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

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One Sentence Summary: High Temperature and High Humidity Reduce the Transmission of COVID-19.

Abstract. This paper investigates the influence of air temperature and relative humidity on the transmission of COVID-19. After estimating the serial interval of COVID-19 from 105 hand-collected pairs of the virus carrier and the infected, we calculate the daily effective reproductive number, *R*, for each of all 100 Chinese cities with more than 40 cases. Using the daily *R* values from January 21 to 23, 2020 as proxies of *non-intervened* transmission intensity, we find, under a linear regression framework, high temperature and high humidity significantly *reduce* the transmission of COVID-19, respectively. One-degree Celsius increase in temperature and one percent increase in relative humidity lower *R* by 0.0225 and 0.0158, respectively. This result is consistent with the fact that the high temperature and high humidity reduce the transmission of influenza and SARS. It indicates that the arrival of summer and rainy season in the northern hemisphere can effectively reduce the transmission of the COVID-19. We also developed a website to provide R of major cities around the world according to their daily temperature and relative humidity: http://covid19-report.com/#/r-value

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Since December 2019, Wuhan, the capital of Hubei Province, China, has reported an outbreak of atypical pneumonia caused by COVID-19 (SARS-CoV-2 or 2019-nCov) (*1, 2*), the virus has transmitted nationwide and internationally (*3-5*). Compared with SARS, the range of the outbreak of COVID-19 is much wider. The transmission of coronaviruses can be affected by a number of factors, including climate conditions (such as temperature and humidity), population density and medical care quality (*6, 7*). Therefore, understanding the relationship between weather and the transmission of COVID-19 is the key to forecast the intensity and end time of this pandemic.

Indirect evidence shows that up to March 22, 2020, 90% of COVID-19 cases have been recorded in non-tropical countries with low temperatures and low humidity; while much fewer cases are recorded in the tropics (*8*). However, up to now, there is no direct evidence on the influence of temperature and humidity on the transmission of the COVID-19. For example, on March 06, 2020, Michael Ryan, the executive director of the WHO Health Emergencies Program, said that people still did not know the activity or behavior of the COVID-19 virus in different climatic conditions (*9*). Our paper aims to provide direct evidence. Since the COVID-19 has spread widely to Chinese cities, and the intensity of transmission and weather conditions in these cities vary largely (Figure 1), we can, therefore, analyze the determinants of COVID-19 transmission, especially the weather factors.

Construction of Effective Reproductive Numbers in 100 Chinese Cities

In order to formally quantify the transmission of COVID-19, we first fit 105 samples of serial intervals with the Weibull distribution (a distribution commonly used to fit the serial interval of influenza (*10*)). The mean and standard deviation of the serial interval are 7.4 and 5.2 days, respectively. With these numbers, we calculate the effective reproductive number, R, a quantity measuring the severity of infectiousness, for each of all 100 Chinese cities with more than 40 cases from the first-case date to February 20 by employing a time-dependent method (*11*). The inputs of the model are epidemic curves, *i.e.* the historical numbers of patients with symptom onset of each day for a certain city.

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Because we aim to study the influences of various factors on R under *natural conditions*,[1] we select our data before China's large-scale intervention in the spread of COVID-19 on 24 January, when the first-level response to major public health emergencies in many major cities and provinces including Beijing and Shanghai are announced. Moreover, after the statement of person-to-person transmission from Professor Nanshan Zhong on the evening of January 20 through a public television interview, Chinese hospitals of all provinces began serious case recording of COVID-19, we, therefore, take the daily R values from January 21 to January 23 to proxy the non-intervened R for each city.[2]

Temperature, Relative Humidity and Effective Reproductive Numbers

The WHO believes that coronavirus carriers are infectious 2 days before the onset of the symptoms (*12*), we, therefore, use three-day average temperature and relative humidity *up to and including* the day when the R-value is measured, respectively. Figure 1 shows the average R values from January 21 to 23 for different Chinese cities geographically. Compared with the southeast coast of China, cities in the northern area of China show relatively larger R values and lower temperatures and relative humidity. The scatter plots in Figure 2 illustrate two negative relations between the 3-day average temperature and R-value and between the 3-day average relative humidity and R-value, respectively.

We then run a pooled cross-sectional regression of the daily R values of various cities on their 3-day average air temperature and relative humidity and control variables observed in 2018 including the GDP per capita, population density, number of hospital beds and the fraction of population over 65 in each city. We use White robust standard errors to adjust the t-statistics of the regression. Table 1 shows that the air temperature and relative humidity have a quite strong influence on R values with significance levels of 1% for all specifications. One-degree Celsius increase in temperature and one

[1]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 contacts between people.
[2]Wuhan City imposed travel restriction at 10 a.m. on January 23, but a large amount of people left Wuhan before 10 a.m. on that day, therefore, our sample still includes January 23.

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percent increase in relative humidity lower the *R*-value by 0.0225 and 0.0158, respectively. The control variables are not as significant as the temperature and relative humidity, but with expected signs. For example, cities with more hospital beds have a smaller transmission intensity, because the infected are treated in hospitals and hence unable to transmit to others.

John Hopkins University has estimated a 5-day incubation period between exposure and symptoms (*13*), although we do not know whether the carriers are infectious in the whole incubation period, as a robustness check, we also use five-day average temperature and relative humidity up to and including the day when the *R*-value is measured, and rerun the regression. The last two columns in Table 1 show that temperature and relative humidity still have a strong influence on *R* values with a 1% significance level, consistent with the previous regression results.

