.020	0.019	0.014
No. of doctors			
coef	-0.0109	-0.0111	-0.0111
95%CI	[-0.0167, -0.0051]	[-0.0167, -0.0054]	[-0.0168, -0.0053]
std.err	0.0021	0.0020	0.0021
t-stat	-5.21	-5.45	-5.37
p-value	0.006	0.006	0.006
Drop of BMI			
coef	-0.5174	-0.4236	-0.5370
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

Supplementary Materials
Supplementary Materials are included in a separate file.


R Value
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3.0
1.5
Low
(a)
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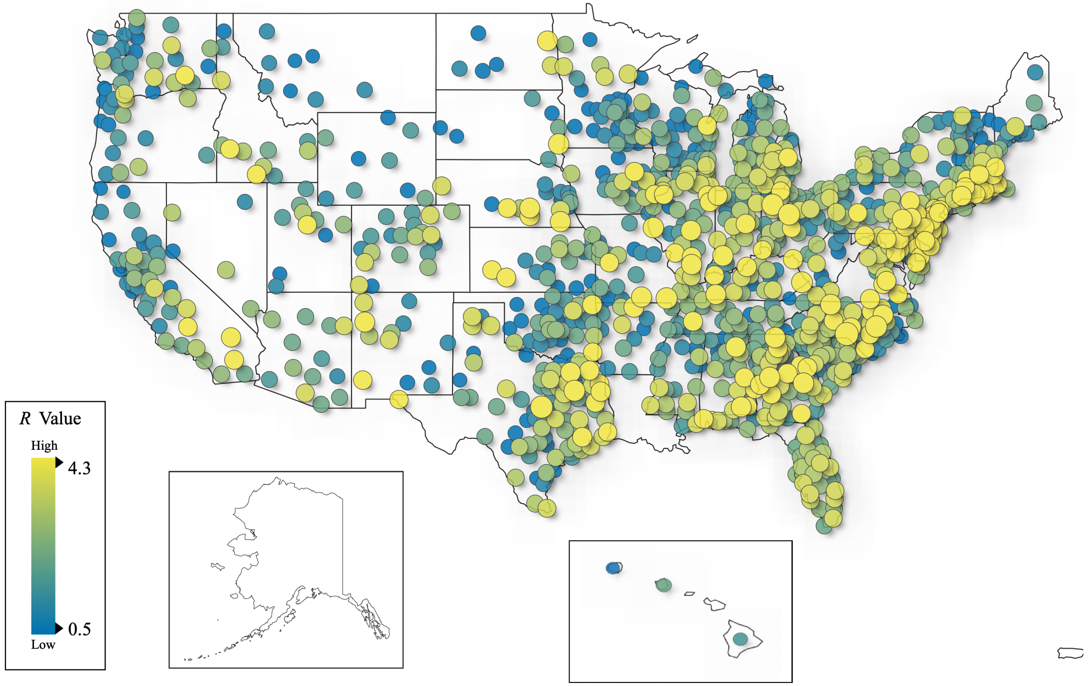
(°C)
High
22
-20
Low
Relative
Humidity (%)
High
100
50
Low
(b)
(c)


R Value
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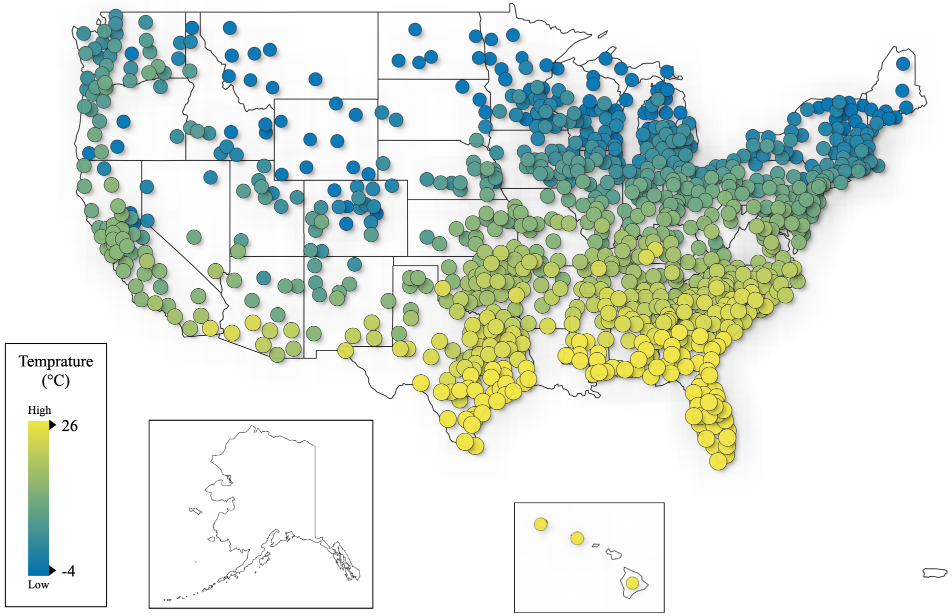
0.5
Low

