A background image showing a microscopic view of COVID-19 virus particles. The particles are spherical with a textured surface and numerous protruding spikes, characteristic of the coronavirus structure. They are set against a dark, reddish-brown background.

# Can mathematical modeling help to understand COVID-19 data?

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Webinar Bordeaux IMB Infectious Disease Outbreaks  
and  
Annual meeting of the SFBT, June 29 2022.

# Scope & aims

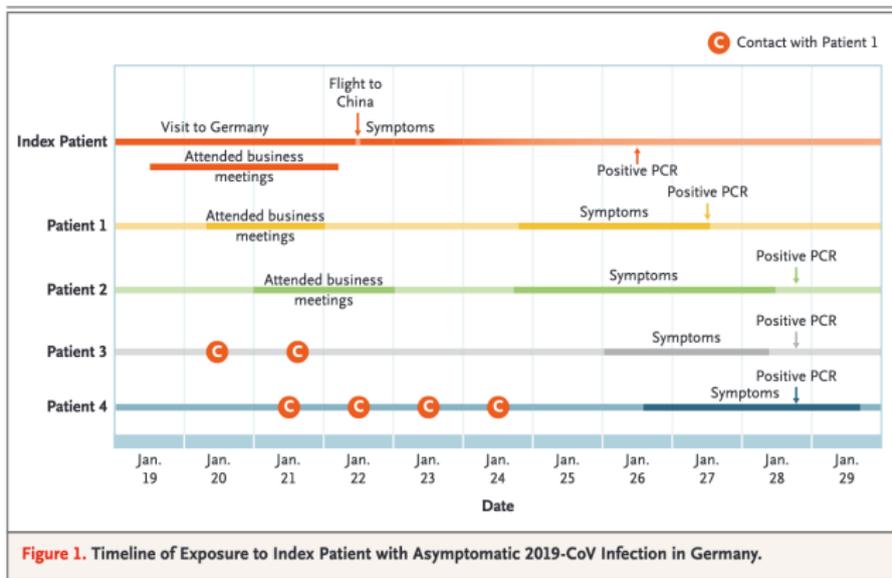
- How to recover information from the **cumulative number of reported cases data**?
- We want to use simple models with a **limited number of parameters**.
- Here the parameters include part of the **initial conditions**.
- We want to **reconstruct** and **forecast** the epidemic.

# **PART I:**

## Unreported cases for COVID-19

# Example of unreported cases

A published study<sup>1</sup> traced COVID-19 infections resulting from a business meeting in Germany attended by a person who was infected but had no symptoms at the time. Four people were eventually infected from this single contact.



<sup>1</sup>Rothe, et al. (2020), Transmission of 2019-nCoV infection from an asymptomatic contact in Germany. *New England Journal of Medicine*, **382**(10), 970-971.

## Example of unreported cases

A team in Japan<sup>2</sup> reports that 13 people evacuated from *Diamond Princess* were infected, 4 of whom, or 31 %, never developed symptoms.

On the French *aircraft carrier Charles de Gaulle*, clinical and biological data for all 1739 crew members were collected on arrival at the Toulon harbor and during quarantine: 1121 crew members (64%) were tested positive for COVID-19 using RT-PCR, and among these, 24% were asymptomatic<sup>3</sup>.

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<sup>2</sup>H. Nishiura, N. M. Linton, & A. R. Akhmetzhanov (2020), Serial interval of novel coronavirus (COVID-19) infections, *Int. J. Infect. Dis.*, **93**, 284-286.

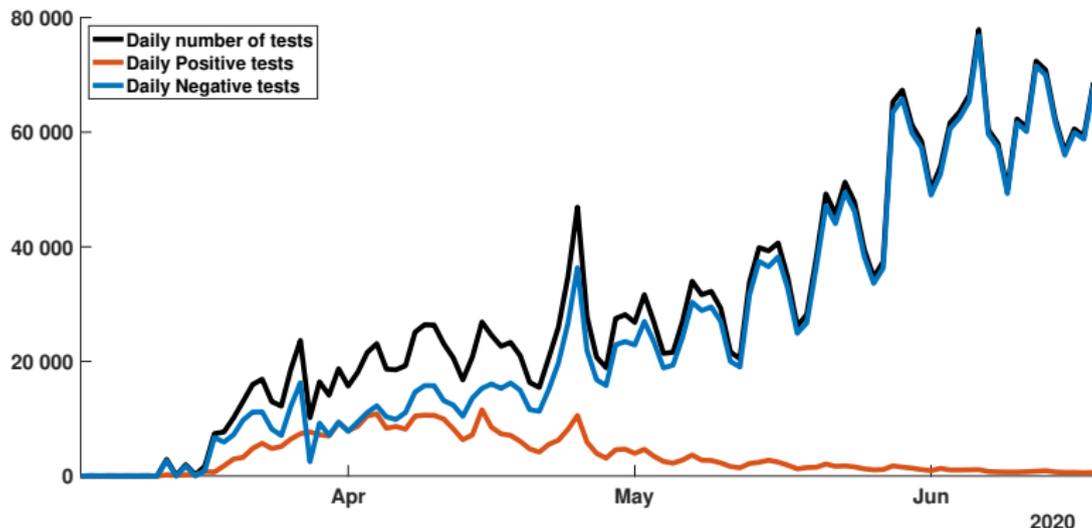
<sup>3</sup>O. Bylicki, N. Paleiron, and F. Janvier (2021), An Outbreak of Covid-19 on an Aircraft Carrier. *New Engl. J. Med.*, **384(10)**, 976–977.

