# Maths vs. COVID-19

Julia Gog

27th May 2021

# 1. Introductions

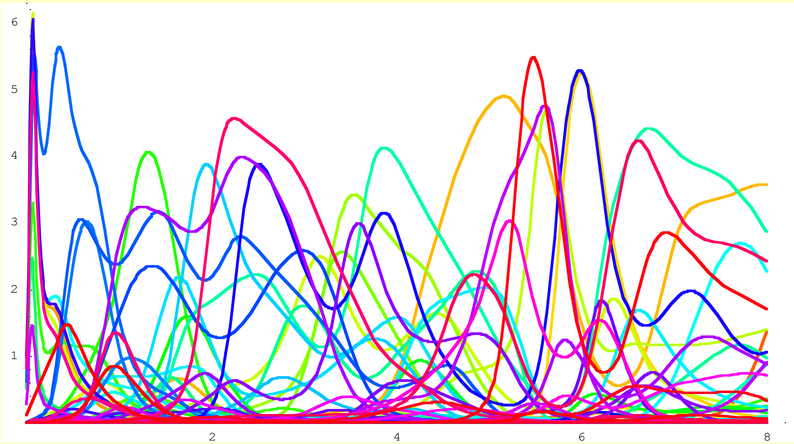
- Me
- Research interests BC (before COVID-19)
- Then COVID-19 happened

My “normal” jobs:
Professor of Mathematical Biology, DAMTP, University of Cambridge
David N. Moore Fellow in Mathematics, Queens’ College, Cambridge

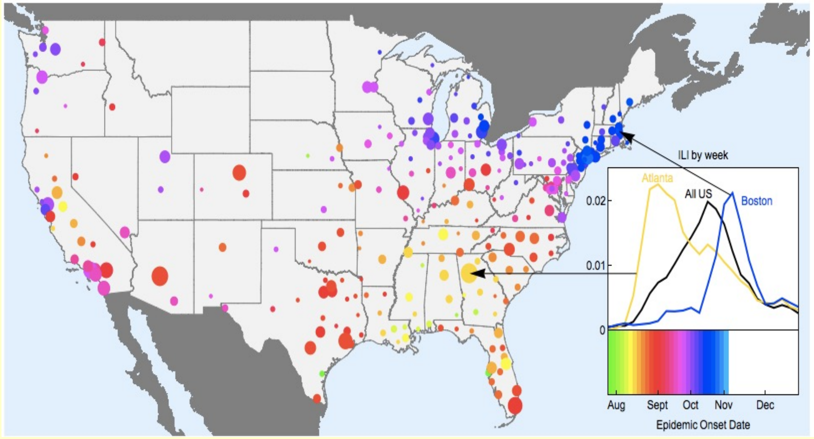
Centre for Mathematical Sciences, University of Cambridge

Queens’ College, Cambridge

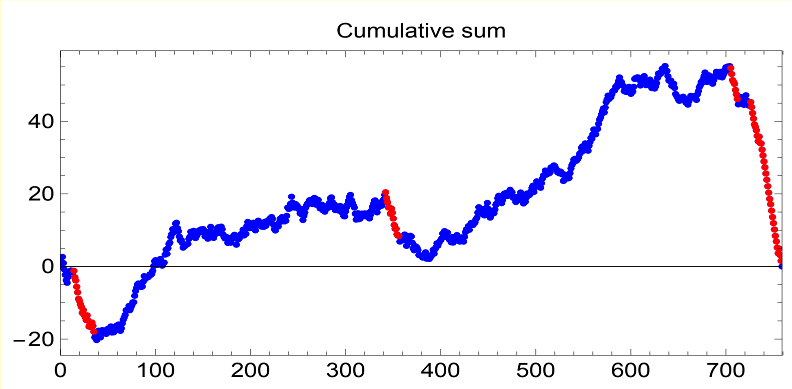
# BC (before COVID-19) – My research areas



