

# Mathematical Epidemiology - Vaccination, Limits, and Rates

Lecture series at Faculty of Mathematics and Physics, CUNI in Prague

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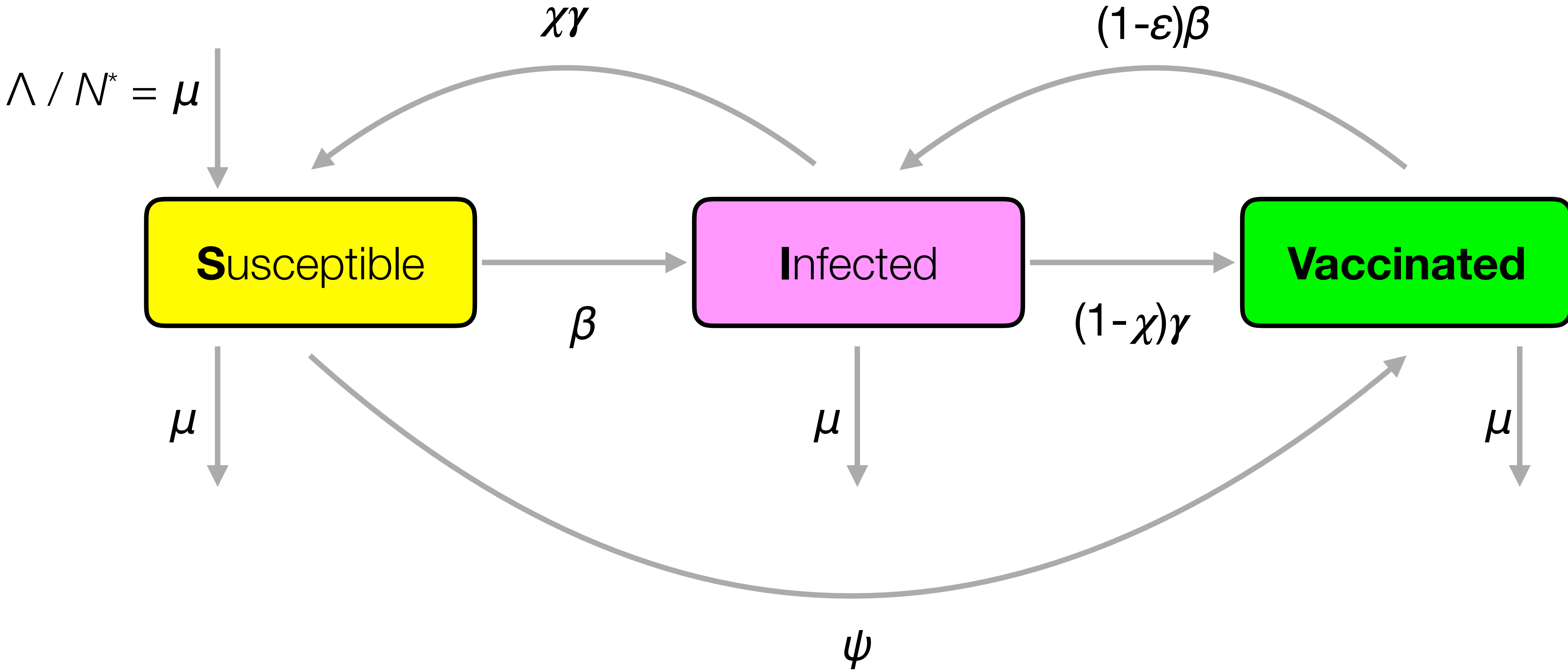
# Still Remember

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- We model it as a **machine**
  - it has its code (*epidemic code*)
  - it consumes energy (of us)
  - it is still going on
- If we do rely on a model, we shall respect all it can tell us fully

# SISV Model for Vaccination

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# ODE “EpiCode” and Disease-Free Equilibrium

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$$\frac{dS}{dt} = \Lambda - \frac{\beta}{N}SI + \chi\gamma I - (\mu + \psi)S$$

$$\frac{dI}{dt} = \frac{\beta}{N}SI + \frac{\beta(1-\varepsilon)}{N}VI - (\mu + \gamma)I$$

$$\frac{dV}{dt} = \psi S - \frac{\beta(1-\varepsilon)}{N}VI + (1-\chi)\gamma I - \mu V$$

