



Challenges in Modeling SARS-CoV-2: Bridging the Best of Both Worlds Between Models and Reality

Michael Li - McMaster University

Background

Math and Statistics

MacTheoBio

Theoretical, statistical and computational approaches to study biology

Infectious diseases

Spatial ecology

Evolution



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Math and Statistics

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Theoretical, statistical and computational approaches to study biology

Infectious diseases

- Malaria
- Ebola
- Influenza
- Canine Rabies
- HIV
- etc..



Background

Math and Statistics

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Theoretical, statistical and computational approaches to study biology

Infectious diseases

- Malaria
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- HIV
- etc..

I can read Chinese!



A large, solid maroon circle is positioned on the left side of the slide, partially overlapping the text 'Part 1'.

Part 1

2019–2020

WuHan Novel Corona Virus Outbreak

Background

2019–2020 WuHan Novel Corona Virus Outbreak



- Late December 2019, several suspicious cases of pneumonia in Wuhan City, Hubei Province of China.
- Unknown virus
- Early January 2020, Chinese authorities confirmed that they had identified a new virus.

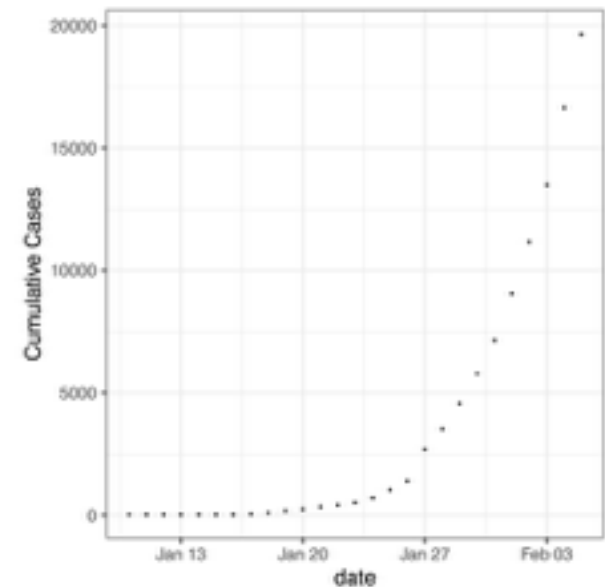
Data collection



Jan 21st 24:00

105 new cases,
3 discharge and 3 death

375 Cumulative cases
28 Discharged
9 death



The Basic Reproductive Number/Ratio (R_0)



- Expected number of new cases per case
- Good index of risk at the population level

The Basic Reproductive Number/Ratio (R_0)

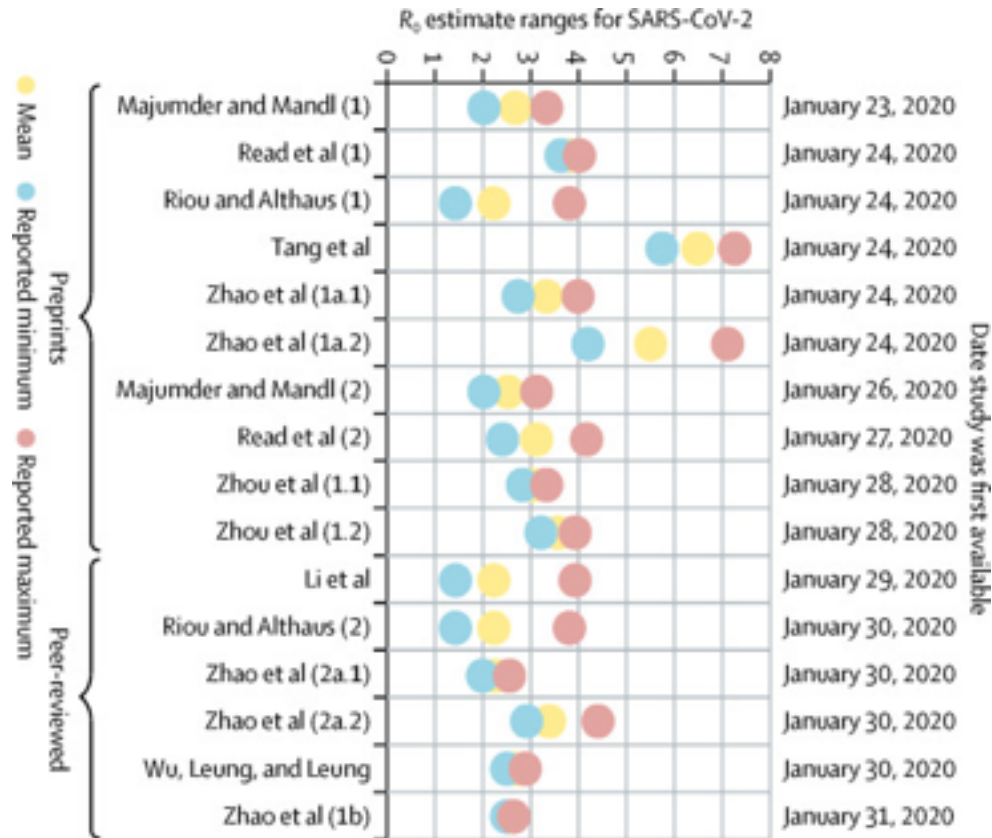


- Expected number of new cases per case
- Good index of risk at the population level

Most Valuable Piece
of information in disease modelling



WH outbreak R_0 Estimates



Majumder, M.S. and Mandl, K.D., 2020. Early in the epidemic: impact of preprints on global discourse about COVID-19 transmissibility. *The Lancet Global Health*, 8(5), pp.e627-e630.

