The Influence of Weather Conditions on 2019-nCovid using Geospatial Data

Francois Coheni, Sihan Liii, Yangsiyu Lui and Moritz Schwarzi,iii

This version: 1st April 2020; first version: 1st April 2020; data update: March 29th, 2020.

Summary

Background

By 31st March 2020, 2019-nCov has infected at least 715,660 people and killed 37,272. Evidence from other coronaviruses suggests that 2019-nCov could be sensitive to weather conditions, but there has been no satisfactory analysis of the influence of the weather on 2019-nCov so far.

Method

We apply a statistical method to estimate the sensitiveness of 2019-nCov to weather conditions. We rely on geospatial data to overcome the issues posed by confounding factors and measurement error that have undermined earlier attempts. We link the global epidemic dataset compiled by Xu et al. (2020)¹ with daily reanalysis weather data from the European Centre for Medium-Range Weather Forecasts. We then use a model that accounts for the effect of the temperatures of preceding days, while controlling for country-level day-to-day changes in government response, population behaviour, and changes in coronavirus testing. This strategy is unprecedented and identifies the response of 2019-nCov to the weather.

Findings

Findings suggest that a 1°C increase in average temperature at time t leads to a subsequent reduction in confirmed cases by 7.3% [4.6 – 10.0%]. This figure may be large because the people who do not get infected will therefore not pass the disease on to others. Our results indicate that 2019-nCov is likely to be very vulnerable to very hot days (>30°C).

Interpretation

We find that 2019-nCov may strongly respond to weather fluctuations. These results should be interpreted with caution since we only have data for the start of the pandemic.

Funding

Oxford Martin School and The Nature Conservancy (Cohen, Li and Lu), Newton Fund (Li), Clarendon Fund (Schwarz), China Scholarship Council and University of Oxford (Lu).

ⁱ Smith School of Enterprise and the Environment, University of Oxford; and Institute for New Economic Thinking at the Oxford Martin School, University of Oxford.

ii Environmental Change Institute, University of Oxford.

iii Climate Econometrics, Nuffield College, Oxford

Introduction

2019-nCov is a novel coronavirus (SARS-CoV-2) first identified in Wuhan, China in December 2019. As of March 31st, 2020, the disease has spread to 177 countries with 715,660 cases confirmed, and 37,272 deaths. ^{iv} 2019-nCov belongs to the coronaviridae family². Lab evidence as well as empirical evidence suggest that higher ambient temperatures and humidity may reduce the incidence of these respiratory infections. ^{3,4,5,6,7} Furthermore, rising temperatures may have contributed to the successful termination of SARS-CoV-1, a coronavirus that spread in 29 countries from November 2002 until the summer of 2003. ^{6,8}

This paper develops and applies a statistical methodology to identify the potential role played by the weather conditions in the 2019-nCov pandemic. This question is at the top of the current policy agenda. Several health experts and world leaders have commented that the onset of summer weather might slow down the spread of the virus. 9,10,11,12 Yet, the empirical evidence so far has been too weak or unsuitable to confirm or reject this hypothesis.

Research in context

Evidence before this study

We searched for recent published and unpublished papers on the topic using key words such as '2019-nCov', 'coronavirus', 'Covid-19' and 'weather', 'seasonality', 'heat', 'cold'. Both in vitro and in vivo analyses have been conducted on other coronaviruses and results so far suggest that these viruses are sensitive to heat and humidity.

For 2019-nCov, we did not find any published scientific material looking at the effect of the weather on the spread of the disease, which is not surprising considering that the crisis only recently emerged. There is however another unpublished manuscript that analyses the impact of weather conditions on 2019-nCov using a daily panel. Their authors use data at country level, and therefore provide rather unreliable results because of the high risks of measurement error and omitted variable bias at this level of data aggregation. Other analyses are mostly correlation analyses that do not aim to provide a causal interpretation of the impact of the weather conditions on the spread of the virus.

_

iv Figure provided by Our World in Data (https://ourworldindata.org/coronavirus), based on European CDC's latest situation updates worldwide: https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases. Website consulted on March 28th, 2020.