# What are the unreported cases?

- **Mild symptoms** induce unreported cases because people will only get tested in case of severe symptoms.
- Unreported cases are partly due to a low daily number of tests.

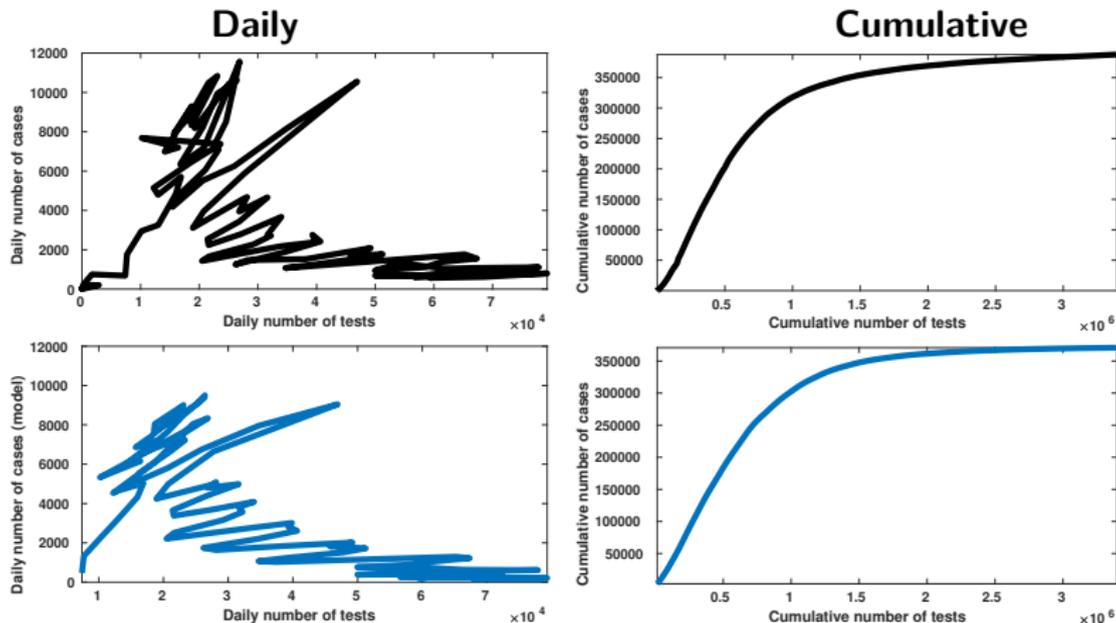
# Testing data for New York state

The dynamic of the daily number of tests is connected to the dynamic of the daily number of reported cases in a complex way<sup>4</sup>.



<sup>4</sup>Q. Griette and P. Magal (2021) Clarifying predictions for COVID-19 from testing data: the example of New York State, *Infectious Disease Modelling*, **6**, 273-283.

# Testing data for New York state<sup>5</sup>



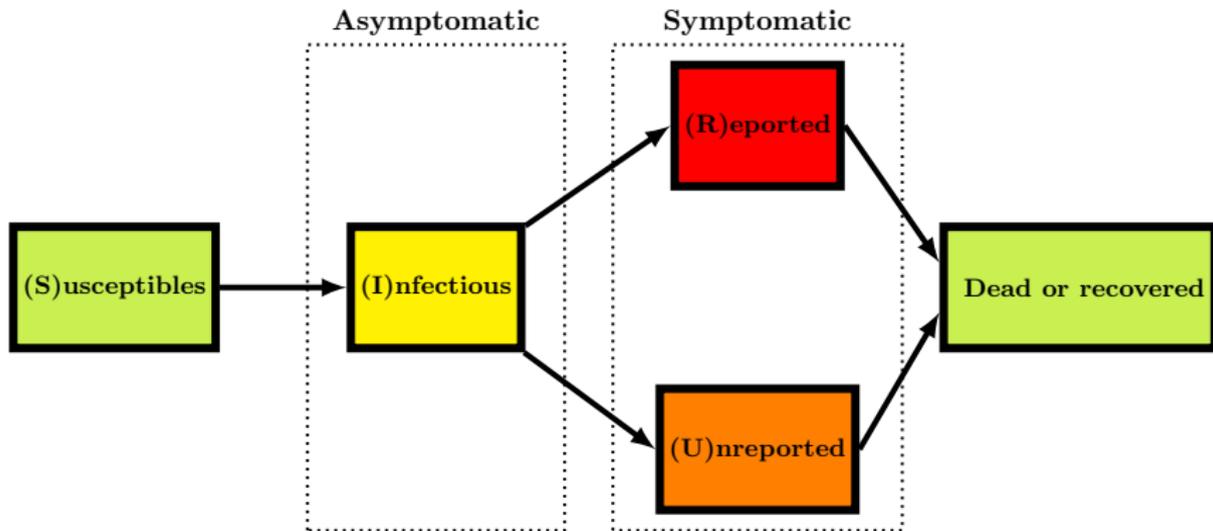
The **black curves** are produced by using **the data only**. The **blue curves** are produced by using **the model with the testing data**.

