A close-up photograph of a person's face in profile, coughing into their elbow. They are holding a white tissue. A fine mist of droplets is visible coming from their mouth. The background is dark.

Infectious Disease
Dynamics from
the Black Death
to COVID-19

David Earn
Mathematics & Statistics
McMaster University

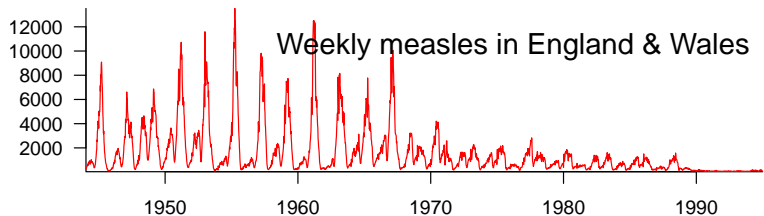
Outline

- ▶ Predicting patterns of epidemic recurrence
- ▶ Puzzles presented by plagues of the past
- ▶ Forecasting the future: modelling and policy

Outline

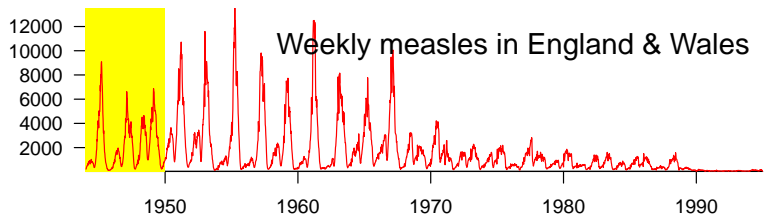
- ▶ **Predicting patterns of epidemic recurrence**
- ▶ Puzzles presented by plagues of the past
- ▶ Forecasting the future: modelling and policy

20th century measles dynamics in England and Wales

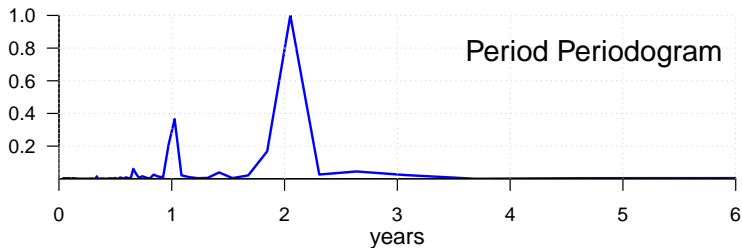
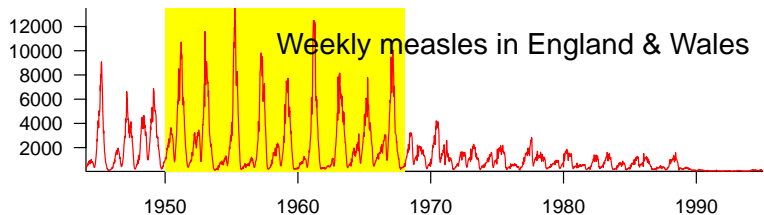


- ▶ Annual epidemics, then biennial, then irregular
- ▶ Why is the pattern of epidemic recurrence so complicated?
- ▶ What causes changes in frequency content over time?

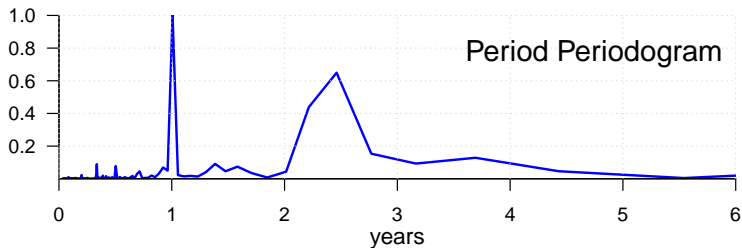
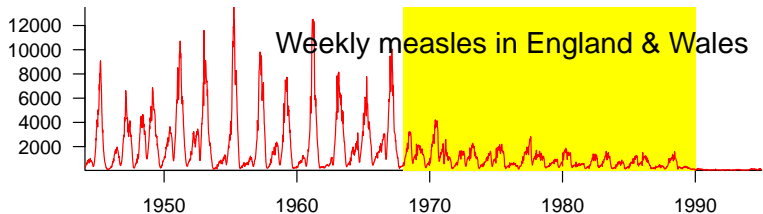
What causes changes in frequency content over time?



What causes changes in frequency content over time?



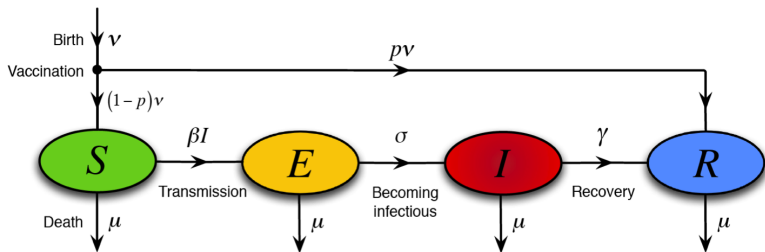
What causes changes in frequency content over time?



What causes changes in frequency content over time?



SEIR model



$$\frac{dS}{dt} = \nu(1 - p) - \beta SI - \mu S$$

$$\frac{dE}{dt} = \beta SI - \sigma E - \mu E$$

$$\frac{dI}{dt} = \sigma E - \gamma I - \mu I$$

$$\frac{dR}{dt} = \nu p + \gamma I - \mu R$$

- ▶ Birth rate (ν for natality)
- ▶ Death rate (μ for mortality)
- ▶ Proportion vaccinated (p)
- ▶ Transmission rate (β)
- ▶ Mean latent period ($T_{\text{lat}} = 1/\sigma$)
- ▶ Mean infectious period ($T_{\text{inf}} = 1/\gamma$)

SEIR with vital dynamics and vaccination: Analysis

- ▶ Two Equilibria
 - ▶ Disease Free Equilibrium (DFE)
 - ▶ Endemic Equilibrium (EE)
- ▶ Periodic solutions ? Chaos? No.
- ▶ *Basic reproduction number* \mathcal{R}_0 : expected infections from one infected entering a wholly susceptible population
 - ▶ Biological derivation: (assuming $\nu = \mu$ and $p = 0$)
$$\mathcal{R}_0 = \beta \times \frac{\sigma}{\sigma + \mu} \times \frac{1}{\gamma + \mu} \simeq \beta \gamma^{-1} \quad \because \frac{1}{\mu} \gg \max\left(\frac{1}{\sigma}, \frac{1}{\gamma}\right)$$
 - ▶ Mathematical derivation:
 $\mathcal{R}_0 = 1$ is stability boundary
- ▶ EE is globally asymptotically stable (GAS) if $\mathcal{R}_0 > 1$;
DFE is GAS otherwise.
- ▶ Approach to EE is typically via *damped oscillations*.
- ▶ But *observed recurrent epidemics* are *undamped*.

van den Driessche & Watmough 2002
Mathematical Biosciences 180:29–48

What are we missing?

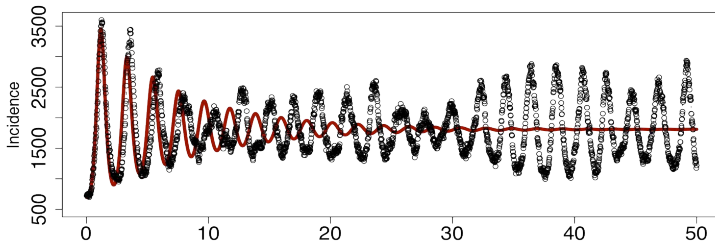


Populations are finite: demographic stochasticity

- ▶ Differential equations describe the expected behaviour in limit that population size $N \rightarrow \infty$
- ▶ Re-cast the **SEIR model** as a stochastic process (continuous time Markov jump process)
- ▶ Simulate with standard **Gillespie algorithm**

Gillespie Simulations: SEIR Results for Measles Parameters

$\mathcal{R}_0 = 17$, $T_{\text{lat}} = 8$ days, $T_{\text{inf}} = 5$ days, $\nu = \mu = 0.02/\text{year}$, $N = 5,000,000$



Earn (2009) *IAS/Park City Mathematics Series* 14:151–186

- ▶ Demographic Stochasticity sustains transient behaviour (oscillations do not damp out) (Bartlett 1950's)
- ▶ Explains undamped oscillations *at a single period*
- ▶ But, unable to explain changes in interepidemic period, or irregularity, *as observed*

What are we **STILL** missing?



Contact rates are higher during school terms!



Sinusoidal SEIR Model

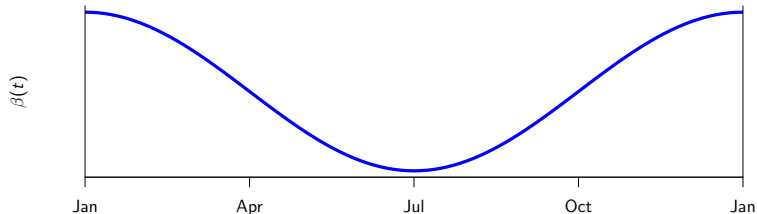
- ▶ Transmission rate β is not constant:
high during school terms, low in summer

London WP, Yorke JA, 1973, *Am. J. Epidemiol.* **98**, 453–468

- ▶ For simplicity, model as a sine wave:

$$\beta(t) = \langle \beta \rangle (1 + \alpha \cos 2\pi t)$$

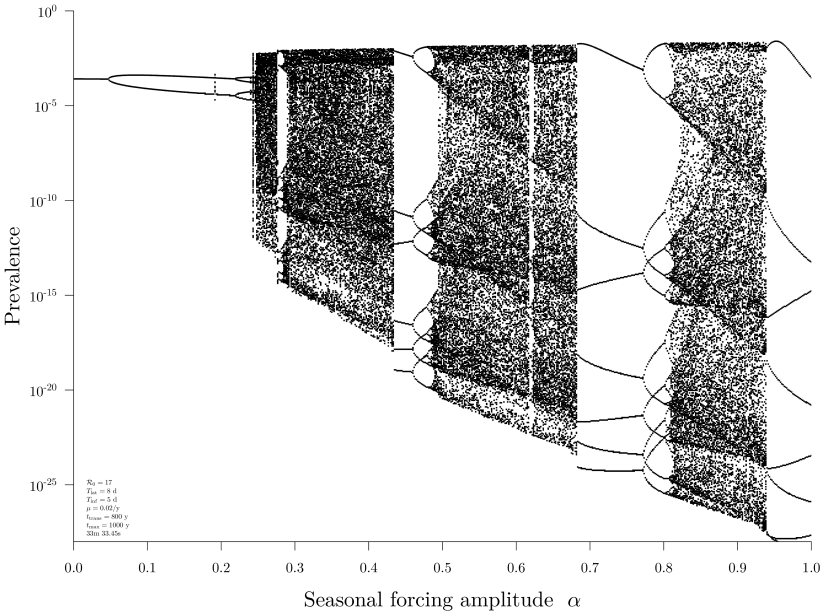
- ▶ $\langle \beta \rangle$ = mean transmission rate
- ▶ α = amplitude of seasonal variation in contact rate



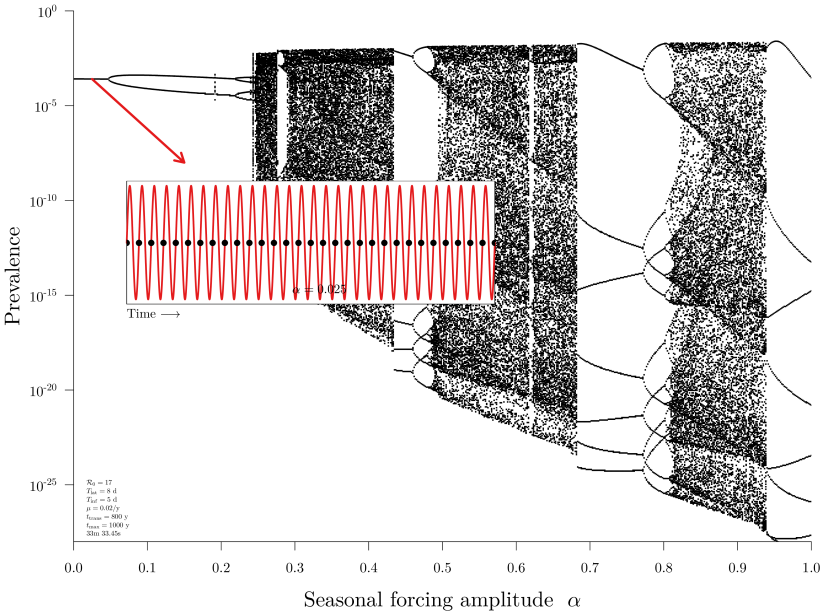
Is this change significant?

