

# Temperature dependence of COVID-19 transmission

Alessio Notari<sup>1\*</sup>

<sup>1</sup> *Departament de Física Quàntica i Astrofísica & Institut de Ciències del Cosmos (ICCUB),  
Universitat de Barcelona, Martí i Franquès 1, 08028 Barcelona, Spain*

The recent coronavirus pandemic follows in its early stages an almost exponential expansion, with the number of cases  $N$  reasonably well fit by  $N \propto e^{\alpha t}$ , in many countries. We analyze the rate  $\alpha$  in 25 different countries, choosing as a starting point in each country the first day with 30 cases and fitting for the following 12 days, capturing thus the early exponential growth in a rather homogeneous way. We look for a link between the rate  $\alpha$  and the average temperature  $T$  of each country, in the month of the epidemic growth. Fitting with a linear behavior  $\alpha(T)$ , we find evidence for a decreasing growth rate as a function of  $T$ . However, a decrease in the growth rate is visible also in the very low- $T$  data. Going beyond a linear model, a peak at about  $(9.5 \pm 2.6)^\circ\text{C}$  seems to be present in the data. Our findings give hope that, for northern hemisphere countries, the growth rate should significantly decrease as a result of both warmer weather and lockdown policies. In general the propagation should be hopefully stopped by strong lockdown, testing and tracking policies, before the arrival of the next cold season.

## I. INTRODUCTION

The recent coronavirus (COVID-19) pandemic is having a major effect in many countries, which needs to be faced with the highest degree of scrutiny. An important piece of information is whether the growth rate of the confirmed cases among the population could decrease with increasing temperature. Experimental research on related viruses found indeed a decrease at high temperature and humidity [1]. We try to address this question using available epidemiological data. A similar analysis for the data from January 20 to February 4, 2020, among 403 different Chinese cities, was performed in [2] and similar studies were recently performed in [3–7]. The paper is organized as follows. In section II we explain our methods, in section III we show the results of our analysis and in section IV we draw our conclusions.

## II. METHOD

We start our analysis from the empirical observation that the data for the coronavirus disease in many different countries follow a common pattern: once the number of confirmed cases reaches order 10 there is a very rapid subsequent growth, which is well fit by an exponential behavior. The latter is typically a good approximation for the following couple of weeks and, after this stage of *free* propagation, the exponential growth typically gradually slows down, probably due to other effects, such as: lockdown policies from governments, a higher degree of awareness in the population or the tracking and isolation of the positive cases.

Our aim is to see whether the temperature of the environment has an effect, and for this purpose we choose to analyze the first stage of *free* propagation in a selected sample of countries. We choose our sample using the following rules:

- we start analyzing data from the first day in which the number of cases in a given country reaches a reference number  $N_i$ , which we choose to be  $N_i = 30$  [8];
- we include only countries with at least 12 days of data, after this starting point.

---

\*Electronic address: notari@fqa.ub.edu

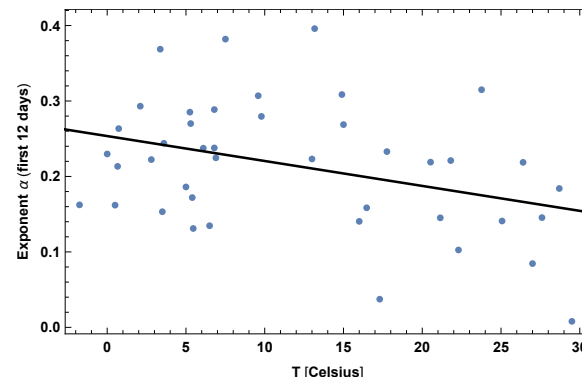


Figure 1: Exponent  $\alpha$  for each country vs. average temperature  $T$ , for the month of March, as defined in the text. We show the data points and the best-fit for the linear interpolation.

The data were collected from [9]. We then fit the data for each country with a simple exponential curve  $N(t) = N_0 e^{\alpha t}$ , with 2 parameters  $N_0$  and  $\alpha$ ; here  $t$  is in units of days. We associate then to each country an average temperature  $T$ , for the relevant weeks, which we take from [10]. More precisely: if for a given country the average  $T$  is tabulated only for its capital city, we directly used such a value. If, instead, more cities are present for a given country, we used an average of the temperature of the main cities, weighted by their population. [11]. For most countries we used the average temperature for the month of March, with a few exceptions [12].

The full list of countries is: Argentina, Australia, Belgium, Brazil, Canada, Chile, China, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Lebanon, Malaysia, Netherlands, Norway, Philippines, Poland, Portugal, Romania, Saudi Arabia, Singapore, Slovenia, South Korea, Sweden, Switzerland, Taiwan, Thailand, United Arab Emirates, United Kingdom, U.S.A..