Added value of this study

This study provides detailed evidence of a link between the weather and the spread of 2019-nCov, with a thorough series of robustness checks to confirm this relationship. Furthermore, we show that very hot days (>30°C) slow the spread of the virus considerably more than warm days.

This study is the first granular, panel data analysis of the impact of weather conditions on Covid-n2019. It is much more reliable than other ongoing efforts. This is because estimating the impact of the weather on 2019-nCov requires isolating the effect of temperatures from confounding factor variables. Governments and the public have quickly taken actions to respond to the pandemic, and these actions may correlate with changes in seasons and in the weather. To solve this issue of potential confounders, we introduce stringent controls – country by day fixed effects – that allow controlling for country-level day-to-day changes in government response and sudden changes in the behaviour of the general public.

Implications of all the available evidence

This paper provides statistical evidence, for the first time, on the potential seasonality of 2019-nCov. It complements the in vitro results showing that coronaviruses, and possibly 2019-nCov, are weather-sensitive. This information may allow government to design more effective strategies against the virus.

Methods

Data

This model requires very detailed geographical information on the distribution of 2019-nCov cases, and on local weather conditions. We link the open access real-time epidemiological data from Xu et al. (2020) (see **Figure 1**) to meteorological data from the 5th generation of European Centre for Medium-Range Weather Forecasts atmospheric reanalyses of the global climate (ECMWF-ERA5).^v

In their own words, Xu et al. (2020) "have built a centralised repository of individual-level information on patients with laboratory-confirmed COVID-19". The data includes data from 6th January onwards and is updated on a regular basis. It provides information on the longitude and the latitude of confirmed 2019-nCov cases globally. We use this information to track the progression of the virus in 2775 areas spanning 99 countries." The main advantage of the data from Xu et al. (2020) is its granularity: it allows us to produce analyses at an area level rather than at a country level. The main drawback of using this data is that it does not cover all 2019-nCov cases but only a sample for the covered areas. Also, it can

v Downloadable from Copernicus Climate Change Service: https://cds.climate.copernicus.eu/

vi The statistical model, however, only relies on the data for 47 countries and 2260 areas, because it needs at least two areas covered within each country in the dataset, and they have to be far enough (e.g. 25km away) to each other to record differences in the weather.

take several days for all the data from all the areas to be updated. The March 29th version has much fewer cases after March 23rd (see below). The data includes 112,970 cases compared to a total 338,298 of confirmed 2019-nCov cases globally^{vii} until March 23rd. These sampling issues are not a problem for our statistical analysis because differences in data collection and reporting across countries and time are fully accounted for by the "country-by-day" fixed effects.

The meteorological dataset used in this study (ECMWF-ERA5) is a climate reanalysis dataset. It provides consistent weather data with high spatial (~0.25 degrees) and temporal (hourly) resolutions. We use daily averages and the variables considered are total precipitation, maximum temperature, minimum temperature, and relative humidity (calculated using temperature and dewpoint temperature). The average daily temperature is calculated as the average between the daily maximum and the daily minimum, which is common practice. We provide summary statistics for the meteorological data in the **supplementary material 3**.

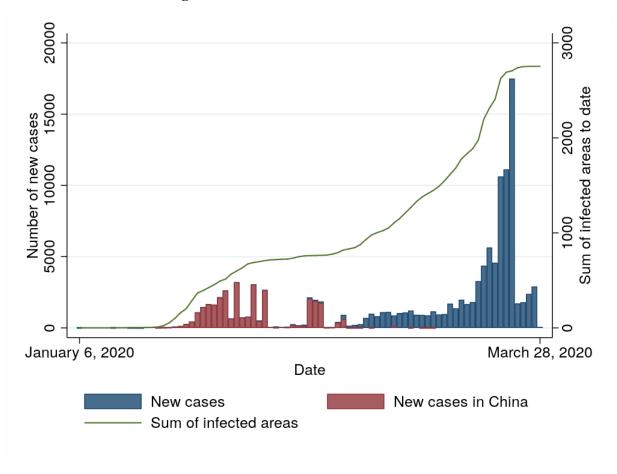


Figure 1: Confirmed cases and infected areas

Sources: own calculations based on Xu et al. (2020)

vii Figure provided by Our World in Data (https://ourworldindata.org/coronavirus), based on European CDC's latest situation updates worldwide: https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases. Website consulted on March 28th, 2020.