- ▶ We now have a forced nonlinear system
- ▶ Forcing frequency can resonate with the natural timescales of the disease (e.g., period of damped oscillations)
- ▶ Very rich dynamical system. . .
(analogy: forced pendulum)

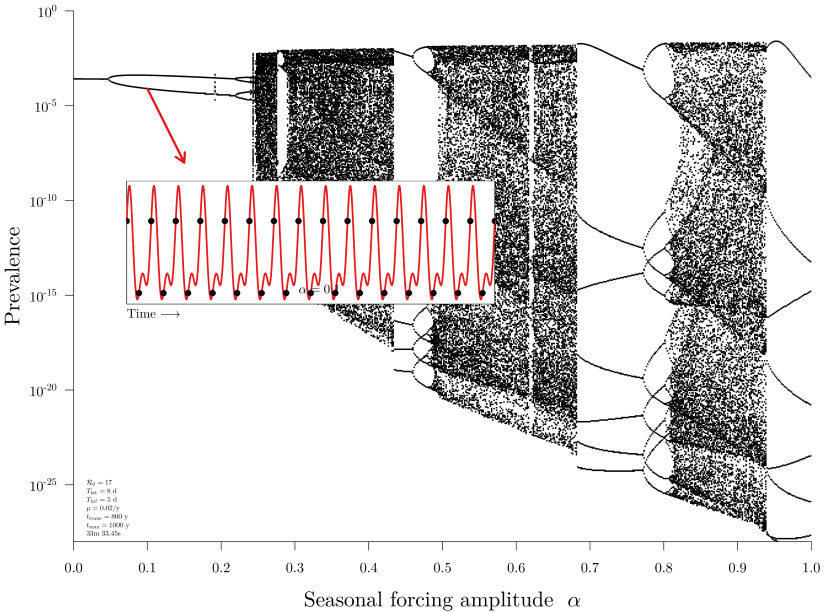
Measles Bifurcation Diagram (Sinusoidal SEIR model)



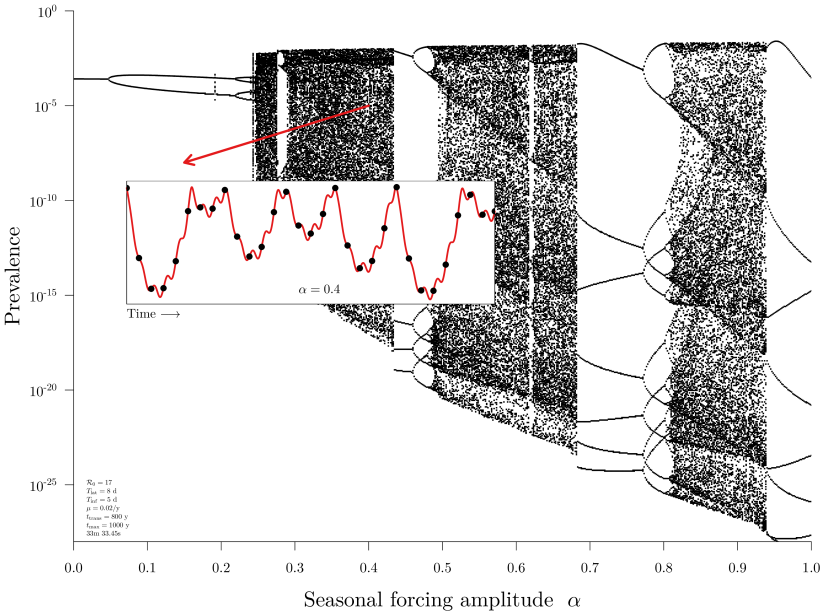
Measles Bifurcation Diagram (Sinusoidal SEIR model)



Measles Bifurcation Diagram (Sinusoidal SEIR model)



Measles Bifurcation Diagram (Sinusoidal SEIR model)



Sinusoidal SEIR Model: Does it explain measles dynamics?

SEIR model with sinusoidal forcing:

- ▶ Produces recurrent undamped epidemics of all frequencies observed in measles time series.

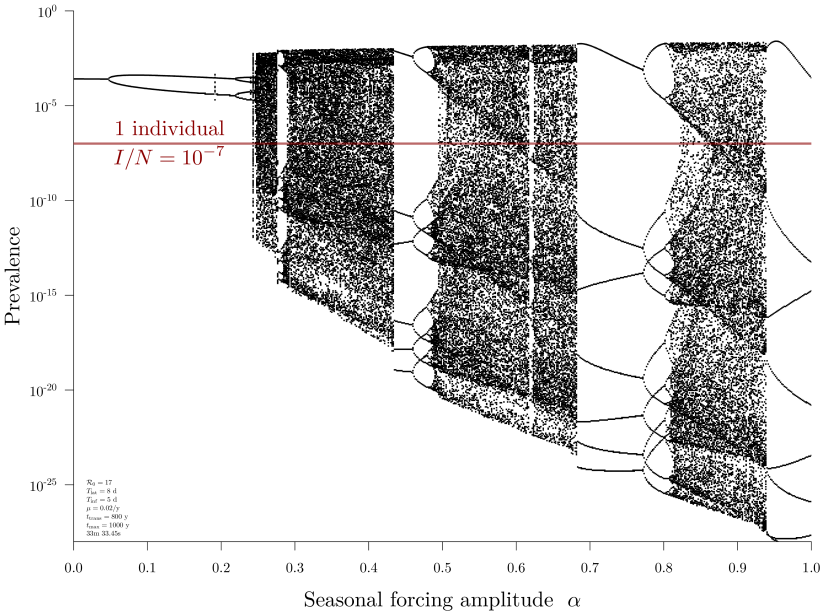
Schwartz IB, Smith HL, 1983, *J. Math. Biol.* **18**, 233–253

- ▶ Produces chaos, which can explain irregular behaviour and transitions from one type of cycle to another

Olsen LF, Schaffer WM, 1990, *Science* **249**, 499–504

- ▶ If correct, this implies these transitions are *unpredictable*.
- ▶ BUT... the model also predicts **rapid extinction** of the virus (not persistence).

Measles Bifurcation Diagram (Sinusoidal SEIR model)



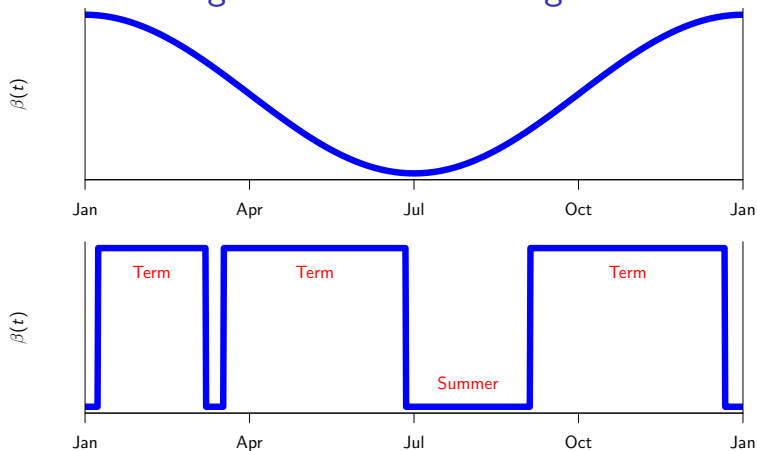
What are we STILL missing?



Contact rates are higher during school terms!



Sinusoidal forcing vs Term-time forcing



- ▶ Term-time SEIR model *predicts a strictly biennial cycle of measles epidemics, at all times and places.*
- ▶ Is superb agreement with post-war measles dynamics *coincidental???*

What **ELSE** might we be missing?



Key Insight

- ▶ Suppose \mathcal{R}_0 is estimated when the birth rate is ν .
- ▶ If the birth rate changes, $\nu \rightarrow \nu'$, then the dynamical effect is identical to changing \mathcal{R}_0 instead:

$$\mathcal{R}_0 \longrightarrow \mathcal{R}_0 \frac{\nu'}{\nu}$$

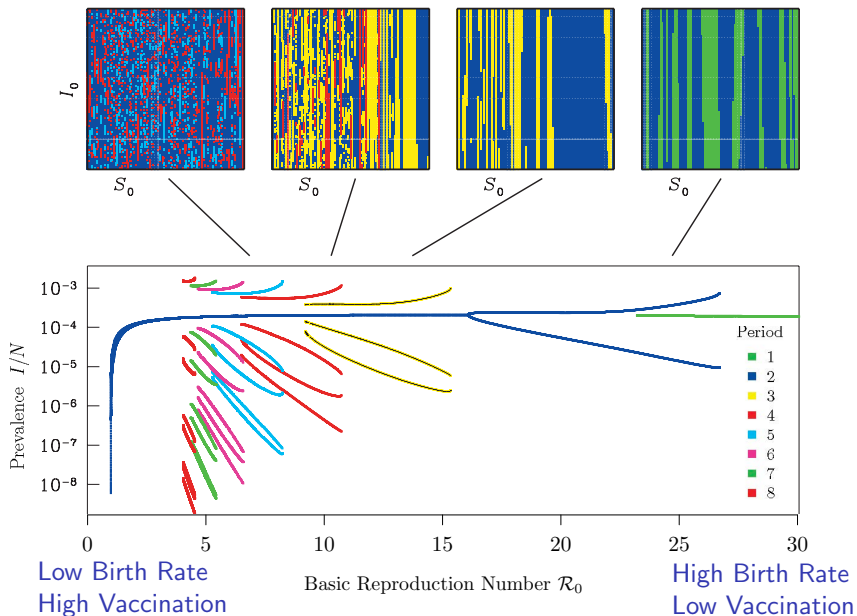
- ▶ More generally, any change in *susceptible recruitment rate* is equivalent dynamically to a change in \mathcal{R}_0 .
- ▶ A change in birth rate $\nu \rightarrow \nu'$ together with a change in vaccine uptake $p \rightarrow p'$ is dynamically equivalent to

$$\mathcal{R}_0 \longrightarrow \mathcal{R}_0 \frac{\nu'(1-p')}{\nu(1-p)}$$

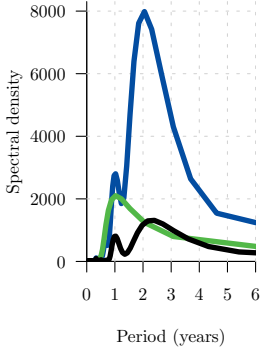
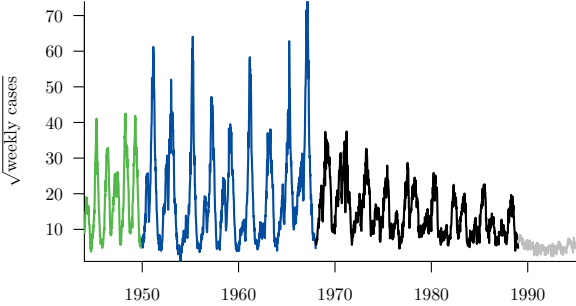
Predicting Epidemic Transitions

- ▶ Changes in
 - ▶ Birth rate (ν)
 - ▶ Vaccination proportion (p)
 - ▶ Transmission rate ($\langle\beta\rangle$ or \mathcal{R}_0)all map onto the same parameter axis.
- ▶ \therefore Summarize possible dynamical changes induced by demographic/behavioural changes with a *one-parameter* (\mathcal{R}_0) *bifurcation diagram*.
- ▶ \therefore Predict epidemic transitions by mapping observed changes in ν , p or \mathcal{R}_0 onto this diagram.