We then run a panel regression of daily *R* values on 3-day average temperatures, relative humidity and control variables with both fixed- and random-effects models. Temperature and relative humidity have quite strong influences on *R* values, with 1% significant levels for both in Table 2. Note that since control variables do not change on a daily basis from January 21 to 23, their effects are, therefore, absorbed in the fixed effects dummies in the fixed-effects panel regressions. We run a Hausman test with a null hypothesis that the random-effects model is preferred to the fixed-effects, and get the test's p-value less than 0.01, and therefore fixed-effects panel is preferred.

Absolute Humidity

Absolute humidity, the mass of water vapor per cubic meter of air, relates to both temperature and relative humidity. A previous work (*14*) shows that absolute humidity is a good solo variable explaining the seasonality of influenza. A significant negative relationship between absolute humidity and *R*-value is also shown in Figure 2. Panel A of Table 3 shows that consistent with (*14*), absolute humidity does out-perform the relative humidity (higher R^2 and larger t-statistics) as a single variable in explaining the cross-variation of the *R* values.

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We then find a better variable from the absolute and relative humidity in explaining the variation of *R* values together with temperatures by performing a Davidson-MacKinnon Test (*15*). Test 1 of Panel B in Table 3 fails to accept that absolute humidity is better than relative humidity (t-stat of -0.2); however, Test 2 of Panel B in Table 3 shows that relative humidity is better than the absolute humidity with a 1% significance level (t-statistics -4.28). Overall, the Davidson-MacKinnon test shows that the model with relative humidity and temperature is better than the one with absolute humidity and temperature in explaining *R* values.

Worldwide COVID-19 Transmission Intensity

Assuming that the same relationship between temperature and relative humidity and *R* values (first column in Table 1) applies to cities outside China and that the temperature and relative humid of 2020 are the same as those in 2019, we can draw a map of *R* values for worldwide cities in Figure 3 by plugging the average March and July temperatures and relative humidity of 2019. This figure cautions people of the transmission risk of COVID-19 worldwide, in March and July of 2020, respectively. As expected, the *R* values are larger for temperate countries and smaller for tropical countries in March, which is consistent with the indirect evidence mentioned previously (*8*). In July, the arrival of summer and rainy season in the northern hemisphere can effectively reduce the transmission of the COVID-19.

Discussions

We find the high temperature and relative humidity reduce the transmission of COVID-19 both with 1% significance levels. This finding is consistent with the evidence that high temperature and high humidity reduce the transmission of influenza (*14, 16-19*), which can be explained by two possible reasons: First, the influenza virus is more stable in cold temperature, and respiratory droplets, as containers of viruses, remain airborne longer in dry air (*20, 21*). Second, cold and dry weather can also weaken the hosts' immunity and make them more susceptible to the virus (*22, 23*). These mechanisms are also likely to apply to the COVID-19 transmission. Our result

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is also consistent with the evidence that high temperature and high relative humidity reduce the viability of SARS coronavirus (*24*, *25*).

Note that the R^2 of our regression is about 20%, which means that 80% of *R*-value fluctuations cannot be explained by temperature and relative humidity (and controls). The three-day average temperatures and relative humidity in our sample range from -21°C to 21°C and from 47 to 100, respectively, therefore it is still not known yet whether these negative relationships between COVID-19 transmission and temperature and humidity still hold in extremely hot, cold, and dry areas. In the meanwhile, although our paper suggests that the arrival of summer and rainy season in the northern hemisphere can effectively reduce the transmission of the COVID-19, it is unlikely that the COVID-19 pandemic diminishes by summer since the central U.S., northwest China and countries in the southern hemisphere (e.g. Australia and South Africa) still have a high coronavirus transmission as shown in Figure 3. Therefore, other measures such as social distancing are still important for blocking the COVID-19 transmission.

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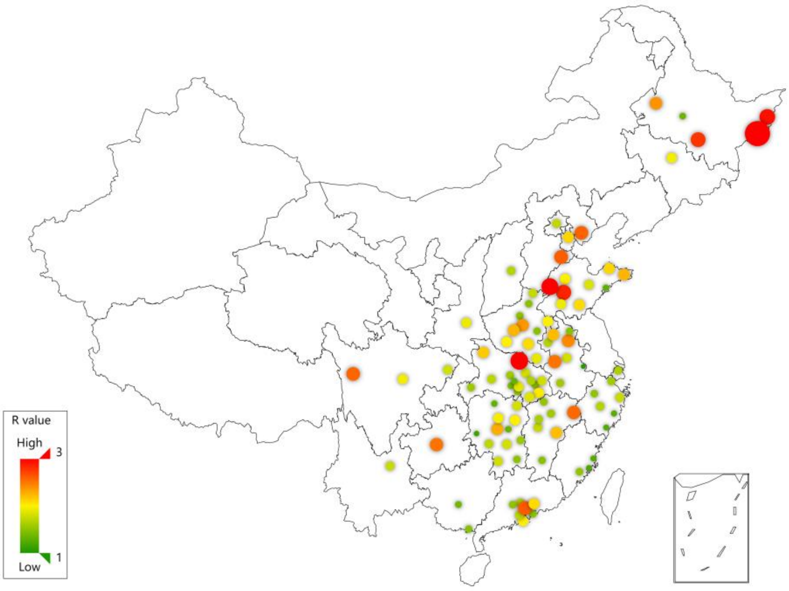
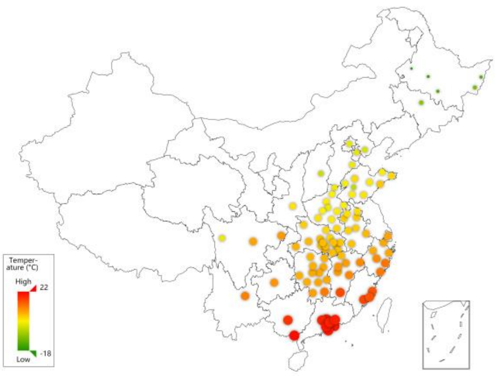
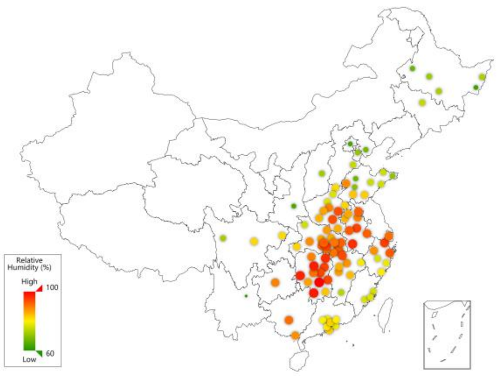