<sup>5</sup>Q. Griette and P. Magal (2021) Clarifying predictions for COVID-19 from testing data: the example of New York State, *Infectious Disease Modelling*, **6**, 273-283.

# **PART II:**

An epidemic model  
with  
unreported cases

# Epidemic with Unreported Cases<sup>6,7</sup>



<sup>6</sup>Z. Liu, P. Magal, O. Seydi, and G. Webb (2020), Understanding unreported cases in the 2019-nCov epidemic outbreak in Wuhan, China, and the importance of major public health interventions, *Biology*, **9**(3), 50.

<sup>7</sup>J. Arino, F. Brauer, P. van den Driessche, J. Watmough and J. Wu (2006), Simple models for containment of a pandemic, *Journal of the Royal Society Interface*, **3**(8), 453-457.

# Epidemic model

Transmissions between infectious and susceptible individuals are described by

$$\begin{cases} S'(t) = -\tau(t) S(t) I(t), \\ I'(t) = \tau(t) S(t) I(t) - \nu I(t), \end{cases} \quad (1)$$

where

- $\tau(t)$  is the rate of transmission.
- $1/\nu$  is the average duration of the asymptomatic infectious period.
- $\tau(t) S(t) I(t)$  is the flux of  $S$ -individuals becoming infected at time  $t$ .
- $\nu I(t)$  is the flux of  $I$ -individuals leaving the  $I$ -compartment.

# Initial distribution of the model

The system (1) is complemented with the initial distribution of the model

$$S(t_0) = S_0 \geq 0, I(t_0) = I_0 \geq 0. \quad (2)$$

The parameter

$$t_0$$

is also unknown.

That is the time  $t_0$  from which the epidemic model (1) becomes applicable.

# Connecting the data and the model<sup>8,9</sup>

To connect the data and the model (1) we use the following equation

$$CR'(t) = f \nu I(t), \text{ for } t \geq t_0, \quad (3)$$

where  $f$  is the **fraction of reported individuals**.

We assume that

- $f$  is the fraction of patients with **severe symptoms**.
- $1 - f$  is the fraction of patients with **mild symptoms**.

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<sup>8</sup>Z. Liu, P. Magal, O. Seydi, and G. Webb (2020), Understanding unreported cases in the 2019-nCov epidemic outbreak in Wuhan, China, and the importance of major public health interventions, *Biology*, **9(3)**, 50.

<sup>9</sup>P. Magal, and G. Webb (2018) The parameter identification problem for SIR epidemic models: Identifying Unreported Cases, *Journal of Mathematical Biology* **77(6-7)**, 1629–1648.

# Given Parameters

- Number of susceptible individuals when the epidemic starts

$$S_0 = 67 \text{ millions for France.}$$

- Time from which the epidemic model starts to be valid, also called initial time of the model

$$t_0.$$

- The average duration of the infectiousness

$$\frac{1}{\nu} = 3 \text{ days.}$$

- The fraction of reported individuals

$$f = 0.9.$$

# Computed parameters

- $I_0$  the number of asymptomatic infectious patients at the start of the epidemic.
- $\tau(t)$  the rate of transmission.

# What factors govern the transmission rate $\tau(t)$ ?

As explained in Magal and Ruan<sup>10</sup> by using stochastic individual based models

$$\tau(t) = \frac{1}{\text{the average duration of a contact}} \times \text{the probability of transmission.}$$

Contact patterns are impacted by **social distancing measures**.

The average number of contacts per unit of time depends on the **density of population**<sup>11,12</sup>.

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<sup>10</sup>**P. Magal and S. Ruan** (2014), Susceptible-Infectious-Recovered Models Revisited: From the Individual Level to the Population Level, *Mathematical Biosciences* **250**, 26-40.

<sup>11</sup>**J. Rocklöv, & H. Sjödin**. (2020), High population densities catalyse the spread of COVID-19. *J Travel Med*, **27(3)**, taaa038.

<sup>12</sup>**H. Seligmann, N. Vuillerme & J. Demongeot** (2020), Summer COVID-19 third wave: faster high altitude spread suggests high UV adaptation, *medRxiv*.

# What factors govern the transmission rate $\tau(t)$ ?

- The probability of transmission depends of the virulence of the pathogen which can depend on the **temperature, the humidity, and the Ultraviolet**<sup>13,14</sup>.
- The probability of transmission depends of the susceptibility of the individuals
  - ▶ **Blood group**<sup>15</sup> : Blood group O is associated with a lower susceptibility to SARS-CoV2;
  - ▶ **Genetic lineage**<sup>16</sup> A gene cluster inherited from Neanderthal has been identified as a risk factor for severe symptoms.

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<sup>13</sup>J. Demongeot, Y. Flet-Berliac, & H. Seligmann (2020), Temperature Decreases Spread Parameters of the New Covid-19 Case Dynamics, *Biology*, **9**, 94.