Measles Bifurcation Diagram (wrt \mathcal{R}_0)

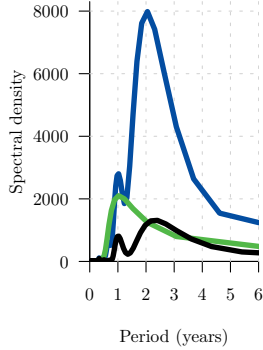
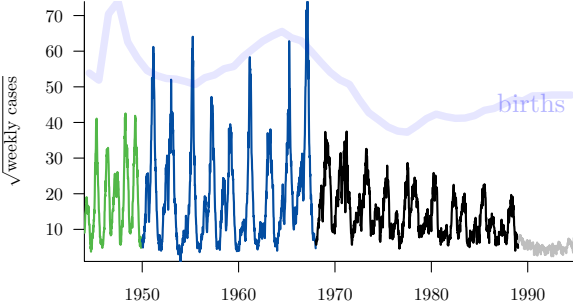


Measles in London, England

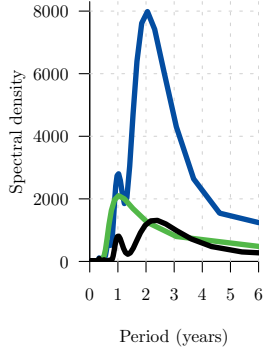
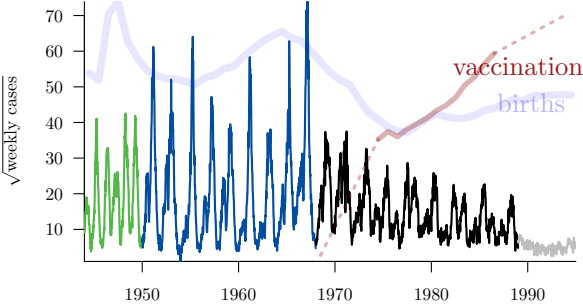


- 1-year cycle
- 2-year cycle
- irregularity; 2.5 year spectral peak
- noise only

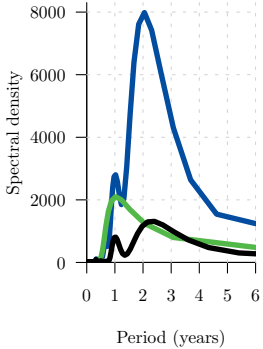
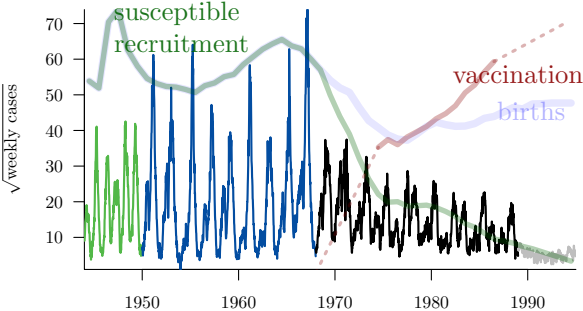
Measles in London, England



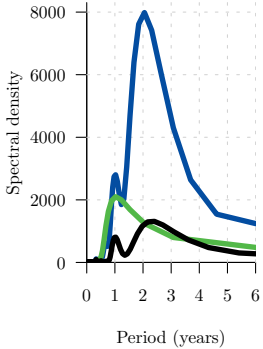
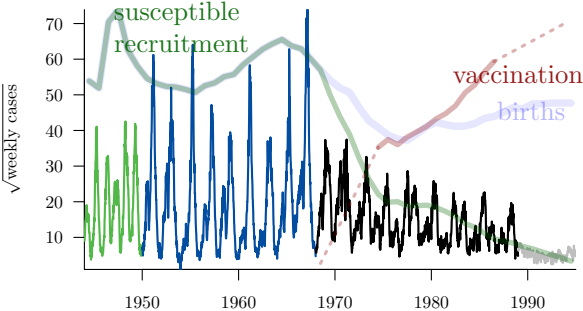
Measles in London, England



Measles in London, England



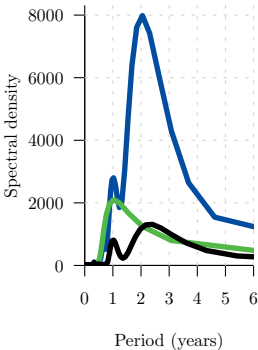
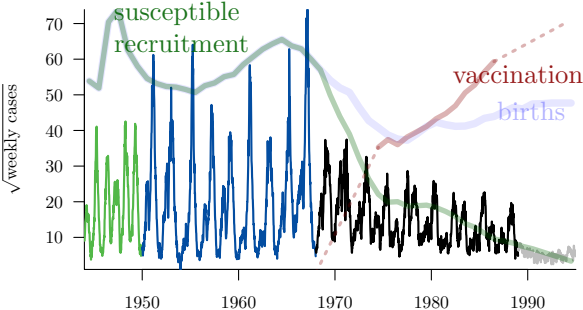
Measles in London, England



- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8



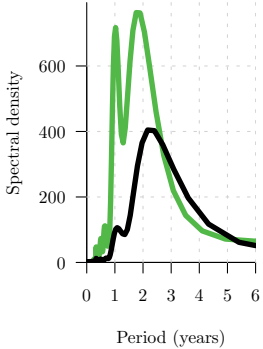
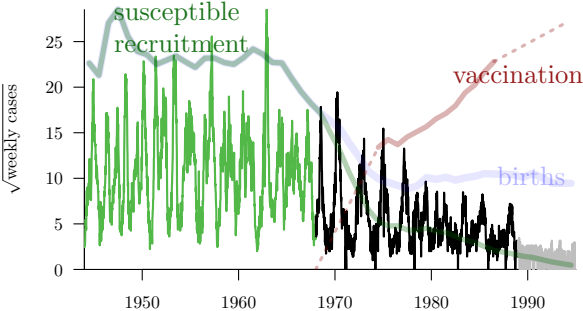
Measles in London, England



- Predicted: 1-year or 2-year cycle
Observed: 1-year cycle
- Predicted: strictly 2-year cycle
Observed: 2-year cycle
- Predicted: multiple co-existing stable cycles
Observed: irregularity; 2.5 year spectral peak
- Predicted: no cycle (above herd immunity threshold)
Observed: noise only

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8

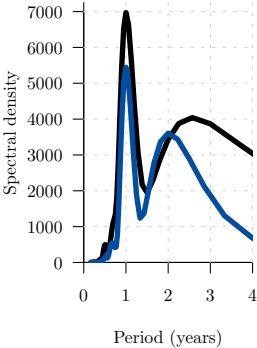
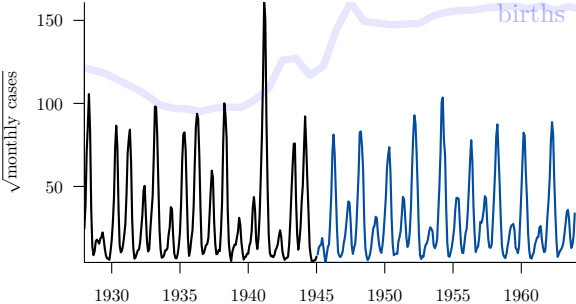
Measles in Liverpool, England



- █ Predicted: 1-year or 2-year cycle
Observed: mixture of 1- and 2-year cycles
- █ Predicted: multiple co-existing stable cycles
Observed: irregularity; 2.5 year spectral peak
- █ Predicted: no cycle (above herd immunity threshold)
Observed: noise only

- █ 1
- █ 2
- █ 3
- █ 4
- █ 5
- █ 6
- █ 7
- █ 8

Measles in New York City

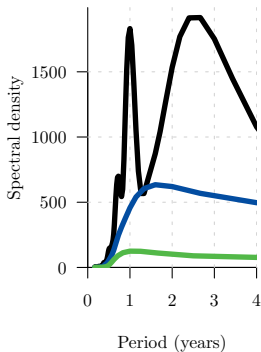
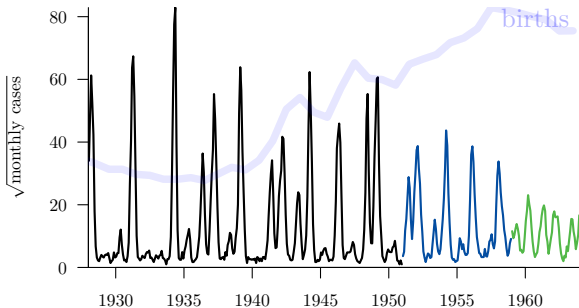


— Predicted: multiple co-existing stable cycles
 Observed: irregularity; 2.8 year spectral peak

— Predicted: strictly 2-year cycle
 Observed: 2-year cycle

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8

Measles in Baltimore



— Predicted: multiple co-existing stable cycles
Observed: irregularity; 2.8 year spectral peak

— Predicted: 1- or 2-year cycle
Observed: 2-year cycle

— Predicted: 1- or 2-year cycle
Observed: 1-year cycle

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8

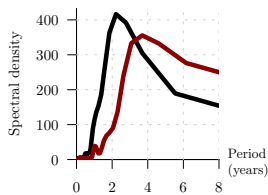
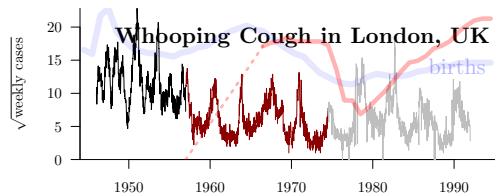
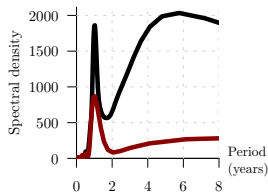
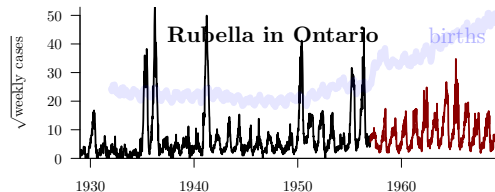
What about other notifiable childhood infectious diseases?

- ▶ Does same analysis explain patterns of recurrent epidemics for rubella? chicken pox? whooping cough?
- ▶ **Alas! No!**



- ▶ Only attractor of term-time **SEIR model** for rubella, chicken pox, or whooping cough is **annual cycle**.
- ▶ Yet these diseases show much more complex dynamics!

Other Childhood Infections (not measles)



Incidence time series of these diseases show strong spectral peaks at periods not predicted by asymptotic analysis (*i.e.*, **not** displayed by attractors of term-time SEIR model)

Argh!

What are we STILL missing?



Demographic Stochasticity Comes to the Rescue (Again!)

- ▶ Sustains transient behaviour
- ▶ *Linear perturbation theory* applied to the attractors of the model *explains other spectral peaks in data*
- ▶ *Whew!*

Get More Ambitious!

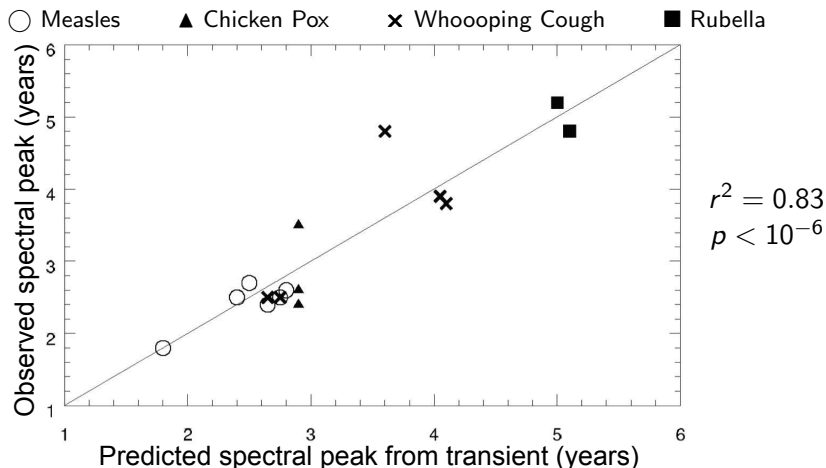
- ▶ Aim to predict **all** spectral peaks in the data
- ▶ **Asymptotic** analysis \longrightarrow spectral peaks from **attractors**
- ▶ **Perturbation** analysis \longrightarrow spectral peaks from **transients**

Bauch & Earn (2003) *Proc. R. Soc. Lond.* **270**:1573–1578

Krylova & Earn (2013) *J. R. Soc. Interface* **18**(10):20130098

Hempel & Earn (2015) *J. R. Soc. Interface* **12**(106):20150024

Predicted vs Observed Spectral Peaks from Transients

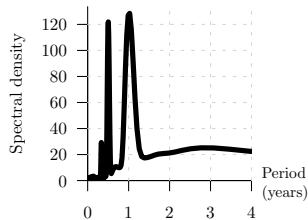
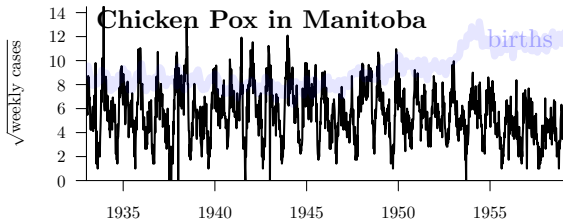
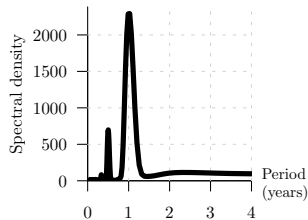
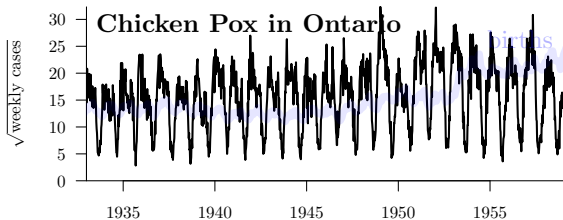


Bauch & Earn (2003) *Proc. R. Soc. Lond.* **270**:1573–1578

► Great! Can we successfully predict even more detail?

Can we predict magnitudes of spectral peaks?

Example:



► Population of MB \ll ON

⇒ more demographic stochasticity

Modelling recurrent epidemics: Summary so far

- ▶ Good understanding of recurrent epidemic patterns of many infectious diseases in the 20th century (e.g., measles, chicken pox, whooping cough, rubella, . . .)
- ▶ *Perfect prediction* of spectral peaks *from attractors*
- ▶ *Excellent prediction* of spectral peaks *from transients*
- ▶ *Population size* is key determinant of *relative magnitude* of peaks from attractors vs. transients (confirmed with stochastic simulations)

Modelling recurrent epidemics: Recent developments

- ▶ Extend time series further back in time
 - ▶ Does theory still allow us to predict epidemic transitions?
- ▶ Measles in New York City, 1891–1984
 - ▶ Success!