Statistical model

The statistical model is presented in detail in the **supplementary material 1**.

In short, the data includes daily counts of confirmed 2019-nCov cases across small geographic areas (either regions or cities). Because infections can only be proportional to the number of people already infected in an area, the model looks at changes in confirmed cases in each area at time t based on the number of confirmed cases on the day before (t-1). We use the following transformation: $\ln (C_{i,t}) - \ln (C_{i,t-1})$, where $\ln (C_{i,t})$ is the natural logarithm of the total number of confirmed cases of 2019-nCov observed in area i on day t.

The model also takes into consideration that the incubation period can be up to two weeks. We estimate the impacts of the temperature, precipitation and humidity levels of the days before time t. The impact of weather conditions is estimated separately for every single day before and on the day when cases are confirmed. The overall impact of weather conditions is then aggregated over a 16-day window period. This can be interpreted as the impact that the weather at time t has had on 2019-nCov cases after 16 days. We consider other time windows in the robustness checks.

We designed the model to separate the impact of weather conditions from other confounding factors such as sudden changes in policy, behaviour, and healthcare practices. To do so, the model includes "country-by-day" fixed effects and area-specific fixed effects. The statistical model only compares areas to each other if located in the same country, and for impacts that have been recorded on the exact same day. This controls for the fixed differences between countries, as well as for day-to-day changes in country-level policy, virus prevalence and 2019-nCov testing. Because some areas may always be more likely to report more cases (e.g. due to wider testing), the model also controls for the average rate of infection observed in each area with area-specific fixed effects. The effect of the weather is identified by comparing contemporaneous differences in the number of reported cases in one area compared to another area located in the same country, while considering the fact that some areas always report more cases compared to the rest of the country.

There has been no involvement of any of the funding sources in the design of the methodology for this paper.

Results

Table 1: Main results includes our main results and a series of alternative models. **Table 1, column 1,** reports our results using average temperature, total precipitation and average relative humidity. We find that increases in average temperature, as well as increases in humidity reduce the rate of confirmed 2019-nCov cases. More precisely, an increase of 1°C is associated with a progressive reduction (over 16 days) in the dependent variable by 0.0031 points, or 7.2% [4.6–10.0%] when reported to the sample

average of the dependent variable. For humidity, a 1-percentage point increase in humidity is associated with a 0.0005 reduction in the dependent variable, this is a 1.2% reduction [0.6–1.8%] when reported to the sample average of the dependent variable. We do not find statistically significant effects for precipitation.

Table 1: Main results

Column	(1)	(2)	(3)	(4)			
Av. Temperature (°C)	-0.0031***	-0.0063***		-0.0047***			
	(0.0006)	(0.0012)		(0.0010)			
x below 0°C		0.0042***					
		(0.0005)					
x above 30°C		-0.0014					
		(0.0011)					
Max. Temperature (°C)			-0.0073***				
			(0.0007)				
Min. Temperature (°C)			0.0042***				
			(0.0008)				
Precipitations (mm)	0.0002	-0.0001	-0.0006	0.0004			
	(0.0014)	(0.0012)	(0.0013)	(0.0015)			
Relative humidity (%)	-0.0005***	-0.0005***	-0.0010***	-0.0007***			
	(0.0001)	(0.0001)	(0.0001)	(0.0002)			
x Av. Temperature (°C)				0.00003**			
				(0.00001)			
Observations	55,712	55,712	55,712	55,712			
Sample average of dependent variable	0.0429						

Notes: Standard errors are in brackets and clustered at country level. *, **, and *** are for statistical significance at 10%, 5% and 1% respectively. The results displayed for the weather variables are for cumulated effects over 16 days. The model includes country-by-day fixed effects (e.g. UK, 24th March 2020) and area-specific fixed effects (e.g. the Latitude-Longitude location of a case in London).

2019-nCov may respond differently to a 1°C increase when temperatures are very low (e.g. below 0°C) or very high (e.g. above 30°C). **Table 1, column 2**, assesses whether this is the case. We find that, at the margin, a reduction in temperature on a very cold day (<0°C) is less damaging than a reduction in temperature on a mildly cold day, even though the disease is more likely to spread on very cold days than on mildly cold days.

