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Dynamics of COVID-19: Near- and Long-Term Challenges

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Technical References:

Shield Immunity: Weitz et al., medrxiv 10.1101/2020.04.01.20049767v1)
Asymptomatic transmission: Park, Cornforth, Dushoff & Weitz, Epidemics, in press (& medrxiv 2020.03.09.20033514v1)
R0 estimation: Park et al. (in review & available on medrxiv: 2020.01.30.20019877v3)
Generation intervals: Park et al., *Epidemics* 27:12 (2019)
Epidemics and behavior change: Eksin, Paarporn and Weitz *Epidemics* 27: 96-105 (2019)
Speed-strength and identifiability problems: Weitz & Dushoff, *Scientific Reports* 5: 8751 (2015)

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- Army Research Office

Dynamics of COVID19: Near- and Long-Term Challenges

Joshua S. Weitz Professor and Director of the Interdisciplinary Ph.D. in Quantitative Biosciences in the School of Biological Sciences at Georgia Tech

bit.ly/weitz-covid-talk Wednesday, April 15, 2020 | 3-4 pm EST (Stream opens at 2:30 for connection checks) Nonlinear Science Talks | School of Physics





This work is the result of ongoing interdisciplinary collaborations:

Georgia Tech Team Collaborators Ashley Coenen Clio Andris, GT Dr. Stephen Beckett Daniel Cornforth, GT Jonathan Dushoff, McMaster Dr. David Demory Marian Dominguez-Mirazo Ceyhun Eksin, Texas A&M Dr. Joey Leung Benjamin Lopman, Emory Guanlin Li Alicia Kraal, Emory Andreea Magalie Kristen Nelson, Emory **Daniel Muratore** Sana Woo Park, Princeton Rogelio Rodriguez-Gonzalez Yorai Wardi, GT Dr. Adriana Sanz Shashwat Shivam Conan Zhao

As advertised



World Health Organization Situation Report

Source: WHO, Feb 9, 2020



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Globally 1 436 198 confirmed (82 837) 85 521 deaths (6286)

European Region 759 661 confirmed (39 442) 61 516 deaths (3877)

Region of the Americas 454 710 confirmed (37 294) 14 774 deaths (2177)

Western Pacific Region 115 852 confirmed (1185) 3944 deaths (22)

85 350 confirmed (3357) 4459 deaths (145)

South-East Asia Region 11 576 confirmed (869)

African Region 8337 confirmed (690) 349 deaths (23)

Global Level

Eastern Mediterranean Region

Very High

468 deaths (42)

2020 2020 2020 Date of report

2020

2020

2020



Situation Report

2020

2020

months later



April 14, 400K new cases and 30K new deaths in 5 days



Today's Talk

Part I – Dynamical Foundations of Epidemics strength, speed, and size

Part 2 – Dynamics and Control

how we got to where we are now

Part 3 – Long-term strategies

how we might get out, in the absence of pharmaceutical interventions

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Basic reproductive number, "R0" Equal to the average number of new infections per sick person <u>Indirectly measured</u>



Basic reproductive number, "R0" Equal to the average number of new infections per sick person <u>Indirectly measured</u>













Tentative conclusion: Many values of R0 can be compatible with the same observed rate of increase in cases – even if projected outbreak sizes are different.

SIR Model - Basics



Population "Classes"

- **S** The number of susceptible individuals
- I The number of infectious individuals

R – The number of "removed" individuals (through recovery or, possibly, death)

Mechanisms

Infection: Requiring contact between a **S** and a **I** individual at rate β .

Recovery: After a period of infectiousness of average duration $T_{\rm l}$.