Exponential Fitting Framework



- Exponential growth rate (r)
- Generation Interval

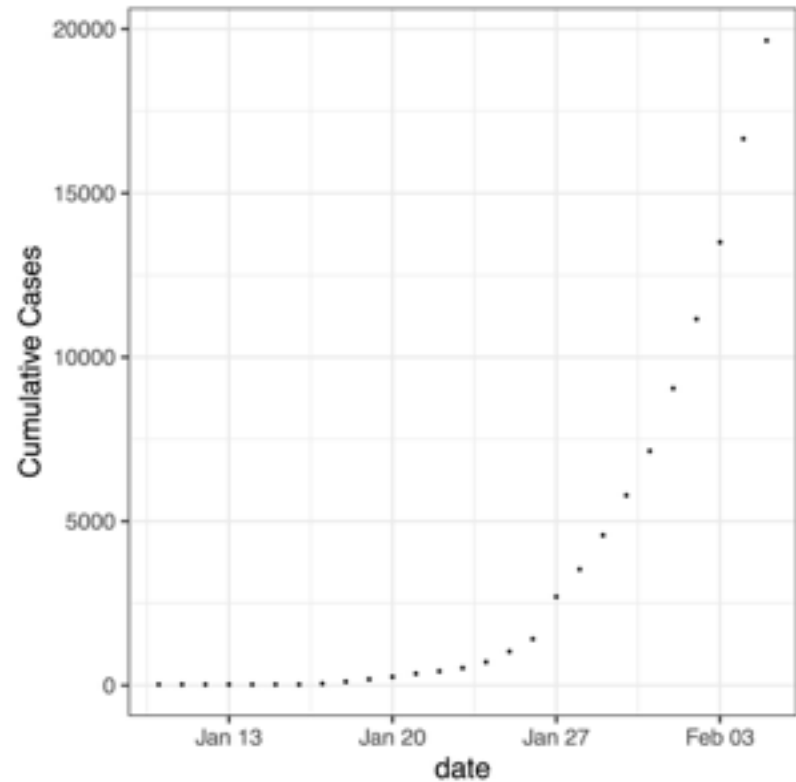
Exponential Fitting Framework



- **Exponential growth rate (r)**
- Generation Interval

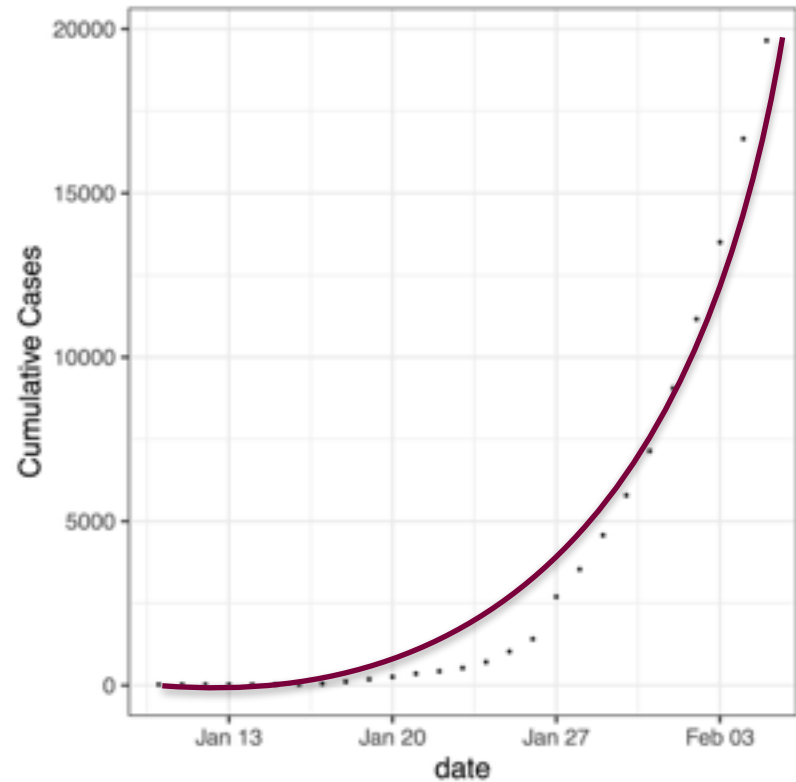
Exponential growth rate (r)

- Estimate from time series data



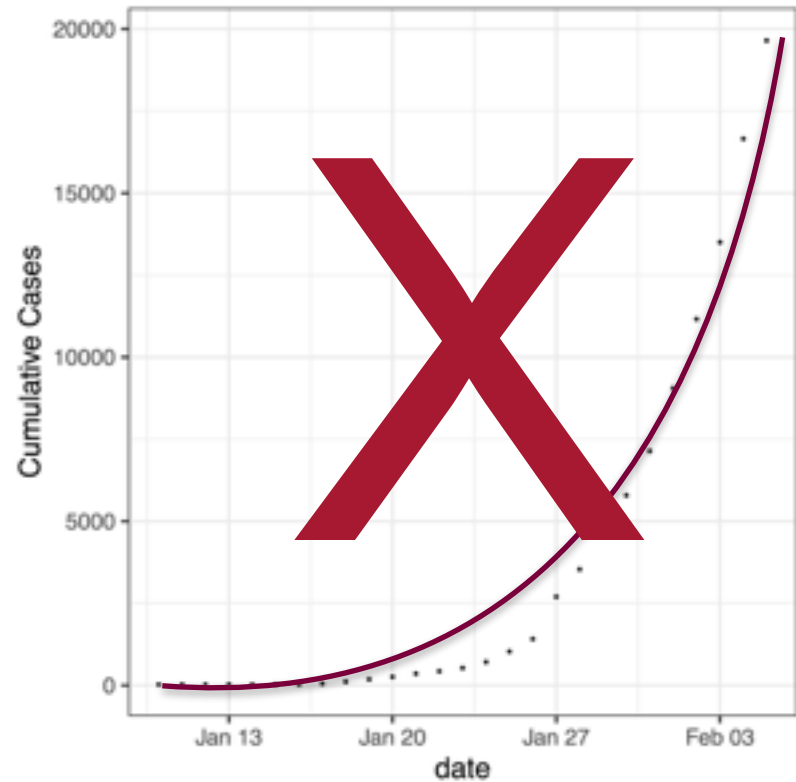
Exponential growth rate (r)

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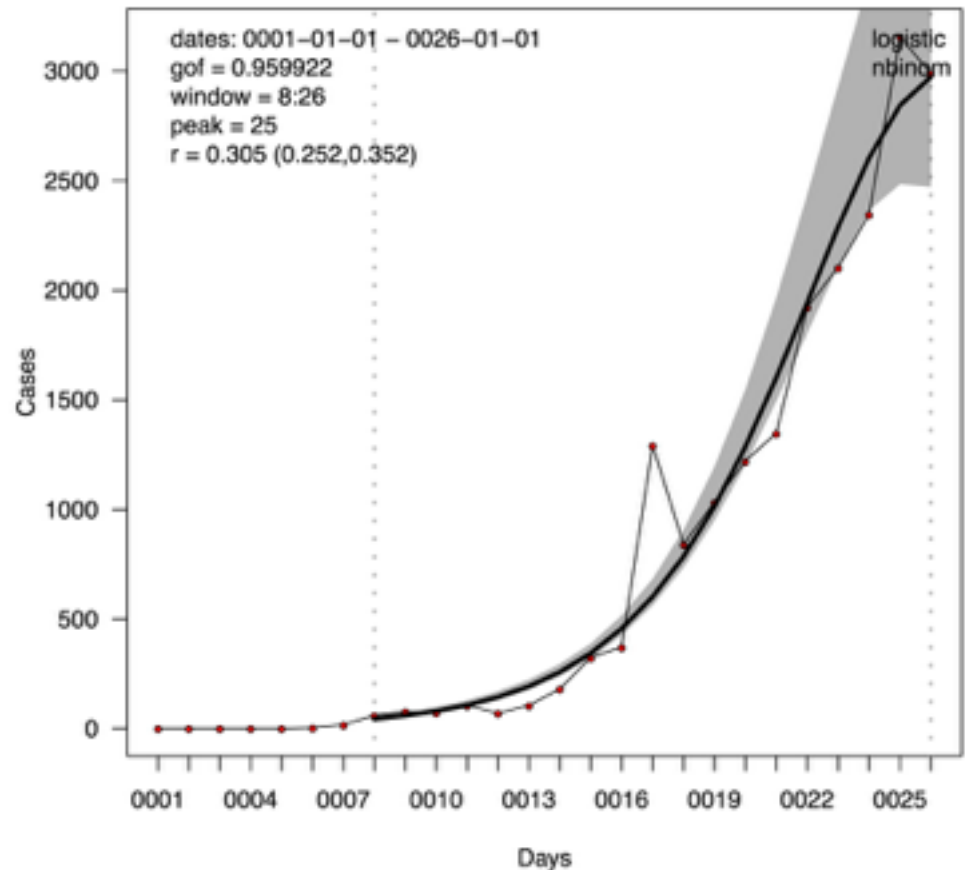
Exponential growth rate (r)

- Estimate from time series data



Exponential growth rate (r)

- Estimate from time series data
- Fitting to incidence data
- Logistic model with negative binomial noise
- epigrowthfit package in R



Ma, J., Dushoff, J., Bolker, B.M. and Earn, D.J., 2014. Estimating initial epidemic growth rates. *Bulletin of mathematical biology*, 76(1), pp.245-260.