(a)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26
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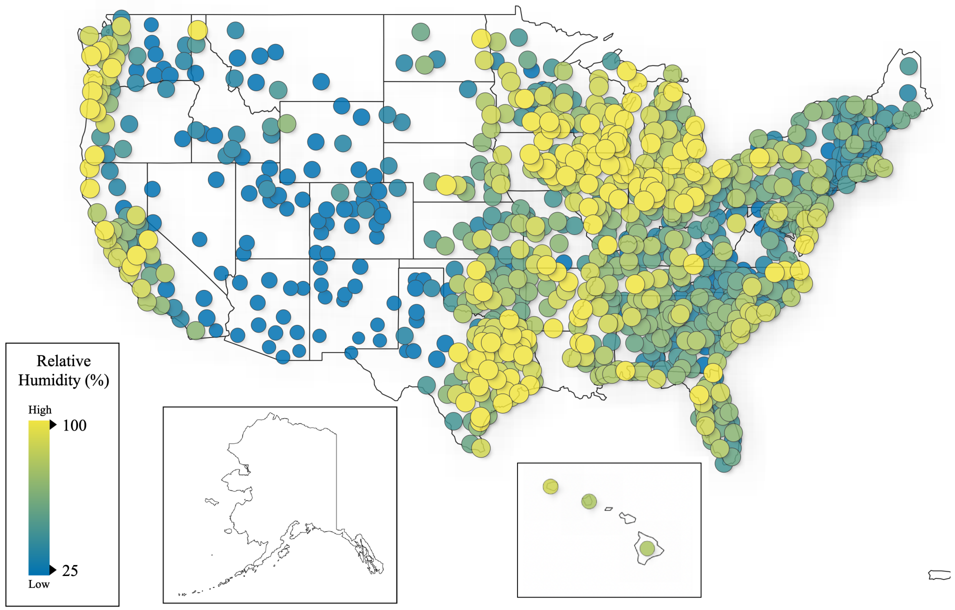
Low

(b)


Relative Humidity (%)
High
100
25
Low

(c)

Supplementary Materials for

Impact of Temperature and Relative Humidity on the Transmission of COVID-19: A Modeling Study in China and the U.S.

Jingyuan Wang, Ke Tang*, Kai Feng, Xin Lin, Weifeng Lv, Kun Chen and Fei Wang

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This PDF file includes:

Materials and Methods
Figs. S1
Tables S1 to S11

Materials and Methods

Fama-MacBeth Regression with Newey-West Adjustment

Fama-MacBeth regression is a way to study the relationship between the response variable and the features in the panel data setup. Particularly, Fama-MacBeth regression runs a series of cross-sectional regressions and uses the average of the cross-sectional regression coefficients as the second step of parameter estimation. In equation form, for n response variables, m features and time series length T

$$
\begin{aligned}
R_{i,1} &= \alpha_1 + \beta_{1,1}F_{1,i,1} + \beta_{2,1}F_{2,i,1} + \cdots + \beta_{m,1}F_{m,i,1} + \epsilon_{i,1},\\
R_{i,2} &= \alpha_2 + \beta_{1,2}F_{1,i,2} + \beta_{2,2}F_{2,i,2} + \cdots + \beta_{m,2}F_{m,i,2} + \epsilon_{i,2},\\
&\cdots\\
R_{i,T} &= \alpha_T + \beta_{1,T}F_{1,i,T} + \beta_{2,T}F_{2,i,T} + \cdots + \beta_{m,T}F_{m,i,T} + \epsilon_{i,T}.
\end{aligned}
$$

where $R_{i,t}, i \in \{1,\ldots,\mathrm{n}\}$ are the response values, $\beta_{k,t}$ are first step regression coefficients for feature k at time t, and $F_{k,i,t}$ are the input features of feature k and sample i at time t. In the second step, the average of the first step regression coefficient, $\hat{\beta}_k$, can be calculated directly, or via the following regression

$$\beta_{k,t} = c_k + \epsilon_t.$$

where ϵ_t is the random noise.