SIR Model – Initial Dynamics Depend on Basic Reproductive Number, R₀

The expected number of cases, initially changes like:

$$\dot{I} = \frac{I}{T_I} \left(\mathcal{R}_0 - 1 \right)$$



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where



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The expected number of cases, initially changes like:

$$\dot{I} = \frac{I}{T_I} \left(\mathcal{R}_0 - 1 \right)$$



where



such that

- Disease spreads whenever the average number of new cases exceeds unity, i.e: $\mathcal{R}_0>1$
- The increase is exponential

Estimating, R_0 , for 2019-nCoV

| | Basic reproductive |
|---------|---------------------------------------|
| | number \mathcal{R}_0 |
| Study 1 | 1.5 - 3.5 |
| Study 2 | $2.5 (1.5 - 3.5)^*$ |
| Study 3 | 2.92 (95% CI: 2.28–3.67) |
| Study 4 | 3.8 (95% CI: 3.6–4.0) |
| Study 5 | 2.2 (90% CI: 1.4–3.8) |
| Study 6 | 5.47 (95% CI: 4.16–7.10) [‡] |
| Study 7 | 2.0-3.1 |

| Bedford et al. [4] |
|------------------------|
| Imai <i>et al.</i> [5] |
| Liu $et al.$ [6] |
| Read $et al.$ [8] |
| Riou and Althaus [10] |
| Zhao et al. [9] |
| Majumder and Mandl [7] |

Many model choices:

Branching process SEIR model (like SIR but with an asymptomatic class) Exponential growth...

Estimating, R₀, for 2019-nCoV

| | Basic reproductive number \mathcal{R}_0 | Mean generation interval \bar{G} (days) | Generation-interval dispersion κ | |
|---------|---|---|---|---------------------------|
| Study 1 | 1.5-3.5 | 10 | 1 | Bedford <i>et al.</i> [4] |
| Study 2 | $2.5 (1.5 - 3.5)^*$ | 8.4 | unspecified [†] | Imai <i>et al.</i> [5] |
| Study 3 | 2.92 (95% CI: 2.28–3.67) | 8.4 | 0.2 | Liu <i>et al.</i> [6] |
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| Study 7 | 2.0-3.1 | 6-10 | 0 | Majumder and Mandl [7] |
| | | | | |

Many model choices & latent assumptions: Branching process SEIR model (like SIR but with an asymptomatic class) Exponential growth...

The brief answer is that speed and strength are linked.

The implicit link between speed and strength



 $\rho = \bar{G}/C = r\bar{G}$

 $g(\tau)\exp(-\tau/C)d\tau$.

This link helps sort through putatively large R_0 claims (assumptions matter!)



EID Journal > Volume 26 > Early Release > Main Article > Figure 5

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ISSN: 1080-6059

Disclaimer: Early release articles are not considered as final versions. Any changes will be reflected in the online version in the month the article is officially released

Volume 26, Number 7—July 2020

Research

High Contagiousness and Rapid Spread of Severe Acute Respiratory Syndrome Coronavirus 2

Steven Sanche¹, Yen Ting Lin¹, Chonggang Xu, Ethan Romero-Severson, Nick Hengartner, and Ruian Ke® Author affiliations: Los Alamos National Laboratory. Los Alamos New Mexico LISA



EDITORS' PICK | 107,243 views | Apr 7, 2020, 05:34pm EDT

The COVID-19 Coronavirus Disease May Be Twice As Contagious As We Thought

Pooled estimates via a speedstrength relationship (technically using generation intervals)

Sang Woo Park

Jonathan Dushoff





Step I: estimate latent uncertainty in 'parameters'.

Step 2: incorporate different types of uncertainty into R0 estimates by study or as part of a 'pooled' estimate (using a Bayesian multi-level model)

$$\mathcal{R}_0 = \left(1 + \kappa r \bar{G}\right)^{1/\epsilon}$$



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Conditions for epidemic growth



Where infections per time, β , is a product of:

- Contacts by infectious individuals per unit time
- Probability of contact with a susceptible (S_0/N)
- Probability that the contact transmits the disease

Conditions for epidemic growth also suggest opportunities for **control**



Where infections per time, β , is a product of:

- Contacts by infectious individuals per unit time
 Conta
- Probability of contact with a susceptible (S_0/N)

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Contact tracing & targeted isolation
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Quarantine, travel control, closures

• Probability that the contact transmits the disease

Process engineering & PPE (masks)

The Imperial Model Forecast – The Scale of the Problem



(B)

Cases per 100,000 populations

The unmitigated problem. This goes back to strength-size.