<sup>14</sup>J. Wang, et al (2020), High temperature and high humidity reduce the transmission of COVID-19. Available at SSRN 3551767.

<sup>15</sup>P. Guillon, et al. (2008), Inhibition of the interaction between the SARS-CoV spike protein and its cellular receptor by anti-histo-blood group antibodies, *Glycobiology* **18.12**, 1085-1093.

<sup>16</sup>H. Zeberg and S. Pääbo, (2020), The major genetic risk factor for severe COVID-19 is inherited from Neanderthals, *Nature*.

# **PART III:**

## Single epidemic wave

# Modeling the exponential phase

At the early stage of the epidemic, we can assume that  $S(t)$  is constant, and equal to  $S_0$ . We can also assume that  $\tau(t)$  remains constant equal to  $\tau_0 = \tau(t_0)$ . Therefore, by replacing these parameters into the I-equation of system (1) we obtain

$$I'(t) = (\tau_0 S_0 - \nu)I(t).$$

Therefore

$$I(t) = I_0 \exp(\chi_2 (t - t_0)),$$

where

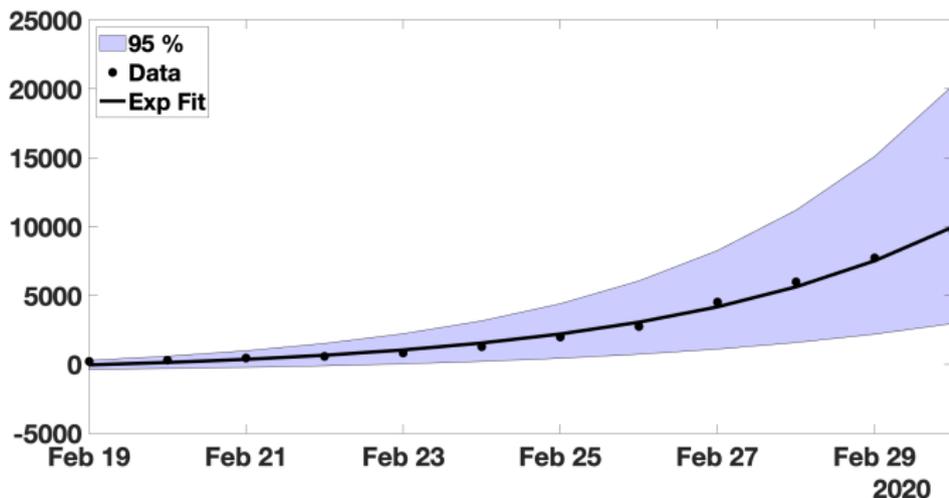
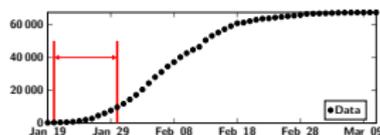
$$\chi_2 = \tau_0 S_0 - \nu.$$

By using (3), we obtain

$$\text{CR}(t) = \chi_1 e^{\chi_2 t} - \chi_3.$$

(4)

# Application to COVID-19 in mainland China <sup>17,18</sup>



<sup>17</sup>Z. Liu, P. Magal, O. Seydi, and G. Webb (2020), Understanding unreported cases in the 2019-nCov epidemic outbreak in Wuhan, China, and the importance of major public health interventions, *Biology*, **9**(3), 50.

<sup>18</sup>J. Demongeot, Q. Griette and P. Magal (2020), SI epidemic model applied to COVID-19 data in mainland China, *Royal Society Open Science* 7:201878.