Exponential Fitting Framework



- Exponential growth rate (r)
- **Generation Interval**

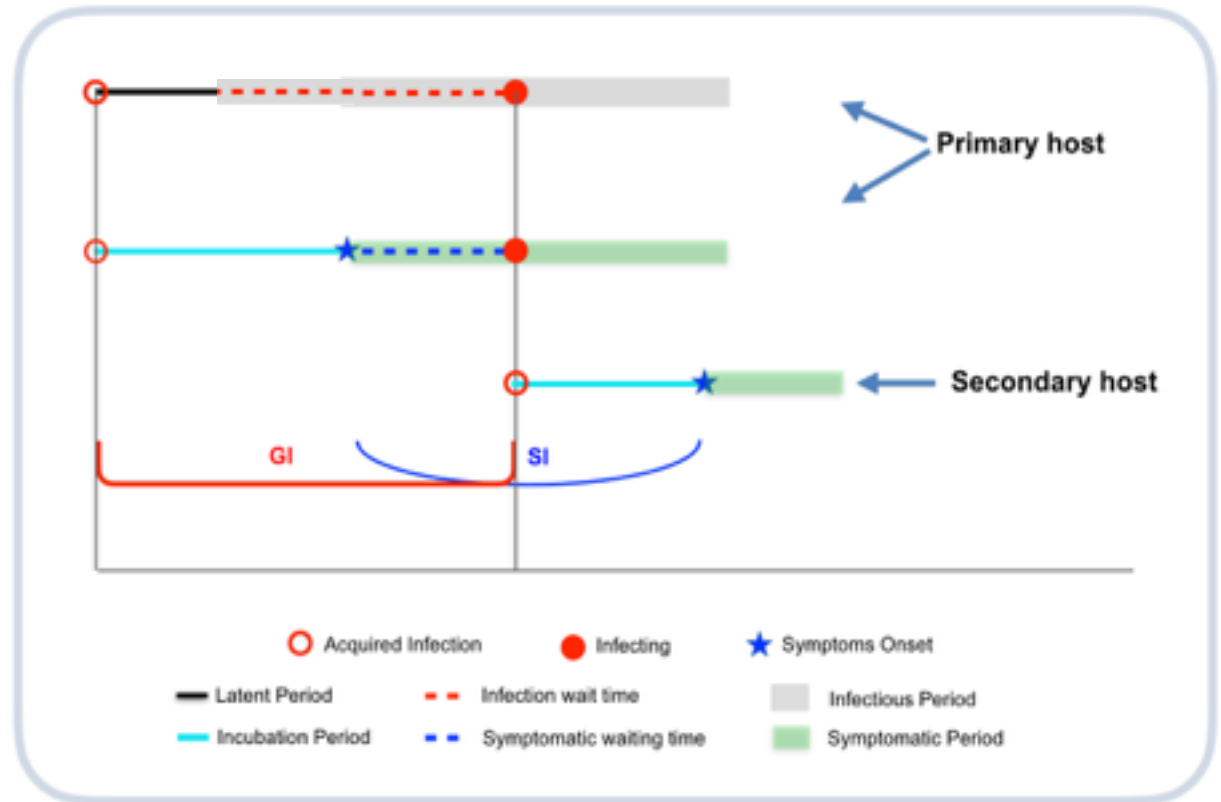
Generation interval

- Time between infections
- Focal individual



Generation interval

- Time between infections
- Focal individual
- Infection are hard to observe
- Serial intervals
- Time between symptom onsets



Exponential Fitting Framework



- Exponential growth rate (r)
- Generation Interval

Exponential Fitting Framework



- Exponential growth rate (r)
- Generation Interval

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

Euler-Lotka equation

Wallinga, J. and Lipsitch, M., 2007. How generation intervals shape the relationship between growth rates and reproductive numbers. *Proceedings of the Royal Society B: Biological Sciences*, 274(1609), pp.599-604.

Gamma approximation framework



- Exponential growth rate (r)
- **Generation Interval (GI)**
 - Mean GI (\bar{G})
 - Dispersion (κ)

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

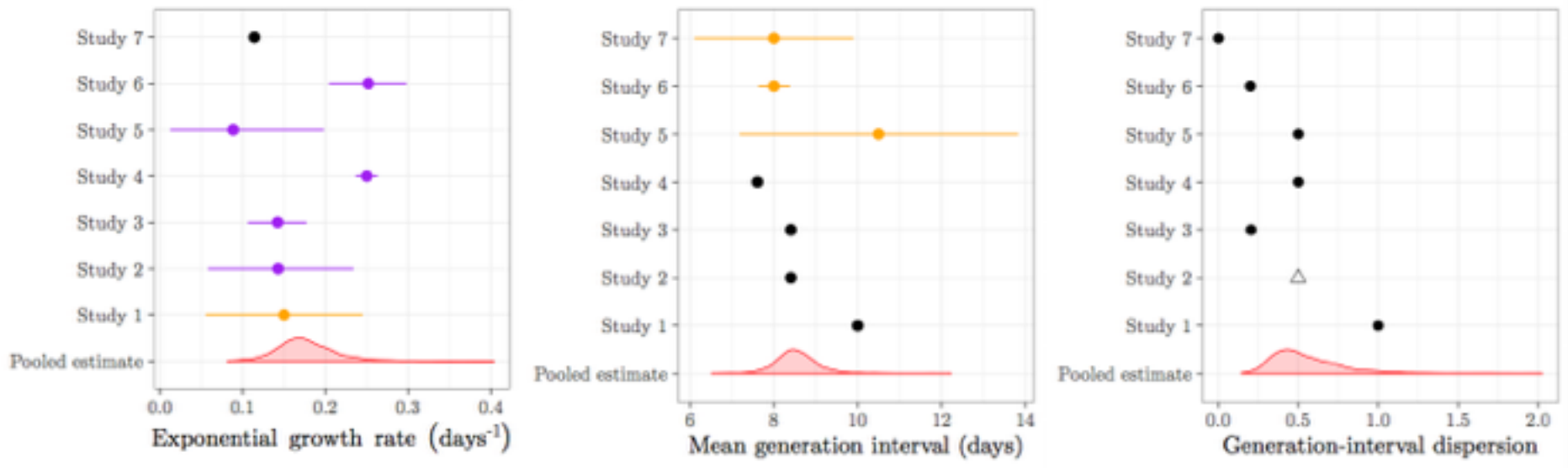
Park, S.W., Champredon, D., Weitz, J.S. and Dushoff, J., 2019. A practical generation-interval-based approach to inferring the strength of epidemics from their speed. *Epidemics*, 27, pp.12-18.