Hempel & Earn (2015) *J. R. Soc. Interface* **12**(106):20150024

- ▶ Key challenge that had to be overcome:
changing patterns of seasonal variation in contact rates

Papst & Earn (2019) *J. R. Soc. Interface* **16**:20190202

Jagan et al. (2020) *PLoS Comp. Biol.* **16**(9):e1008124

- ▶ Smallpox in London, 1664–1930
 - ▶ Many observed epidemiological transitions, correlated with policy changes and historical events

Krylova & Earn (2020) *PLoS Biology* **18**(12):e3000506

- ▶ Dynamical transition analysis in progress

Outline

- ▶ Predicting patterns of epidemic recurrence
- ▶ **Puzzles presented by plagues of the past**
- ▶ Forecasting the future: modelling and policy

The Diseases and Casualties this Week.



A Bortive	6
A Aged	50
Ague	1
Apoplexie	2
Childbed	42
Chirromes	11
Cold	1
Consumption	99
Convulsion	63
Cough	1
Drople	22
Drown'd at St. Martin in the Fields	1
Feaver	268
Fistula	2
Flox and Small-pox	4
Flux	1
Found dead in the Fields at St. Mary Iflington	1
Frighted	1
Gout	1
Grief	1
Gripping in the Guts	3
Jaundies	35
Imposthame	2
Infans	8
Kingfevil	9
Meagrome	2
Plague	2
Purples	5533
Rickets	10
Rising of the Lights	13
Rupture	1
Scurvy	5
Spotted Feaver	65
Stilborn	10
Stone	3
Stopping of the stomach	6
Suddenly	1
Surfeit	36
Teeth	112
Thrush	3
Tiffick	5
Vomiting	4
Winde	1
Wormes	12

Christned	Males	68	Buried	Males	3212	Plague	5533
	Females	78		Females	3248		
	In all	146		In all	6460		
Decreased in the Burials this Week				1837			
Parishes clear of the Plague				7 Parishes Infected 123			

The Assize of Bread set forth by Order of the Lord Mayor and Counc of Aldermen, A penny Wheaten Loaf to contain Nine Ounces and a half, and three half-penny White Loaves the like weight.

Bar.	Plig.	Bar.	Plig.
S ^t Alban Woodstreet	16 12	S ^t George Botolphane	1 1
Alballows Barking	40 34	S ^t Gregory by S ^t Pauls	26 25
Alballows Breadstreet	1 1	S ^t Hellen	6 5
Alballows Great	42 41	S ^t James Dukes place	17 23
Alballows Hovias	20 24	S ^t James Garlickhithe	10 12
Alballows Letic	17 17	S ^t John Baptist	11 10
Alballows Lumbarstreet	5 5	S ^t John Evangelist	1 1
Alballows Staining	21 18	S ^t John Zachary	12 9
Alballows the Wall	33 28	S ^t Katharine Coleman	20 16
S ^t Alphege	13 5	S ^t Katharine Creechurch	34 29
S ^t Andrew Hubbard	4 4	S ^t Lawrence Jewry	6 5
S ^t Andrew Underhafe	16 14	S ^t Lawrence Pountney	14 10
S ^t Andrew Wardrobe	28 24	S ^t Leonard Eastcheap	3 3
S ^t Ann Alderfer	28 27	S ^t Leonard Finsbury	16 13
S ^t Ann Blackeners	57 50	S ^t Margaret	5 4
S ^t Anthonis Parish	7 4	S ^t Margaret Louthbury	7 6
S ^t Austins Parish	4 3	S ^t Margaret Newfillstreet	13 13
S ^t Bartholomew Exchange	7 7	S ^t Margaret Patton	4 3
S ^t Bennet Fynack	4 2	S ^t Mary Abchurch	7 5
S ^t Bennet Gracechurch	4 2	S ^t Mary Aldermanbury	14 14
S ^t Bennet Paulwharf	15 7	S ^t Mary Aldermay	4 4
S ^t Bennet Sherehog	2 8	S ^t Mary le Bow	1 1
S ^t Boroloh Billinggate	8 8	S ^t Mary Bothaw	6 4
Christs Church	44 39	S ^t Mary Colechurch	3 1
S ^t Christophers	4 4	S ^t Mary Hill	11 8
S ^t Clement Eastcheap	1 1	S ^t Mary Mounshaw	4 3
S ^t Dionis Backchurch	9 2	S ^t Mary Sommerset	44 38
S ^t Dunstan East	28 24	S ^t Mary Swayning	3 3
S ^t Edmund Lumbarstreet	3 1	S ^t Mary Woolchurch	7 4
S ^t Ethelborough	7 4	S ^t Mary Woolnoth	7 5
S ^t Faith	8 6	S ^t Martin Ironmongerlane	2 2
S ^t F. Peter	8 6		
S ^t Gabriel Fenchurch	3 3		

Christned in the 97 Parishes within the Walls 39 Buried 1149 Plague 9

S ^t Andrew Holborn	173 151	S ^t Boroloh Aldgate	374 338	S ^t Vincent Southwark	364
S ^t Bartholomew Great	17 15	S ^t Boroloh Bishopsgate	153 121	S ^t Sepulchres Parish	147
S ^t Bartholomew Little	7 7	S ^t Dunstan West	63 59	S ^t Thomas Southwark	2
S ^t Bridge	92 67	S ^t George Southwark	140 133	Trinity Minorities	8
Bridewel Precinct	23 23	S ^t Giles Cripplegate	196 151	at the Pesthouse	24
S ^t Boroloh Alderigate	71 64	S ^t Olave Southwark	378 281		

Christned in the 16 Parishes without the Walls 45 Buried, and at the Pesthouse 2358 Plague 1

S ^t Giles in the fields	95 78	Lambeth Parish	49 39	S ^t Mary Abington	35
Hackney Parish	14 12	S ^t Leonard Shoreditch	95 94	S ^t Mary Whitechappel	32
S ^t James Clerkenwell	48 42	S ^t Magdalen Newmenny	138 106	Rothsith Parish	21
S ^t Kath near the Tower	55 49	S ^t Mary Newington	31 21	Sceopy Parish	67

Christned in the 12 out Parishes in Middlesex and Surry 40 Buried 1623 Plague 1

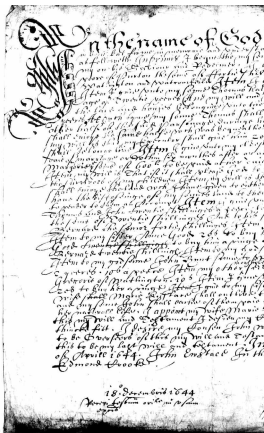
S ^t Clement Danes	15 8	110 S ^t Martin in the fields	209 143	S ^t Margaret Westminster	30
S ^t Paul Covent Garden	35 24	S ^t Mary Savoy	19 16	at the Pesthouse	

Christned in the 5 Parishes in the City and Liberties of Westminster 18 Buried 690 Plague 1

<u>Frighted</u>	1
Gowt	1
<u>Grief</u>	3
Griping in the Guts	35
Jaundies	2
Imposthume	8
Infants	9
Kingsevil	2
Meagrome	2
<u>Plague</u>	5533
Purples	2
Rickets	10
Rif	(the Light)

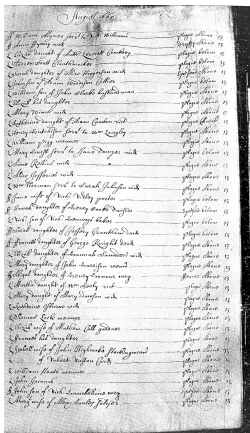
Sources of mortality data for London, England

Wills



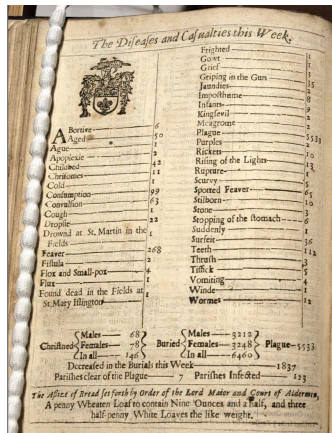
since 1258

Parish Registers



since 1538

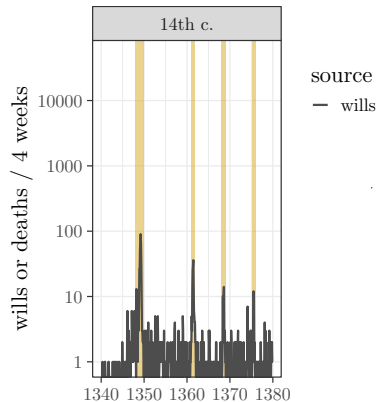
Bills of Mortality



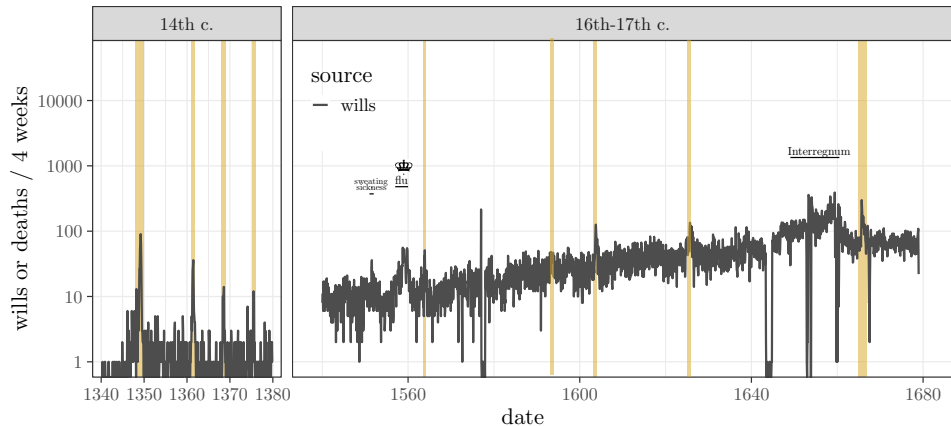
since 1563

(continuous since 1661)

Mortality in London, England, 1348–1680

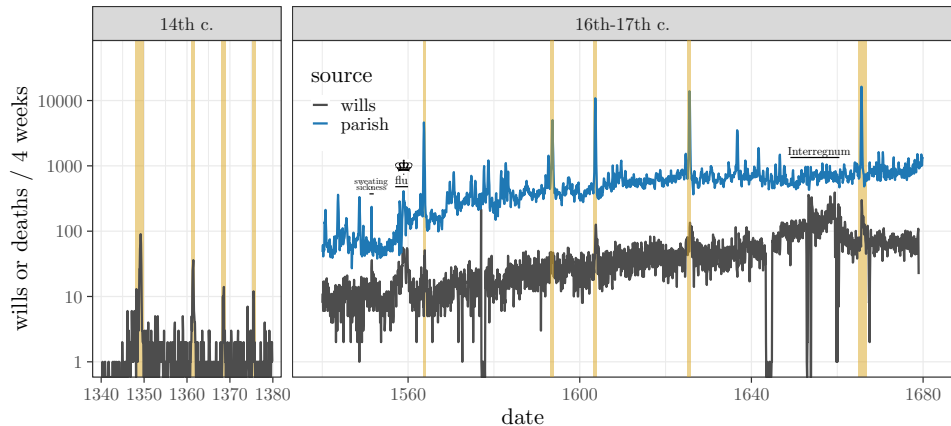


Mortality in London, England, 1348–1680



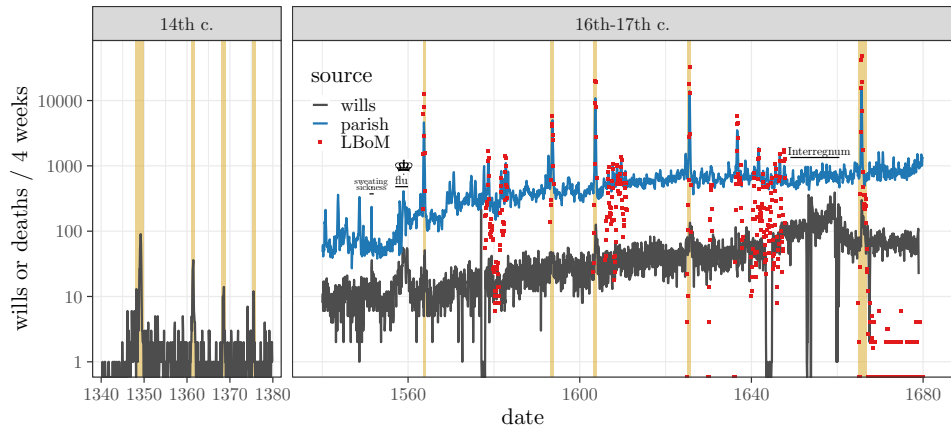
Earn, Ma, Poinar, Dushoff, Bolker (2020) *PNAS* 117:27703–27711