# Initial number of infected and transmission rate

Remember that (3) and (4) are respectively

$$\text{CR}'(t) = f \nu I(t), \text{ for } t \geq t_0,$$

and

$$\text{CR}(t) = \chi_1 e^{\chi_2 t} - \chi_3.$$

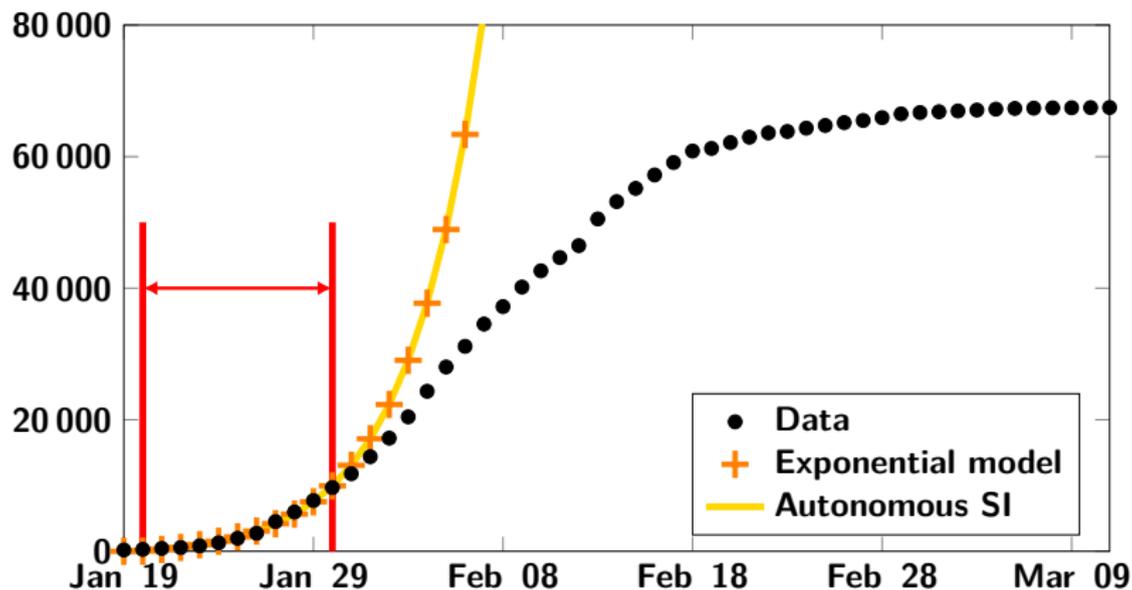
By using (3) and (4) we obtain

$$I_0 = \frac{\text{CR}'(t_0)}{\nu f} = \frac{\chi_1 \chi_2 e^{\chi_2 t_0}}{\nu f},$$

and by using (4)

$$\tau_0 = \frac{\chi_2 + \nu}{S_0}.$$

# Why do we need a time-dependent transmission rate?



# **PART IV:**

## Multiple epidemic waves

# Earlier results with a transmission rate reconstructed from the data

This problem has already been considered in several articles. In the early 70s, London and Yorke<sup>19,20</sup> discussed the time dependent rate of transmission in the context of measles, chickenpox and mumps.

Motivated by applications to the data for COVID-19 the group of Bakhta, Boiveau, Maday, & Mula<sup>21</sup> also obtained some new results about reconstructing the rate of transmission.

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<sup>19</sup>W. P. London, and J. A. Yorke (1973), Recurrent outbreaks of measles, chickenpox and mumps: I. Seasonal variation in contact rates. *Am J Epidemiol*, **98(6)**, 453-468.

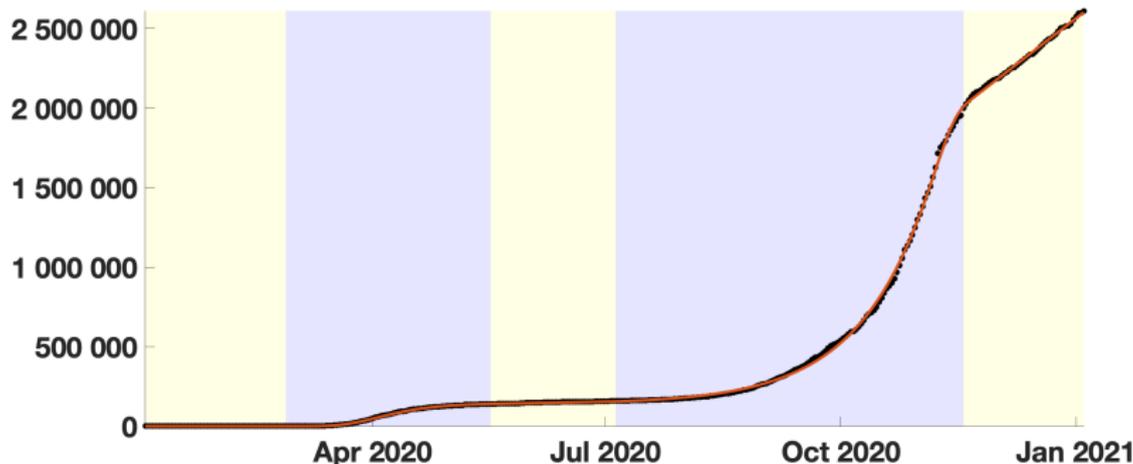
<sup>20</sup>J. A. Yorke, and W. P. London (1973), Recurrent outbreaks of measles, chickenpox and mumps: II. Systematic differences in contact rates and stochastic effects. *Am J Epidemiol*, **98(6)**, 469-482.

<sup>21</sup>A. Bakhta, T. Boiveau, Y. Maday, & O. Mula (2021), Epidemiological Forecasting with Model Reduction of Compartmental Models. Application to the COVID-19 Pandemic. *Biology*, **10(1)**, 22.

# Epidemic and Endemic phases in France

*We fit a Bernoulli-Verhulst model during each epidemic phase. Then we extend the model by lines outside the epidemic phases. We regularize the junction points by a convolution with a Gaussian function with standard deviation of 7 days.*