A strength of R0~2.4 implies ~80% infected (in a 'mean-field' scenario).

Population of 330M \times 80% \times ~0.8% IFR ~ 2M+ fatalities.



The reality of the Ebola outbreak is not reflected by model projections of high case numbers.

EPIDEMIOLOGY

Models overestimate Ebola cases

Rate of infection in Liberia seems to plateau, raising questions over the usefulness of models in an outbreak.

0.0

18 | NATURE | VOL 515 | 6 NOVEMBER 2014



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0.0

18 | NATURE | VOL 515 | 6 NOVEMBER 2014



Model Purpose: to explain the need, scope, and potential outcome of **interventions**.

Different measures both reduce and 'flatten' the curve (i.e., reducing total burden)

The Atlantic

TECHNOLOGY Don't Believe the COVID-19 Models That's not what they're for.

ZEYNEP TUFEKCI APRIL 2, 2020

The Atlantic

TECHNOLOGY Don't Believe the COVID-19 Models That's not what they're for.

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What Evidence Is There on the Impact of Interventions?

Measures of Impact of Interventions Scarpino and colleagues (Science 3/25/20)



Cordon sanitaire' lead to rapid drop in 2. Human mobility, spread and synchrony of COVID-19 outbreak in China. (a) Human mobility data extracted in real time from Baidu. Travel restrictions from Wuhan and large scale control measures started on January. 23,2020. Dark and red lines represent fluxes of human movements for 2019 and 2020, respectively. (b) Relative movements from Wuhan to other provinces in China. (c) Timeline of the correlation between daily incidence in Wuhan and incidence in all other provinces, Bets net by community disans, mission is the dominant factor.

M. U. G. Kraemer et al., Science 10.1126/science.abb4218 (2020).

Measures of Impact of Interventions Imperial College London Report, 3/30/20





"[E]stimate that interventions across all 11 countries will have averted 59,000 deaths up to 31 March [95% credible interval 21,000-120,000].

Many more deaths will be averted through ensuring that interventions remain in place until transmission drops to low levels."

Flaxman et al.

Measures of Impact of Interventions (4/12/20)INSERM – IIe De France (Vittoria Colizza & team)



Take-away:

Lockdown interventions have rapidly shifted the curve from perilous exponential-like growth to severe (2-5% infected).

Di Domenico et al. (EPICX Lab, V. Colizza)

But there are still deep uncertainties which make COVID-19 hard to predict and control



Asymptomatic cases may be a significant driver of transmission (and bias estimates of RO and control)

Renewal equation formalism

$$\dot{S} = -i(t)$$

$$i(t) = \mathcal{R}_a S(t) \int_0^\infty i_a(t-\tau) g_a(\tau) d\tau + \mathcal{R}_s S(t) \int_0^\infty i_s(t-\tau) g_s(\tau) d\tau.$$

and assuming exponential growth with an observed rate *r* yields:

$$\frac{1}{\mathcal{R}_0} = \int \exp(-r\tau)g(\tau)\mathrm{d}\tau.$$

Speed *r* : measured Generation interval : assumed (and informed by clinical data)

Leads to an estimate of:

Strength R_0

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Epidemics (in press) – w/SW Park, D. Cornforth & J. Dushoff

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Speed *r* : measured Generation interval : assumed (and informed by clinical data)

Leads to an estimate of:

Strength R_0



Asymptomatic transmission is a double-edged sword:

(i) Many more cases(ii) Cases are not as bad

Measures of Impact of Interventions Georgia – Weitz Group Modeling

COVID-19 model w/asymptomatic transmission



and GA age demographics along with age-stratified risk (via Imperial estimates).

Measures of Impact of Interventions Georgia – Weitz Group Modeling

COVID-19 model w/asymptomatic transmission

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Measures of Impact of Interventions Georgia – Weitz Group Modeling

COVID-19 model w/asymptomatic transmission



Key Points:

Reported deaths and hospitalizations show effect of large-scale orders (averting far worse outcomes)

Case ascertainment rate may be 1/10 to 1/30 suggesting prevalence ~1%-4% in Georgia vs. 'reported' prevalence of 0.1%.