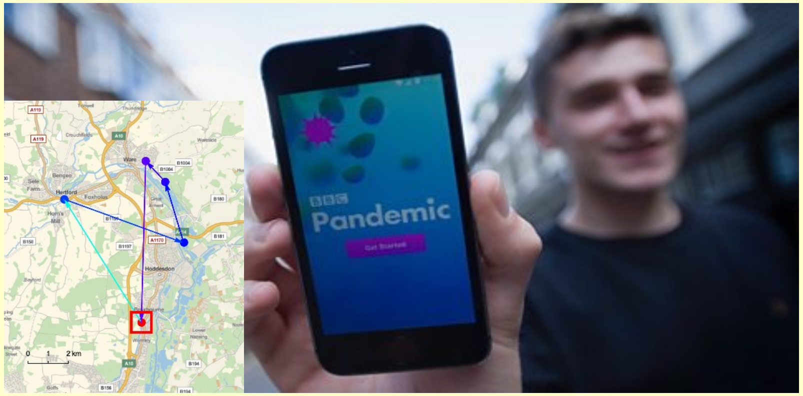

**Multiple cocirculating strains**
models for evolving viruses




**Patterns of spatial transmission**
Influenza pandemic 2009 in the US

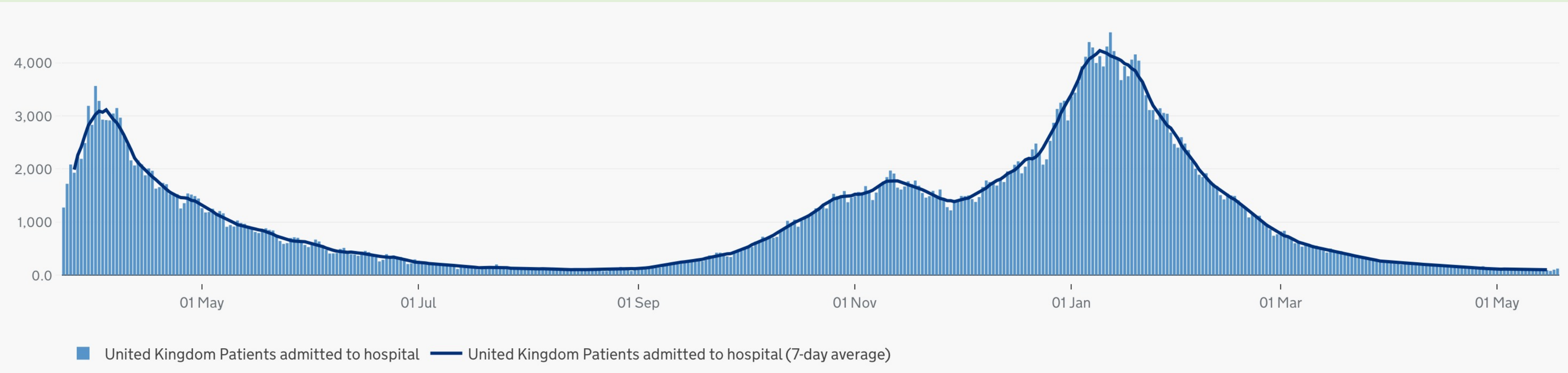



**Signals -** virus bioinformatics

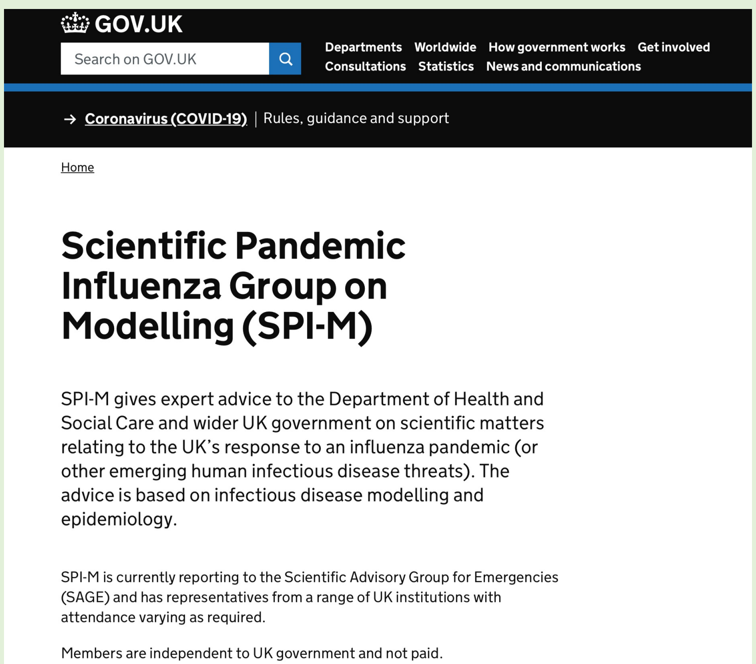


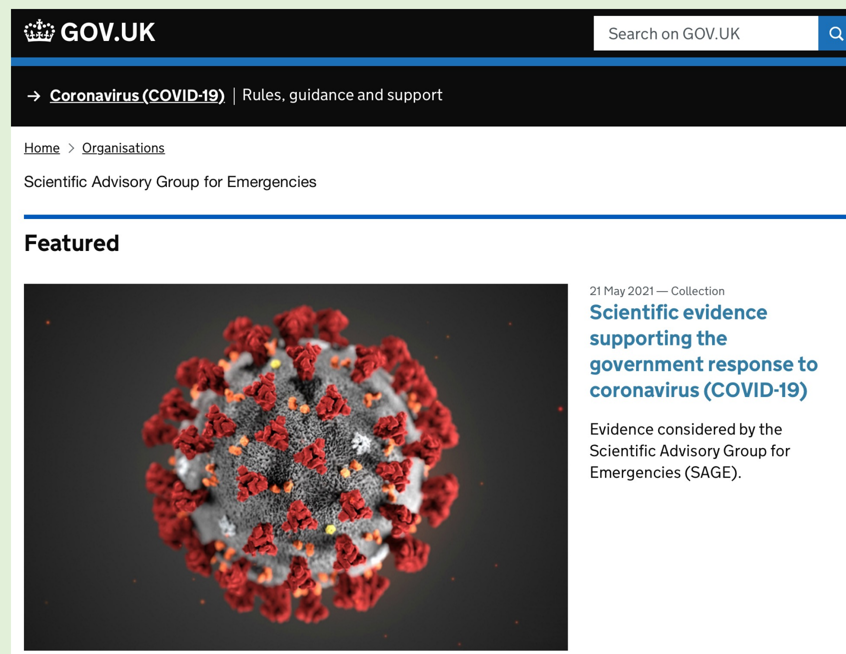

**Contagion! – the BBC pandemic**
Citizen science on UK mixing and movement

**Broadly, using mathematics to understand infectious disease dynamics**




COVID-19 patents admitted to hospital UK by day
Source: UK Government Coronavirus Dashboard



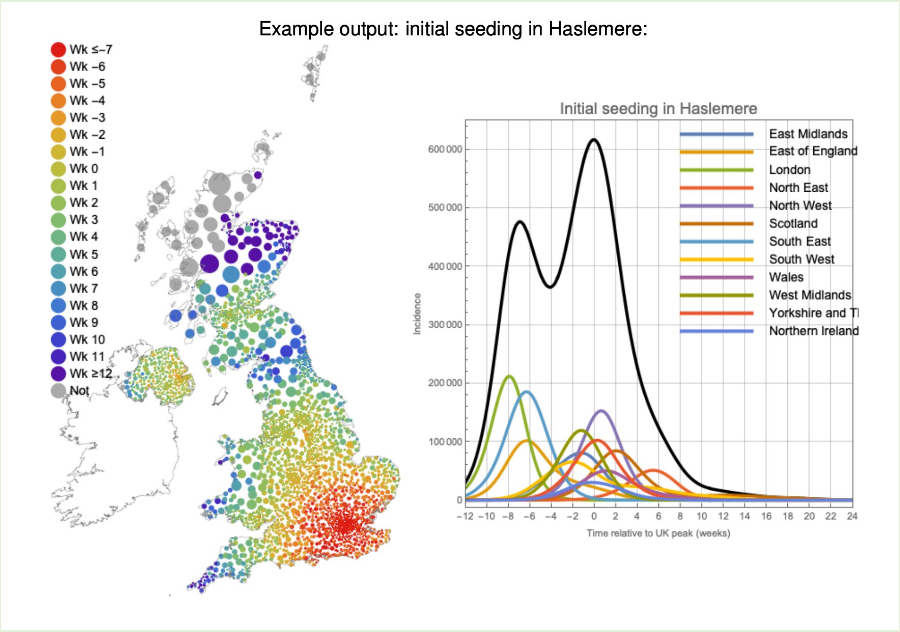
## 2. Maths of epidemics… applied to COVID-19

- Roles of modelling
- What we can learn from classic results
- Building insight and intuition

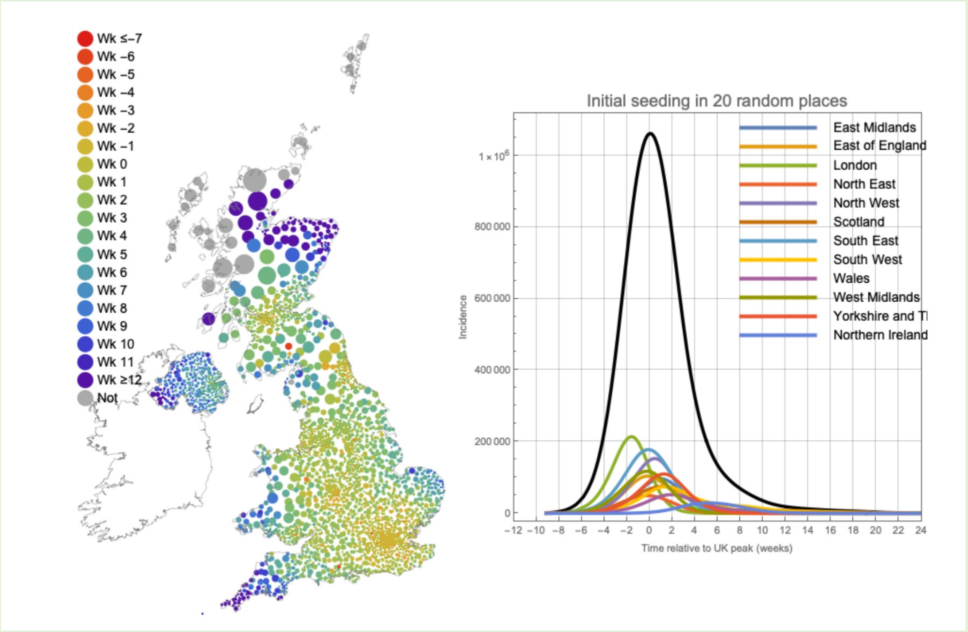
# Roles of modelling for fighting COVID-19

- Specific predictions (forecasting)
- Exploratory scenarios ("what if we do this intervention?")
- Understanding drivers behind observed patterns (see below)
- Building intuition and useful language (see next 2 slides)

With few introductions, expect heterogeneity in timing:
Epidemic upswing in some regions weeks before others




With many introductions, expect synchrony and spikier:
Trajectory similar in different regions, only 1-2 week lags



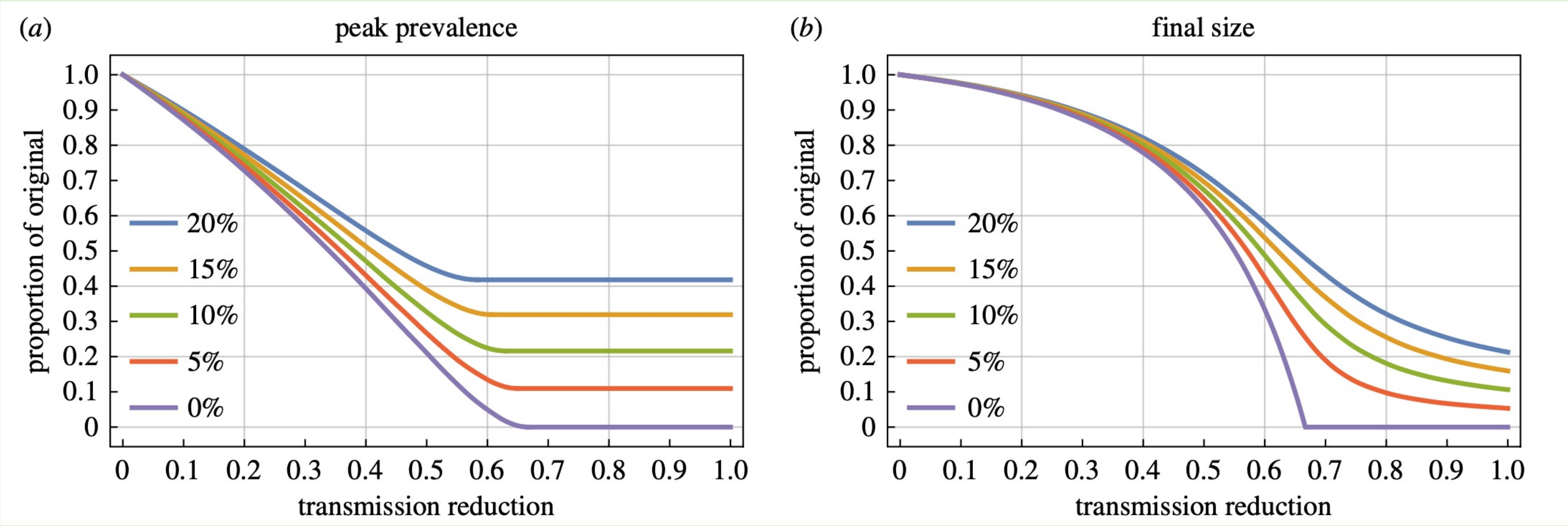

(Observed patterns emerging at the time were consistent with many introductions.)