Since βs might have time-series autocorrelation, in the second step, we thus use the Newey-West approach [1] to adjust the time-series autocorrelation (and heteroscedasticity) in calculating standard errors. Specifically, for the second step, we have

$E[\epsilon] = 0$ and $E[\epsilon\epsilon'] = \sigma^2\Omega$.

The covariance matrix of c_k is

$$V_{c_k} = \frac{1}{T}\left(\frac{1}{T}\mathbf{1}'\mathbf{1}\right)^{-1}\left(\frac{1}{T}\mathbf{1}'(\sigma^2\Omega)\mathbf{1}\right)\left(\frac{1}{T}\mathbf{1}'\mathbf{1}\right)^{-1},$$

where $\mathbf{1}$ is a $T \times 1$ vector of 1 and $\sigma^2\Omega$ is the covariance matrix of errors.

The middle matrix can be rewritten as

$$Q = \frac{1}{T}\mathbf{1}'(\sigma^2\Omega)\mathbf{1}$$
$$= \frac{1}{T}\sum_{i=1}^{T}\sum_{j=1}^{T}\sigma_{ij}$$

The Newey-West estimators give a consistent estimation of Q when the residuals are autocorrelated and/or heteroscedastic. The Newey-West estimator can be expressed as

$$S = \frac{1}{T}\left(\sum_{t=1}^{T} e_t^2 + \sum_{l=1}^{L}\sum_{t=l+1}^{T} w_l e_t e_{t-l}\right),$$

where $w_l = 1 - \frac{l}{1+L}$, e represents residuals and L is the lag.

We use Fama-Macbeth regressions for two reasons. First, the temperature and relative humidity series have trends with the arrival of summer and the R value series also has downward trends. In this case, panel regression will obtain spurious regression results from the time-series perspective. However, the cross-sectional regression involving cities (counties) of various meteorological conditions and COVID-19 spread intensities will not have spurious regression issues. Second, Fama-MacBeth regression is valid even in the presence of cross-sectional heteroskedasticity (including complex spatial covariance) because in the second-step regression, only the value of the first step estimates βs are used, not their standard errors. Therefore, as long as the first-step estimator is unbiased, which is the case for heteroskedasticity (including complex spatial covariance), the Fama-MacBeth estimation is correct.

Less rigorously speaking, we use the first step of Fama-MacBeth regression to determine the extent to which the transmissibility of the areas of high temperature and high relative humidity are compared with that of low temperature and low relative humidity areas each day. We then use the second step to test whether daily relationships are a common fact during a given time period.

Estimating the Effective Reproduction Number

The basic reproduction number R_0, which characterizes the transmission ability of an epidemic, is defined as the average number of people who will contract the contagious disease from a typical infected case in a population where everyone is susceptible. When an epidemic spreads through a population, the time-varying effective reproduction number R_t is of greater concern. The effective reproduction number R_t, the R value at time step t, is defined as the actual average number of secondary cases per primary case cause[2].

We then calculate the effective reproductive number R_t for each city through a time-dependent method based on maximun likelihood estimation (MLE)[3]. The inputs to the method are epidemic curves, *i.e.*, the historical numbers of patients in each day, for a certain city. Specifically, we denote $w(\tau|\theta)$ as the probability distribution for the serial interval, which is defined as the time between symptom onset of a case and symptom onset of her/his secondary cases. Let $p_{(i,j)}$ be the relative likelihood that case i has been infected by case j, given the difference in time of symptom onset $t_i - t_j$, which can be expressed in terms of $w(\tau|\theta)$. That is, the relative likelihood that case i has been infected by case j can be expressed as

$$p_{ij} = \frac{w(t_i - t_j)}{\sum_{i \neq k} w(t_i - t_k)}$$

The relative likelihood of case i infecting case j is independent of the relative likelihood of case i infecting any other case k. The distribution of the effective reproduction number for case i is

$$R_i \sim \sum_j \text{Bernoulli}[p_{(j,i)}]$$

With the expected value

$$E(R_i) = \sum_j p_{(j,i)}$$

The average daily effective reproduction number R_t is estimated as the average over R_i for all cases i who develop the first symptom of onset on day t.