Does "My" Country Have an Epidemic? Hint: Yes. (Lauren Meyers et al., UT-Austin)

Does My County Have an Epidemic? Estimates Show Hidden Transmission

By James Glanz, Matthew Bloch and Anjali Singhvi April 3, 2020



By The New York Times - Source: Emily Javan, Spencer Fox and Lauren Ancel Meyers, the University of Texas at Austin

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Imperial: Long-Term Prospects in the Absence of a Vaccine



Current "Zero-Sum" Dichotomy: Infection Control or Economic Engagement

"Was the Dow to die for today, or what?!"

Are Countries Flattening the Curve for the Coronavirus?

Jobless Claims Hit 3.3 Million in the Last Report. This Week's Will Probably Be Worse.

TheUpshot

By Quoctrung Bui April 1, 2020

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| 20 | 06 2 | 2008 | 2010 | 2012 | 2014 | 2016 | 2018 | 2020 |

The Perils of 'Exit' Scenarios and Forecasting (IHME Model via U of Washington)

On March 28 – Predicted April 15th as Peak w/~2000 deaths per day

IHME Model Chris Murray

The Perils of 'Exit' Scenarios and Forecasting (IHME Model via **U** of Washington)

But now, the tail extends and there is no uncertainty after June 1 (!!)

IHME Model Chris Murray

6k 5k

Deaths per day 4

> Deaths per day === Deaths per day (projected) All deaths specific to COVID-19 patients. Shaded area indicates uncertainty ①

Date

The Perils of 'Exit' Scenarios and Forecasting (IHME Model via U of Washington)

But now, the tail extends and there is no uncertainty after June 1 (!!)

2. Functional Form for Covid-19

We considered several functional forms to model the death rate of the Covid-19 virus. Based both currently available data, the log rate starts slowly, increases quickly, and then flattens c again as either social distancing or saturation goes into effect. This is the classic sigmoid shap We first tried building the analysis using the sigmoidal function

Figure 1. Expit function \widetilde{D} (left) and ERF function D (right). The ERF function fits the available Covid-19 data better than Expit.

$$\widetilde{D}(t; lpha, eta, p) = rac{p}{1 + \exp(-lpha(t - eta))}$$

where p controls the level, β the shift, and α the growth. We quickly discovered that the ERF error function provided a better fit to the data:

$$D(t;\alpha,\beta,p) = \frac{p}{2} \left(\Psi(\alpha(t-\beta)) = \frac{p}{2} \left(1 + \frac{2}{\sqrt{\pi}} \int_0^{\alpha(t-\beta)} \exp\left(-\tau^2\right) d\tau \right)$$

Buyer beware:

A curve fitting model based on an 'ERF' function should be used only for short-term predictions and its utility has already passed the expiration date.

Hint: the future is not that certain.

Thoughtful Exit Scenarios and Forecasting (INSERM/EPICX Lab)

| | _ | У. |
|--------|----------|----|
| \sim | | - |

| | March | April | May | June | July | Aug | Sept | Oct | Nov | Dec | Jan | Feb |
|--------------|--------|----------------------|-------------|--------------|--------------|---------|---------|---------|---------|---------|---------|---------|
| LD(Apr) | | | | | | | | | | | | |
| LD(May) | | | | | | | | | | | | |
| LD(June) | | | | | | | | | | | | |
| LD(Apr)+Str | rict | Strict interventions | | | | | | | | | | |
| LD(Apr)+Mo | bd | | Moderate i | nterventions | | | | | | | | |
| LD(Apr)+Mi | ild | | Mild interv | entions | | | | | | | | |
| LD(Apr)+SC | C,SI | | School clos | ure and seni | or isolation | | | | | | | |
| Exit 1 | | | +50% Cl | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI |
| Exit 2 | | | +25% Cl | +25% CI | +25% Cl | +25% CI | +25% CI | +25% CI | +25% CI | +25% Cl | +25% CI | +25% Cl |
| Exit 3 | | | +75% CI | +75% Cl | +75% CI | +75% Cl | +75% Cl | +75% Cl | +75% CI | +75% Cl | +75% Cl | +75% CI |
| Exit 4 | | | +75% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI |
| Exit 1 (1m a | after) | | | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI |
| Exit 2 (1m a | after) | | | +25% CI | +25% Cl | +25% CI | +25% CI | +25% CI | +25% CI | +25% Cl | +25% CI | +25% Cl |
| Exit 3 (1m a | after) | | | +75% Cl | +75% Cl | +75% Cl | +75% Cl | +75% CI | +75% CI | +75% CI | +75% Cl | +75% CI |
| Exit 4 (1m a | after) | | | +75% Cl | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI | +50% CI |