(Extract from report presented to SPI-M 2nd March 2020, using insights from the spatial model for the UK calibrated by the BBC pandemic project, adapted for COVID-19)

# Classic SIR results – valuable for building robust insight

What happens when we intervene to reduce transmission (e.g. a lockdown)? Depends on strength of transmission reduction, when the intervention is applied.

Maximum cases (relative to unmitigated epidemic) | Total number of cases in whole epidemic




Coloured lines give different trigger values for application of intervention (after X% have been infected), and assume intervention continues to end of epidemic. Horizontal axis gives strength of intervention (0 stops all transmission, 1 does nothing). Vertical axis is (left) peak prevalence or (right) final size relative to an unmitigated epidemic. R=3 for this plot.

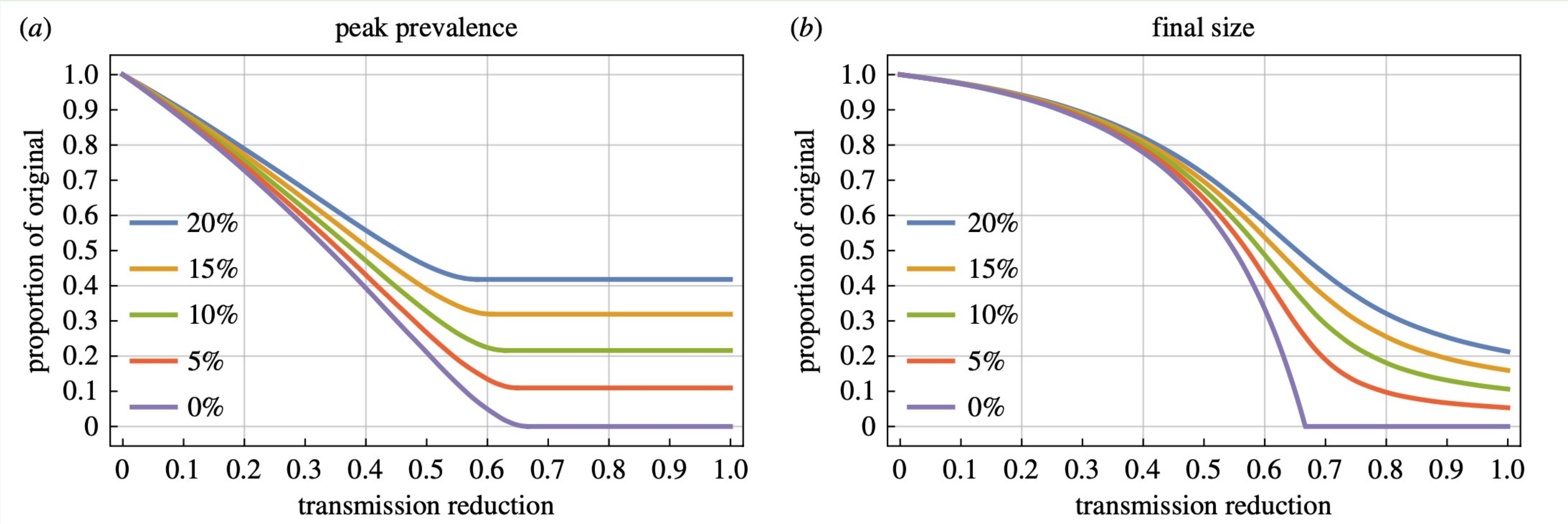
Crux of the maths: SIR has a constant of motion.

$$\dot{S} = -rSI$$
$$\dot{I} = +rSI - I,$$

$$F(S, I) = S + I - r^{-1} \log S.$$

Some of the things we can see from this:

- Need intervention early and strong
- If intervention weak: can bring down peak more than total size (c.f. "*flatten the curve*")
- If intervention strong: even more important to apply early




Paper to SAGE, 24/2/2020:
https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/891872/S0021_SAGE10_Transmission-reducing_Interventions_SIMPLE_MODELS.pdf

This simple approach should not replace models including more details, but if predictions from more complex models deviate substantially from those shown here, the factors behind that difference should be identified.

Written up here with more discussion on use in this context:
Gog & Hollingsworth, 2021 Epidemic interventions: insights from classic results. Phil. Trans. R. Soc. B
https://doi.org/10.1098/rstb.2020.0263

## Not always true that more elaborate models are better.

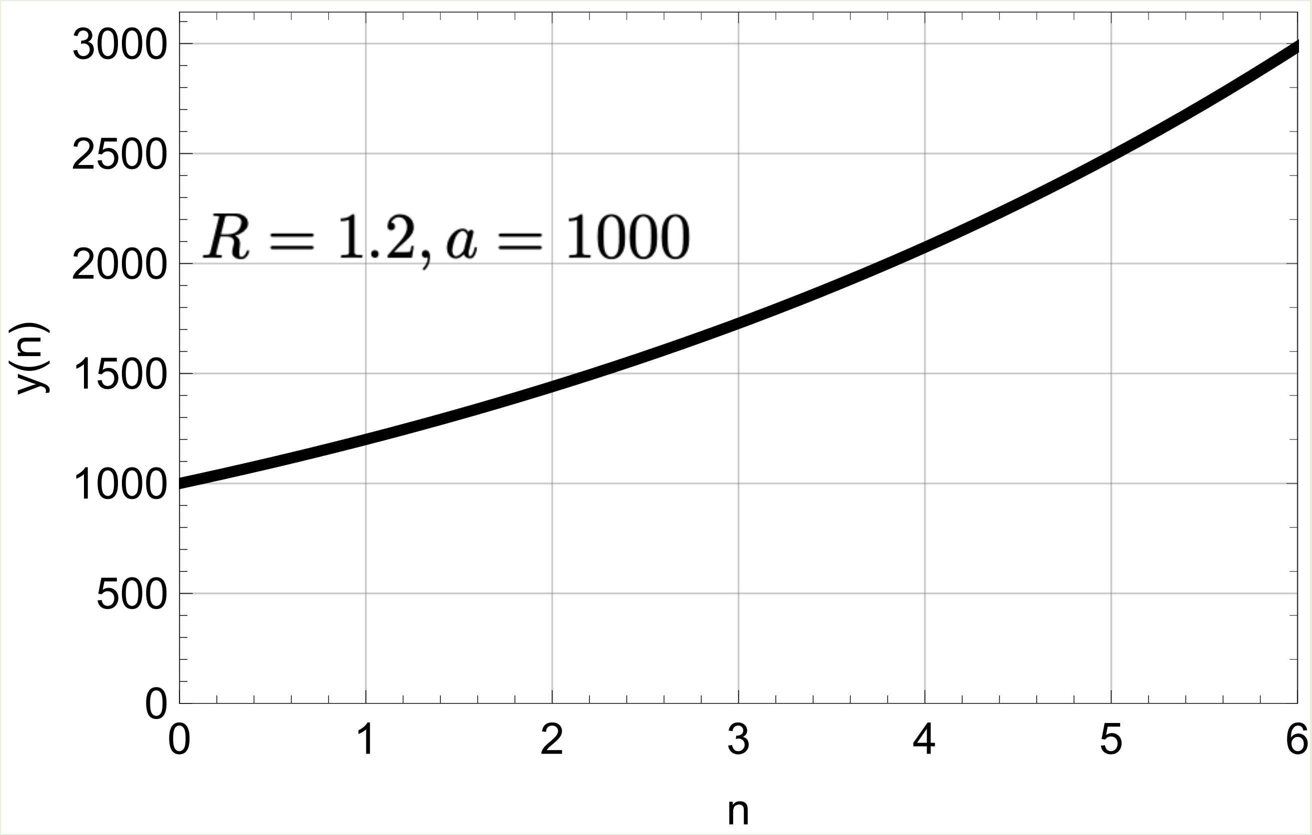
For yielding insights and building intuition, simple is good:

$$y(n) = aR^n$$

Most famous parameter of 2020

Cases after *n* infection generations

Multiplicative constant

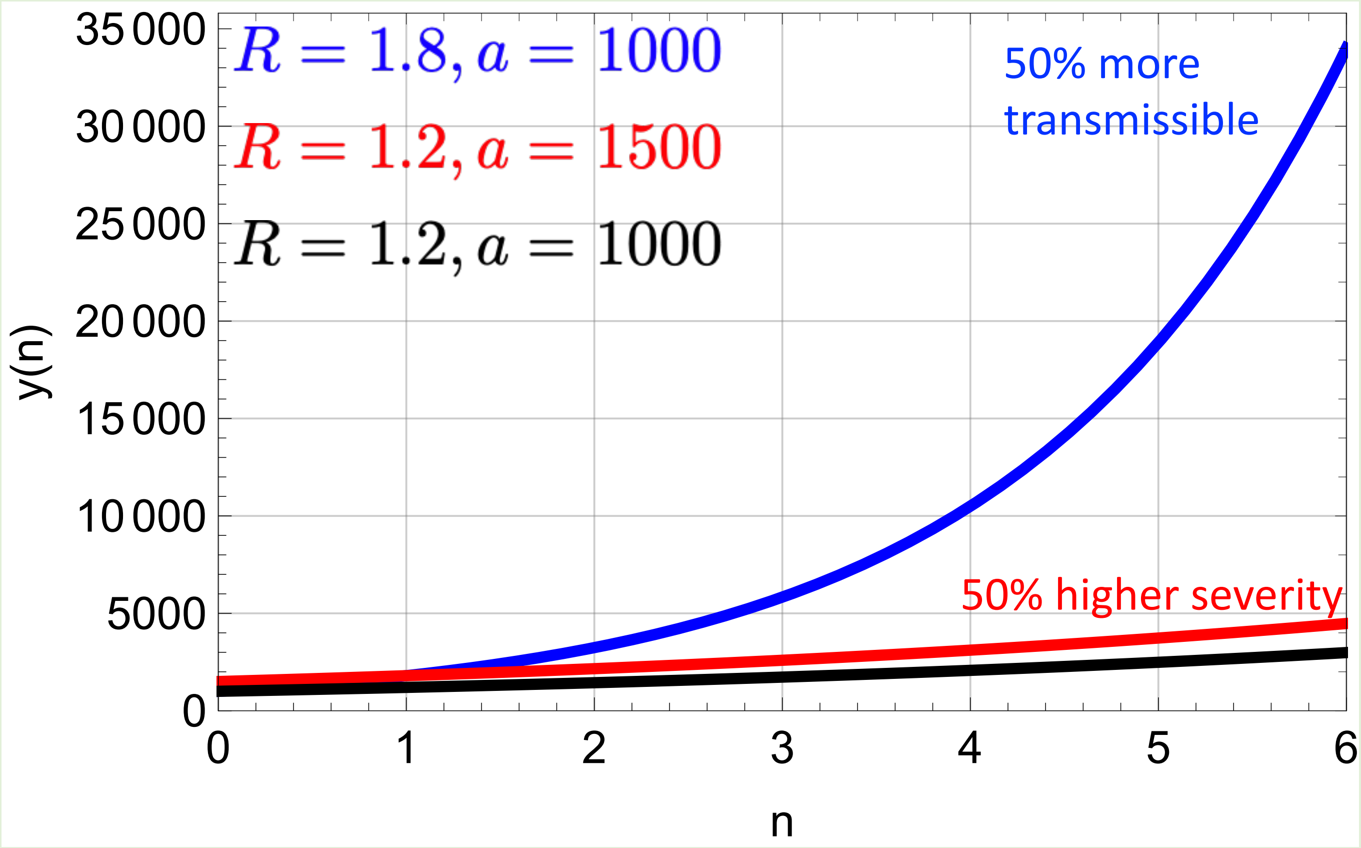


Suppose this represents hospitalisations.
What happens if the parameters change?

$$y(n) = aR^n$$

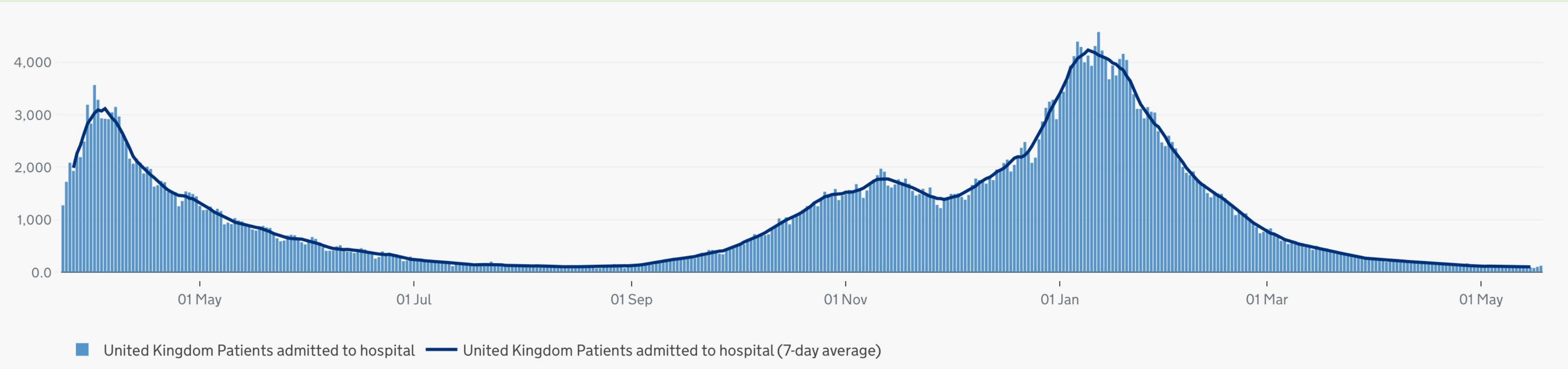
In red:
boost ***a*** **by 50%**

**In blue:**
**boost *R* by 50%**

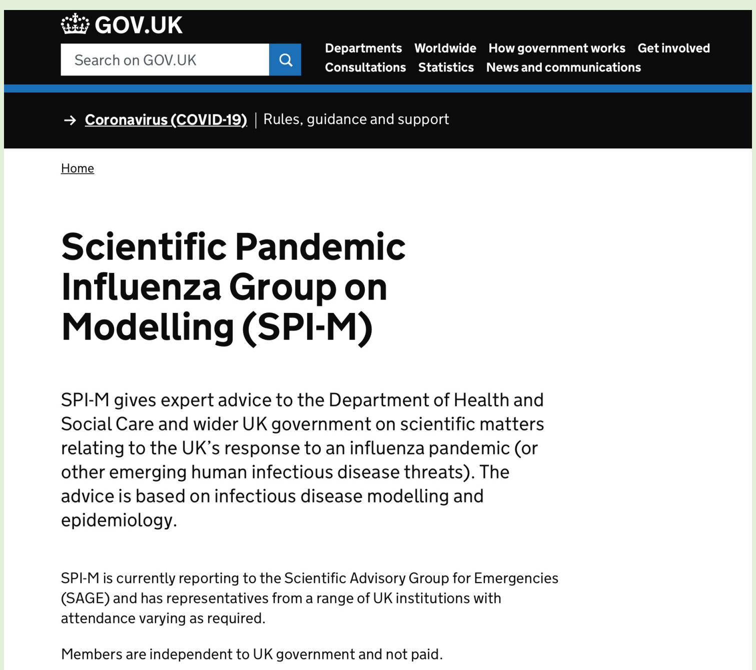


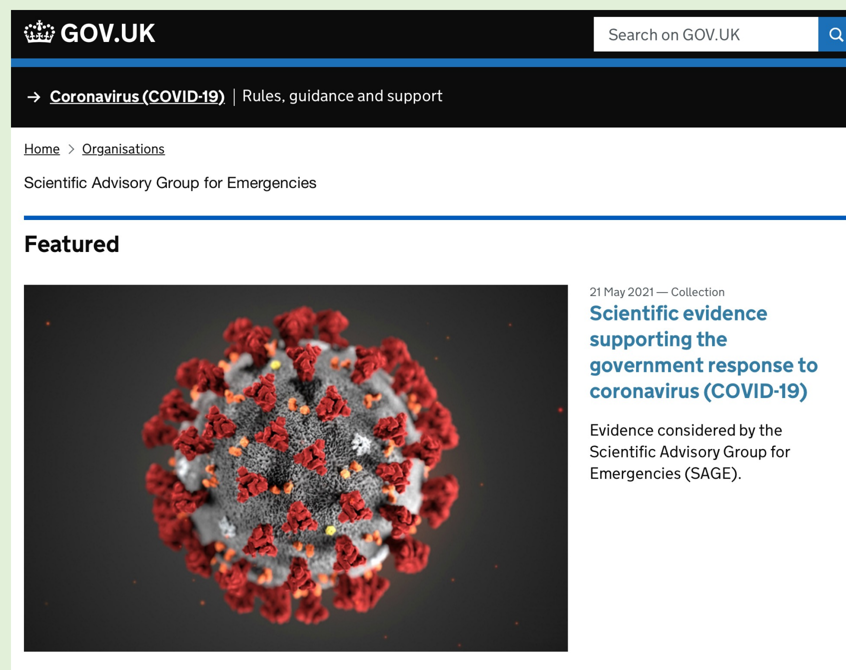
## 3. The scientific response to modelling COVID-19