The above calculation is implemented with the package ‘R0’ developed by Boelle & Obadia with R version 3.6.2 and ‘R0’ version 1.2_6 (https://cran.r-project.org/web/packages/R0/index.html).

Modeling Spatial Effect

We use a generalized linear mixed model (GLMM) with spatial random effects to account for spatial autocorrelation between cities or counties in each cross-sectional regression. The form of the model is

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u} + \boldsymbol{\epsilon},$$

where $\boldsymbol{y}$ is the $N \times 1$ outcome vector, $\boldsymbol{X}$ is the $N \times p$ matrix of the p explanatory variables (the intercept term can be included by setting the first column of X as a vector of ones), $\boldsymbol{\beta}$ is the vector of regression coefficients, $\boldsymbol{u}$ is the vector of spatial random effects, and $\boldsymbol{\epsilon}$ is the random error vector whose entries are independent and identically distributed as $N(0, \sigma^2)$. We assume $\boldsymbol{u} \sim N(0, \boldsymbol{\sigma_s^2 G})$, *where* $\boldsymbol{\sigma_s^2}$ is the spatial variance and $\boldsymbol{G}$ follows a Matérn correlation structure[4].

The Matérn model flexibly specifies the correlation between any two cities or counties as a function of their geographical distance; the model has two parameters, a scale parameter ρ and a "smoothness" parameter ν, and it subsumes the exponential and squared exponential models as special cases. The maximum likelihood method is used for parameter estimation[5].

We have also tried a conditional autoregressive model (CAR)[6] in which the spatial correlation is described by an adjacency matrix of the cities/counties. The Matérn model performs better than the CAR model as judged by the Akaike information criterion (AIC); the average AIC value across all cross-sectional regressions is 896.9 and 936.5 for the Matérn model and the CAR model, respectively.

All computations are performed in the R package "spaMM" version 3.3.0[7]. We report the results from the Matérn model in Table S9 and S10.

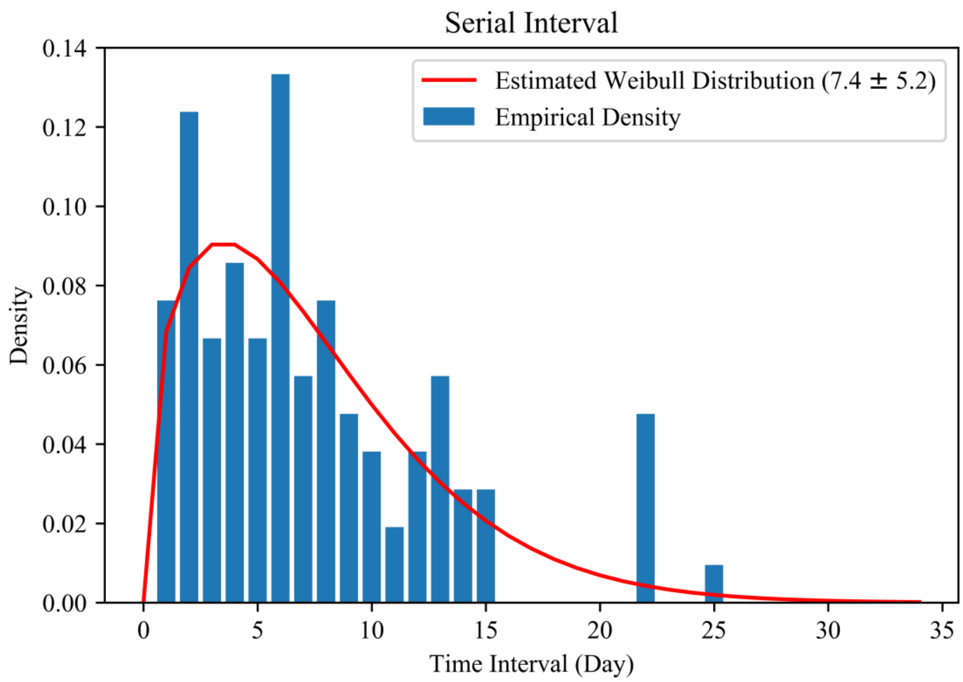

Fig. S1. Estimation of the serial interval with the Weibull distribution

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

Table S1. Data Summary

This table summarizes the variables used in this paper. Panel A and B summarize the data of Chinese cities 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 S2: 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 S3: 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 S4: Unit Root Test for R, Temperature and Relative Humidity

Panel A and B show the results of Handri LM test [8] 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 S5: Coefficients of temperature and relative humidity in first step of Fama-Macbeth Regression

Panel A and B show regression coefficients of temperature and relative humidity in the first step of Fama-Macbeth regression, for Chinese cities and the U.S. counties, respectively.