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$$\frac{dN}{dt} = \Lambda - \mu N \Rightarrow N^* = \frac{\Lambda}{\mu}$$

$$\begin{aligned} \mathbf{E}_{\text{disease-free}} &= (S_0^*, I_0^*, V_0^*) \\ &= \left( \frac{\Lambda}{\mu + \psi}, 0, \frac{\Lambda\psi}{\mu(\mu + \psi)} \right) \end{aligned}$$

$$s_0^* = \frac{S_0^*}{N^*} = \frac{\mu}{\mu + \psi}$$

$$v_0^* = \frac{V_0^*}{N^*} = \frac{\psi}{\mu + \psi}$$

# Disease-Free Equilibrium Stability and R0 Identification

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Considering Jacobian in  $\mathbf{E}_{\text{disease-free}}$ , we can find the following **eigenvalues**

$$\lambda_1 = -\mu$$

$$\lambda_2 = -(\mu + \psi)$$

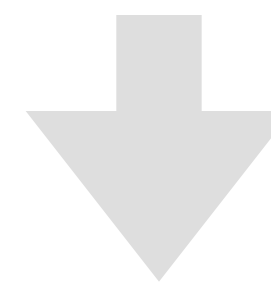
$$\lambda_3 = \beta s_0^* + \beta(1 - \varepsilon)v_0^* - (\mu + \gamma)$$

$$\lambda_3 < 0$$



$$\frac{\beta(s_0^* + (1 - \varepsilon)v_0^*)}{\mu + \gamma} < 1$$

$$\frac{\beta(\mu + (1 - \varepsilon)\psi)}{(\mu + \gamma)(\mu + \psi)} < 1$$



$$R_0(\psi) = \frac{\beta(\mu + (1 - \varepsilon)\psi)}{(\mu + \gamma)(\mu + \psi)} < 1$$

# Vaccination Planning

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$$\mathcal{R}(\psi) = \frac{\beta(\mu + (1 - \varepsilon)\psi)}{(\mu + \gamma)(\mu + \psi)}$$

$$\mathcal{R}(\psi = 0) = \mathcal{R}_0 = \frac{\beta}{\mu + \gamma}$$

$$\mathcal{R}(\psi \rightarrow \infty) \rightarrow (1 - \varepsilon)\mathcal{R}_0$$

$$\mathcal{R}(\psi_{critical}) = 1 \Rightarrow \psi_{critical} = \frac{(\mathcal{R}_0 - 1)\mu}{1 - (1 - \varepsilon)\mathcal{R}_0}$$

note  $\psi_{critical} \rightarrow \infty$  for  $(1 - \varepsilon)\mathcal{R}_0 \rightarrow 1$

- efficacy & speed (!)
- uniformity (!)
- after all, vaccination dynamics is
  - complicated enough for the backward bifurcation to occur
  - coexistence mechanism for multiple pathogen variants

And then, we can formulate the threshold

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$$\textit{threshold} = v_{critical} = \frac{\psi_{critical}}{\mu + \psi_{critical}} = \frac{1}{\epsilon} \left( 1 - \frac{1}{\mathcal{R}_0} \right)$$

- Despite having stochastic interpretation, the vaccinated fraction threshold is given as a result of the vaccination dynamics, now.
- Similarly to  $R_0$  which is formulated primarily as a stability indicator instead of purely statistical parameter.
- Nevertheless, these variables still provide us a useful bridge in between deterministic and stochastic models.