- Modellers are go!
- JUNIPER and friends
- Some of the topics we have been addressing




COVID-19 patents admitted to hospital UK by day
Source: UK Government Coronavirus Dashboard



# A call to wider maths and physics research community

**Amplify signal, not noise**
(e.g. reviews, sharing key papers to colleagues)

**Communicate to public**
(dispel misinformation, comment on what models can and can't do)

**Contribute to research**
(join up with larger efforts, start from state of the art)

## How you can help with COVID-19 modelling

*Julia R. Gog*

Many physicists want to use their mathematical modelling skills to study the COVID-19
Julia Gog, a mathematical epidemiologist, explains some ways to contribute.

Credit: Marisa Crimlis-Brown

While the COVID-19 pandemic continues its global devastation, the instinctive reaction from scientists is "how can we help?" I will try to answer this in general terms for colleagues with expertise in mathematics and modelling, but who may have little or no prior experience with infectious disease modelling.

Clearly, the set of things that would not help includes rediscovering results that disease modellers have known for decades — or for more than a century in the case of some things circulating now as if they are new ideas. Nor would it help to send your first attempts at running the classic susceptible–infectious–recovered (SIR) epidemic model to your local epidemiologist, who already has an e-mail folder full of 'my_first_epidemic.xls' from well-meaning friends and also a small outbreak of plots from correspondents who have just discovered the log-scale option. But, then, the question is how to usefully contribute. Here are some immediate options.

**Signal to noise**
Rather than adding noise, amplify the signal. The num-

**Communicating to the public**
The world wants to know what the science
decisions, but there is great danger of mis
when media interest is amplifying the voices
but not necessarily those most qualified
You can learn the mathematical and scientif
the broader literature, including some gre
(Real-time papers are aimed at colleagues w
literature already; reading only these will n
to get you up to speed.) If you have ener
share what you learn with people aroun
the wider public, if you have that gift. Com
ideas behind the models, the dynamics o
the explorations of control measures and t
of synthesizing data in real time. The ma
literate community can identify and expl
gers of overly simplistic readings of the r
example, early in the epidemic many websit
outlets reported the infection fatality rati
the current number of deaths by the curre
confirmed cases, even though it is known

Nat. Rev. Phys., written March 2020.
Editor: Zoe Budrikis
https://doi.org/10.1038/s42254-020-0175-7

**Then RAMP!**
**(Rapid Assistance in Modelling the Pandemic – a scheme convened by the Royal Society)**

JUNIPER

# Joint UNIversities Pandemic and Epidemiological Research

**JUNIPER was created informally mid-2020, funded by UKRI from November 2020, brings together researchers from several universities**

**Principal Investigators**
Professor Matt Keeling, University of Warwick
Professor Julia Gog, University of Cambridge

**Senior Scientific Programme Manager**
Dr Ciara Dangerfield, University of Cambridge

**Co-Investigators**
Dr Ellen Brooks-Pollock, University of Bristol
Dr Hannah Christensen, University of Bristol
Dr Leon Danon, University of Bristol
Professor Daniela De Angelis, University of Cambridge
Dr Louise Dyson, University of Warwick
Dr Ian Hall, University of Manchester
Professor Deirdre Hollingsworth, University of Oxford
Dr Thomas House, University of Manchester
Dr Christopher Jewell, Lancaster University
Dr Petra Klepac, University of Cambridge & LSHTM
Dr TJ McKinley, University of Exeter
Dr Lorenzo Pellis, University of Manchester
Dr Jonathan Read, Lancaster University
Dr Michael Tildesley, University of Warwick

**Scientific Writers** (Plus Magazine & Millennium Maths Project)
Rachel Thomas, University of Cambridge
Dr Marianne Freiberger, University of Cambridge

+MANY more

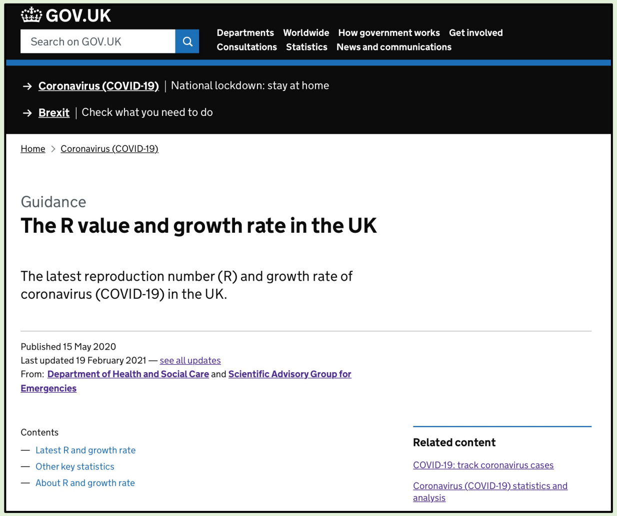
maths.org/juniper
Twitter: @JuniperConsort1

Isaac Newton Institute for Mathematical Sciences

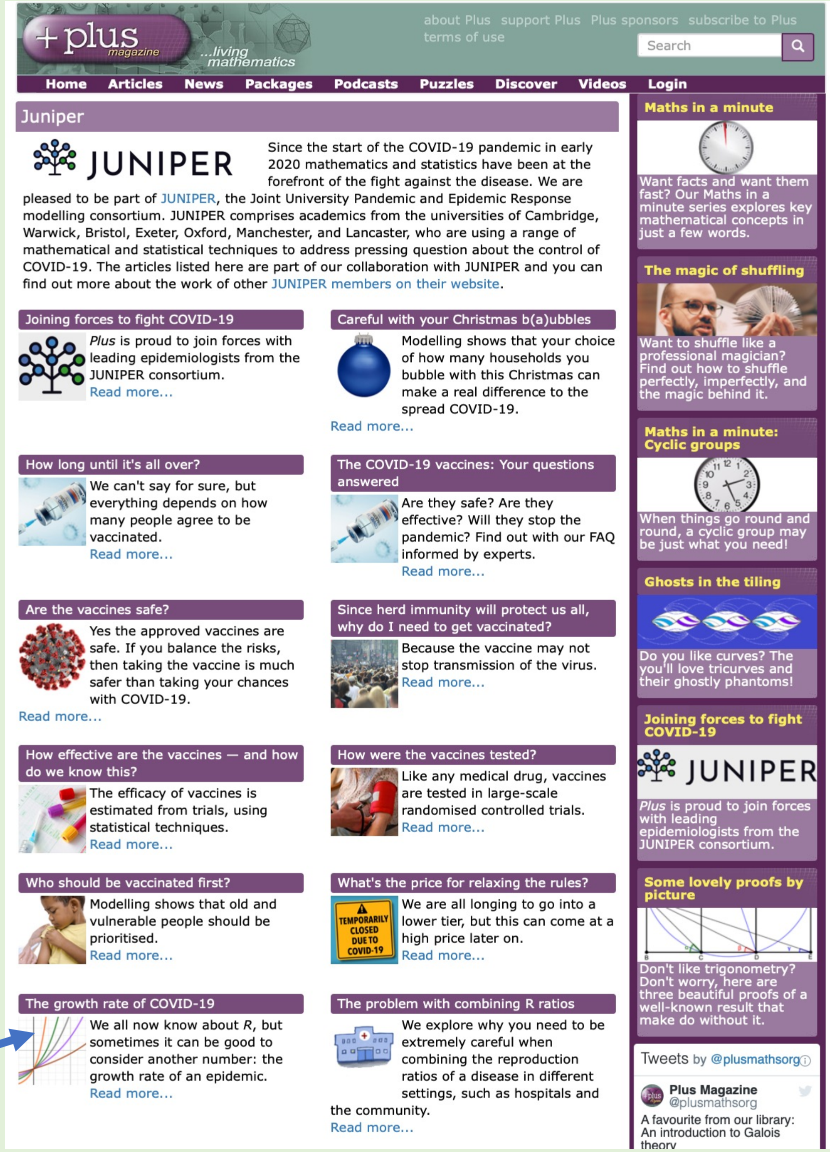
# Science communication

**Marianne Freiberger and Rachel Thomas**
Editors, Plus magazine, Millennium mathematics project

JUNIPER has in-house science writing expertise with direct interaction with researchers, and rapid and wide dissemination through plus magazine http://plus.maths.org/

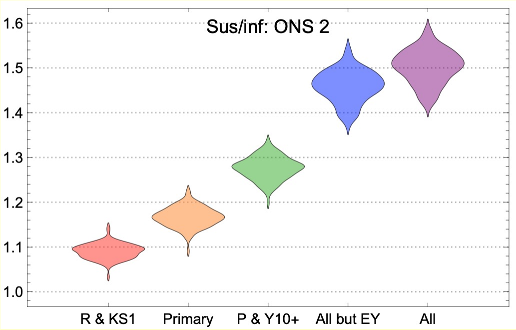



For broad audience – school students, public, media and also 'explainers' e.g. as cited on gov.uk every week with R and growth rates.