R₀ estimates

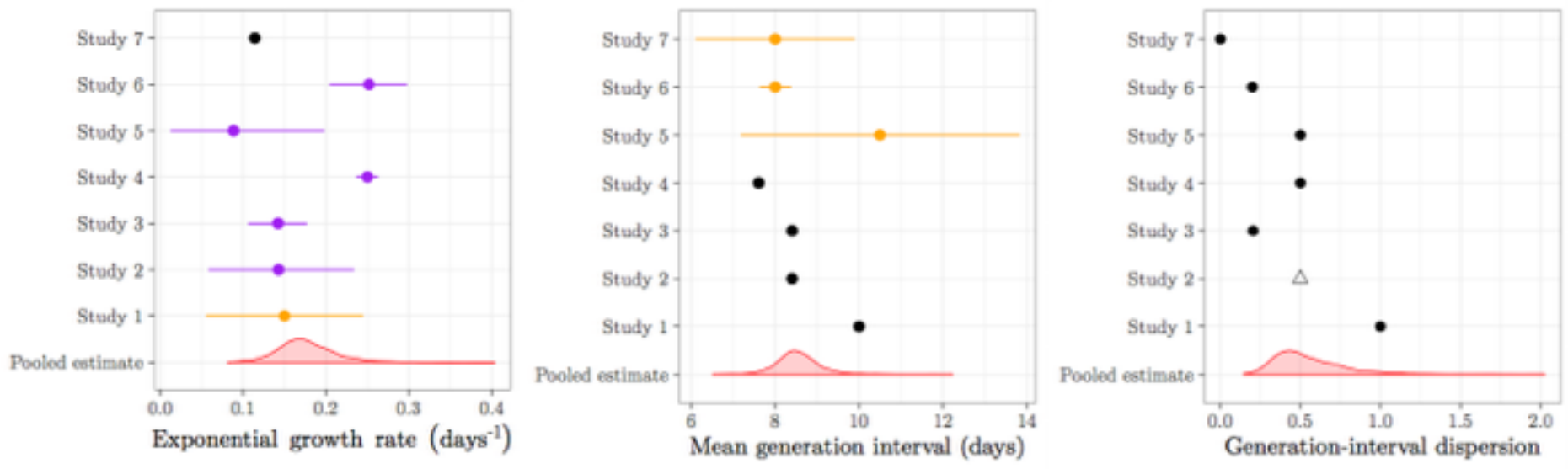
	Model	Data (study period)	Data source	Basic reproductive number \mathcal{R}_0	Mean generation interval \bar{G} (days)	Generation-interval dispersion κ	Reference
Study 1	Deterministic branching process model	Total number of cases in Wuhan City, China (Jan 18, 2020)	Estimated by Imai et al. (2020)	1.5–3.5	10	1	Bedford et al. (2020)
Study 2	Stochastic branching process model	Total number of cases in Wuhan City, China (Jan 18, 2020)	Estimated by Imai et al. (2020)	2.6 (1.5–3.5)*	8.4	Not reported [†]	Imai et al. (2020)
Study 3	Poisson offspring distribution model	Confirmed cases from China and other countries (Dec 29, 2019–Jan 23, 2020)	Medical records and epidemiological investigations from Guangdong Province, China, and official websites of other regions in China	2.92 (95% CI: 2.28–3.67)	8.4	0.2	Liu et al. (2020)
Study 4	Deterministic Metapopulation Susceptible–Exposed–Infected–Recovered (SEIR) model	Confirmed cases from China and other countries (Jan 1–21, 2020)	Not reported	3.8 (95% CI: 3.6–4.0)	7.6	0.5	Read et al. (2020a)
Study 5	Stochastic branching process model	Total number of cases in Wuhan City, China (Jan 18, 2020)	Estimated by Imai et al. (2020)	2.2 (90% CI: 1.4–3.8)	7–14	0.5	Riou and Althaus (2020a)
Study 6	Exponential growth model	Confirmed cases from China (Jan 10–22, 2020)	Wuhan Municipal Health Commission, China and National Health Commission of China	5.47 (95% CI: 4.16–7.10) [‡]	7.6–8.4	0.2	Zhao et al. (2020)
Study 7	Incidence Decay and Exponential Adjustment (IDEA) model	Reported cases from Wuhan City, China (Dec 1, 2019–Jan 26, 2020)	World Health Organization, National Health Commission of China, Wuhan Municipal Health Commission, and Huang et al. (2020)	2.0–3.1	6–10	0	Majumder and Mandl (2020a)

Park, S.W., Bolker, B.M., Champredon, D., Earn, D.J., Li, M., Weitz, J.S., Grenfell, B.T. and Dushoff, J., 2020. Reconciling early-outbreak estimates of the basic reproductive number and its uncertainty: framework and applications to the novel coronavirus (SARS-CoV-2) outbreak. (In press)