# Basic Vaccination Equation for HIT

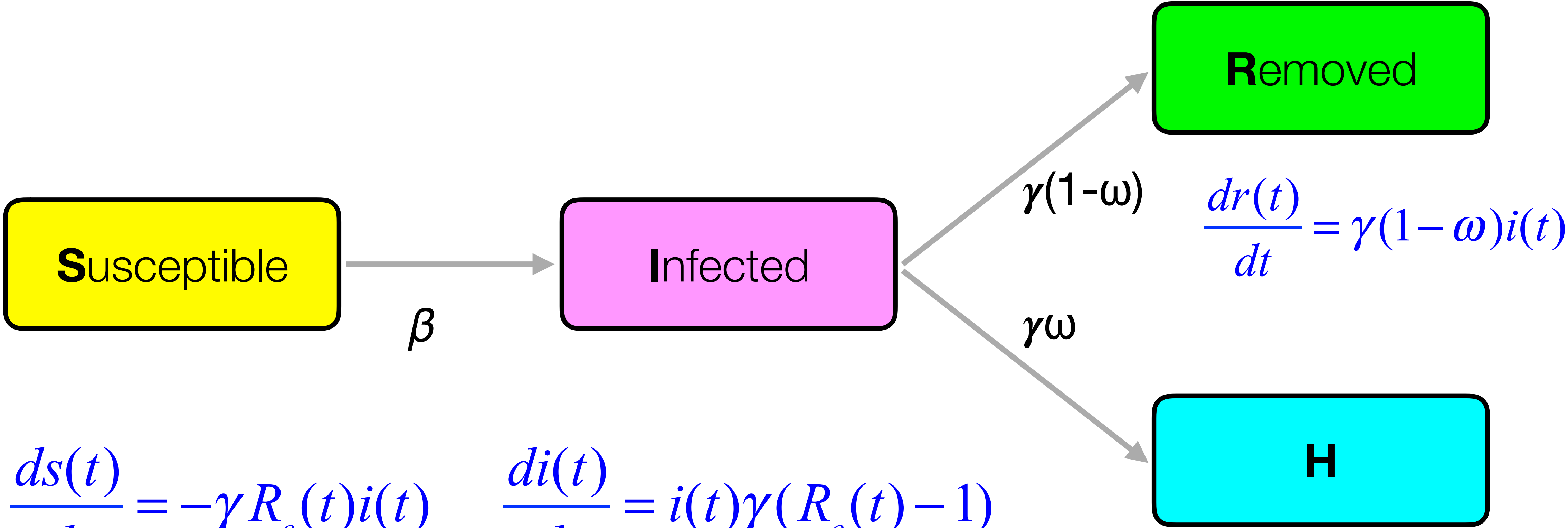
$$\text{threshold}(\mathcal{R}_0, \varepsilon) = \frac{1}{\varepsilon} \left( 1 - \frac{1}{\mathcal{R}_0} \right)$$

$\varepsilon$	$R_0$				
	2.7	3.5	4.5	5.5	6.45
92 %	68 %	78 %	85 %	89 %	92 %
86 %	73 %	83 %	90 %	95 %	98 %
80 %	79 %	89 %	97 %	—	—
63 %	100 %	—	—	—	—

- Assumptions:
  - vaccine distributed **uniformly among yet-susceptible** people
  - vaccine efficacy  $\varepsilon$  - **for spreading**
  - immunity does not vanish in near time (circa one year, at least)
- Recovered people fraction bearing natural immunity then sum up with the vaccinated fraction
  - not shown here for clarity
  - be careful with overlaps



# SIRH to Study Incidence Growth Rates Correlations



$$\frac{ds(t)}{dt} = -\gamma R_e(t)i(t)$$

$$\frac{di(t)}{dt} = i(t)\gamma(R_e(t) - 1)$$

$$\frac{dh(t)}{dt} = \gamma\omega i(t)$$

$$R_e(t) = R_0 s(t), R_0 = \frac{\beta}{\gamma}$$

- the gamma-omega split preserves  $R_0$  formulation w.l.o.g.
- Hospital path to Removed omitted for clarity, as we keep focus on incidences

# Generalised Incidences of Many Kinds

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$$\frac{ds(t)}{dt} = -\gamma R_e(t)i(t) \\ = -\textit{incidence}(t)$$

$$\frac{dr(t)}{dt} = \gamma(1-\omega)i(t) = \textit{ric}(t)$$

$$\frac{dh(t)}{dt} = \gamma\omega i(t) = \textit{hic}(t)$$

- *incidence(t)* is the observable number of daily new cases
- *ric(t)* is the observable number of daily new recovered cases (formerly infectious)
- *hic(t)* is the observable number of daily new hospital admissions