Panel A: Regression Coefficients for Chinese Cities

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Jan, 19	-0.0373	-0.0109
Jan, 20	-0.0064	0.0009
Jan, 21	-0.0127	-0.0093
Jan, 22	-0.0309	-0.0121
Jan, 23	-0.0427	-0.0066
Jan, 24	-0.0249	0.0010
Jan, 25	-0.0238	-0.0062
Jan, 26	-0.0506	-0.0174
Jan, 27	-0.0526	-0.0159
Jan, 28	-0.0196	-0.0063
Jan, 29	-0.0340	-0.0101
Jan, 30	-0.0305	-0.0096
Jan, 31	-0.0391	-0.0087
Feb, 1	-0.0388	-0.0102
Feb, 2	-0.0248	-0.0097
Feb, 3	-0.0108	-0.0022
Feb, 4	-0.0091	0.0020
Feb, 5	0.0039	0.0040
Feb, 6	-0.0061	-0.0037
Feb, 7	-0.0034	0.0006
Feb, 8	0.0103	-0.0030
Feb, 9	-0.0077	-0.0067
Feb, 10	-0.0150	0.0052

Panel B: Regression Coefficients for U.S. Counties

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Mar, 15	-0.0402	-0.0190
Mar, 16	-0.0309	-0.0192
Mar, 17	-0.0052	-0.0129
Mar, 18	-0.0192	-0.0146
Mar, 19	-0.0412	-0.0237
Mar, 20	0.0224	-0.0114
Mar, 21	-0.0112	-0.0158
Mar, 22	-0.0138	-0.0169
Mar, 23	-0.0021	-0.0195
Mar, 24	-0.0107	-0.0166
Mar, 25	-0.0184	-0.0073
Mar, 26	-0.0231	-0.0095
Mar, 27	-0.0241	-0.0010
Mar, 28	-0.0468	0.0013
Mar, 29	-0.0314	0.0007
Mar, 30	-0.0533	0.0076
Mar, 31	-0.0403	0.0071
Apr, 1	-0.0386	-0.0003
Apr, 2	-0.0234	-0.0017
Apr, 3	0.0029	-0.0024
Apr, 4	0.0037	-0.0031
Apr, 5	-0.0177	-0.0010
Apr, 6	-0.0057	-0.0040
Apr, 7	-0.0041	-0.0028
Apr, 8	-0.0116	-0.0029
Apr, 9	-0.0138	-0.0032
Apr, 10	-0.0123	-0.0032
Apr, 11	-0.0211	-0.0021

Date	Coefficient of Temperature	Coefficient of Relative Humidity
Apr, 12	-0.0297	-0.0002
Apr, 13	-0.0244	-0.0008
Apr, 14	-0.0310	-0.0016
Apr, 15	-0.0295	-0.0012
Apr, 16	-0.0271	-0.0010
Apr, 17	-0.0297	0.0022
Apr, 18	-0.0245	0.0027
Apr, 19	-0.0196	0.0020
Apr, 20	-0.0110	-0.0012
Apr, 21	0.0068	-0.0002
Apr, 22	0.0126	-0.0015
Apr, 23	0.0061	-0.0033
Apr, 24	0.0216	-0.0028
Apr, 25	0.0186	-0.0030

Table S6: Fama-Macbeth Regression for Chinese Cities except Wuhan

Daily *R* values from January 19 to February 10 and the average 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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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
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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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 S7: 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 the 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

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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
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			

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
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 S8: 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 the 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

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
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
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			

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
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

Table S9: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with a social distancing dummy variable for the U.S. Counties.

U.S. states lifted stay-at-home orders, namely a series of social distancing policies, at different times. This table shows the regression results for the U.S. Counties with an additional dummy explanatory variable recording whether the state where a county is located already lifted a stay-at-home order. The regression is estimated by the Fama-MacBeth approach.