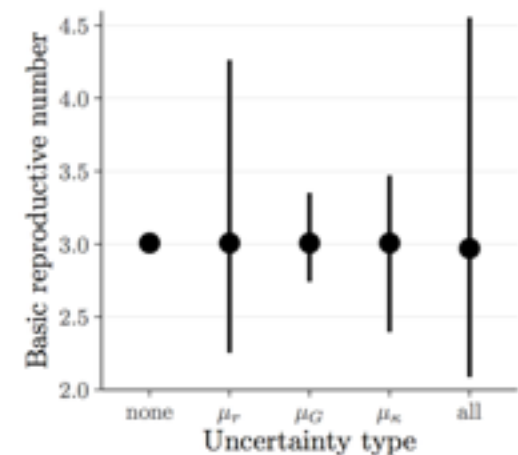
Parameter Uncertainties



Parameter Uncertainties

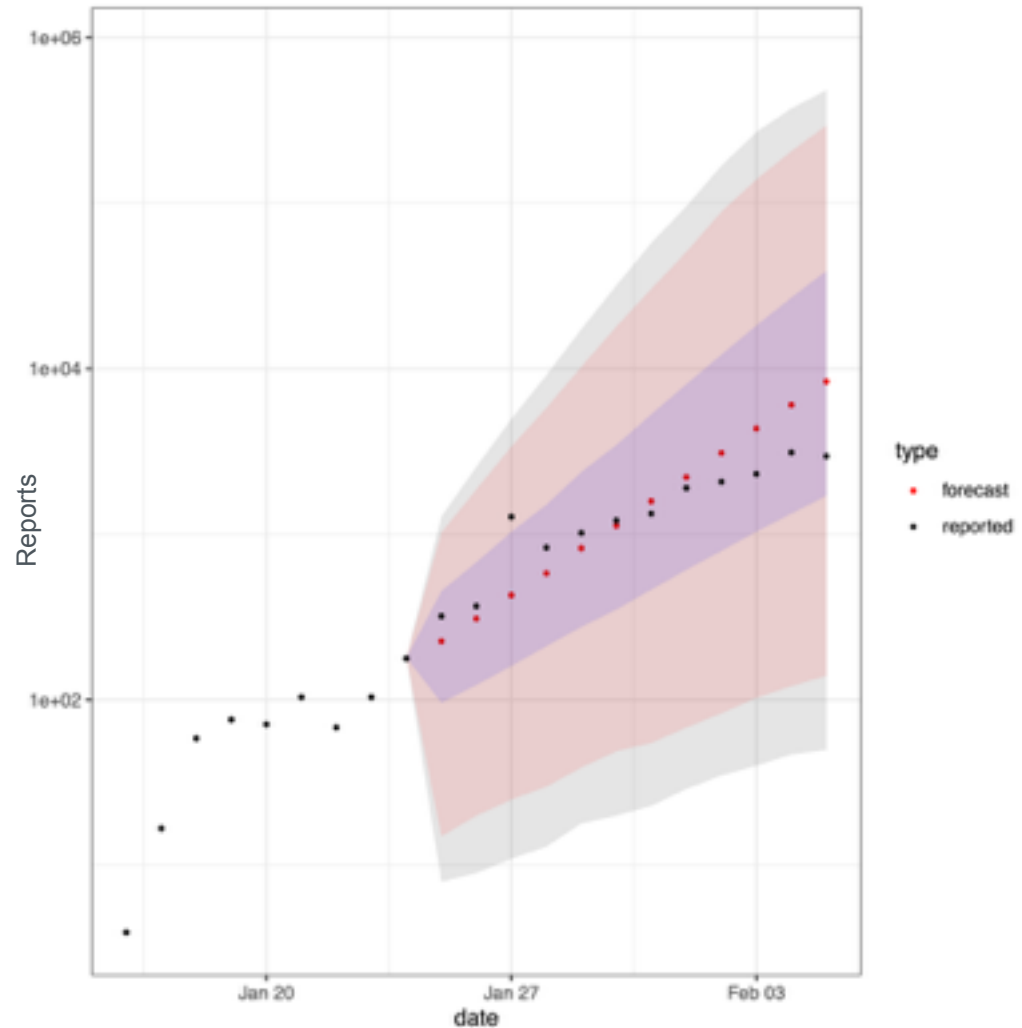


- Uncertain of R_0 comes from these parameters
- Important to propagate uncertainties from all the parameters



Forecasting

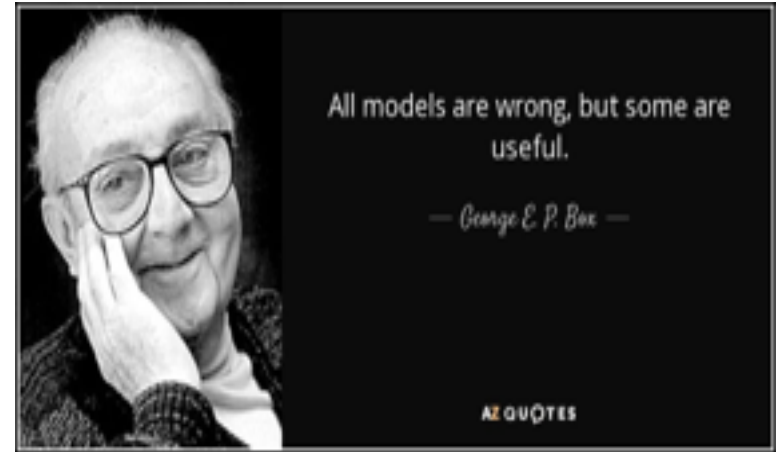
- Bayesian Discrete-time SIR
 - Dual beta-binomial process
 - Transmission and observation
- 2 week projection



Li, M., Dushoff, J. and Bolker, B.M., 2018. Fitting mechanistic epidemic models to data: A comparison of simple Markov chain Monte Carlo approaches. *Statistical methods in medical research*, 27(7), pp. 1956-1967.

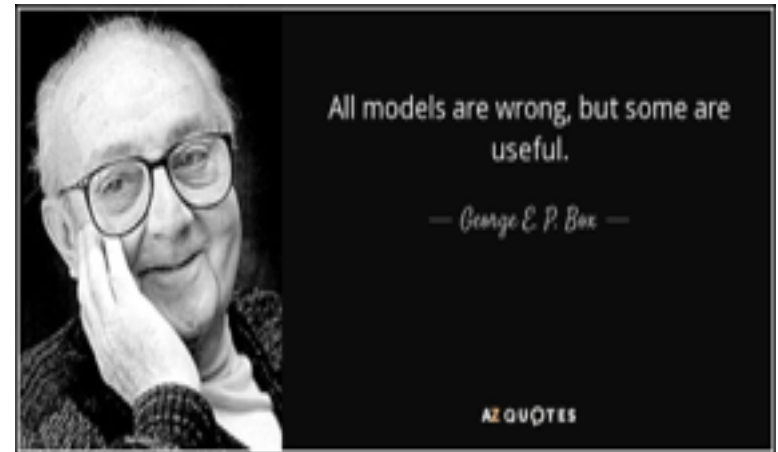
Summary

- Easy to make a model
- Extremely hard to make models that:
 - are informative
 - predict well
 - work in real time
- Discrepancies between R_0 estimates is hard to understand
 - Method
 - Data
- Hard to communicate clearly.
 - E.g. $R_0 \sim 3$ (2,4)