Mortality in London, England, 1348–1680



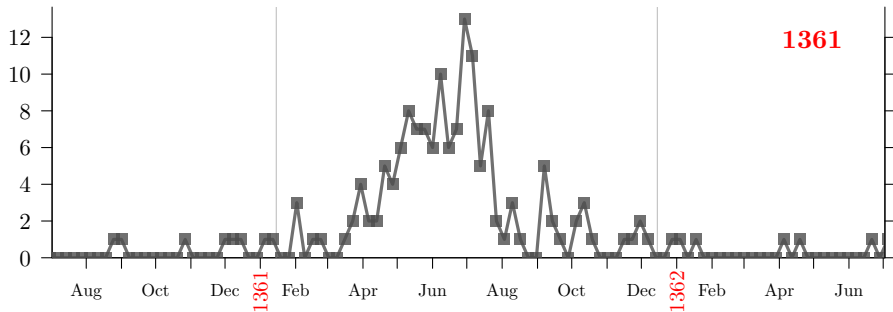
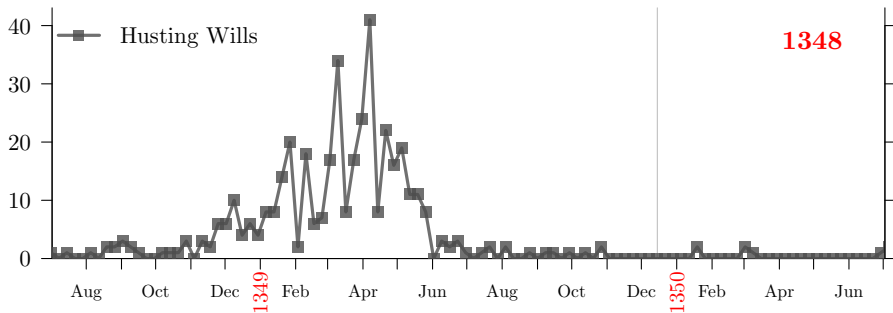
Earn, Ma, Poinar, Dushoff, Bolker (2020) *PNAS* 117:27703–27711

Mortality in London, England, 1348–1680

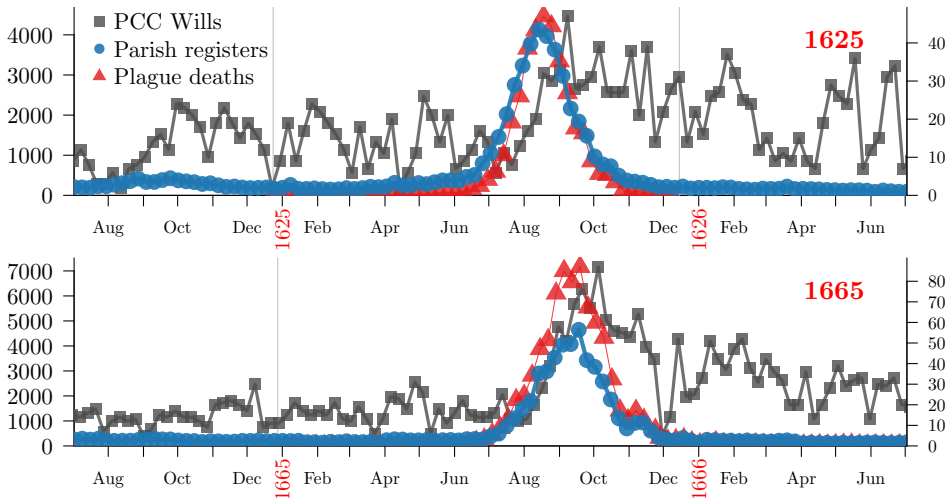


Earn, Ma, Poinar, Dushoff, Bolker (2020) *PNAS* 117:27703–27711

14th c. plague epidemics in London

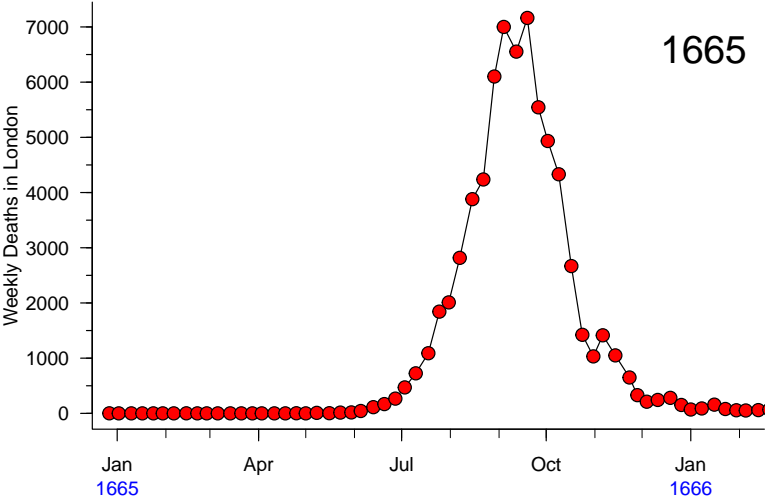


17th c. plague epidemics in London

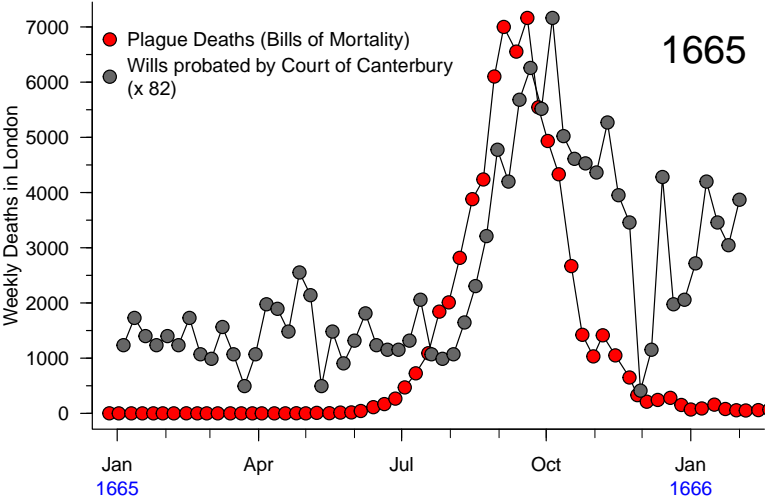


Is it OK to compare
results based on wills
with results from
mortality data?

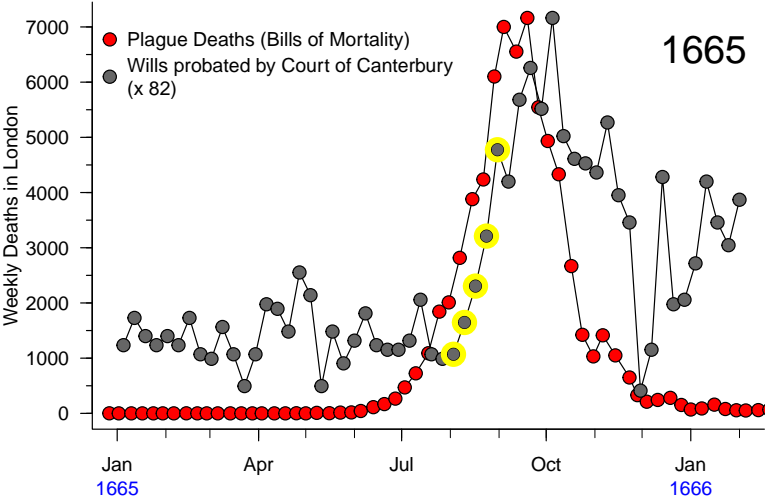
Plague in London



Plague in London



Plague in London

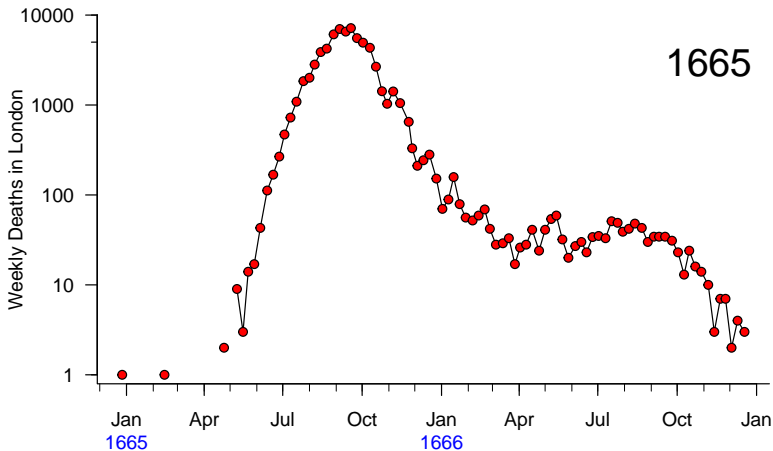


Compare growth rates of plague epidemics in London

- ▶ Property of the epidemic curve (*the data alone*)
- ▶ Estimate without assumptions about processes that generated the data (since we don't know the mode of transmission)
 - ▶ *human-to-human* (pneumonic plague)
 - ▶ *rat-to-flea-to-human* (bubonic plague)

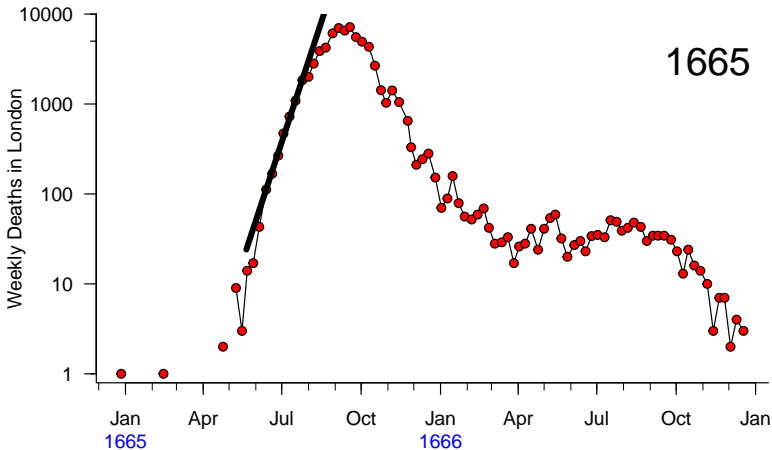
Estimating the initial growth rate of an epidemic

- ▶ Naïvely, we just fit a straight line to the log of the mortality time series.



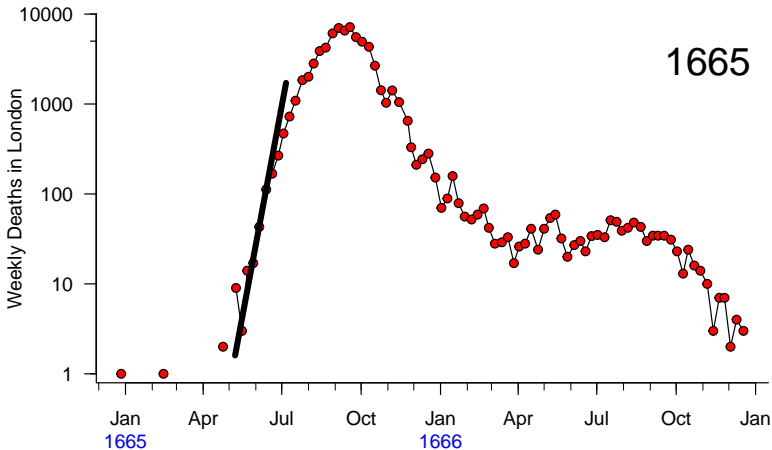
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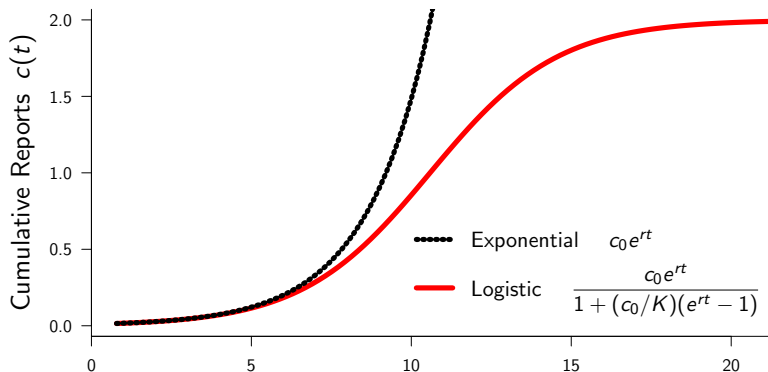
Estimating the initial growth rate of an epidemic

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Estimating the initial growth rate of an epidemic

Instead fit a **saturing** rather than a **purely exponential** curve.



- ▶ Both curves have same initial exponential growth rate r .
- ▶ Test extensively using **simulated epidemics** for which we know the correct answer.

Initial growth rates for plague in London, 1348–1665

- ▶ Later plagues grew 4× faster than early plagues!

Doubling time:

- ▶ In 1348: ~ 45 days
 - ▶ In 1665: ~ 11 days
-
- ▶ **Why** did plague epidemics “accelerate”?
 - ▶ Evolution of increased infectiousness? longer infectious period?
 - ▶ Changes in population density? social structure? contact patterns?
 - ▶ Changes in weather?
 - ▶ Bubonic vs. pneumonic plague?

Bubonic or pneumonic plague?

Suppose pneumonic plague during second pandemic was exactly like modern pneumonic plague.