*Statistical warning: "Observable" does not necessarily imply truly observed! But this is not in our scope here.*

Let us investigate growth-like equations for our incidences

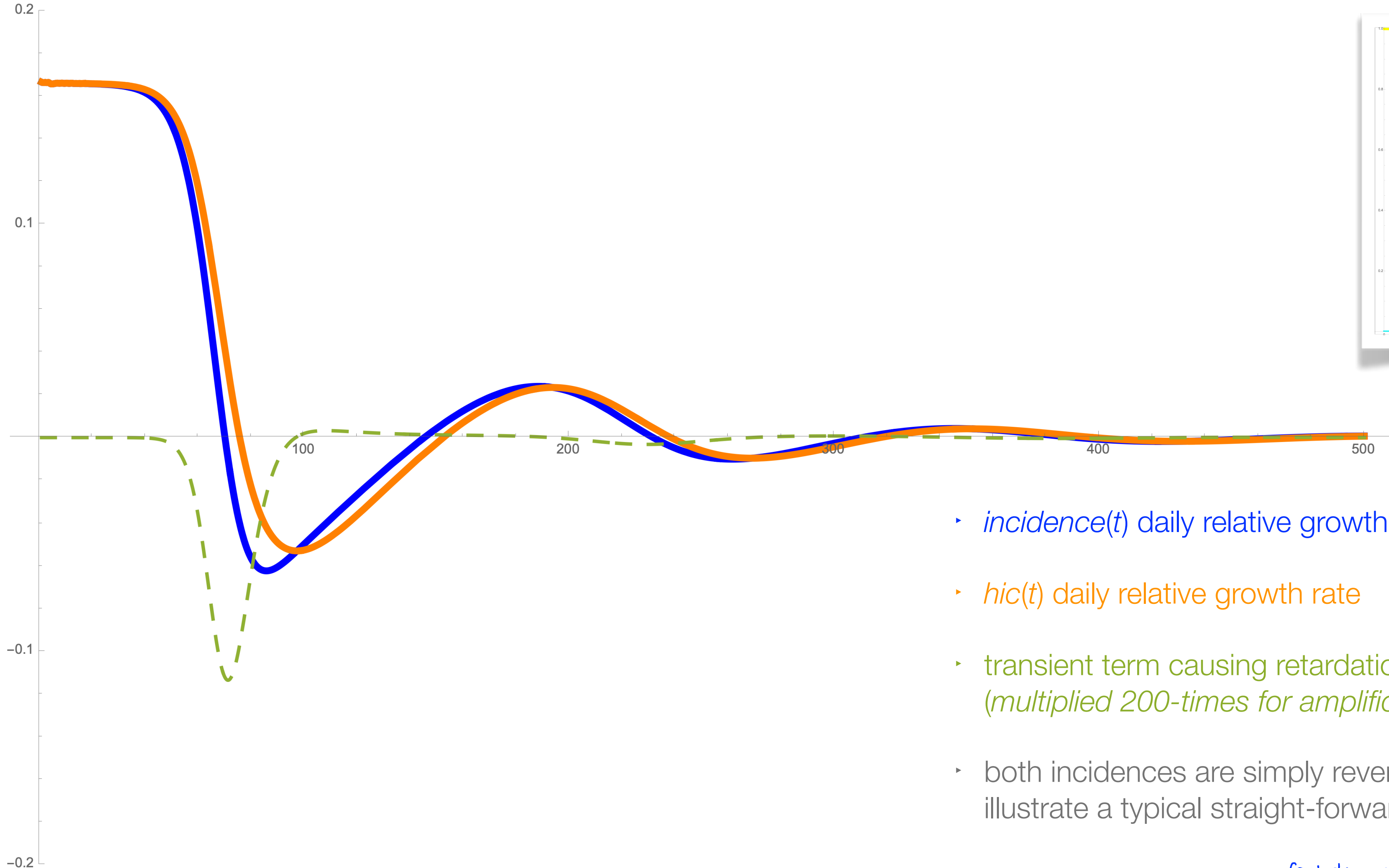
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$$\frac{d(\textit{incidence}(t))}{dt} = \gamma R_e(t) i(t) [\gamma(R_e(t) - 1)] + \gamma i(t) \frac{dR_e(t)}{dt} = \textit{incidence}(t) [\gamma(R_e(t) - 1)] + \gamma i(t) \frac{dR_e(t)}{dt}$$