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
R2	0.1201	0.1403	0.0956
Temperature			
coef	-0.0158	-0.01988	-.01092
95%CI	[-0.0246,-0.0071]	[-0.0300,-0.0097]	[-0.0265,0.0047]
std.err	0.0043	0.0049	0.0074
t-stat	-3.65	-4.07	-1.47
p-value	0.0007	0.0005	0.159
Relative Humidity			
coef	-0.0050	-0.0080	-0.0014
95%CI	[-0.0104,0.0004]	[-0.0151,-0.0010]	[-0.0026,0.0002]
std.err	0.0027	0.0034	0.0006
t-stat	-1.88	-2.37	-2.46
p-value	0.067	0.027	0.024
Population Density			
coef	4.56e-06	7.77e-06	6.89e-07
95%CI	[-1e-5,2e-2]	[-2.53e-5,4.08e-5]	[-1.10e-6,2.48e-6]
std.err	8.34e-06	1.59e-05	8.53e-07
t-stat	0.55	0.49	0.81
p-value	0.587	0.631	0.430
Percentage over 65			
coef	-0.948	-1.1645	-0.6851
95%CI	[-1.3747,-0.5205]	[-1.8362,-0.4927]	[-1.0610,-0.3092]

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
std.err	0.2115	0.3239	0.1789
t-stat	-4.48	-3.60	-3.83
p-value	6e-5	0.002	0.001
Gini			
coef	-1.8813	-1.9719	-1.7717
95%CI	[-3.5537,-0.2090]	[-4.5293,0.5855]	[-2.5073,-1.0360]
std.err	0.8281	1.2331	0.3502
t-stat	-2.27	-1.60	-5.06
p-value	0.028	0.124	8e-5
Socio-economic factor			
coef	0.0891	0.1321	0.0371
95%CI	[0.0372,0.1411]	[0.0835,0.1807]	[-0.0048,0.0790]
std.err	0.0257	0.02343	0.0200
t-stat	3.47	5.64	1.86
p-value	0.001	1e-05	0.079
No. of ICU beds per capita			
coef	-0.0096	-0.0084	-0.0111
95%CI	[-0.0235,0.0043]	[-0.0301,0.0133]	[-0.0172,-0.0050]
std.err	0.0069	0.0104	0.0029
t-stat	-1.40	-0.80	-3.83
p-value	0.169	0.430	0.001
Fraction of maximum moving distance over normal time			
coef	0.0041	0.0031	0.0054
95%CI	[0.0016,0.0066]	[-0.0004,0.0067]	[0.0043,0.0065]
std.err	0.0012	0.0017	0.0005
t-stat	3.35	1.82	10.25
p-value	0.002	0.082	0
Home-stay minutes			
coef	0.0003	0.0007	-0.0002

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
95%CI	[-0.0002,0.0007]	[0.0004,0.0010]	[-0.0004,-3e-05]
std.err	0.0002	0.0002	9e-5
t-stat	1.33	4.73	-2.42
p-value	0.191	0.0001	0.026
Latitude			
coef	-0.0182	-0.0348	0.0018
95%CI	[-0.0371,0.0007]	[-0.0510,-0.0185]	[-0.0188,0.0225]
std.err	0.0094	0.0078	0.0098
t-stat	-1.95	-4.43	0.19
p-value	0.058	0.0002	0.854
Longitude			
coef	0.0069	0.0103	0.0029
95%CI	[0.0033,0.0106]	[0.0082,0.0124]	[0.0008,0.0050]
std.err	0.0018	0.0010	0.0010
t-stat	3.82	10.13	2.85
p-value	0.0005	0	0.011
Stay-at-home order			
coef	0.0199	0.0939	-0.0695
95%CI	[-0.0651,0.1049]	[0.0199,0.1678]	[-0.13026,-0.088]
std.err	0.0421	0.0356	0.0289
t-stat	0.47	2.63	-2.40
p-value	0.638	0.015	0.027
const			
coef	1.7395	2.1976	1.1850
95%CI	[1.1800,2.2989]	[1.6645,2.7306]	[1.1695,1.2005]
std.err	0.2770	0.2570	0.0074
t-stat	6.28	8.55	160.27
p-value	0	0	0

Table S10: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with spatial random effect of Chinese cities.

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between cities.