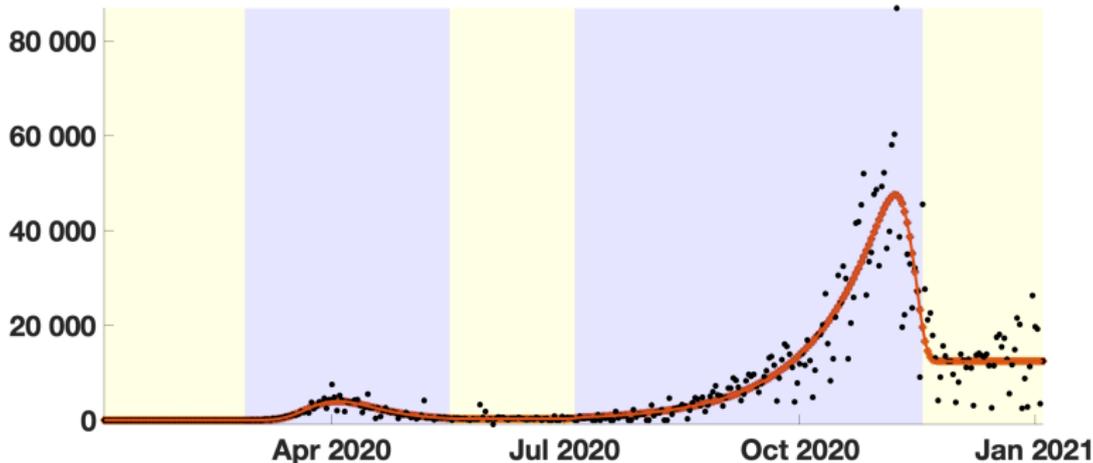
**Cumulative number of reported cases**



*The red curve corresponds to the phenomenological model and the black dots correspond to the data of the number of cumulative cases. **We use  $16 = 2 \times 5 + 3 \times 2$  parameters for more than 365 points.***

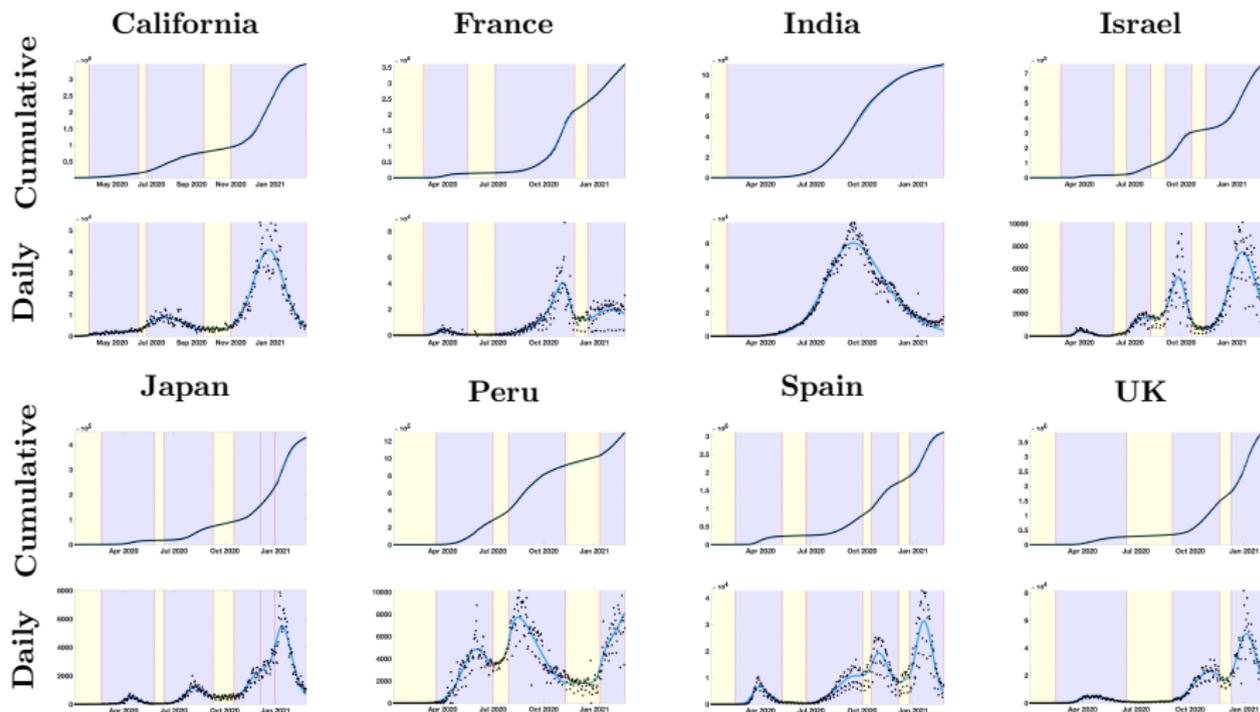
# Epidemic and Endemic phases in France

Daily number of reported cases



*The red curve corresponds to the first derivative of the phenomenological model and the black dots correspond to the data of the daily number of cases.*

# Phenomenological Model<sup>22</sup>



<sup>22</sup>Q. Griette, J. Demongeot and P. Magal (2021), What can we learn from COVID-19 data by using epidemic models with unidentified infectious cases? *Mathematical Biosciences and Engineering*, **19(1)**: 537–594.