$$\frac{d(\textit{ric}(t))}{dt} = \gamma(1 - \omega) \frac{di(t)}{dt} = \gamma(1 - \omega) i(t) [\gamma(R_e(t) - 1)] = \textit{ric}(t) [\gamma(R_e(t) - 1)]$$

$$\frac{d(\textit{hic}(t))}{dt} = \gamma\omega \frac{di(t)}{dt} = \gamma\omega i(t) [\gamma(R_e(t) - 1)] = \textit{hic}(t) [\gamma(R_e(t) - 1)]$$

# Growth Rates Are Strongly Correlated (regardless $\omega$ )



- *incidence(t)* daily relative growth rate
- *hic(t)* daily relative growth rate
- transient term causing retardation effects due to  $R(t)$  change (multiplied 200-times for amplification)
- both incidences are simply reverse-estimated from synthetic values to illustrate a typical straight-forward observation scenario

fast demography included to see both decreasing and increasing rates

## Vaccinations

### People vaccinated

Up to and including 6 December 2021

Daily – first dose  
**19,979**

Daily – second dose  
**25,012**

Daily – booster or third dose  
**329,165**

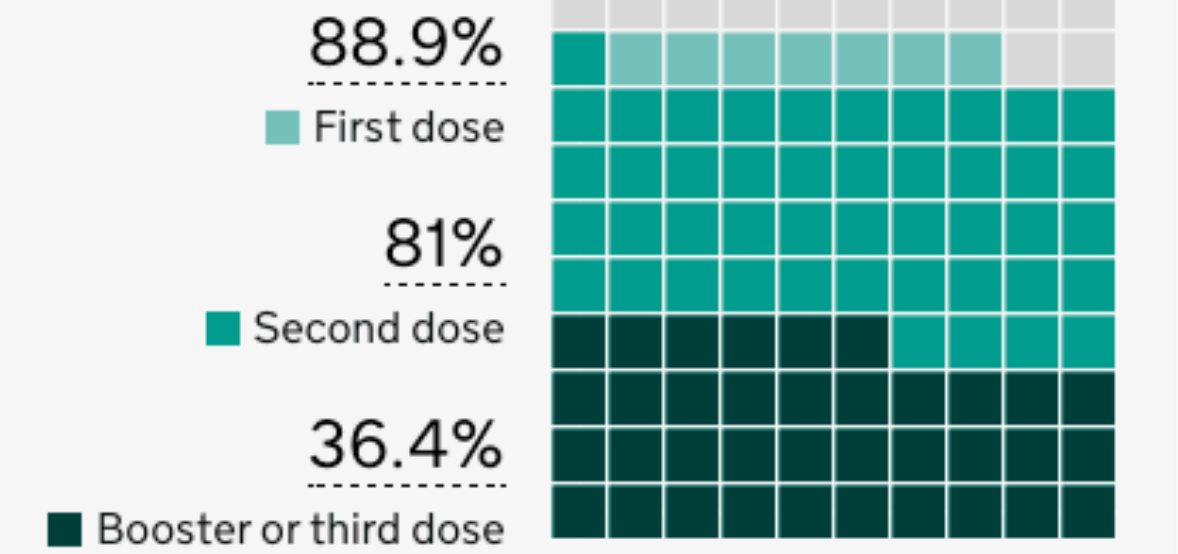
Total – first dose  
**51,138,245**

Total – second dose  
**46,582,425**

Total – booster or third dose  
**20,909,809**

[All vaccinations data](#)