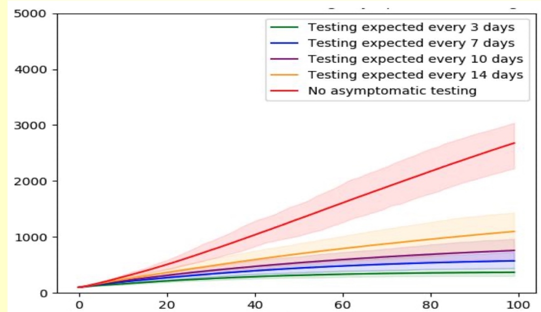



Likewise, a growth rate of -4% indicates the epidemic is shrinking faster than a growth rate of -1%. Further technical information on growth rate can be found on Plus magazine.

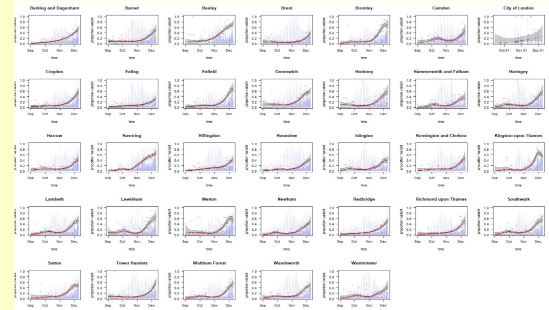
http://plus.maths.org/




Schools




Higher Education



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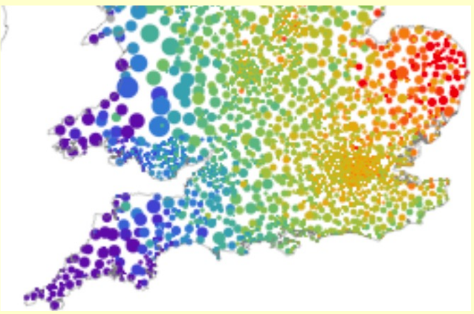
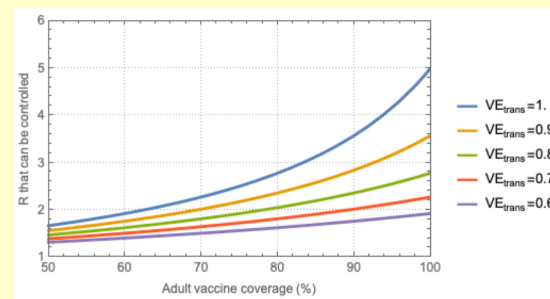
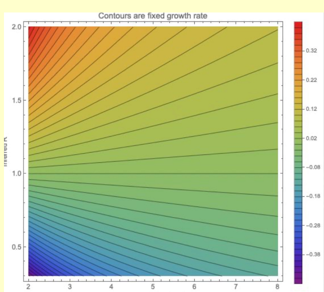


Spatial patterns

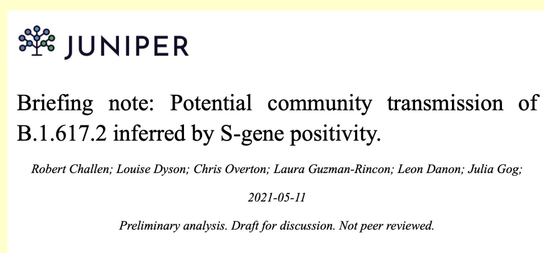
Some of the topics
I've been involved in
(as one researcher among many)




NPI options




Understanding R biases


JUNIPER

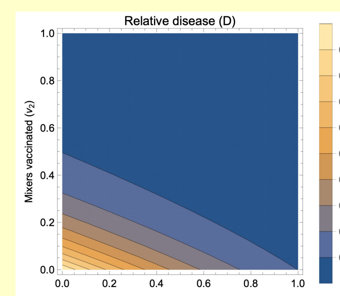
Briefing note: Potential community transmission of B.1.617.2 inferred by S-gene positivity.

*Robert Challen; Louise Dyson; Chris Overton; Laura Guzman-Rincon; Leon Danon; Julia Gog;*

*2021-05-11*

*Preliminary analysis. Draft for discussion. Not peer reviewed.*

B.1.617.2

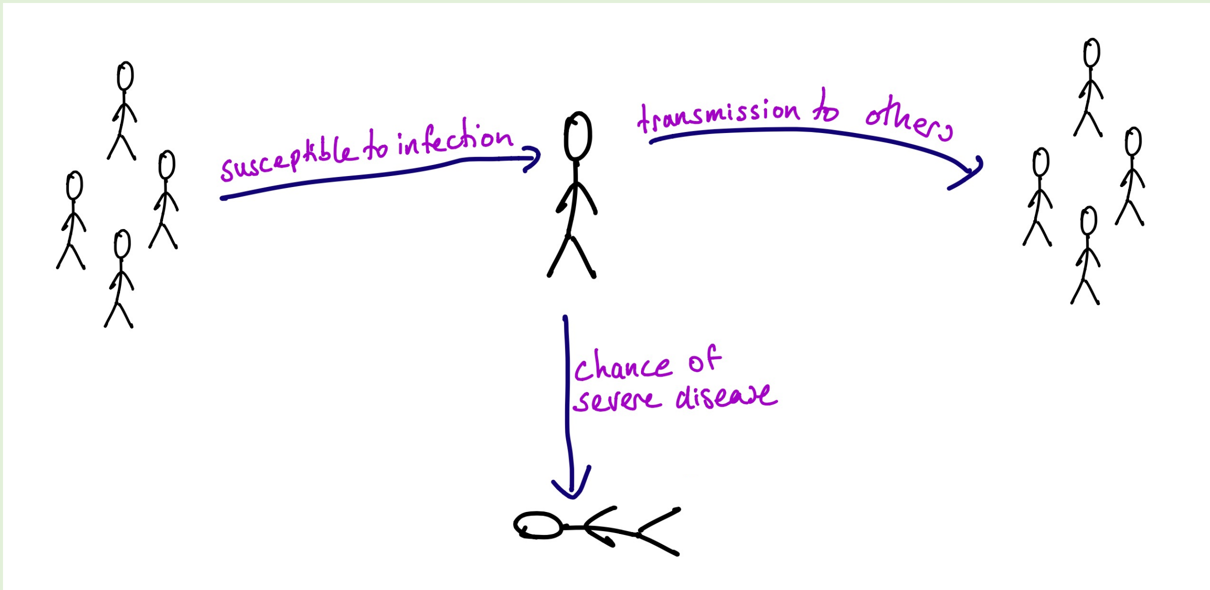



Vaccination

## 4. Some very live research themes

- The effects of vaccination
- Who to target with vaccination?