In a similar spirit, **Table 1, column 3**, evaluates if 2019-nCov is more responsive to minimum temperatures or maximum temperatures. We find that the virus is nearly twice as responsive to maximum temperatures (i.e. maximum heat) than it is to minimum temperatures. Also, effects go in opposite directions. This suggests that while the virus does not like heat, it does not like it too cold either. **Table 1, column 4** interacts humidity with temperature. The negative association between humidity and 2019-nCov seems stronger in colder environments.

Figure 2 suggests that extreme heat is the main factor responsible for the response of 2019-nCov to temperature. The figure estimates separate impacts of different temperature ranges (e.g. "below 0°C" compared to "10-20°C") for average, maximum and minimum temperatures. It shows a sharp decline in infections for days with average temperatures above 30°C, and/or maximum temperatures above 40°C. This could explain why warm regions can still suffer from a substantial amount of 2019-nCov infections, since the effect of heat might only be strong at very high temperatures.

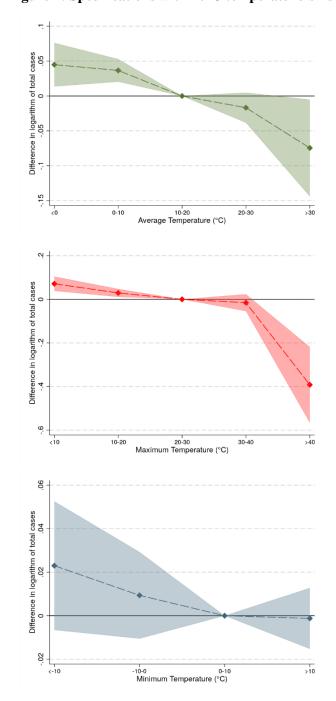


Figure 2: Specifications with 10°C temperature bins

Notes: Shaded areas represent 95% confidence intervals. These graphs have been obtained using 10°C-wide temperature bins (and their 15 lags) to capture non-linearities in the response of 2019-nCov to the weather. These bins take the value of 1 (and 0 otherwise) if the temperature on the specified day falls within a specific range, e.g.

either "<0°C", "0-10°C", "10-20°C", "20-30°C" or ">30°C" in the case of average temperatures. The graph for average temperature is obtained by replacing the temperature averages by their bins, using the same model as Table 1, column 1. The two other graphs (minimum and maximum temperatures) display results from the same regression, adapted from Table 1, column 3.

Table 2 provides separate estimates for China; the EU and the UK; the USA and all the other countries. Estimates are precisely estimated for China, while inconclusive for other areas, plausibly because sample size is smaller for areas infected later. If taken together though, all countries excluding China (column 5) seem to experience very similar average effects to those experienced in China. The general lack of precision may also be due to the linear approximation for the effect of temperature. When looking at maximum and minimum temperatures separately, the EU and the UK also seem to behave very similarly compared to China. As we get more data about the pandemic, it should be possible to refine these estimates.

Table 2: Region-specific responses

Column	(1)	(2)	(3)	(4)	(5)
Column	(1)	(2)	(3)	(4)	(3)
Only in sample if total cases in country are:	China	EU and UK	USA	Other	All but China
Av. Temperature (°C)	-0.0030**	0.0157	0.0026	-0.0074	-0.0021
	(0.0012)	(0.0184)	(0.0046)	(0.0043)	(0.0031)
Max. Temperature (°C)	-0.0069***	-0.0152**	0.0034	-0.0061	-0.0067
	(0.0015)	(0.0055)	(0.0078)	(0.0056)	(0.0044)
Min. Temperature (°C)	0.0038***	0.0310*	0.0016	-0.001	0.0052
	(0.0014)	(0.0172)	(0.0088)	(0.0063)	(0.0050)
Observations	32,417	6,565	5,742	10,988	23,295
Sample average dependent variable	0.0262	0.0918	0.1098	0.0488	0.0760

Notes: Standard errors in brackets (computed at area level for China and the USA since they cannot be computed at country level). The first row reports the results for average temperatures when the same model as Table 1, column 1 is run separately on different regions. The second and third rows are from models similar to Table 1, column 3. *, **, and *** are for statistical significance at 10%, 5% and 1% respectively.