Percentage of population aged 12+



## Cases

### People tested positive

Latest data provided on 7 December 2021

Daily  
**45,691**

Last 7 days  
**336,893** ↑ 36,339 (12.1%)

▶ Rate per 100,000 people: **478.9**



## Deaths

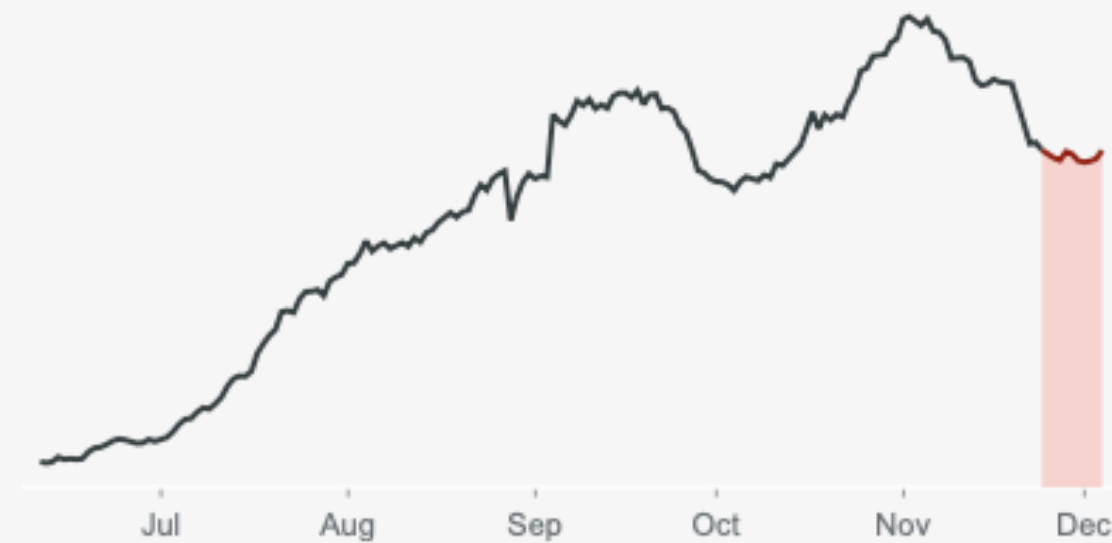
### Deaths within 28 days of positive test

Latest data provided on 7 December 2021

Daily  
**180**

Last 7 days  
**857** ↑ 25 (3%)

▶ Rate per 100,000 people: **1.1**



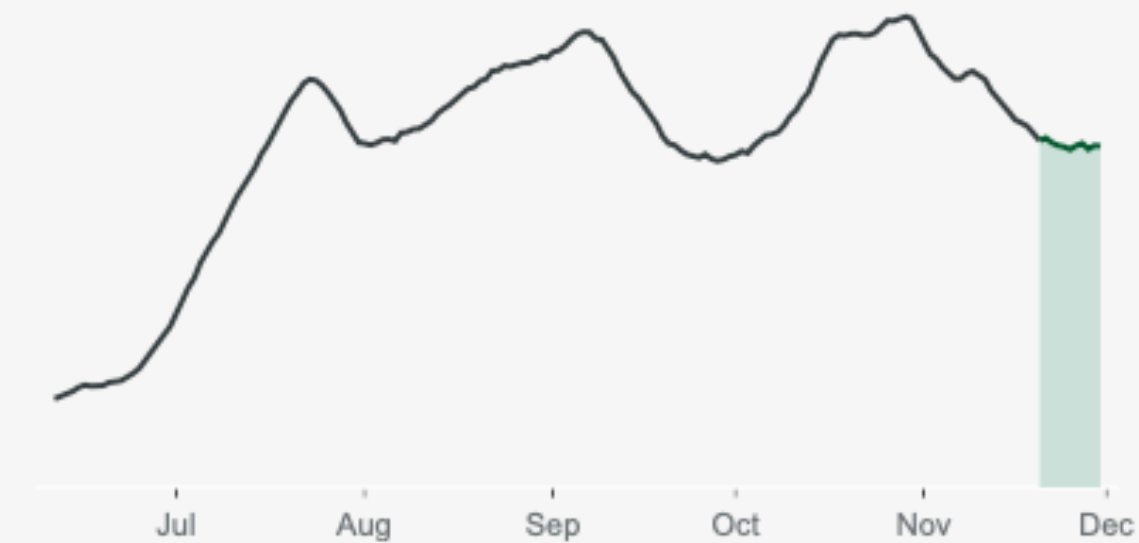
## Healthcare

### Patients admitted

Latest data provided on 3 December 2021

Daily  
**713**

Last 7 days  
**5,349** ↓ -8 (-0.1%)