# Capturing the effect of vaccination




Vaccine, three effects, ($\theta_{\cdot}=1$ in each case is no effect)

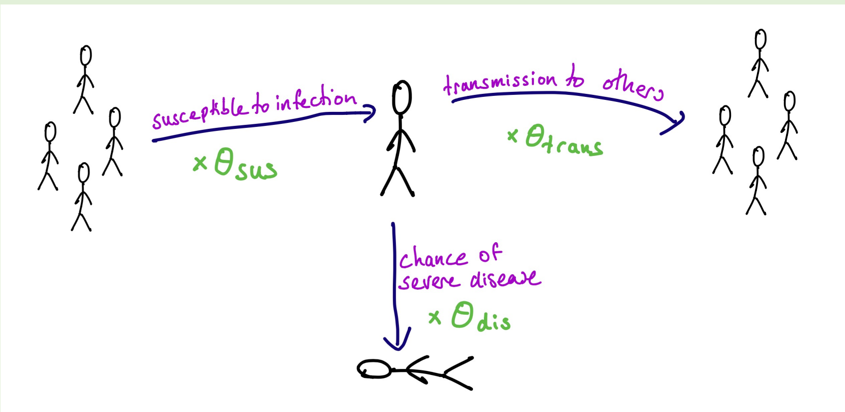
$\theta_{sus}$ : reduced rate of becoming infected — susceptibility reduction

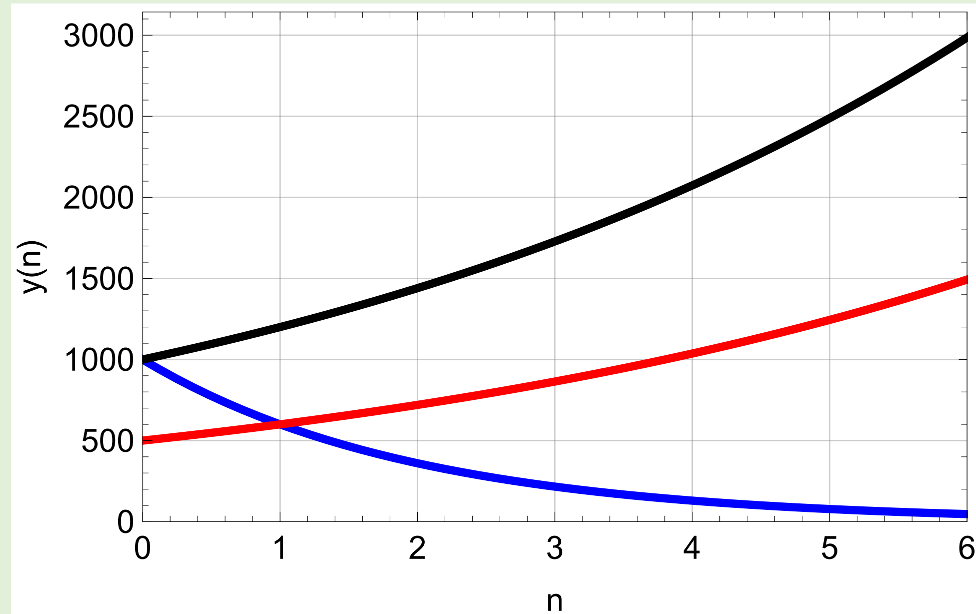
$\theta_{trans}$ : reduced infectiousness (if infected) — transmission reduction

$\theta_{dis}$ : reduced chance of severe disease — disease reduction.

Note:
Disease blocking: $\theta_{sus} \times \theta_{dis}$
Transmission blocking: $\theta_{sus} \times \theta_{trans}$

# Connect this back to insights from earlier



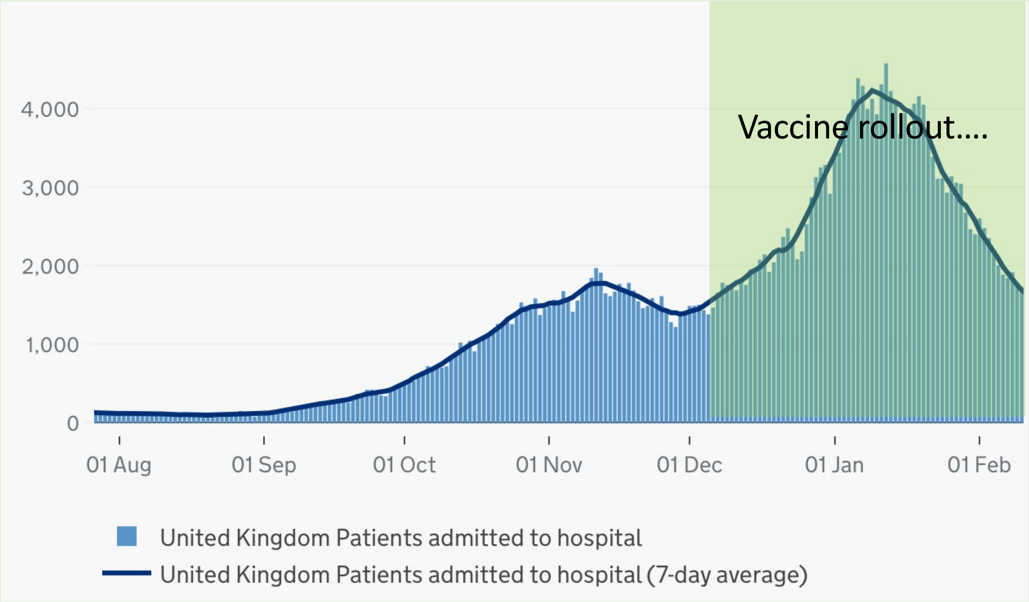




$$y(n) = aR^n$$

**In red:**
**drop *a* by 50%**

**In blue:**
**drop *R* by 50%**

# Vaccination rollout – who should we target with vaccination




**What should the vaccine priority order be?**

- The most vulnerable (highest chance of severe disease)?
- Those put at risk by their work?
- Those most needed at work?
- Those most connected with other people?

Complex ethical issues here for society. Mathematical modelling can show the population consequences of the options…

# What insights can we gain from simple approach?

Model population as two equally sized groups:

*d* times higher probability of severe disease (e.g. hospitalization)

Vulnerable

Mixers

*m* times higher rate of mixing (with anyone)

Mixing matrix proportion to:

$$\mathbf{M}_0 = \begin{bmatrix} 1 & m \\ m & m^2 \end{bmatrix}$$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Posted March 28, 2021.
Julia R. Gog, Edward M. Hill, Leon Danon, Robin Thompson
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doi: https://doi.org/10.1101/2021.03.14.21253544

https://www.medrxiv.org/content/10.1101/2021.03.14.21253544v2 *d* times higher probability of severe disease (e.g. hospitalization)

Vulnerable

Mixers

*m* times higher rate of mixing (with anyone)

Vaccinate proportion $v_1$

Vaccinate proportion $v_2$

Vaccinated Vulnerable

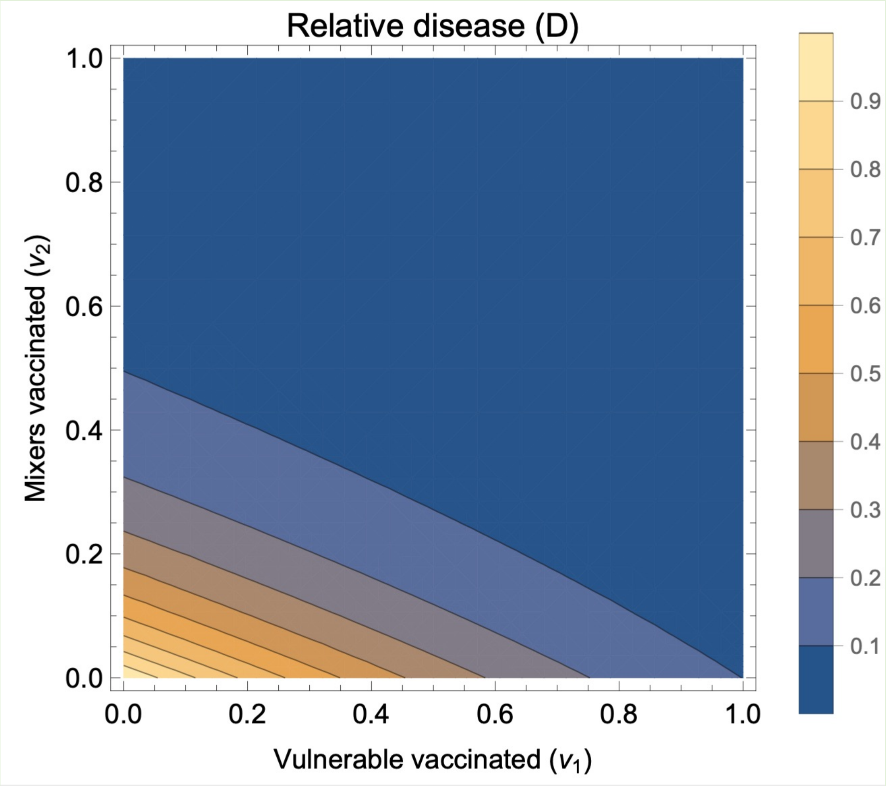
Vaccinated Mixers

$$
\begin{bmatrix}
(1-v_1) & (1-v_1)m & (1-v_1)\theta_I & (1-v_1)m\theta_I \\
(1-v_2)m & (1-v_2)m^2 & (1-v_2)m\theta_I & (1-v_2)m^2\theta_I \\
\theta_S v_1 & \theta_S v_1 m & \theta_S v_1 \theta_I & \theta_S v_1 m \theta_I \\
\theta_S v_2 m & \theta_S v_2 m^2 & \theta_S v_2 m \theta_I & \theta_S v_2 m^2 \theta_I
\end{bmatrix}
=
\begin{bmatrix}
(1-v_1) \\
(1-v_2)m \\
\theta_S v_1 \\
\theta_S v_2 m
\end{bmatrix}
\begin{bmatrix}
1 \\
m \\
\theta_I \\
m\theta_I
\end{bmatrix}^{\mathsf{T}}
$$

$$
R_0 \frac{(1-v_1)+(1-v_2)m^2+\theta_S\theta_I(v_1+v_2m^2)}{1+m^2}
$$

# Best strategy to reduce disease?

If vaccine has some transmission blocking effects, then it *can* be better to target vaccination to reduce transmission, rather than directly protecting the vulnerable.