(a)





(b) (c)

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

Average *R* values from January 21 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). Subplots (a), (b) and (c) together inform that the *R* values are larger in the cold and dry northern regions of China.

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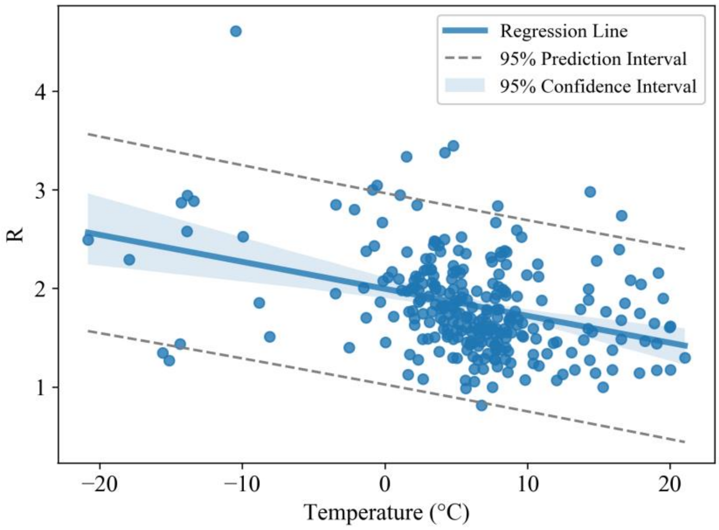
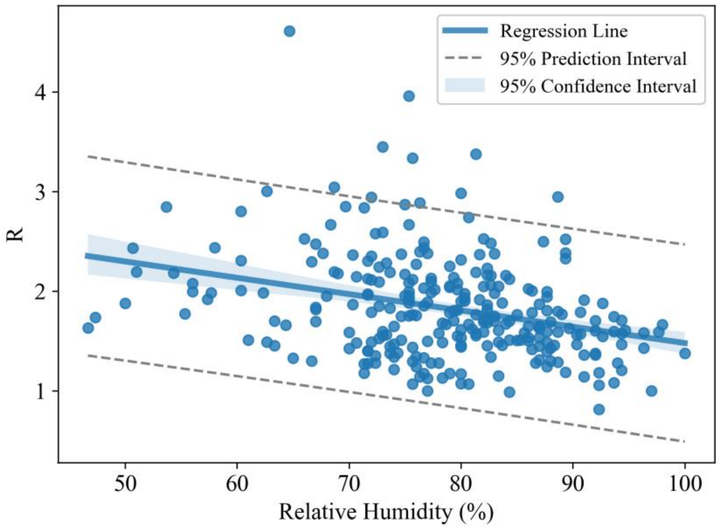


(a) Effective reproduction number R v.s. temperature



(b) Effective reproduction number R v.s. relative humidity

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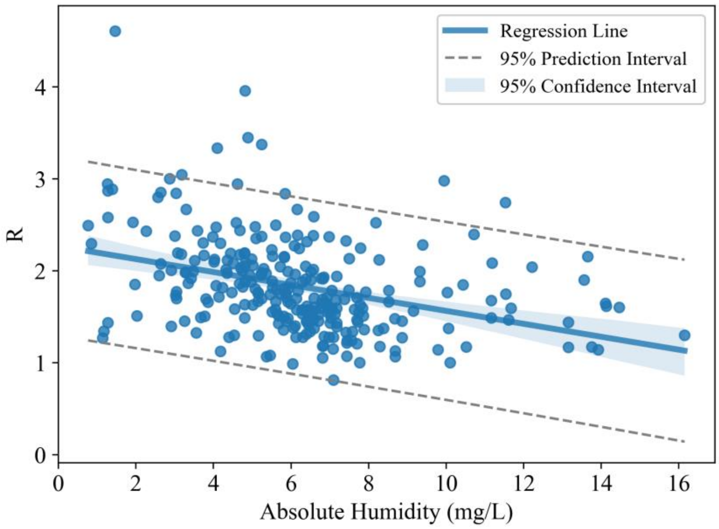

(c) Effective reproduction number *R* v.s. absolute humidity

Figure 2: Effective reproductive number R v.s. temperature, relative humidity and absolute humidity for 100 Chinese cities

Daily *R* values from January 21 to 23 and temperature, relative humidity and absolute humidity averaged 3 days up to and including the day of *R* measurement are used in this figure. Negative relationships between temperature and *R*, relative humidity and *R* and absolute humidity and *R* are shown in (a), (b) and (c), respectively.