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
Temperature			
coef	-0.0212	-0.0269	-0.0196
95%CI	[-0.0361, -0.0063]	[-0.0429, -0.0108]	[-0.0377, -0.0016]
std.err	0.0072	0.0058	0.0085
t-stat	-2.96	-4.65	-2.30
p-value	0.007	0.010	0.034
Relative Humidity			
coef	-0.0045	-0.0074	-0.0037
95%CI	[-0.0090, -0.00003]	[-0.0103, -0.0044]	[-0.0091, 0.0017]
std.err	0.0022	0.0011	0.0026
t-stat	-2.09	-6.90	-1.46
p-value	0.049	0.002	0.162
Population Density			
coef	0.0257	0.1059	0.0034
95%CI	[-0.0197, 0.0711]	[0.0208, 0.1911]	[-0.0200, 0.0268]
std.err	0.0219	0.0307	0.0111
t-stat	1.17	3.45	0.31
p-value	0.253	0.026	0.764
Percentage over 65			
coef	0.0783	0.2110	0.0415
95%CI	[-1.5748, 1.7315]	[-1.1675, 1.5894]	[-2.0603, 2.1432]
std.err	0.7971	0.4965	0.9962
t-stat	0.10	0.42	0.04

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
p-value	0.923	0.693	0.967
GDP per capita			
coef	-0.0022	-0.0155	0.0015
95%CI	[-0.0203, 0.0159]	[-0.0262, -0.0048]	[-0.0187, 0.0218]
std.err	0.0087	0.0038	0.0096
t-stat	-0.25	-4.04	0.16
p-value	0.805	0.016	0.876
No. of doctors			
coef	-0.0056	-0.0101	-0.0044
95%CI	[-0.0083, -0.0030]	[-0.0163, -0.0039]	[-0.0059, -0.0029]
std.err	0.0013	0.0022	0.0007
t-stat	-4.40	-4.52	-6.10
p-value	0.0003	0.011	0.0002
Drop of BMI			
coef	0.2327	-0.3903	0.4057
95%CI	[-0.3638, 0.8291]	[-0.6699, -0.1106]	[-0.2111, 1.0225]
std.err	0.2876	0.1007	0.2924
t-stat	0.81	-3.87	1.39
p-value	0.427	0.018	0.183
Inflow population from Wuhan			
coef	-0.0028	-0.0001	-0.0035
95%CI	[-0.0055, -0.00004]	[-0.0011, 0.0008]	[-0.0063, -0.0007]
std.err	0.0013	0.0003	0.0013
t-stat	-2.11	-0.43	-2.62
p-value	0.047	0.688	0.018
Latitude			
coef	0.0063	0.0076	0.0059
95%CI	[-0.0161, 0.0286]	[-0.0191, 0.0343]	[-0.0221, 0.0339]
std.err	0.0108	0.0096	0.0133

	Overall	Before Lockdown (Jan 24)	After Lockdown (Jan 24)
t-stat	0.58	0.79	0.44
p-value	0.566	0.472	0.662
Longitude			
coef	-0.0100	-0.0258	-0.0056
95%CI	[-0.0195, -0.0006]	[-0.0514, -0.0003]	[-0.0141, 0.0028]
std.err	0.0046	0.0092	0.0040
t-stat	-2.20	-2.81	-1.40
p-value	0.039	0.048	0.178
const			
coef	1.1002	2.1148	0.8183
95%CI	[0.5229, 1.6774]	[1.5587, 2.6710]	[0.5551, 1.0815]
std.err	0.2784	0.2003	0.1247
t-stat	3.95	10.56	6.56
p-value	0.001	0	0.0002

Table S11: Relationship between Temperature, Relative Humidity, and *R* Value: Robustness Check with spatial random effect of the U.S. counties.

Spatial random effects are introduced in first step of Fama-Macbeth regression to account for spatial correlation. The neighborhood structure is calculated from the Earth distances between counties.