Many caveats – including:

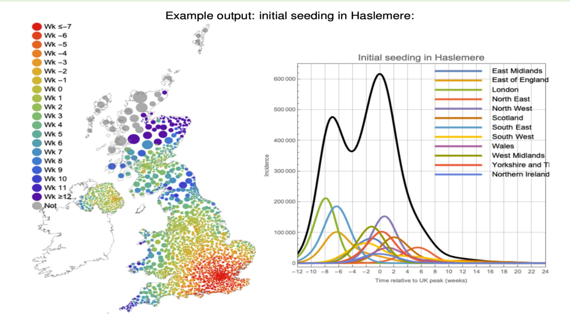
This slightly depends on timescales: a very short term optimum is often to vaccinate the vulnerable.

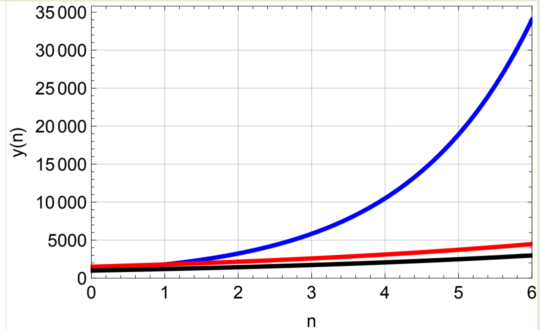
This is also limited to two populations, but reality is a spectrum of mixing and vulnerability.

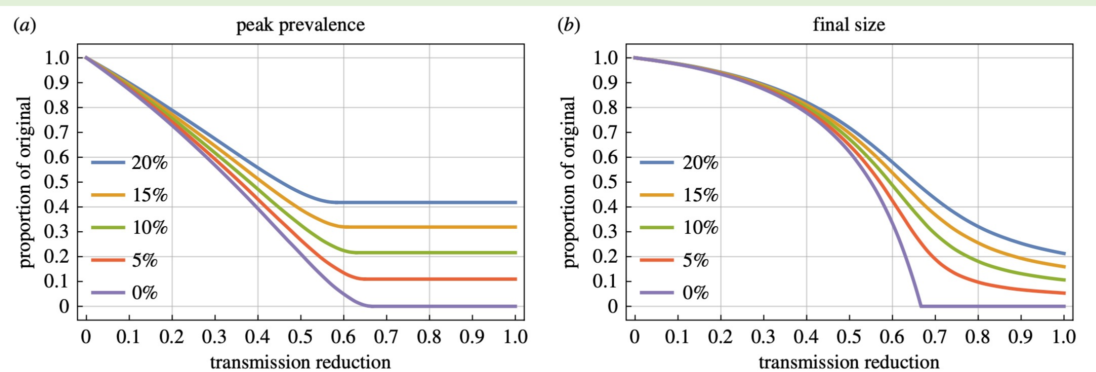
Combining these: optimal strategy under more realistic conditions could be to vaccinate the extremely vulnerable first, and then pivot to the most mixing (but will depend on precise population distribution).

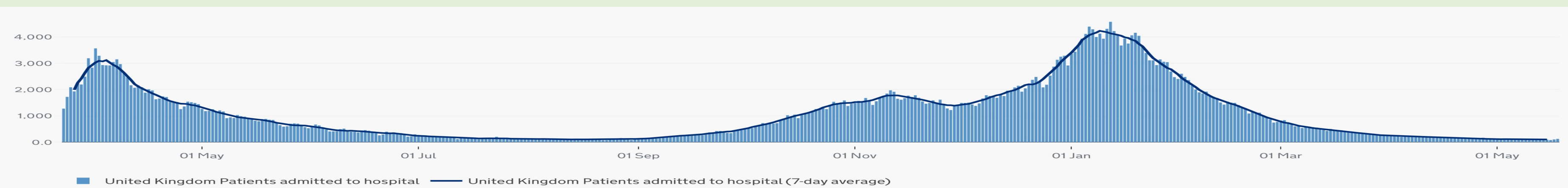
+ see ongoing work on vaccine escape…

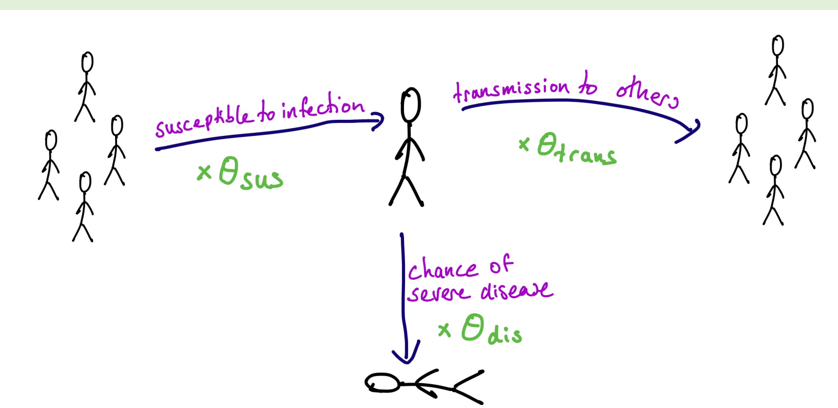
https://www.medrxiv.org/content/10.1101/2021.03.14.21253544v2

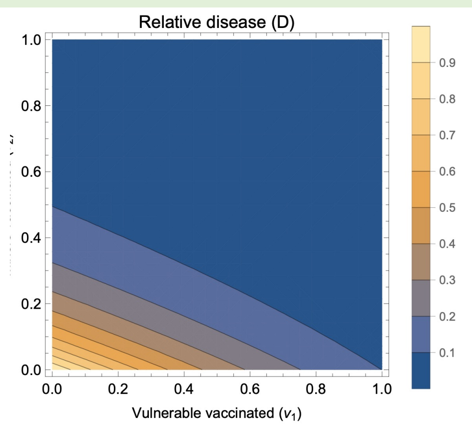

Example output: initial seeding in Haslemere:
Initial seeding in Haslemere
East Midlands
East of England
London
North East
North West
Scotland
South East
South West
Wales
West Midlands
Northern Ireland
Time relative to UK peak (weeks)

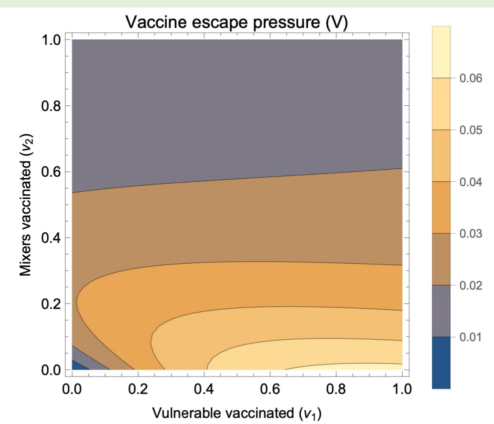

y(n)
n


(a)
peak prevalence
proportion of original
transmission reduction
20%
15%
10%
5%
0%
(b)
final size
proportion of original
transmission reduction
20%
15%
10%
5%
0%


01 May
01 Jul
01 Sep
01 Nov
01 Jan
01 Mar
01 May
United Kingdom Patients admitted to hospital
United Kingdom Patients admitted to hospital (7-day average)


susceptible to infection
× θsus
transmission to others
× θtrans
chance of
severe disease
× θdis


Relative disease (D)
Vulnerable vaccinated (v1)


Vaccine escape pressure (V)
Mixers vaccinated (v2)
Vulnerable vaccinated (v1)