Using such a dataset for  $\alpha$  and  $T$  for each country, we fit it with two functions  $\alpha(T)$ , as explained in the next section. Note that the statistical errors on the  $\alpha$  parameters, considering Poissonian errors on the daily counting of cases, are typically much smaller than the spread of the values of  $\alpha$  among the various countries. This is due to systematic effects, which are dominant, as we will discuss later on. For this reason we disregarded statistical errors on  $\alpha$ . The analysis was done using the software *Mathematica*, from Wolfram Research, Inc..

### III. RESULTS

We first fit with a simple linear function  $\alpha(T) = \alpha_0 + \beta T$ , to look for an overall decreasing behavior. Results for the best fit, together with our data points, are shown in fig. 1. The parameter estimation contours are shown in fig. 2, and the estimate, standard deviation and confidence intervals for the parameters are shown in Table I. From such results a clear decreasing trend is visible, and indeed the slope is negative, at 95% C.L..

Parameter	estimate	$\sigma$	95% lower	95% upper
$\alpha_0$	0.253	0.020	0.213	0.294
$\beta$	-0.00330	0.00134	-0.00602	-0.000583

Table I: Best-estimate, standard deviation ( $\sigma$ ) and 95% C.L. intervals for the parameters of the linear interpolation.

However, the linear behavior is able to explain only a small part of the variance of the data, with  $R^2 = 0.13$ , and its adjusted value  $R^2_{\text{adjusted}} = 0.11$ . In addition, a decreasing trend is also

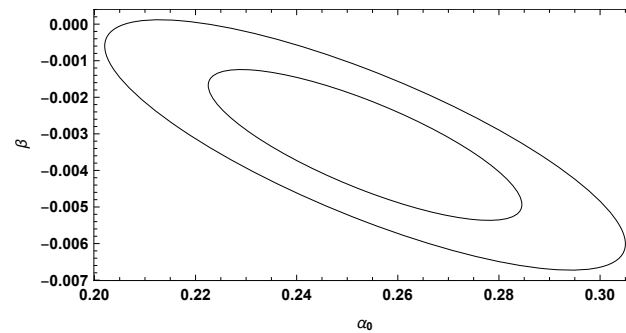


Figure 2: Confidence regions for the parameters of the linear model. Contours represent 68% C.L. and 95% C.L., respectively.

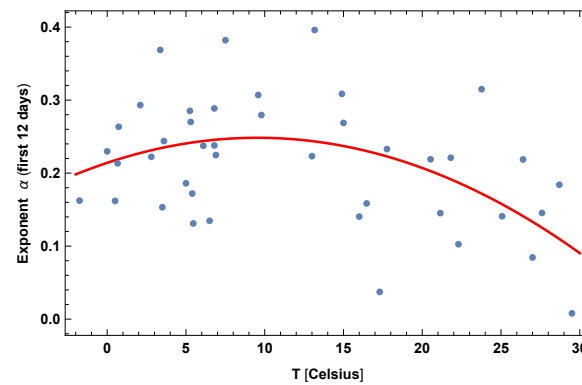


Figure 3: Exponent  $\alpha$  for each country vs. average temperature  $T$ , for the month of March, as defined in the text. We show here the quadratic best-fit.

visible in the data, below about  $10^\circ\text{C}$ . For these reasons we also fit below with a quadratic function  $\alpha(T) = \alpha_0 + \beta(T - T_M)^2$ .

Results for the quadratic best fit are presented in fig. 3. The relative estimate, standard deviation and confidence intervals for the parameters are shown in Table II. From such results a peak is visible at around  $T_M \approx 10^\circ\text{C}$ . The quadratic model is able to explain a much larger part of the variance of the data, since  $R^2 \approx R_{\text{adjusted}}^2 \approx 0.9$ . Moreover, despite the presence of an extra parameter, one may quantify the improvement of the fit, using for instance the Akaike Information Criterion (AIC) for model comparison,  $\Delta AIC \equiv 2\Delta k - 2\Delta \ln(\mathcal{L})$ , where  $\Delta k$  is the increase in the number of parameters, compared to the simple linear model, and  $\Delta \ln(\mathcal{L})$  is the change in the maximum log-likelihood between the two models. This gives  $\Delta AIC = -3$ , in favor of the quadratic model.

Parameter	estimate	$\sigma$	95% lower	95% upper
$\alpha_0$	0.248	0.0169	0.2194	0.2872
$\beta$	0.000377	0.000168	0.0000363	0.000717
$T_M$	9.53	2.59	4.28	14.77

Table II: Best-estimate, standard deviation ( $\sigma$ ) and 95% C.L. intervals for the parameters of the quadratic interpolation.