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
Temperature			
coef	-0.0136	-0.0135	-0.0136
95%CI	[-0.0215, -0.0057]	[-0.0236, -0.0034]	[-0.0280, 0.0007]
std.err	0.0039	0.0049	0.0068
t-stat	-3.46	-2.78	-2.00
p-value	0.001	0.011	0.061
Relative Humidity			
coef	-0.0052	-0.0072	-0.0029
95%CI	[-0.0095, -0.0010]	[-0.0130, -0.0014]	[-0.0042, -0.0016]
std.err	0.0021	0.0028	0.0006
t-stat	-2.51	-2.57	-4.59
p-value	0.016	0.017	0.0003
Population Density			
coef	3.26e-8	2.98e-6	-3.54e-6
95%CI	[-0.00002, 0.00002]	[-0.00003, 0.00004]	[-5.13e-6, -1.95e-6]
std.err	8.58e-6	0.00002	7.57e-7
t-stat	0.00	0.18	-4.67
p-value	0.997	0.858	0.0002
Percentage over 65			
coef	-0.7988	-1.0894	-0.4471
95%CI	[-1.4330, -0.1647]	[-2.0771, -0.1017]	[-0.7620, -0.1322]
std.err	0.3140	0.4763	0.1499
t-stat	-2.54	-2.29	-2.98

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
p-value	0.015	0.032	0.008
Gini			
coef	-1.8186	-2.2916	-1.2460
95%CI	[-3.3837, -0.2534]	[-4.5288, -0.0543]	[-2.1425, -0.3495]
std.err	0.7750	1.0788	0.4267
t-stat	-2.35	-2.12	-2.92
p-value	0.024	0.045	0.009
Socio-economic factor			
coef	0.1131	0.1480	0.0708
95%CI	[0.0682, 0.1580]	[0.0903, 0.2056]	[0.0451, 0.0965]
std.err	0.0222	0.0278	0.0122
t-stat	5.08	5.32	5.78
p-value	0.0002	0.0002	0.0002
No. of ICU beds per capita			
coef	-0.0092	-0.0127	-0.0050
95%CI	[-0.0238, 0.0054]	[-0.0359, 0.0105]	[-0.0101, 0.0002]
std.err	0.0072	0.0112	0.0025
t-stat	-1.27	-1.14	-2.01
p-value	0.210	0.267	0.059
Fraction of maximum moving distance over normal time			
coef	0.0040	0.0024	0.0059
95%CI	[0.0012, 0.0068]	[-0.0014, 0.0063]	[0.0054, 0.0064]
std.err	0.0014	0.0019	0.0002
t-stat	2.93	1.30	25.03
p-value	0.005	0.207	0
Home-stay minutes			
coef	0.0003	0.0005	0.00002
95%CI	[0.00002, 0.0006]	[0.0001, 0.0009]	[-0.0002, 0.0002]
std.err	0.0001	0.0002	0.0001

	Overall	Before Lockdown (April 7)	After Lockdown (April 7)
t-stat	2.15	2.81	0.19
p-value	0.038	0.010	0.851
Latitude			
coef	-0.0152	-0.0278	-0.00004
95%CI	[-0.0308, 0.0003]	[-0.0423, -0.0133]	[-0.0208, 0.0207]
std.err	0.0077	0.0070	0.0099
t-stat	-1.98	-3.97	-0.00
p-value	0.055	0.001	0.997
Longitude			
coef	0.0060	0.0084	0.0032
95%CI	[0.0033, 0.0088]	[0.0064, 0.0104]	[0.0015, 0.0049]
std.err	0.0014	0.0010	0.0008
t-stat	4.45	8.78	3.86
p-value	0.0003	0	0.001
const			
coef	1.7377	2.2018	1.1759
95%CI	[1.1715, 2.3039]	[1.6623, 2.7413]	[1.1594, 1.1923]
std.err	0.2803	0.2601	0.0078
t-stat	6.20	8.46	150.10
p-value	0	0	0

References

1 Newey WK, West KD. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 1987;**55**:703–8.

2 Li Q, Guan X, Wu P, *et al*. Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *N Engl J Med* 2020.

3 Wallinga J, Teunis P. Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am J Epidemiol* 2004;**160**:509–516.

4 Stein ML. *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media 2012.

5 Breslow NE, Clayton DG. Approximate inference in generalized linear mixed models. *J Am Stat Assoc* 1993;**88**:9–25.

6 Cressie N. *Statistics for spatial data*. John Wiley & Sons 2015.

7 Rousset F, Ferdy J-B. Testing environmental and genetic effects in the presence of spatial autocorrelation. *Ecography* 2014;**37**:781–790.

8 Hadri K. Testing for stationarity in heterogeneous panel data. *Econom J* 2000;**3**:148–161.