# Instantaneous reproduction number

We use our method to compute the transmission rate, and we consider the **instantaneous reproduction number**

$$\mathbf{R}_e(\mathbf{t}) = \tau(\mathbf{t})\mathbf{S}(\mathbf{t})/\nu,$$

and the **quasi-instantaneous reproduction number**

$$\mathbf{R}_e^0(\mathbf{t}) = \tau(\mathbf{t})\mathbf{S}_0/\nu,$$

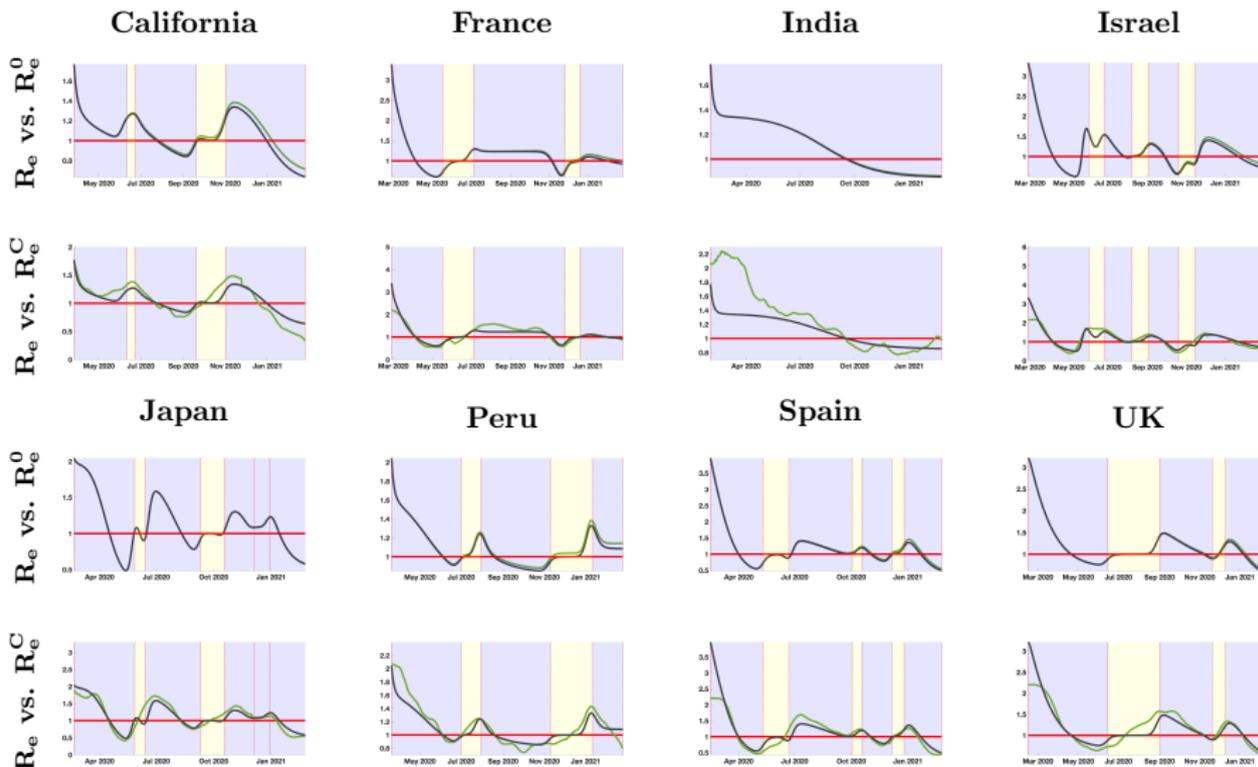
We compare the above indicators with  $\mathbf{R}_e^C(\mathbf{t})$  the classical notion of **instantaneous reproduction number**<sup>23,24</sup>.

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<sup>23</sup>T. Obadia, R. Haneef, & P. Y. Boëlle (2012), The  $R_0$  package: a toolbox to estimate reproduction numbers for epidemic outbreaks. *BMC medical informatics and decision making*, **12(1)**, 1-9.

<sup>24</sup>A. Cori, N. M. Ferguson, C. Fraser, & S. Cauchemez (2013), A new framework and software to estimate time-varying reproduction numbers during epidemics. *American journal of epidemiology*, **178(9)**, 1505-1512. 27/33

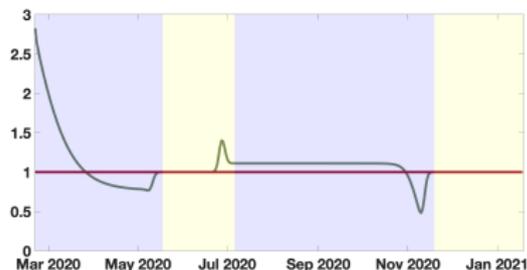
# Instantaneous reproduction numbers<sup>25</sup>



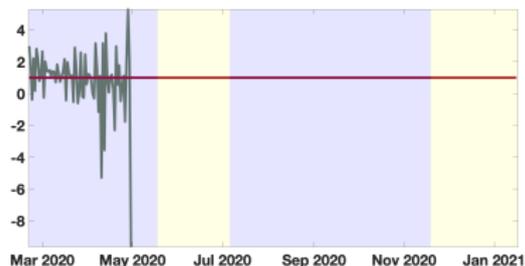
<sup>25</sup>Q. Griette, J. Demongeot and P. Magal (2021), What can we learn from COVID-19 data by using epidemic models with unidentified infectious cases? *Mathematical Biosciences and Engineering*, **19**(1): 537–594.