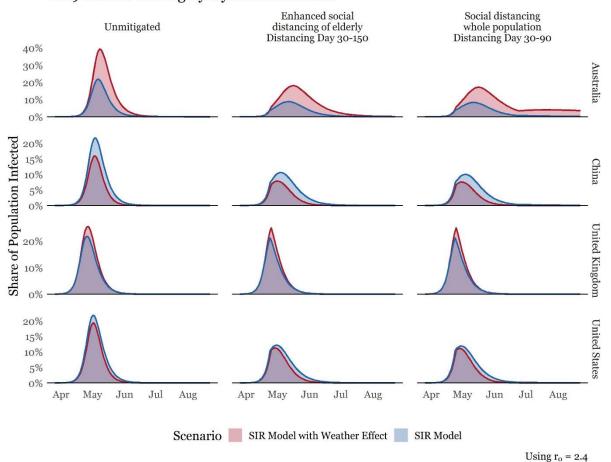
We conducted several robustness checks in the **supplementary material 2**. We check how important the fixed effects are to avoid mis-identifying the impact of the weather on 2019-nCov. Taking out the fixed effects lead to attenuated results, possibly because the virus is starting to spread to new locations while temperatures are increasing. We check if increasing or reducing the window period to look at the impact of the weather has an impact on the results. We find that results are robust to changes in the window period. We finally look at the impact of the weather on the early spread of the disease in new areas. We find that, in the early stages as well, the weather may play a role in how fast the disease spreads, but results lack significance, plausibly because we have less observations.

Projections

Our findings could be used to calibrate projections of the pandemic based on local weather conditions. We illustrate this point below with a very simple susceptible-infectious-recovered (SIR) compartment model.¹³ The model is initialised with the parameters used in Walker et al. (2020)¹⁴ (see methodological details in the **supplementary material 4**).

Results across different scenarios suggest that weather conditions alone will not wipe out the virus. Some countries, especially in the Northern Hemisphere, could expect a sizeable decrease in cases, while others, especially in the Southern Hemisphere could unfortunately expect a surge in cases because of weather conditions. This is illustrated across three scenarios (no mitigation, social isolation of the elderly, isolation for the whole population, as in Walker et al. 2020) in **Figure 3**, assuming a basic reproduction number R_0 of 2.4.

Figure 3: Illustrative projection with and without taking the weather into account 2019-nCovid in a highly stylized SIR Model



Notes: see methodological details in supplementary material 4.

Please note that this exercise is only illustrative. Projecting the actual number of cases on a country-level would require a better understanding of key other parameters and more complex modelling beyond the scope of this study.

Discussion

This study is the first to be able to conclude with high confidence that 2019-nCov is responsive to changes in the weather. To our knowledge, the only other attempt to produce estimates of the impact of weather conditions on Covid-n2019 is by Carleton and Meng (unpublished)¹⁵. Unfortunately, the authors are limited by the data they use: case counts at country level. This level of data aggregation may introduce two severe biases. Firstly, national-level analyses can only imperfectly control for sudden policy decisions, changes in people's behaviour or in the level of 2019-nCov testing. Viii Secondly, they are forced to aggregate the weather data at national scale too, leaving too much room for error. This could be particularly problematic for countries with a wide latitudinal range. Several other unpublished manuscripts provide correlation analyses with data from China^{16,17,18,19,20} and other countries^{21,22,23,24,25}, but cannot provide a causal interpretation.

It is however important to note that, since we use confirmed 2019-nCov cases, our figures may largely underestimate the actual number of infections. Our results should however properly identify whether the virus is sensitive to the weather or not. The main assumption of our model is that daily changes in reporting practices are homogenous within countries (i.e. New York does not systematically start testing people while Chicago stops doing so). Heterogeneous actions to contain the virus by sub-national governments are not considered at this moment, but our approach could be able to encompass these as soon as more data is available.

Our use of 2019-nCov confirmed cases has an implication for the interpretation of the results. We cannot distinguish whether there are less cases being reported because people do not get ill; or because their symptoms are less severe and they do not seek medical assistance.