- ▶ Pneumonic in 14th century London?
 - ⇒ ~ 20% of population infected
 - BUT ~ 30–50% of total population died in 1348
 - ⇒ early plagues probably not (primarily) pneumonic

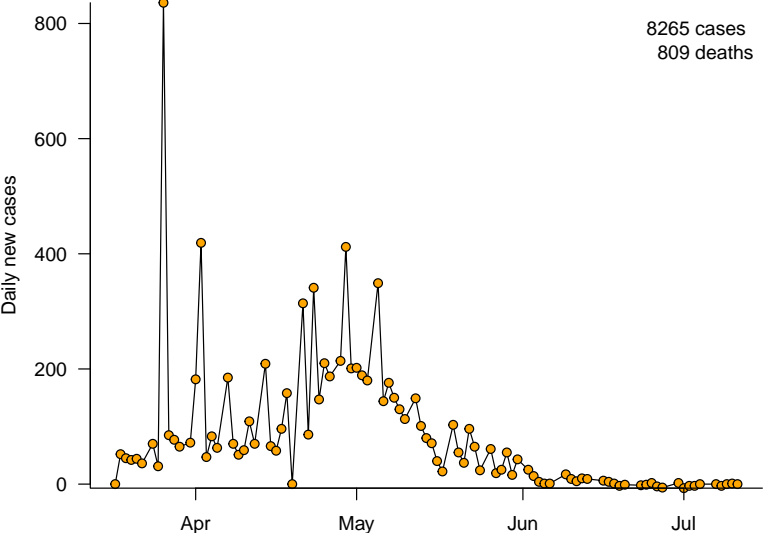
- ▶ A remarkable inference to be able to make based on counting wills! (and a little mathematical modelling)

Outline

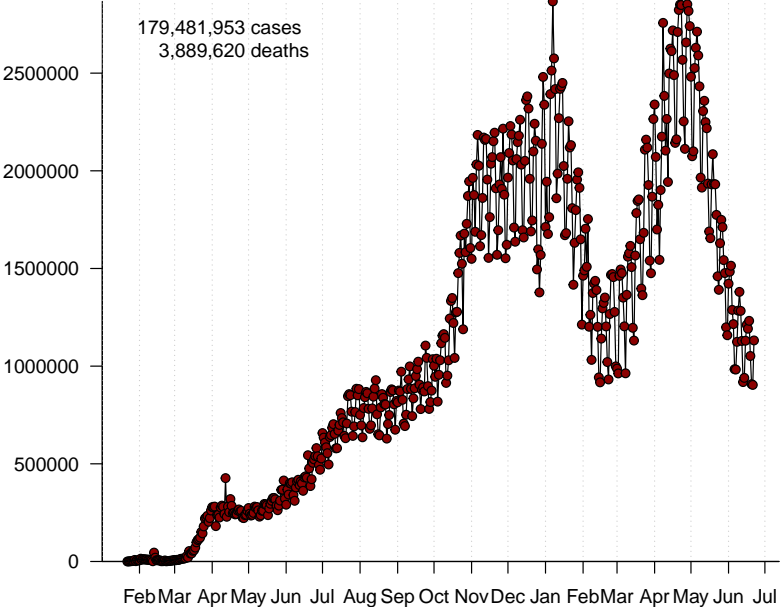
- ▶ Predicting patterns of epidemic recurrence
- ▶ Puzzles presented by plagues of the past
- ▶ **Forecasting the future: modelling and policy**

SARS

Daily SARS-CoV-1 in 2003 (Worldwide)



Daily SARS-CoV-2 in 2020–2021 (Worldwide)



Daily SARS-CoV-2 vs SARS-CoV-1 (Worldwide)

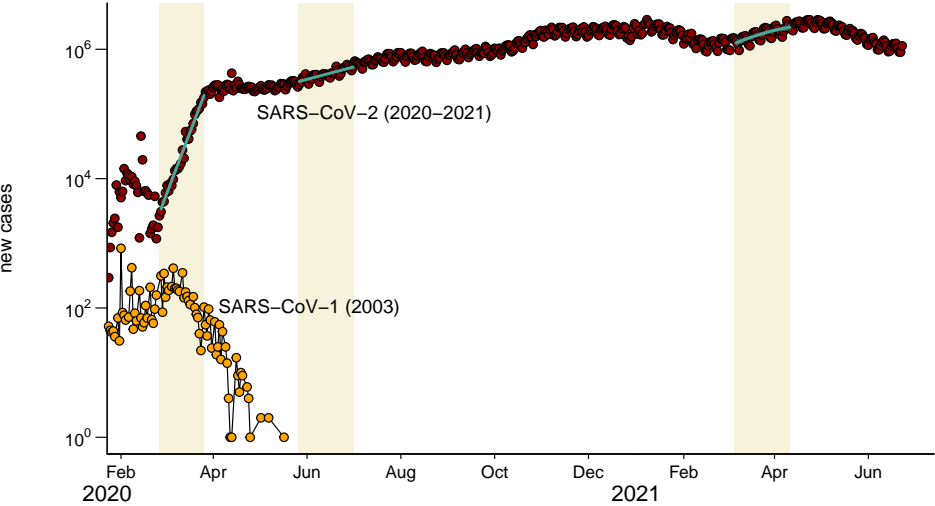
initial doubling time, days:

estimate
(95% CI)

4.8
(4.6, 5.0)

46.4
(36.3, 59.4)

21.8
(7.6, 62.7)

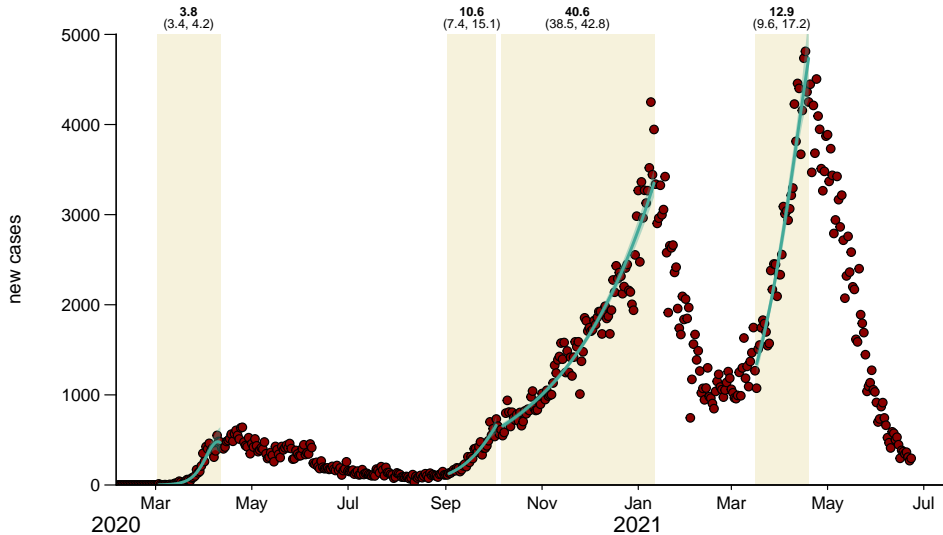


SARS-CoV-2 in Ontario

COVID-19 cases in Ontario

initial doubling time, days:

estimate
(95% CI)



Modelling SARS-CoV-2 / COVID-19

Much richer data (compared with historical epidemics):

- ▶ Daily counts of positive tests, hospital occupancy, ICU occupancy, deaths, . . .
- ▶ Daily vaccine doses administered
- ▶ Daily measures of weather, mobility
- ▶ Info on policy changes, travel restrictions, new virus variants, . . .

Harder problem:

- ▶ Forecast the future!

Modelling SARS-CoV-2 / COVID-19

Approach:

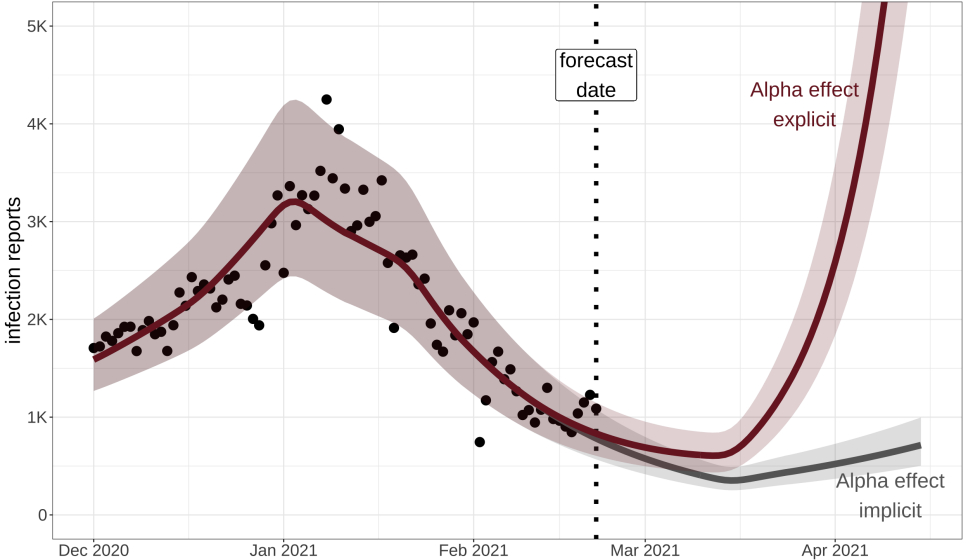
- ▶ Expand SEIR model to include compartments for cases, deaths, hospital occupancy, *etc*
- ▶ Simultaneously fit model to all the types of data we have
- ▶ Predict the future based on various scenarios

Interpret forecasts with caution:

- ▶ Quantify uncertainties we understand (parameter estimates, observation and process noise)
- ▶ Be aware that models cannot capture all processes

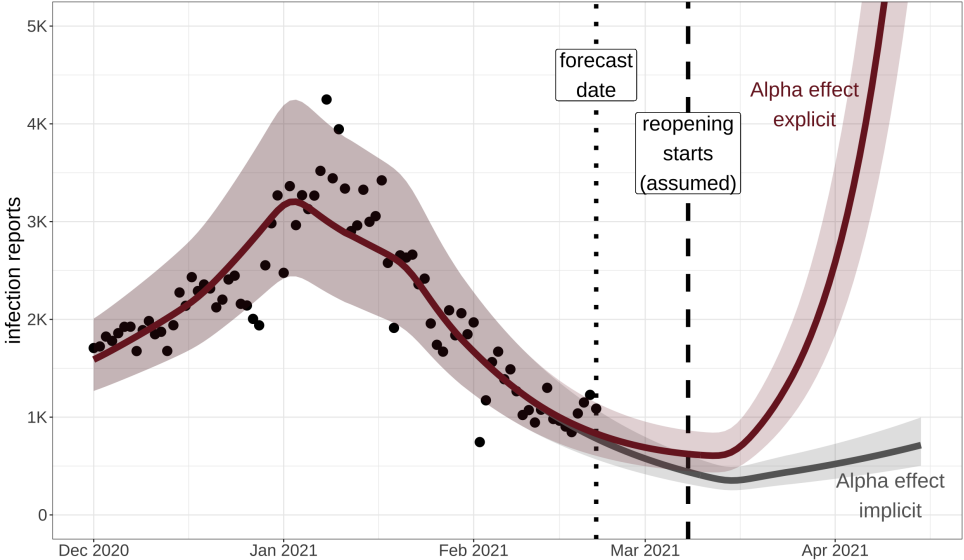
Fitting and forecasting COVID-19 in Ontario

Forecast from 21 Feb 2021



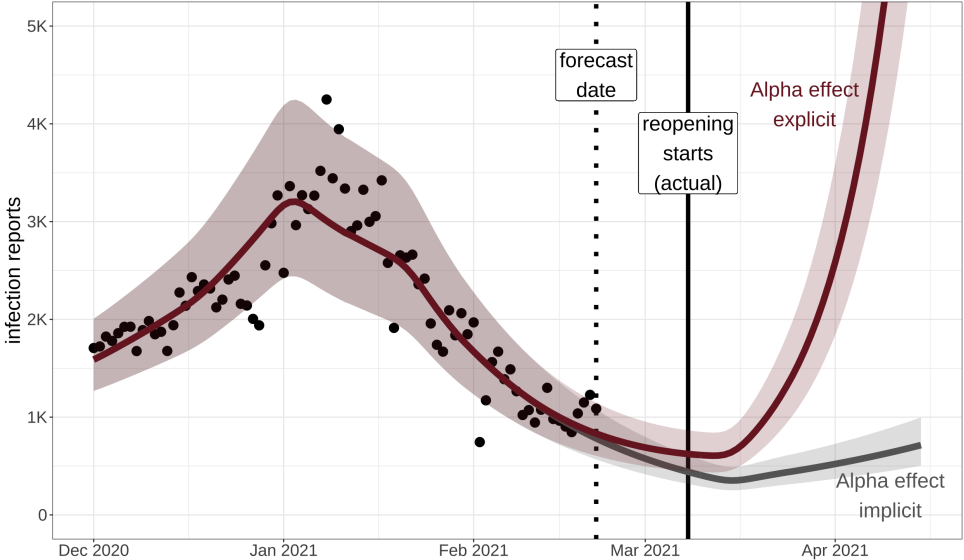
Fitting and forecasting COVID-19 in Ontario