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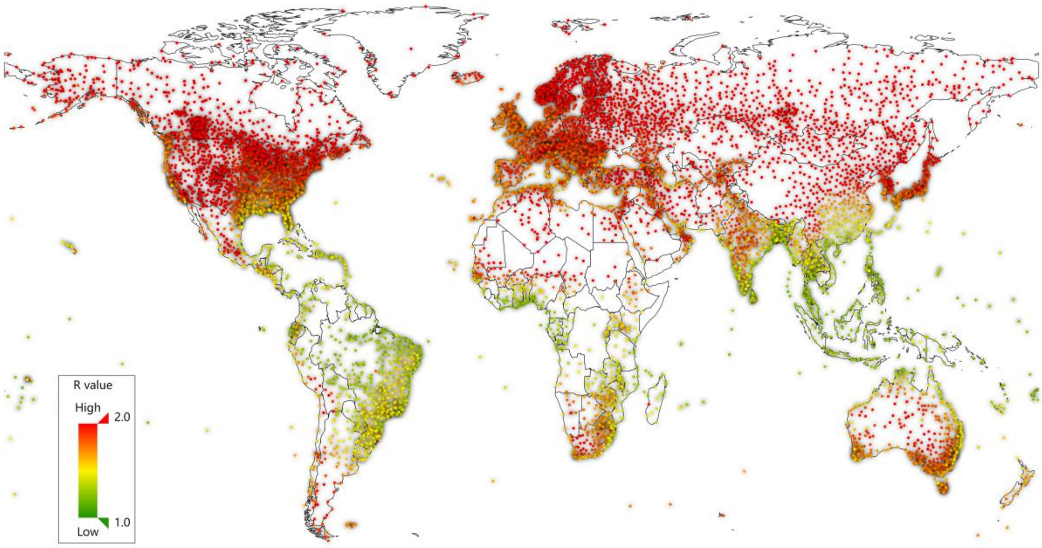
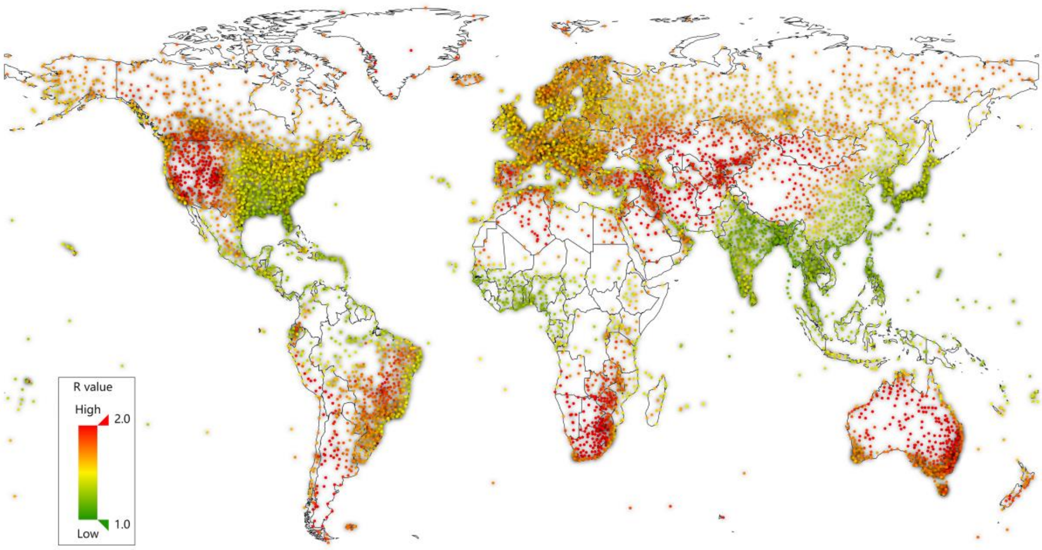


(a) *R* values in March



(b) *R* values in July

Figure 3: Worldwide risks of COVID-19 outbreak in March and July 2020

We use coefficients from the first column of Table 1 to estimate *R* values of worldwide cities (represented by dots) for March and July 2020, where temperatures and relative humidity in 2019 are obtained from https://www.ncdc.noaa.gov/ and assumed to be the same as those of 2020.

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Table 1: Cross-sectional regression analysis

Daily *R* values from January 21 to 23 and temperature and relative humidity averaged over 3 and 5 days, respectively, up to and including the day when *R* is measured, are used in the regression for 100 Chinese cities with more than 40 cases. The regression is estimated by an Ordinary Least Square (OLS) method with White robust standard errors to adjust heteroskedasticity. T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

	3-day average	**3-day average**	**5-day average**	**5-day average**
Temperature	-0.0233	-0.0225	-0.0269	-0.0271
t-statistics	*-3.96****	*-3.23****	*-4.33****	*-3.75****
Relative Humidity	-0.0133	-0.0158	-0.00954	-0.0122
t-statistics	*-5.17****	*-5.66****	*-2.80****	*-3.29****
GDP per Capita		-0.0171		-0.0158
t-statistics		*-1.93**		*-1.71**
Population Density		0.0821		0.0769
t-statistics		1.93*		1.82*
No. hospital beds		-0.00246		-0.00205
t-statistics		-2.43**		-1.91*
Percentage over 65		0.357		-0.191
t-statistics		0.19		-0.10
const	3.011	3.298	2.709	3.061
t-statistics	*14.06****	*10.38****	*9.80****	*8.16****
R^2	18%	21%	14%	17%

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Table 2: Panel regression analysis

Daily *R* values from January 21 to 23 and temperature and relative humidity averaged over 3 and 5 days, respectively, up to and including the day when *R* is measured, are used in the regression for 100 Chinese cities with more than 40 cases. Fixed and random effects models are both performed with White robust standard errors to adjust heteroskedasticity. T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