Furthermore, there are three mechanisms that can explain these results. Firstly, 2019-nCov itself may be sensitive to hotter weather, like other coronaviruses (I.e. SARS-CoV-1). Secondly, human immune systems may be impaired by colder and dryer weather, and therefore people may be more likely to be infected or develop stronger symptoms during colder weather. Thirdly, household behaviour may correlate with the weather, and exposure to 2019-nCov may increase during colder days, e.g. because people do not ventilate their rooms when it's cold outside. The results presented above encompass all these effects, and our modelling strategy is not able to separate these different effects. However, the very strong effects on days above 30°C suggest that results are dominated by the virus' own response to hot weather.

autumn.

viii We know that these are confounding factors because these actions have been concomitant to changes in the weather – the Northern hemisphere has progressively left winter, while the Southern hemisphere is entering

In addition, the results for the non-linear response of 2019-nCov cases to the weather do not account for acclimation. It is possible that populations used to colder weather are less likely to contract the disease at a given temperature than populations used to hotter weather.

There are many versions of the virus, however our data does not specify these different versions and therefore does not allow us to assess if some versions are more sensitive to the weather than others. Likewise, we were unable to provide estimates by age, gender or according to medical preconditions due to lack of data.

We are only at the start of the pandemic and will update these results regularly to better identify the response of 2019-nCov to the weather over the full duration of the pandemic.

Conclusion

This paper provides the first georeferenced statistical analysis of the impact of the weather on 2019-nCov infections. It links detailed data on confirmed 2019-nCov cases to detailed meteorological data. This allows us to separate the effect of the weather from a long list of potential confounders, especially sudden changes – from one day to the other – in government response, population awareness or even healthcare practices and 2019-nCov testing.

We provide evidence confirming the hypothesis, raised by several experts, that 2019-nCov is sensitive to the weather. Considering how fast the virus has spread, it would be very damaging to think that the weather alone will put an end to the pandemic. However, this piece of information may allow health professionals to predict peaks in demand for healthcare during the pandemic, to make long term projections about its diffusion, or to identify the regions that are most at risk as a function of the weather. In that regard, our analysis also suggests that cold countries, and those entering the winter, are at increasing risk in their fight against the virus.

Conflict of interest statement

The authors have no conflict of interest.

Authors' contributions

Cohen is the first author. He had the original idea, wrote most of the paper and the code to produce the econometric analysis. He also coordinated the team. Li produced the required climate data. Lu helped on literature review, on coding the econometric analysis and on producing the tables. Schwarz helped on data coding and matching and created the projections. All authors copyedited the text.

Acknowledgements

For useful comments, we thank Doyne Farmer, David Hendry, Cameron Hepburn, Anant Jani, Francois Lafond and Rafael Perera. For technical IT assistance, we thank David Ford. For copyediting, we thank Jack Smith.

REFERENCES

¹ Xu, B., Gutierrez, B., Mekaru, S., Sewalk, K., Goodwin, L., Loskill, A., ... & Zarebski, A. E. (2020). Epidemiological data from the COVID-19 outbreak, real-time case information. *Scientific Data*, 7(1), 1-6.

² Weiss and Navas-Martin (2005). Coronavirus pathogenesis and the emerging pathogen severe acute respiratory syndrome coronavirus. Microbiol. Mol. Biol. Rev. 69, 635–664 .11.

³ Shaman and Kohn (2009). Absolute humidity modulates influenza survival, transmission, and seasonality. Proceedings of the National Academy of Sciences 106.9: 3243-3248.

⁴ Mäkinen et al. "Cold temperature and low humidity are associated with increased occurrence of respiratory tract infections." Respiratory medicine 103.3 (2009): 456-462.

⁵ Lowen et al. (2007). Influenza virus transmission is dependent on relative humidity and temperature. PLoS Pathog. 3, 1470–1476

⁶ Chan, K. H. et al. The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus. Advances in Virology vol. 2011 1–7 (2011)

⁷ Schoeman et al. (2019). "Coronavirus envelope protein: current knowledge." Virology journal 16.1 69.

⁸ Stadler et al. (2003), SARS—beginning to understand a new virus." *Nature Reviews Microbiology* 1.3: 209-218. Advances in Virology vol. 2011 1–7 (2011).