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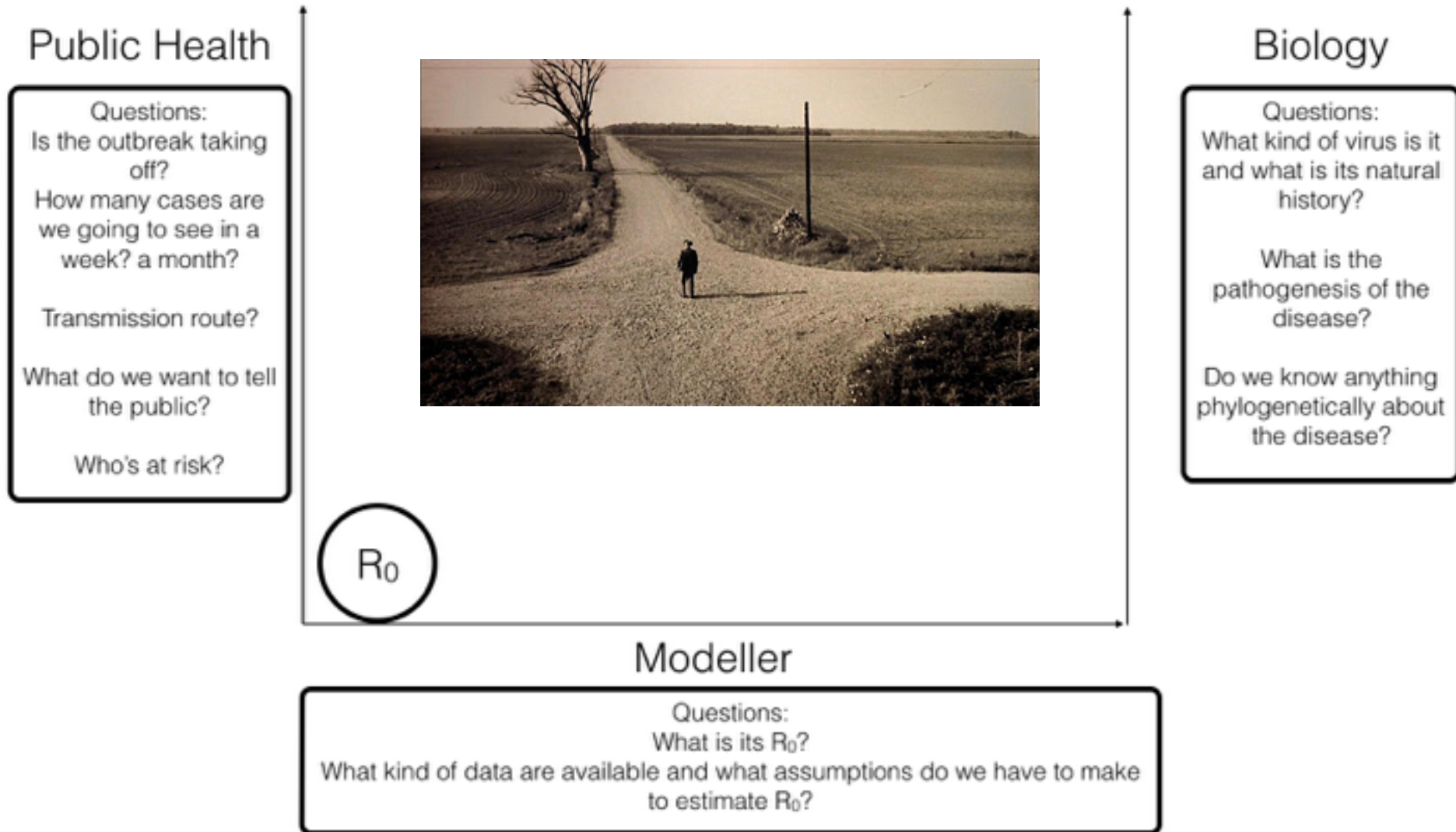
- Predictions of the short-term trajectories are useful

Moving forward and preparing for the global pandemic

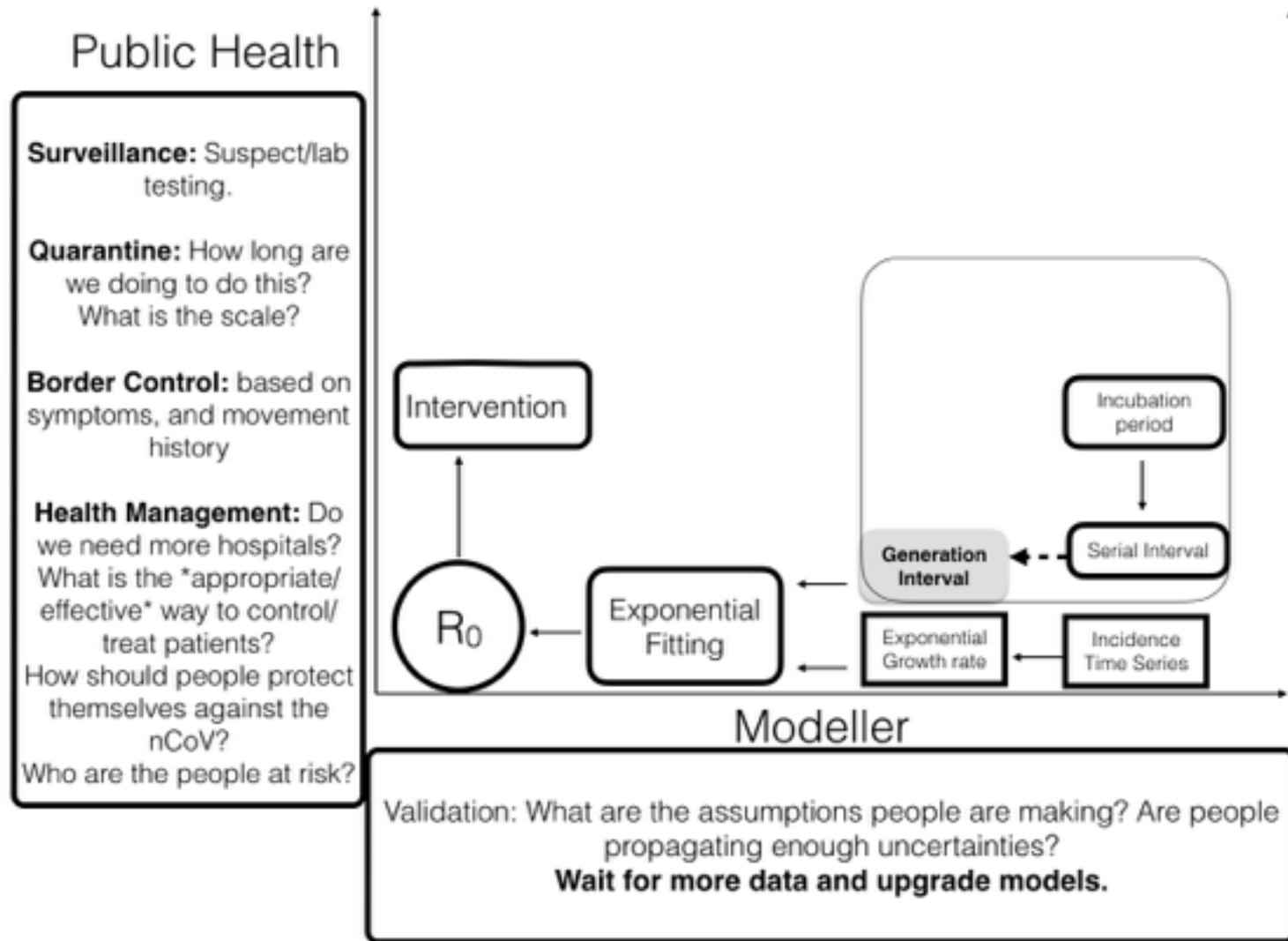
- Interesting and important to figure out the discrepancies
- What else? What do people want to know?