	3-day average fixed effects	**3-day average random effects**	**5-day average fixed effects**	**5-day average random effects**
Temperature	-0.0928	-0.0419	-0.204	-0.0553
t-statistics	*-6.48****	*-4.44***	*-7.75****	*-4.52****
Relative Humidity	-0.0302	-0.0288	-0.0334	-0.0280
t-statistics	*-10.01****	*-10.23****	*-3.16****	*-4.73****
GDP per Capita		-0.0102		-0.00761
t-statistics		*-0.67*		*-0.49*
Population Density		0.120		0.120
t-statistics		1.49		1.54
No. hospital beds		-0.00481		-0.00443
t-statistics		-2.55**		-2.02**
Percentage over 65		-0.120		-1.664
t-statistics		-0.04		-0.54
const	4.758	4.517	5.478	4.608
t-statistics	*21.08****	*9.43****	*7.28****	*7.00****
R^2	17%	21%	14%	16%

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Table 3: Absolute humidity as an explanatory variable

Panel A of Table 3 shows the explanatory power of the absolute humidity compared with the relative humidity. Panel B finds a better one in absolute and relative humidity in explaining the variation of R values together with temperatures via a Davidson-MacKinnon Test. To run a Davidson-MacKinnon test, we first perform Test 1:

$$R = const + b * Temporature + c * RelativeHumidity + controls + u$$

After obtaining the fitted R-value $\hat{R}$, we run:

$$R = const + a * \hat{R} + b * Temporature + c * AbsoluteHumidity + controls + u$$

Similarly, for Test 2 we first run

$$R = const + b * Temporature + c * AbsoluteHumidity + controls + u$$

After obtaining the fitted R-value $\check{R}$, we run:

$$R = const + a * \check{R} + b * Temporature + c * RelativeHumidity + controls + u$$

T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

Panel A: Absolute humidity or relative humidity in a uni-variable regression

	3-day average	**3-day average**	**5-day average**	**5-day average**
Relative Humidity		-0.0164		-0.130
t-statistics		*-5.64****		*-3.38****
Absolute Humidity	-0.0704		-0.0786	
t-statistics	*-5.39****		*-5.05****	
const	2.268	3.116	2.284	2.841
t-statistics	*24.59****	*12.98****	*22.54****	*9.17****
R^2	13%	10%	12%	4%

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Panel B: The Davidson-MacKinnon test

	Test 1	**Test 2**
$\hat{R}$	1.127	
t-statistics	*4.28****	
$\breve{R}$		-0.356
t-statistics		*-0.74*
Temperature	-0.00531	-0.0322
t-statistics	*-0.50*	*-2.26***
Absolute Humidity	0.0270	
t-statistics	*0.74*	
Relative Humidity		-0.0178
t-statistics		*-4.28****
GDP per Capita	0.00133	-0.0217
t-statistics	*0.13*	*-1.82**
Population Density	-0.0146	0.109
t-statistics	*-0.30*	*1.94**
Number of hospital beds	0.000306	-0.00305
t-statistics	*0.24*	*-2.08***
Rate of people over 65	0.601	0.0943
t-statistics	*0.30*	*0.05*
const	-0.448	4.228
t-statistics	*-0.57*	*3.24****
R^2	21%	21%

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References and Notes

1. F. Wu, S. Zhao, B. Yu, Y.-M. Chen, W. Wang, Z.-G. Song, Y. Hu, Z.-W. Tao, J.-H. Tian, Y.-Y. Pei, M.-L. Yuan, Y.L. Zhang, F.H. Dai, Y. Liu, Q.-M. Wang, J.-J. Zheng, L. Xu, E. C. Holmes, Y.Z. Zhang, A new coronavirus associated with human respiratory disease in China. *Nature* (2020); doi: 10.1038/s41586-020-2008-3.

2. P. Zhou, X.-L. Yang, X.-G. Wang, B. Hu, L. Zhang, W. Zhang, H.-R. Si, Y. Zhu, B. Li, C.-L. Huang, H.-D. Chen, J. Chen, Y. Luo, H. Guo, R.-D. Jiang, M.-Q. Liu, Y. Chen, X.-R. Shen, X. Wang, X.-S. Zheng, K. Zhan, Q.-J. Chen, F. Deng, L.-L. Liu, B. Yan, F.-X. Zhan Y.-Y. Wang, G.-F. Xiao, Z.-L. Shi, A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature* (2020); doi: 10.1038/s41586-020-2012-7.

3. Q. Li, X.-H. Guan, P. Wu, X.-Y. Wang, L. Zhou, Y.-Q. Ting, R.-Q. Ren, K. S. M. Leung, J. Y. Wong, X.-S. Xing, N.-J. Xiang, Y. Wu, C. Li, Q. Chen, D. Li, T. Liu, J. Zhao, M. Liu, W.-X. Tu, C.-D. Chen, L.-M. Jin. R. Yang, Q. Wang, S.-H. Zhou, R. Wang, H. Liu, Y.-B. Luo, Y. Liu, G. Shao, H. Li, Z.-F. Tao, Y. Yang, Z.-Q. Deng, B.-X. Liu, Z.-T. Ma, Y.-P. Zhang, G.-Q. Shi, T. T. Y. Lam, J. T. Wu, G. F. Gao, B. J. Cowling, B. Yang, G. M. Leung, Z.-J. Feng, Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus-Infected Pneumonia. *N. Engl. J. Med.* (2020) ; doi: 10.1056/NEJMoa2001316.

4. J. Cohen, K. Kupferschmidt, Coutries test tactics in ‘war’ against COVID-19. *Science* **367** 1287-1288 (2020). doi: 10.1126/science.367.6484.1287.

5. A. L. Phelan, R. Katz, L. O. Gostin, The Novel Coronavirus Originating in Wuhan, China: Challenges for Global Health Governance. *JAMA* **323,** 709-710 (2020). doi:10.1001/jama.2020.1097.