⁹ Ravilious, K. (2020). Will spring slow spread of coronavirus in northern hemisphere? *The Guardian*, 11th March 2020.

¹⁰ Clive Cookson. (2020). Scientists hopeful warmer weather can slow spread of coronavirus. *The Financial Times*, 25th March 2020.

¹¹ Sheikh K. & Londoño, E. (2020). Warmer Weather May Slow, but Not Halt, Coronavirus. *The New York Times*, 22nd March 2020.

¹² CNBS. (2020). It's a 'false hope' coronavirus will disappear in the summer like the flu, WHO says. Published 6th March, 2020: https://www.cnbc.com/2020/03/06/its-a-false-hope-coronavirus-will-disappear-in-the-summer-like-the-flu-who-says.html [Accessed March 31st, 2020]

¹³ Kermack, W. O., and A. G. McKendrick. 1927. "A Contribution to the Mathematical Theory of Epidemics." *Proceedings of the Royal Society, Series A* 115: 700–721.

¹⁴ Walker et al. (2020). Report 12: The Global Impact of COVID-19 and Strategies for Mitigation and Suppression. Imperial College COVID-19 Response Team. Available at: https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-Global-Impact-26-03-2020v2.pdf [Accessed March 31st, 2020]

¹⁵ Carleton, T., & Meng K. (2020). *Causal empirical estimates suggest COVID-19 transmission rates are highly seasonal*. Unpublished draft available at: http://www.kylemeng.com/ [Accessed 1st April, 2020]

 $^{^{16}}$ Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., ... & Luo, B. (2020). Effects of temperature variation and humidity on the mortality of COVID-19 in Wuhan. medRxiv.

¹⁷ Wang, J., Tang, K., Feng, K., & Lv, W. (2020). High Temperature and High Humidity Reduce the Transmission of COVID-19. *Available at SSRN 3551767*.

¹⁸ Poirier, C., Luo, W., Majumder, M. S., Liu, D., Mandl, K., Mooring, T., & Santillana, M. (2020). The Role of Environmental Factors on Transmission Rates of the COVID-19 Outbreak: An Initial Assessment in Two Spatial Scales. *Available at SSRN 3552677*.

¹⁹ Gupta, D. (2020). Effect of Ambient Temperature on COVID-19 Infection Rate. *Available at SSRN 3558470*.

²⁰ Oliveiros, B., Caramelo, L., Ferreira, N. C., & Caramelo, F. (2020). Role of temperature and humidity in the modulation of the doubling time of COVID-19 cases. *medRxiv*.

²¹ Bannister-Tyrrell, M., Meyer, A., Faverjon, C., & Cameron, A. (2020). Preliminary evidence that higher temperatures are associated with lower incidence of COVID-19, for cases reported globally up to 29th February 2020. *medRxiv*.

²² Bukhari, Q., & Jameel, Y. (2020). Will Coronavirus Pandemic Diminish by Summer? *Available at SSRN* 3556998.

- ²³ Chen, B., Liang, H., Yuan, X., Hu, Y., Xu, M., Zhao, Y., ... & Zhu, X. (2020). Roles of meteorological conditions in COVID-19 transmission on a worldwide scale. *medRxiv*.
- ²⁴ Wang, M., Jiang, A., Gong, L., Luo, L., Guo, W., Li, C., ... & Chen, Y. (2020). Temperature significant change COVID-19 Transmission in 429 cities. *medRxiv*.
- ²⁵ Araujo, M. B., & Naimi, B. (2020). Spread of SARS-CoV-2 Coronavirus likely to be constrained by climate. medRxiv.
- ²⁶ Thomas Pietschmann, Will warmer weather stop the spread of the coronavirus?, available at: https://www.dw.com/en/will-warmer-weather-stop-the-spread-of-the-coronavirus/a-52570290 [Accessed March 31st, 2020]
- ²⁷ van Doremalen et al. (2020) "Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1." *New England Journal of Medicine*.
- ²⁸ Gasparrini, Antonio, et al. "Mortality risk attributable to high and low ambient temperature: a multicountry observational study." *The Lancet* 386.9991 (2015): 369-375.