# Why do we need a phenomenological model to regularize the data?

With phenomenological model



Without phenomenological model



# Conclusions

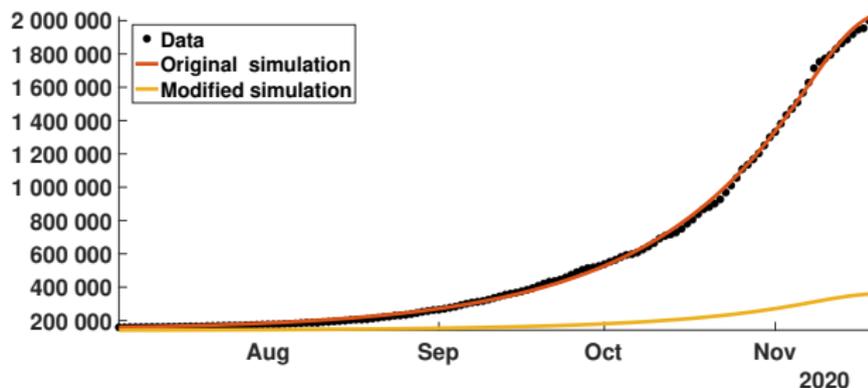
The population of susceptible patients is almost unchanged after the epidemic passed. Therefore, the system behaves almost like the non-autonomous system

$$I'(t) = \tau(t)S_0I(t) - \nu I(t), \forall t \geq t_0, \text{ and } I(t_0) = I_0,$$

This means that  $I(t)$  depends linearly on  $I_0$ .

# Conclusions

The average daily number of cases during the endemic phases matters a lot.<sup>26</sup>



We start the simulation at time  $t_0 = \text{July } 05$  with the initial value  $I_0 = \frac{CR'(t_2)}{\nu f}$

for **red curve** and with  $I_0 = \frac{1}{10} \frac{CR'(t_2)}{\nu f}$  for **yellow curve**.

<sup>26</sup>Q. Griette, J. Demongeot and P. Magal (2021) A robust phenomenological approach to investigate COVID-19 data for France, *Mathematics in Applied Sciences and Engineering*, **2(3)**, 149-218.

# Conclusions

## How to extend the same kind of idea to large systems?

In Liu et al. <sup>27</sup> we consider a 2-dimensional example. This example corresponds to a system of the form

$$I'(t) = L I(t)$$

where  $L \in M_n(\mathbb{R})$  is a  $n$  by  $n$  matrix with non negative off diagonal elements.

Then we use the **Perron-Frobenius theorem**, and assume that an **asynchronous exponential growth regime** that is

$$I(t) = e^{\lambda_0 t} I_0 \in \mathbb{R}^n$$

which gives

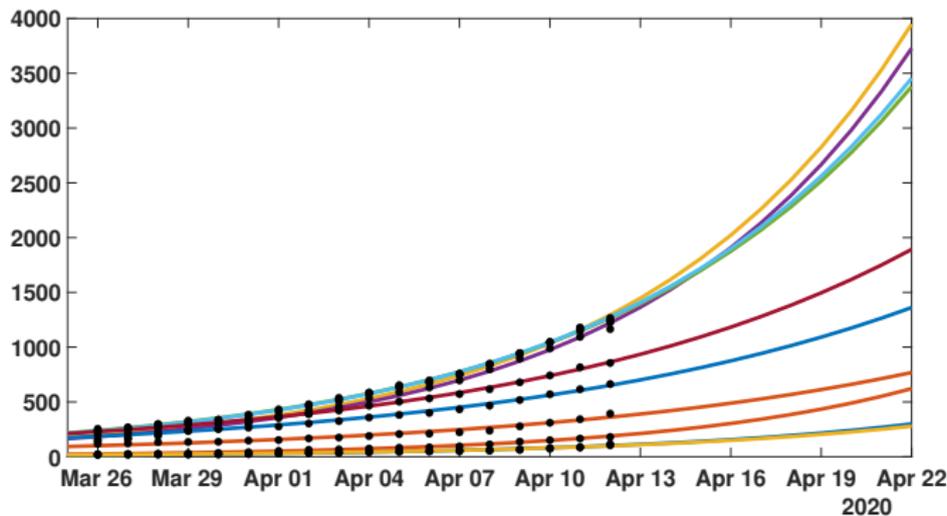
$$\lambda_0 I_0 = L I_0, \text{ with } I_0 \geq 0 \text{ and } I_0 \neq 0.$$

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<sup>27</sup>Z. Liu, P. Magal, O. Seydi, and G. Webb (2020), Understanding unreported cases in the 2019-nCov epidemic outbreak in Wuhan, China, and the importance of major public health interventions, *Biology*, **9(3)**, 50.

# Conclusions

In the figure below we use an exponential fit for age group data for Japan<sup>28</sup>. **The exponential growth depend on the age group.**



**We observe the transient behavior of a linear system with a weak coupling between compartments!**

<sup>28</sup>Q. Griette, P. Magal and O. Seydi (2020), Unreported cases for Age Dependent COVID-19 Outbreak in Japan, *Biology* 9, 132.

A detailed 3D rendering of coronavirus particles. The central focus is a single, large, spherical virus particle with a greenish-grey base and numerous white, club-shaped spike proteins protruding from its surface. It is surrounded by several other similar but smaller and more blurred virus particles. The background is a vibrant, textured red, suggesting a biological or cellular environment.

**Thank you for your attention**