## IV. DISCUSSION AND CONCLUSIONS

We have collected data for countries, which had at least 12 days of data after a starting point, which we fixed to be at the threshold of 30 confirmed cases. We have fit such data with an exponential and extracted the exponents  $\alpha$ , for each country. Then we have analyzed such exponents as a function of the temperature  $T$ , using the average temperature for the month of March (or slightly earlier in some cases), for each of the selected countries.

We have then shown that the growth rate of the transmission of the COVID-19 has a decreasing trend, as a function of  $T$ . In addition, using a quadratic fit, we have shown that a peak of maximal transmission seems to be present at around  $(9.5 \pm 2.6)^\circ C$ . Such findings are in good agreement with a similar study, performed for Chinese cities [2], which also finds the existence of an analogous peak and an overall decreasing trend. Other similar recent studies [3–6] find results which seem to be also in qualitative agreement.

The decrease at high temperatures is expected, since the same happens also for other coronaviruses [1]. It is unclear instead whether the decrease at low temperature (less than  $10^\circ C$ ) is due to physical properties of the virus or perhaps to other factors. One possible reason could be the lower degree of interaction among people in countries with very low temperatures, which slows down the propagation of the virus.

A general observation is also that a large scatter in the residual data is present, clearly due to many other systematic factors, such as variations in the methods and resources used for collecting data and variations in the amount of social interactions, due to cultural reasons. It is also possible that variations in resources biases the testing procedure (*i.e.* poorer countries have less intense testing), which might be partially degenerate with effects of temperature. Further study would be required to assess such factors.

As a final remark, our findings can be very useful for policy makers, since they support the expectation that with growing temperatures the coronavirus crisis should become milder in the coming few months, for countries in the Northern Hemisphere. As an example the estimated doubling time, with the quadratic fit, at the peak temperature of  $9.5^\circ C$  is of 2.8 days, while at an average temperature of  $26.5^\circ C$  is expected to go to about 5 days. For countries with seasonal variations in the Southern Hemisphere, instead, this should give motivation to implement lockdown policies before the arrival of the cold season.

We stress that, in general, it is important to fully stop the propagation, using strong lockdown, testing and tracking policies, taking also advantage of the warmer season, and before the arrival of the next cold season.

## Acknowledgments

We would like to acknowledge Alberto Belloni for useful discussions.

- 
- [1] K. H. Chan, J. S. Malik Peiris, et al. *The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus*. *Advances in Virology*, Vol. 2011(Article ID 734690), 2011.
  - [2] Mao Wang, Aili Jiang, Lijuan Gong, Lina Luo, Wenbin Guo, Chuyi Li, Jing Zheng, Chaoyong Li, Bixing Yang, Jietong Zeng, Youping Chen, Ke Zheng, and Hongyan Li. Temperature significant change covid-19 transmission in 429 cities. 2020.
  - [3] Miguel B. Araujo and Babak Naimi. *Spread of SARS-CoV-2 Coronavirus likely to be constrained by climate*. 2020.
  - [4] Qasim Bukhari and Yusuf Jameel. *Will Coronavirus Pandemic Diminish by Summer?*. 2020.
  - [5] Kai Feng Weifeng Lv Jingyuan Wang, Ke Tang. *High Temperature and High Humidity Reduce the Transmission of COVID-19*. 2020.
  - [6] Mohammad M. Sajadi, Parham Habibzadeh, Augustin Vintzileos, Shervin Shokouhi, Fernando Miralles-Wilhelm, and Anthony Amoroso. *Temperature, Humidity and Latitude Analysis to Predict Poten-*

- tial Spread and Seasonality for COVID-19*; available at ssrn: <https://ssrn.com/abstract=3550308> or <http://dx.doi.org/10.2139/ssrn.3550308>.
- [7] Wei Luo, Maimuna S Majumder, Dianbo Liu, Canelle Poirier, Kenneth D Mandl, Marc Lipsitch, and Mauricio Santillana. *The role of absolute humidity on transmission rates of the COVID-19 outbreak*. 2020.
  - [8] In practice we choose, as the first day, the one in which the number of cases  $N_i$  is closest to 30. In some countries, such a number  $N_i$  is repeated for several days; in such cases we choose the last of such days as the starting point.
  - [9] <https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases>
  - [10] [https://en.wikipedia.org/wiki/List\\_of\\_cities\\_by\\_average\\_temperature](https://en.wikipedia.org/wiki/List_of_cities_by_average_temperature)
  - [11] The only two exceptions to this procedure are: Japan and U.S.A.. For Japan we have subdivided into three regions: Hokkaido, Okinawa and the rest of the country, using respectively the temperatures of Sapporo, Naha and Tokio. For the U.S.A. we have used the national average of about 5.3 degrees from <https://www.ncdc.noaa.gov/sotc/national/201903>.
  - [12] For China, South Korea, Singapore, Iran, Taiwan and Japan we considered an interpolating function of the temperature for the months of January, February and March and we took an average of such function in the relevant 12 days of the epidemic.