6. J. H. Hemmes, K. C. Winkler, S. M. Kool, Virus survival as a seasonal factor in influenza and poliomyelitis. *Nature* **188**, 430-431 (1960). doi: 10.1007/BF02538737.

7. B. D. Dalziel, S. Kissler, J. R. Gog, C. Viboud, O. N. Bjornstad, C. J. E. Metcalf, B. T. Grenfell, Urbanization and humidity shape the intensity of influenza epidemics in U.S. cities, *Science* **362**, 75-79 (2018). doi: 10.1126/science.aat6030.

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=3551767

8. Q. Bukhari, Y. Jameel, Will Coronavirus Pandemic Diminish by Summer? *SSRN* (2020); doi: 10.2139/ssrn.3556998.

9. Xinhuanet, “No evidence to suggest coronavirus will disappear in summer: WHO expert” (Mar 7, 2020); www.xinhuanet.com/english/2020-03/07/c_138851282.htm.

10. B. J. Cowling, V. J. Fang, S. Riley, J. S. M. Peiris, G. M. Leung, Estimation of the serial interval of influenza. *Epidemiology* **20**, 344 (2009). doi: 10.1097/EDE.0b013e31819d1092.

11. J. Wallinga, P. Teunis, Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am. J. Epidemiol.* **160**, 509–516 (2004). doi: 10.1093/aje/kwh255.

12. WHO, “Coronavirus disease 2019 (COVID-19) Situation Report–46” (Mar 06, 2020); www.who.int/docs/default-source/coronaviruse/situation-reports/20200306-sitrep-46-covid-19.pdf?sfvrsn=96b04adf_2.

13. Johns Hopkins University, “Coronavirus symptoms start about five days after exposure, Johns Hopkins study finds” (Mar 10, 2020); https://hub.jhu.edu/2020/03/09/coronavirus-incubation-period/.

14. J. Shaman, M. Kohn, Absolute humidity modulates influenza survival, transmission, and seasonality. *Proc. Natl. Acad. Sci. USA* **106**, 3243-3248 (2009). doi: 10.1073/pnas.0806852106.

15. R. Davidson, J. MacKinnon, Several Tests for Model Specification in the Presence of Alternative Hypotheses. *Econometrica* **49**, 781-793 (1981). doi: 10.2307/1911522.

16. A. C. Lowen, J. Steel, S. Mubareka, P. Palese. High temperature (30^{o}C) blocks aerosol but not contact transmission of influenza virus. *J. Virol.* **82**, *5650*–5652 (2018). doi: 10.1128/JVI.00325-08.

17. J. Park, W.-S. Son, Y.-H. Rye S. B. Choi, O. Kwon, I. Ahn, Effects of temperature, humidity, and diurnal temperature range on influenza incidence in a temperate region. *Influenza. Other. Respir. Viruses* **14**, 11–18 (2020). doi: 10.1111/irv.12682.

18. J. Steel, P. Pales, A. C. Lowen, Transmission of a 2009 pandemic influenza virus shows a sensitivity to temperature and humidity similar to that of an H3N2 seasonal strain. *J. Virol.* **85**, 1400-1402 (2011). doi: 10.1128/JVI.02186-10.

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=3551767

19. M. Lipsitch, C. Viboud, Influenza seasonality: Lifting the fog, *Proc. Natl. Acad. Sci.* **106**,3645-3646 (2009). doi: 10.1073/pnas.0900933106.

20. A. C. Lowen, J. Steel, Roles of humidity and temperature in shaping influenza seasonality. *J. Virol.* **88**, 7692–7695 (2014). doi: 10.1128/JVI.03544-13.

21. R. Tellier, Aerosol transmission of influenza A virus: a review of new studies. *J. R. Soc. Interface* **6**, S783–S790 (2009). doi: 10.1098/rsif.2009.0302.focus.

22. R. Eccles, An explanation for the seasonality of acute upper respiratory tract viral infections. *Acta Otolaryngol.* **122**, 183-191 (2002). doi: 10.1080/000164802 52814207.

23. E. Kudo, E. Song, L. J. Yockey, T. Rakib, P. W. Wong, R. J. Homer, A. Iwasaki, Low ambient humidity impairs barrier function and innate resistance against influenza infection. *Proc. Natl. Acad. Sci. USA* **116**, 10905–10910 (2019) . doi: 10.1073/pnas.1902840116.

24. K. H. Chan, J. S. M. Peiris, S. Y. Lam, L. L. M. Poon, K. Y. Yuen, W. H. Seto, The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus, *Adv. Virol.*, 734690-734696 (2011). doi: 10.1155/2011/734690.

25. J.-S. Yuan, H.-M. Yun, W. Lan, W. Wang, S. G. Sullivan, S.-W. Jia, A. H. Bittles, A climatologic investigation of the SARS-CoV outbreak in Beijing, China, *Am. J. Infect. Control* 34, 234-236 (2006). doi: 10.1016/j.ajic.2005.12.006.

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Supplementary Materials for

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

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Materials and Methods

Data

We hand-collect 4,711 cases from the epidemiological survey data 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 209 close contacts. Among them, if a group of patients travel (e.g. go to Wuhan) together, we hence cannot distinguish between the carrier and the infected, and, therefore, remove such samples from the data. We finally screen out 105 pairs of virus carriers and the infected, which are used to estimate serial intervals of COVID-19. We also construct epidemic curves for all 100 Chinese cities with more than 40 cases from their first-case dates to February 20, which are constructed using more than 70,000 cases. The epidemic curves are used to estimate the daily effective reproductive number, *R*, for different cities.

Temperature and relative humidity data are obtained from 699 meteorological stations in China from http://data.cma.cn/. If a city does not have a meteorological station inside it, the closest station is used instead. Population density, GDP per capita, number of hospital beds and the fraction of the population over 65 years old in 2018 for different cities are obtained from https://data.cnki.net.