Forecast from 21 Feb 2021



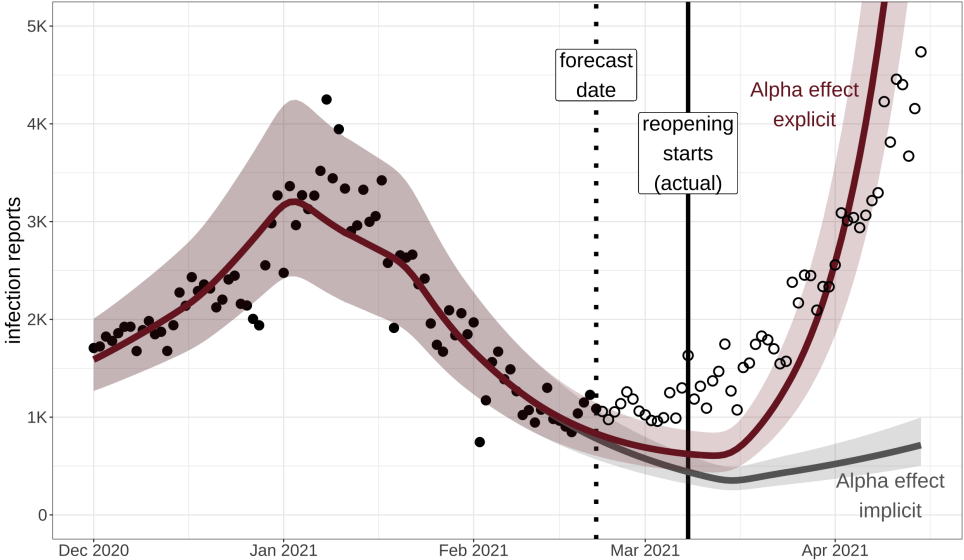
Fitting and forecasting COVID-19 in Ontario

Forecast from 21 Feb 2021



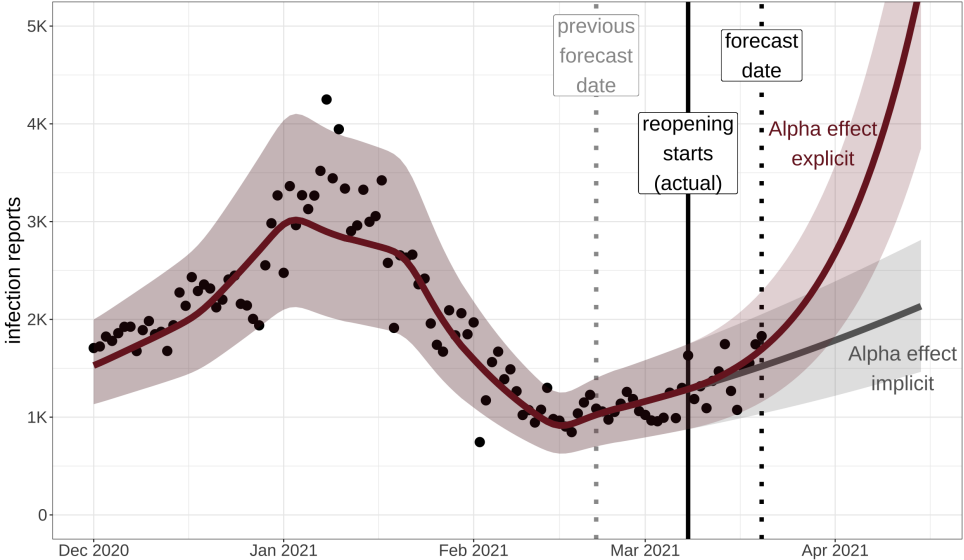
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Forecast from 21 Feb 2021



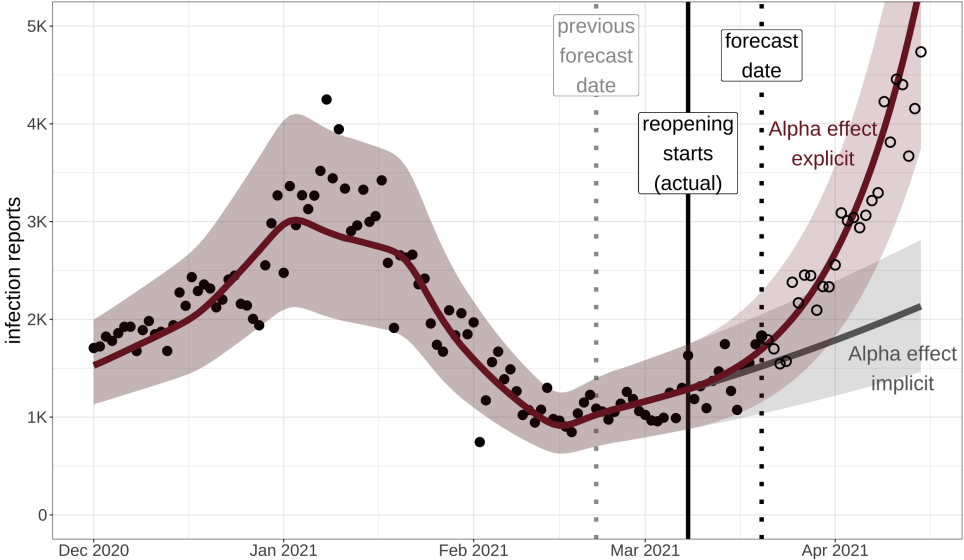
Fitting and forecasting COVID-19 in Ontario

Forecast from 20 Mar 2021



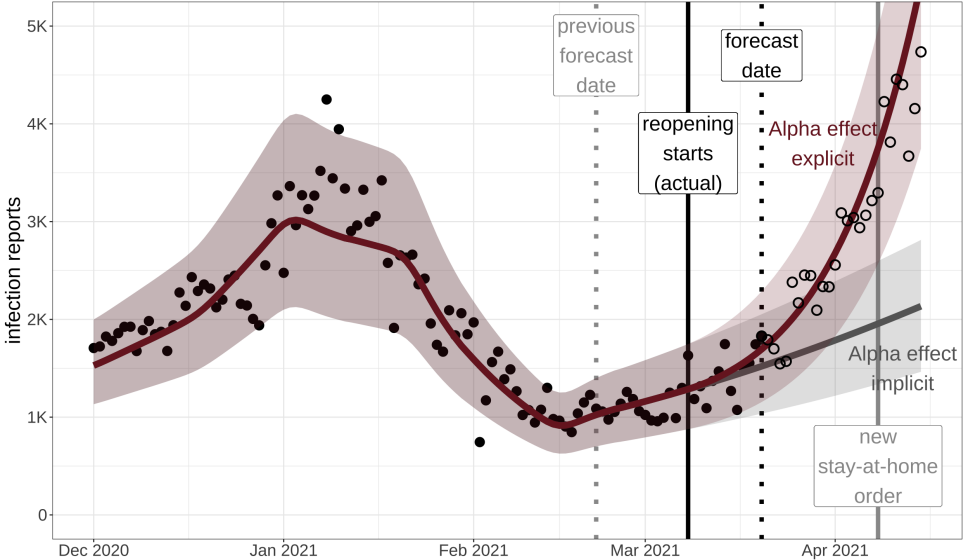
Fitting and forecasting COVID-19 in Ontario

Forecast from 20 Mar 2021



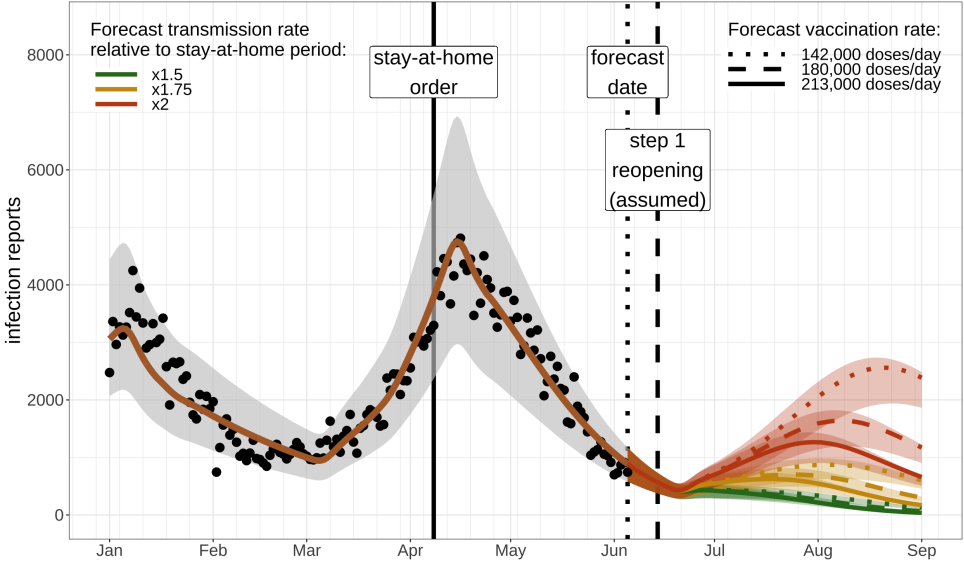
Fitting and forecasting COVID-19 in Ontario

Forecast from 20 Mar 2021



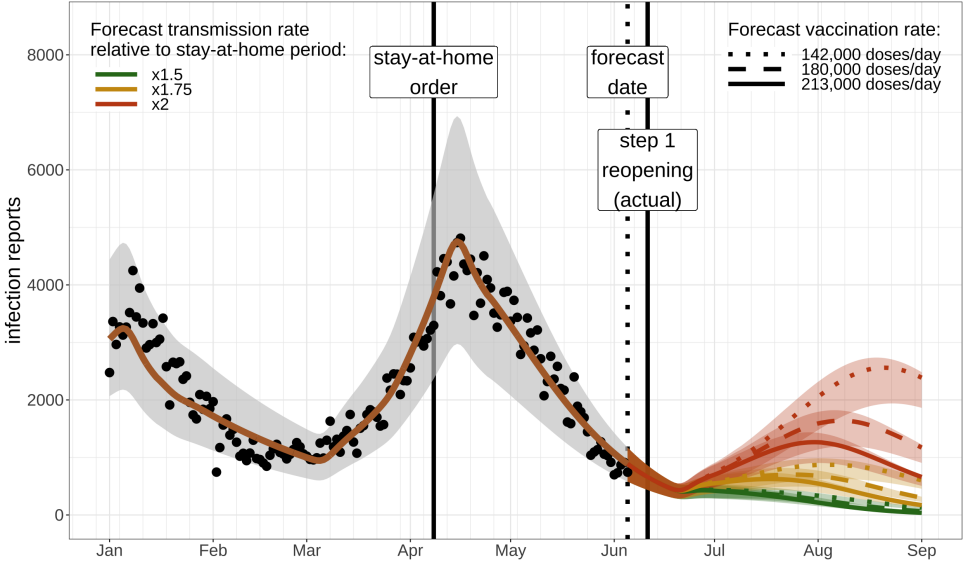
Fitting and forecasting COVID-19 in Ontario

Forecast from 5 Jun 2021



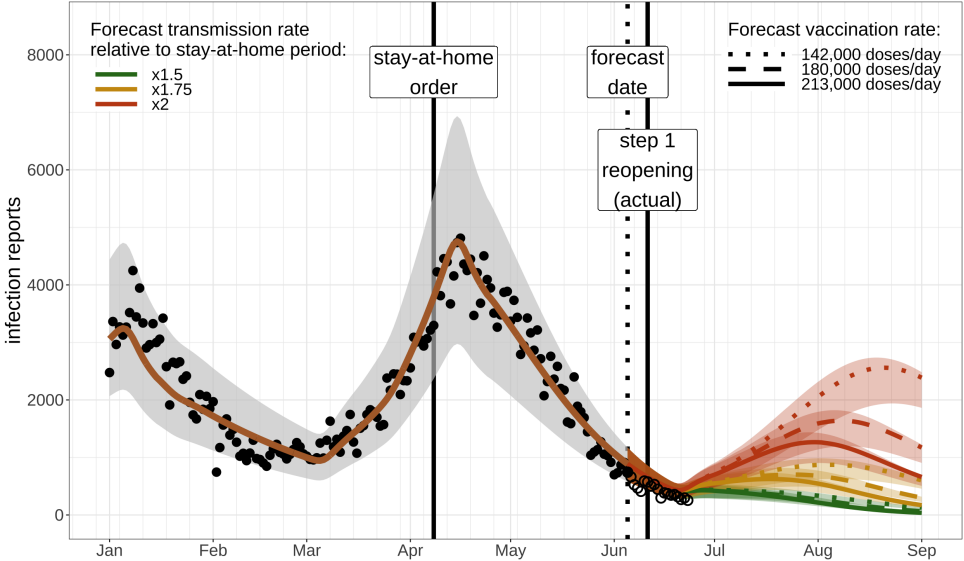
Fitting and forecasting COVID-19 in Ontario