Figure 3. Scenarios (color code as in Table 1; Cl refers to case isolation).

Take-away:

Sustained infection control is needed for $\sim I$ year to prevent large-scale waves of new cases.

Testing and Tracing as a Means of Prevention not just Pathology

The Bulk of Interventions Focus on Reducing New Transmission by Closures and/or Tracing

but what about all those who have already been sick and recovered...

could these infections (far from herd immunity) help reduce collective risk?

Our 'Shield Immunity' Proposal: Large-Scale Serological Testing to Reduce Transmission and Enable Economic Development

Weitz et al., medrxiv (in press, to be announced soon)

What is 'Shield Immunity'?

What is 'Shield Immunity'?

What is 'Shield Immunity'?

Take-away: the <u>scale</u> and <u>type</u> of testing matters

PCR provides a snapshot, i.e., 'are you shedding virus now'?

Recovered

Infectious

Serological testing for antibodies provides a history, i.e., 'have you been infected recently or in the past'? Recovered implies immune (duration still unknown).

Shield Immunity Dynamics

SIR model w/shielding

Recovered individuals have preferential interactions relative to other individuals.

This dilutes the susceptible fraction at levels well below the herd immunity threshold.

$$\dot{S} = -\beta \frac{SI}{1 + \alpha R}$$
$$\dot{I} = \beta \frac{SI}{1 + \alpha R} - \gamma I$$
$$\dot{R} = \gamma I$$

What could we do if we could identify recovered individuals?

Recovered individuals could elevate their interactions relative to other individuals – we call this 'shield strength'.

Combining (less intense) social distancing and shielding could have significant population-wide benefits.

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Closing Thoughts

Part I – Dynamical Foundations of Epidemics

COVID-19 has epidemiological features of high R0, relatively fast spread, elevated fatality rates, and asymptomatic transmission that increase its epidemic potential.

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Part 2 – Dynamics and Control

Interventions have made an enormous impact (averting tens/hundreds of thousands of fatalities). But, even if a peak has been averted, we remain immunologically naive.

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Part 2 – Dynamics and Control

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Part 3 – Long-term strategies

Testing (PCR and serology) & contact tracing are needed at scale! Strategic and coordinated responses – we have a long road ahead, we'll be better off working collectively.

Georgia Tech Sciences

Georgia Tech Team Ashley Coenen Dr. Stephen Beckett Dr. David Demory Marian Dominguez-Mirazo Dr. Joey Leung Guanlin Li Andreea Magalie **Daniel Muratore** Rogelio Rodriguez-Gonzalez Yorai Wardi, GT Dr. Adriana Sanz Shashwat Shivam Conan Zhao

Collaborators Clio Andris, GT Daniel Cornforth, GT Jonathan Dushoff, McMaster Ceyhun Eksin, Texas A&M Benjamin Lopman, Emory Alicia Kraal, Emory Kristen Nelson, Emory Sang Woo Park, Princeton

Code:

https://github.com/WeitzGroup/covid shield immunity

Preprint (now in press, to be announced soon) https://www.medrxiv.org/content/10.1101/2020.04.01.20049767v1

Tweet thread:

https://twitter.com/joshuasweitz/status/1245071163744645121?s=20

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