Distribution of the serial interval

The serial interval, defined as the time span between symptom onset dates of a primary case to a successive case, is calculated based on the 105 samples of the carrier and the infected. Specifically, we fit the Weibull distribution (*2*, *3*) using the Maximum Likelihood Estimation (MLE) method[1] and obtain the parameters of the mean and standard deviation of 7.4 and 5.2 days, respectively, which are consistent with the preliminary estimation (*4*) using 10 cases (7.5 days average with 95%

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[1] We fitted the Weibull distribution by Python package 'Scipy' and R package 'MASS', which can be found at https://www.scipy.org/ and https://cran.r-project.org/web/packages/MASS/index.html. The two results are consistent to each other.

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confidence interval of 5.3 to 19). Compared to SARS (*3*), the COVID-19's serial interval has a smaller average but a larger standard deviation. The fitted Weibull distribution is shown in Figure S1.

Estimation of the effective reproductive number

We estimate the daily effective reproductive number, *R*, for 100 cities with more than 40 cases from the first-case date to February 20 by employing a time-dependent method (*5*). The inputs of the model are epidemic curves, *i.e.* the historical numbers of patients with symptom onset of each day for a certain city. We estimate the daily *R* values using a package 'R0' (*6*). In this package, we particularly use a function named 'est.R0.TD' in our estimation. We use the daily *R* values from January 21 to 23, 2020 for each city in this paper. The average *R*-value of these 100 cities is 1.83 with the minimum and maximum values of 0.81 and 4.61, respectively. Table S1 provides summary statistics of the variables used in this paper.

Robustness Checks

Among these 100 cities, Wuhan is a special sample because of the double standards for the confirmation of cases. For example, there was a sudden increase of more than 13,000 cases in a single day (February 12, 2020) in Wuhan, and the majority of them were previously left unable to seek medical treatment. Therefore, as a robustness check, we remove Wuhan city in our sample and redo both the cross-sectional and panel regressions. The results of robustness checks, presented in Table S2, are consistent with those in Table 1 and 2. All regressions are performed with the econometrics software *Stata*.

It might be some outliers in the sample that can influence the estimation of the coefficients. We, therefore, bootstrap the sample for 1000 times; in each iteration, we rerun the regression and obtain the coefficients. The percentile values for each coefficient are shown in Table S3. If the regression coefficients are mainly caused by one outlier (*i.e.* an extreme *R*-value), in cases where the outlier is not sampled (about 37% probability (*7*)), the regression coefficients will be quite different, and the

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distribution of the coefficients will be highly skewed. However, in Table S3, the mean and median of the bootstrapped coefficients are quite similar, which means the coefficient distribution is not skilled. Furthermore, the 99% percentiles for temperature and relative humidity are still negative. All of these show that our results are robust with outliers.

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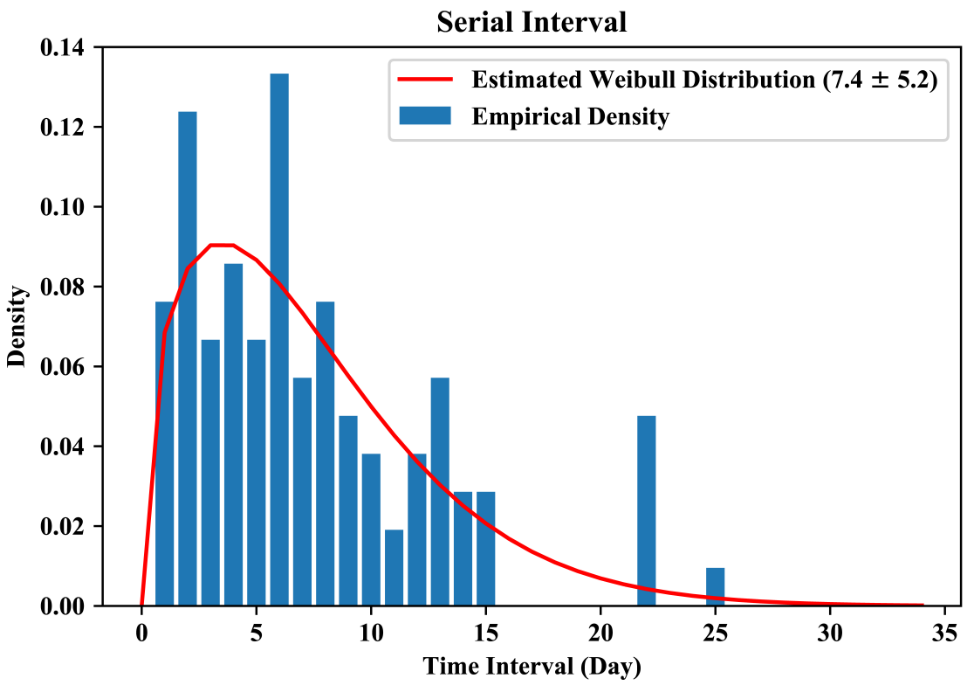

Figure S1: Estimation of the serial interval with the Weibull distribution

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

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Table S1: Data Summary

This table summarizes variables for 100 cities: the daily *R* values from January 21 to 23, 3-day and 5-day average temperature and relative humidity, and the GDP per capita, the population density, number of hospital beds and the fraction of people over 65 years old in 2018.