Forecast from 5 Jun 2021



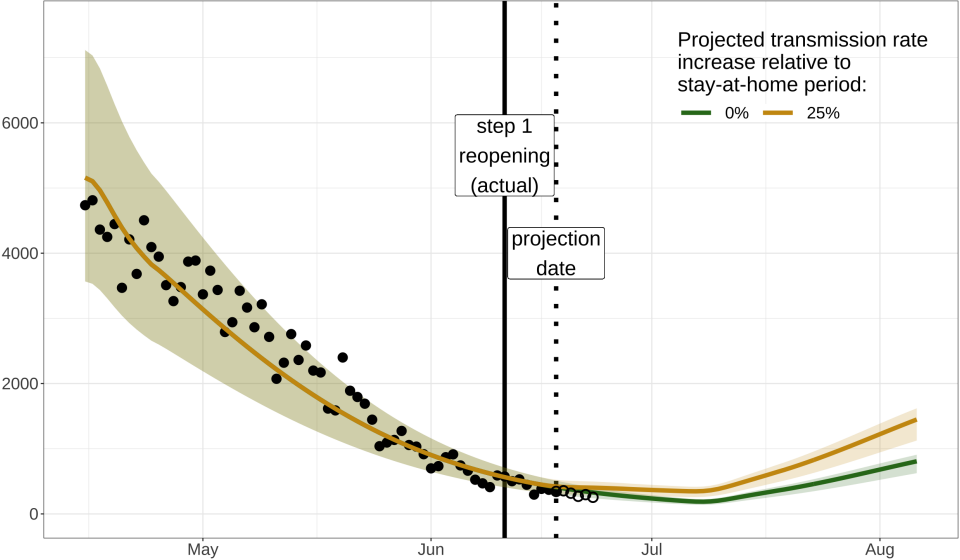
Fitting and forecasting COVID-19 in Ontario

Forecast from 5 Jun 2021



Fitting and forecasting COVID-19 in Ontario

Projections from 18 Jun 2021



Acknowledgements

- ▶ *McMaster University:*
Ben Bolker, Jonathan Dushoff, Hendrik Poinar
- ▶ *University of Victoria:*
Junling Ma
- ▶ *University of Alberta:*
Karsten Hempel
- ▶ *Public Health Agency of Canada:*
Michael Li, David Champredon
- ▶ *University of Waterloo:* Mikael Jagan
- ▶ *Cornell University:* Irena Papst
- ▶ *Canadian Institute for Health Information (CIHI):*
Olga Krylova

Funders:



Thanks for your interest!

<https://davidearn.mcmaster.ca>

<https://mac-theobio.github.io/covid-19/>

6 Mechanistic Modelling of Recurrent Epidemics II; \mathcal{R}_0



Mathematics
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 6

Mechanistic Modelling of Recurrent Epidemics II
Tuesday 8 October 2024

Announcements

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 - *Date:* Tuesday 5 November 2024
 - *Time:* 2:30pm – 4:30pm
 - *Location:* in class, HH-102

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 - *Date:* Tuesday 5 November 2024
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- **Assignment 4** is due the day of the midterm.

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Due Monday 4 November 2019 before class.

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Due Monday 4 November 2019 before class.
 - Make sure *you personally* can do the question on calculating \mathcal{R}_0 on this assignment *before* the midterm test.

\mathcal{R}_0 : biological definition

The *basic reproduction number* \mathcal{R}_0 is:
the expected number of secondary cases produced, in a completely susceptible population, by a typical infective individual

e.g., Anderson and May (1991) "Infectious Diseases of Humans"

\mathcal{R}_0 : more mathematical definition

The *basic reproduction number* \mathcal{R}_0 is:

the number of new infections produced by a typical infective individual in a population at a disease free equilibrium (DFE)

van den Driessche and Watmough (2002) *Mathematical Biosciences* **180**, 29–48

\mathcal{R}_0 : most mathematical definition

The *basic reproduction number* \mathcal{R}_0 is:
the spectral radius of the next generation operator at a disease free equilibrium (DFE)

Diekmann, Heesterbeek & Metz (1990) *J. Math. Biol.* **28**, 365–382

Definitions from matrix analysis

Definitions from matrix analysis

Definition (Spectrum of a matrix)

Let M be an $n \times n$ real (or complex) matrix. The *spectrum of M* is

$$\sigma(M) = \{ \lambda : Mv = \lambda v \text{ for some non-zero } v \in \mathbb{C}^n \},$$

i.e., $\sigma(M)$ is the set of eigenvalues of M .

Definitions from matrix analysis

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i.e., $\rho(M)$ is the maximum modulus of the eigenvalues of M .

Computing \mathcal{R}_0

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- Mathematically, the spectral radius of the next generation operator at the DFE is exactly this quantity. With this definition, it is also true that the disease persists if $\mathcal{R}_0 > 1$ and goes extinct if $\mathcal{R}_0 < 1$.

SEIR model (with vital dynamics)

$$\frac{dS}{dt} = \mu N - \frac{\beta SI}{N} - \mu S$$

$$\frac{dE}{dt} = \frac{\beta SI}{N} - \sigma E - \mu E$$

$$\frac{dI}{dt} = \sigma E - \gamma I - \mu I$$

$$\frac{dR}{dt} = \gamma I - \mu R$$

- Birth and death rate (μ)
- Transmission rate (β)
- Mean latent period ($1/\sigma$)
- Mean infectious period ($1/\gamma$)

Next generation matrix for the SEIR model

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- Consider flows in and out of the infected compartments

Next generation matrix for the SEIR model

- Consider flows in and out of the infected compartments, and **highlight** flows that correspond to **new infections**:

$$\frac{d}{dt} \begin{pmatrix} E \\ I \end{pmatrix} = \begin{pmatrix} \beta SI - \sigma E - \mu E \\ \sigma E - \gamma I - \mu I \end{pmatrix}$$

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- \mathcal{F} = inflow of **new infecteds** to infected compartments = $\begin{pmatrix} \beta SI \\ 0 \end{pmatrix}$
- \mathcal{V} = outflow from infected compartments minus inflow of non-new infecteds = $\begin{pmatrix} \sigma E + \mu E \\ -\sigma E + \gamma I + \mu I \end{pmatrix}$

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- Let F = linearization of \mathcal{F} at DFE
- Let V = linearization of \mathcal{V} at DFE

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- Then the **next generation matrix** is FV^{-1}

Next generation matrix for the SEIR model

- Consider flows in and out of the infected compartments, and **highlight** flows that correspond to **new infections**:

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- Analogous to $\beta\gamma^{-1}$ in simple case.

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- Hence, the (i, k) entry of the product FV^{-1} is the expected number of new infections in compartment i produced by the infected individual originally introduced into compartment k .

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- Hence, the (i, k) entry of the product FV^{-1} is the expected number of new infections in compartment i produced by the infected individual originally introduced into compartment k .
- Following Diekmann et al. (1990), we call FV^{-1} the next generation matrix for the model and set

$$\mathcal{R}_0 = \rho(FV^{-1}),$$

where $\rho(A)$ denotes the **spectral radius** of a matrix A .

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- Note wrt [previous slide](#) that the (2, 1) entry of V^{-1} is the average time an individual who enters the E compartment spends in the I compartment: only a proportion $\sigma / (\sigma + \mu)$ of such individuals make it to the I compartment, where the average time spent—by individuals who get there—is $1 / (\gamma + \mu)$.

Computing \mathcal{R}_0 for other compartmental ODE models

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- 1 \mathcal{R}_0 can be computed as $\rho(FV^{-1})$;
- 2 if $\mathcal{R}_0 < 1$ then the disease-free equilibrium (DFE) is locally asymptotically stable (LAS), whereas if $\mathcal{R}_0 > 1$ then there is a LAS endemic equilibrium (EE).

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- If possible, it is best to use both methods to find an expression for \mathcal{R}_0 , and make sure they agree.
- A completely different challenge is to estimate \mathcal{R}_0 for a real epidemic from data. . .

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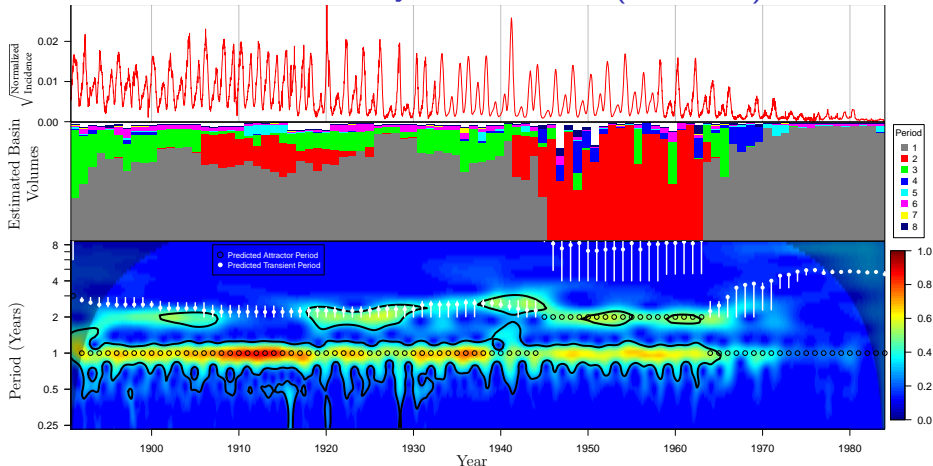
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- Solving this for β we obtain: $\beta = \frac{(r + \sigma + \mu)(r + \gamma + \mu)}{\sigma}$

Measles in New York City, 1891–1984 (success!)



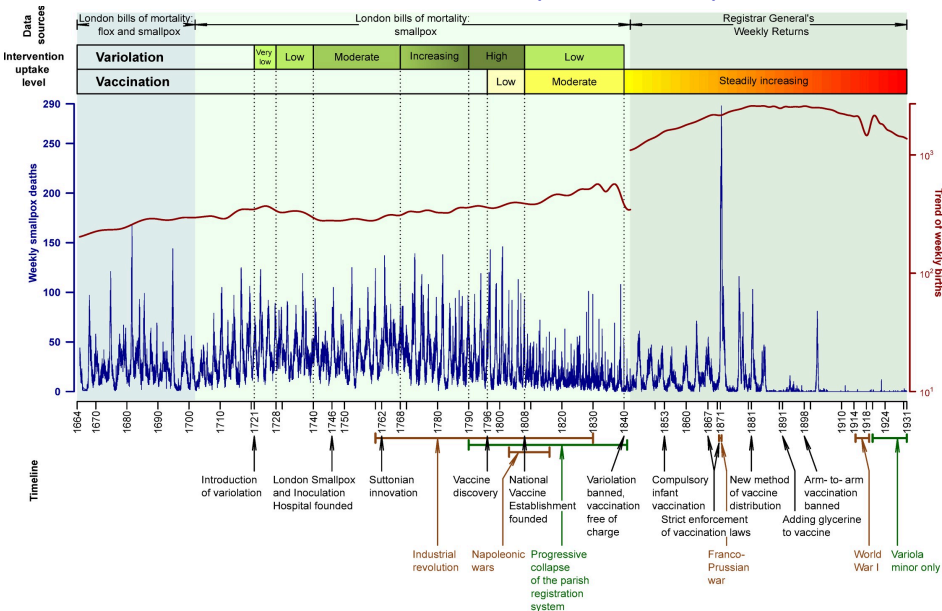
Hempel & Earn (2015) *J. R. Soc. Interface* 12(106):20150024

- ▶ Key challenge that had to be overcome:
changing patterns of seasonal variation in contact rates

Papst & Earn (2019) *J. R. Soc. Interface* 16:20190202

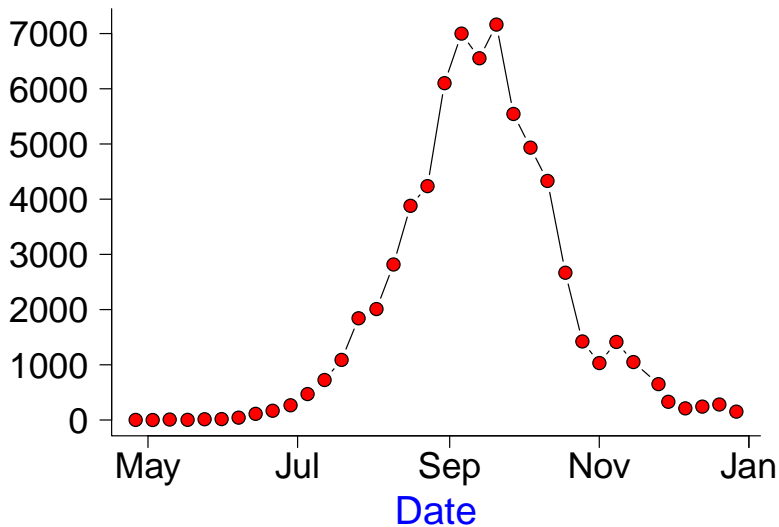
Jagan et al. (2020) *PLoS Comp. Biol.* 16(9):e1008124

Smallpox in London, 1664–1930 (in progress)



The Great Plague of London, 1665

Weekly Deaths from Plague



SEIR Model Fit to the Great Plague of London

Weekly Deaths from Plague