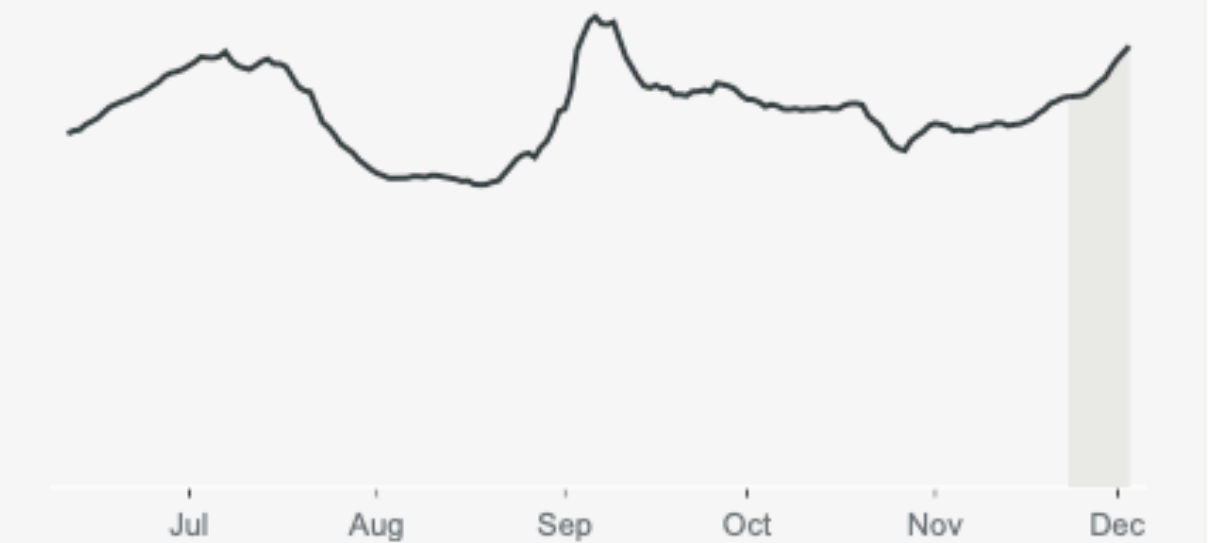
## Testing

### Virus tests conducted

Latest data provided on 6 December 2021

Daily  
**1,122,003**

Last 7 days  
**7,500,219** ↑ 810,521 (12.1%)



# References and Further Reading

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- (1) Bjornstad, O.-N.: *Epidemics - Models and Data Using R*, Springer, 2018**
- (2) Brauer, F., Castillo-Chavez, C., and Feng, Z.: *Mathematical Models in Epidemiology*, Texts in Applied Mathematics, Vol. 69, Springer, 2019
- (3) Kiss, I.-Z., Miller, J.-C., and Simon, P.-L.: *Mathematics of Epidemics on Networks – From Exact to Approximate Models*, Interdisciplinary Applied Mathematics, Vol. 46, Springer, 2017
- (4) Li, M.-Y.: *An Introduction to Mathematical Modelling of Infectious Diseases*, Springer, 2018
- (5) Martcheva, M.: *An Introduction to Mathematical Epidemiology*, Texts in Applied Mathematics, Vol. 61, Springer, 2015**
- (6) Vynnycky, E. and White, R.-G.: *An Introduction to Infectious Disease Modelling*, Oxford University Press, 2010



# Revision History

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- 2021/11/24: release version 1
- 2021/12/01: release version 2
- 2021/12/08: UK chart updated, release version 2b