	Mean	**Std**	**Min**	**Max**
R	1.831	0.522	0.813	4.609
3-Day Average Temperature (Celsius)	6.017	6.549	-20.833	21.033
3-Day Average Relative Humidity (%)	78.456	9.898	46.667	100.0
5-Day Average Temperature (Celsius)	5.172	6.368	-20.780	18.52
5-Day Average Relative Humidity (%)	77.541	7.764	49.000	91.800
GDP per Capita (RMB 10k)	6.800	3.721	2.159	18.957
Population Density (k/km^2)	0.692	0.813	0.00800	6.522
No. of Hospital Beds (k)	30.785	26.790	2.232	162.100
Fraction over 65	0.121	0.0186	0.0826	0.152

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Table S2: Relationship between Temperature, relative humidity, and effective reproductive number for samples without Wuhan

The table reports the linear regression coefficients of the effective reproductive number, R, on an intercept, temperature, relative humidity and control variables for samples without Wuhan. Both cross-sectional and panel regressions in Tables 1 and 2 are re-performed. T-statistics are in the italic format with *, ** and *** representing significance at the 10%, 5% and 1% levels, respectively.

	3-day average	**3-day average Panel Fixed Effects**	**3-day average Panel Random Effects**
Temperature	-0.0223	-0.0928	-0.0416
t-statistics	*-3.19****	*-6.46****	*-4.41***
Relative Humidity	-0.0159	-0.0302	-0.0289
t-statistics	*-5.56****	*-9.98****	*-10.16****
GDP per Capita	-0.0178		-0.0113
t-statistics	*-1.96**		*-0.73*
Population Density	0.0828		0.121
t-statistics	*1.95**		*1.51*
Number of hospital beds	*-0.00253*		0.00491
t-statistics	*-2.45***		*-2.54***
Rate of people over 65	*0.368*		-0.124
t-statistics	*0.20*		*-0.04*
const	3.314	4.759	4.527
t-statistics	*10.25****	*20.99****	*9.41****
R^2	21%	17%	21%

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Table S3: A bootstrapping analysis

The table reports the bootstrapping results for the linear regression of the effective reproductive number, *R*, on an intercept, temperature, relative humidity and control variables for 1000 times. The exact values of the regression coefficients are reported at various percentiles.

Percentiles	**Mean**	**1%**	**2.5%**	**5%**	**25%**	**50%**	**75%**	**95%**	**97.5%**	**99%**
Temperature	-0.0232	-0.0403	-0.0379	-0.0351	-0.0276	-0.0229	-0.0185	-0.0120	-0.0100	-0.0072
Relative Humidity	-0.0159	-0.0227	-0.0213	-0.0207	-0.0177	-0.0158	-0.0139	-0.0112	-0.0105	-0.0099
GDP per capita	-0.0174	-0.0388	-0.0348	-0.0323	-0.0237	-0.0173	-0.0112	-0.0030	-0.0007	0.0014
Population Density	0.0883	-0.0082	0.0079	0.0205	0.0553	0.0831	0.1168	0.1704	0.1885	0.2150
No. Hospital Beds	-0.0025	-0.0052	-0.0048	-0.0044	-0.0032	-0.0025	-0.0018	-0.0009	-0.0005	-0.0002
Fraction over 65	0.2531	-3.6479	-3.2140	-2.6845	-0.9650	0.1780	1.4404	3.2955	3.9977	4.7850
Const	3.3234	2.6102	2.7054	2.8077	3.1030	3.3139	3.5364	3.8428	3.9651	4.0526

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References and Notes

1. CCDC Weekly, "The Epidemiological Characteristics of an Outbreak of 2019 Novel Coronavirus Diseases (COVID-19)-China, 2020" (Feb 17, 2020); http://weekly.chinacdc.cn/en/article/id/e53946e2-c6c4-41e9-9a9b-fea8db1a8f51.

2. B. J. Cowling, V. J. Fang, S. Riley, J. S. M. Peiris, G. M. Leung, Estimation of the serial interval of influenza. *Epidemiology* **20**, 344 (2009). doi: 10.1097/ EDE.0b013e31819d1092.

3. M. Lipsitch, T. Cohen, B. Cooper, J. M. Robins, S. Ma, L. James, G. Gopalakrishna, S. K. Chew, C. C. Tan, M. H. Samore, D. Fishman, M. Murray, Transmission dynamics and control of severe acute respiratory syndrome. *Science* **300**, 1966–1970 (2003). doi: 10.1126/science.1086616.

4. Q. Li, X.-H. Guan, P. Wu, X.-Y. Wang, L. Zhou, Y.-Q. Ting, R.-Q. Ren, K. S. M. Leung, J. Y. Wong, X.-S. Xing, N.-J. Xiang, Y. Wu, C. Li, Q. Chen, D. Li, T. Liu, J. Zhao, M. Liu, W.-X. Tu, C.-D. Chen, L.-M. Jin. R. Yang, Q. Wang, S.-H. Zhou, R. Wang, H. Liu, Y.-B. Luo, Y. Liu, G. Shao, H. Li, Z.-F. Tao, Y. Yang, Z.-Q. Deng, B.-X. Liu, Z.-T. Ma, Y.-P. Zhang, G.-Q. Shi, T. T. Y. Lam, J. T. Wu, G. F. Gao, B. J. Cowling, B. Yang, G. M. Leung, Z.-J. Feng, Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus-Infected Pneumonia. *N. Engl. J. Med.* (2020) ; doi: 10.1056/NEJMoa2001316.

5. J. Wallinga, P. Teunis, Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures. *Am. J. Epidemiol.* **160**, 509–516 (2004). doi: 10.1093/aje/kwh255.

6. R0 package in R, "R0: Estimation of R0 and Real-Time Reprodunction Number from Epidemic" (2015); https://cran.r-project.org/web/packages/R0/index.html.

7. Z.-H. Zhou, Machine Learning (Chinese Edition). 27 (*Tsinghua University Press*, 2016).

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