Preparing for the global pandemic



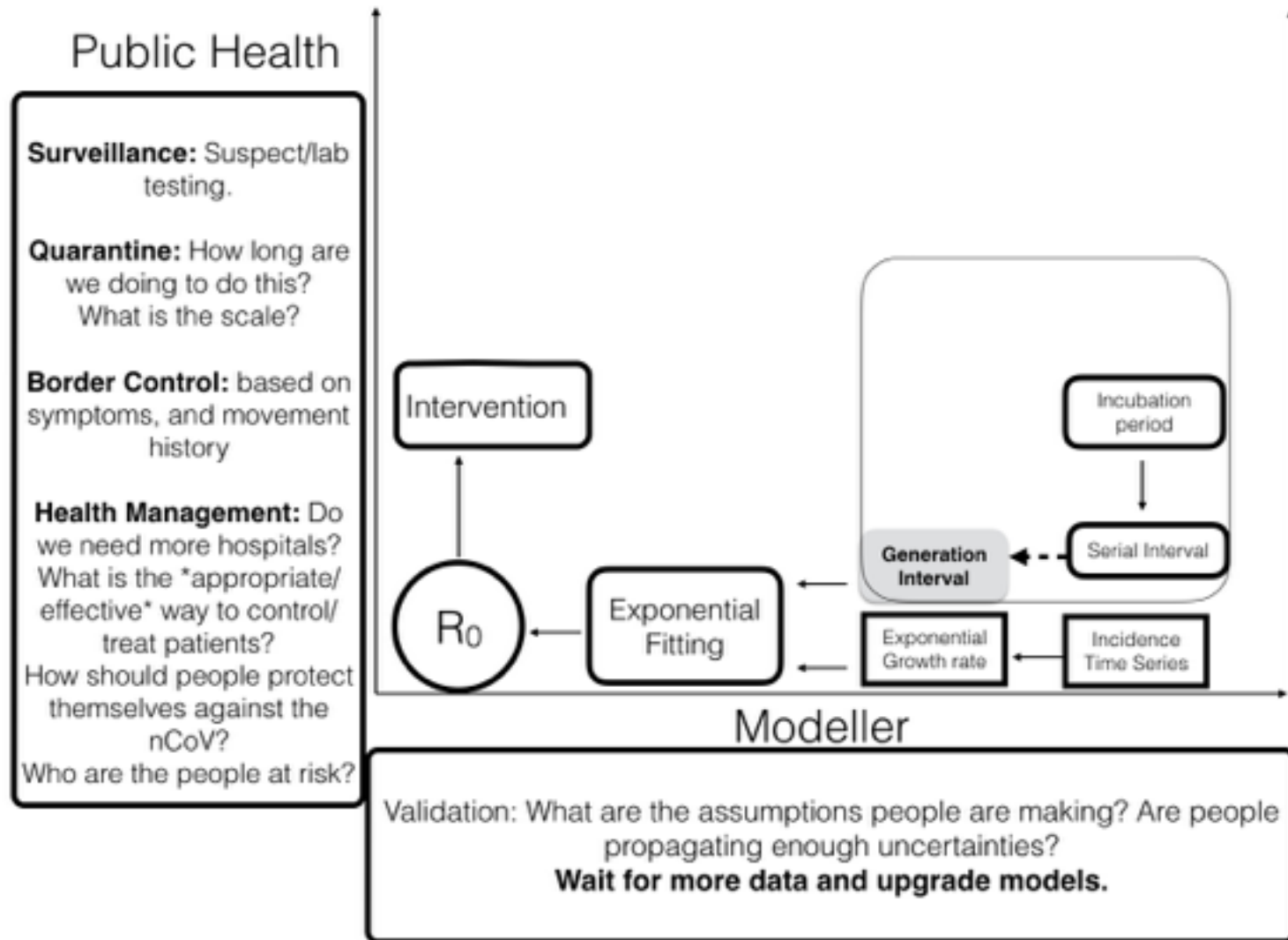
Preparing for the global pandemic



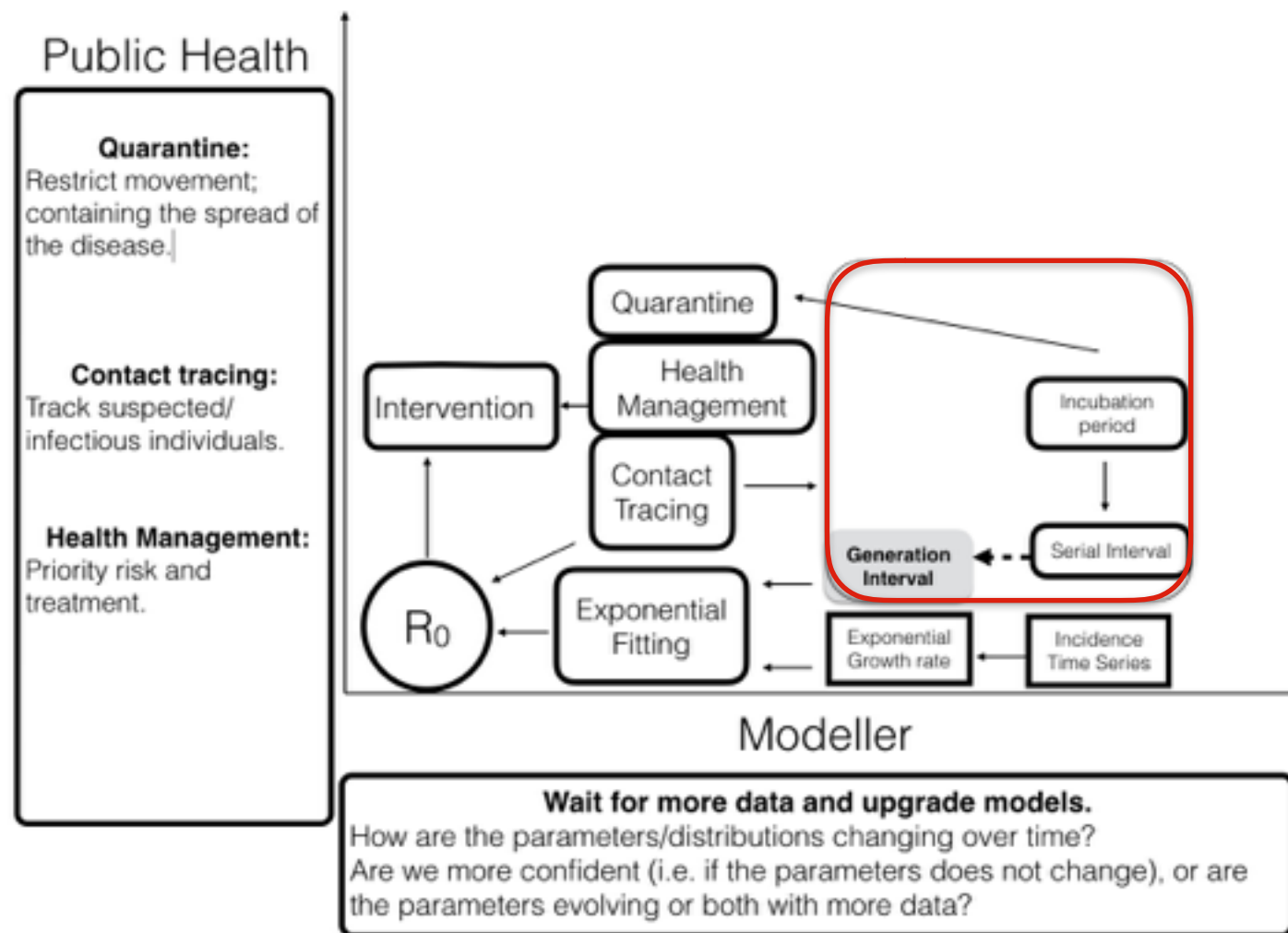
Part 2

Distributions of delays associated with COVID-19 healthcare in Ontario, Canada

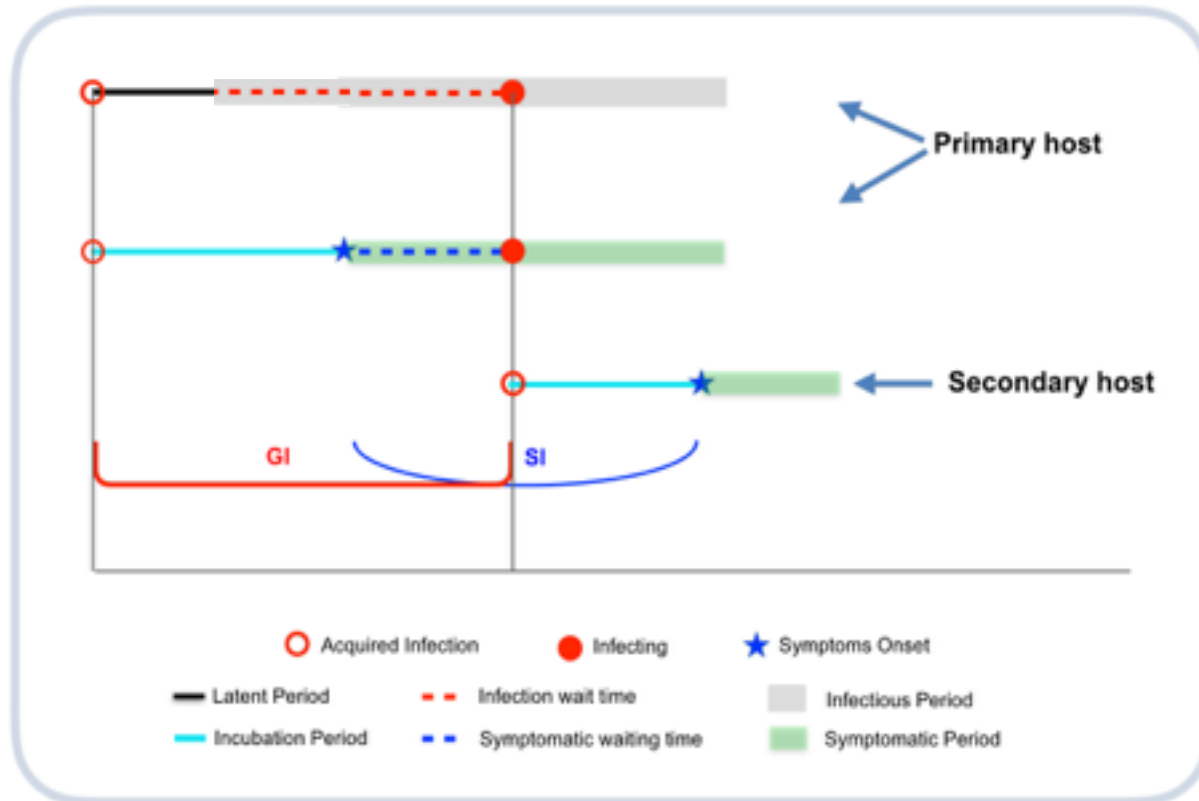
Preparing for the global pandemic



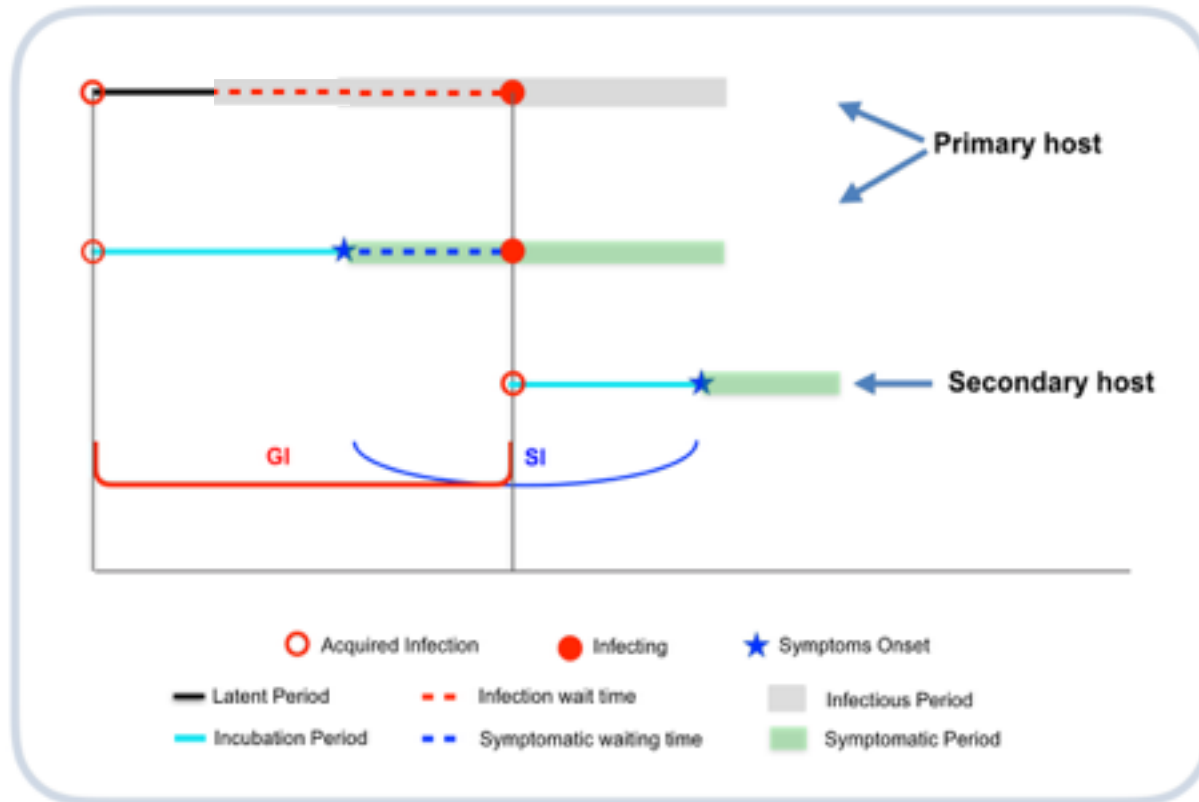
Distributions of delays associated with COVID-19 healthcare in Ontario, Canada



Time intervals



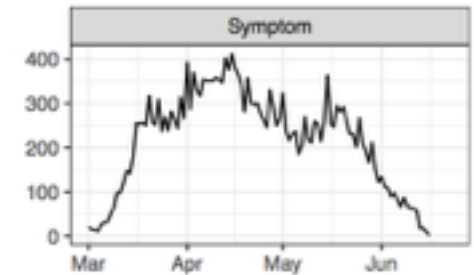
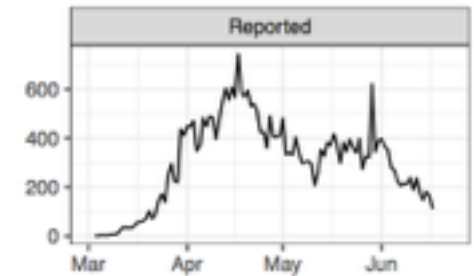
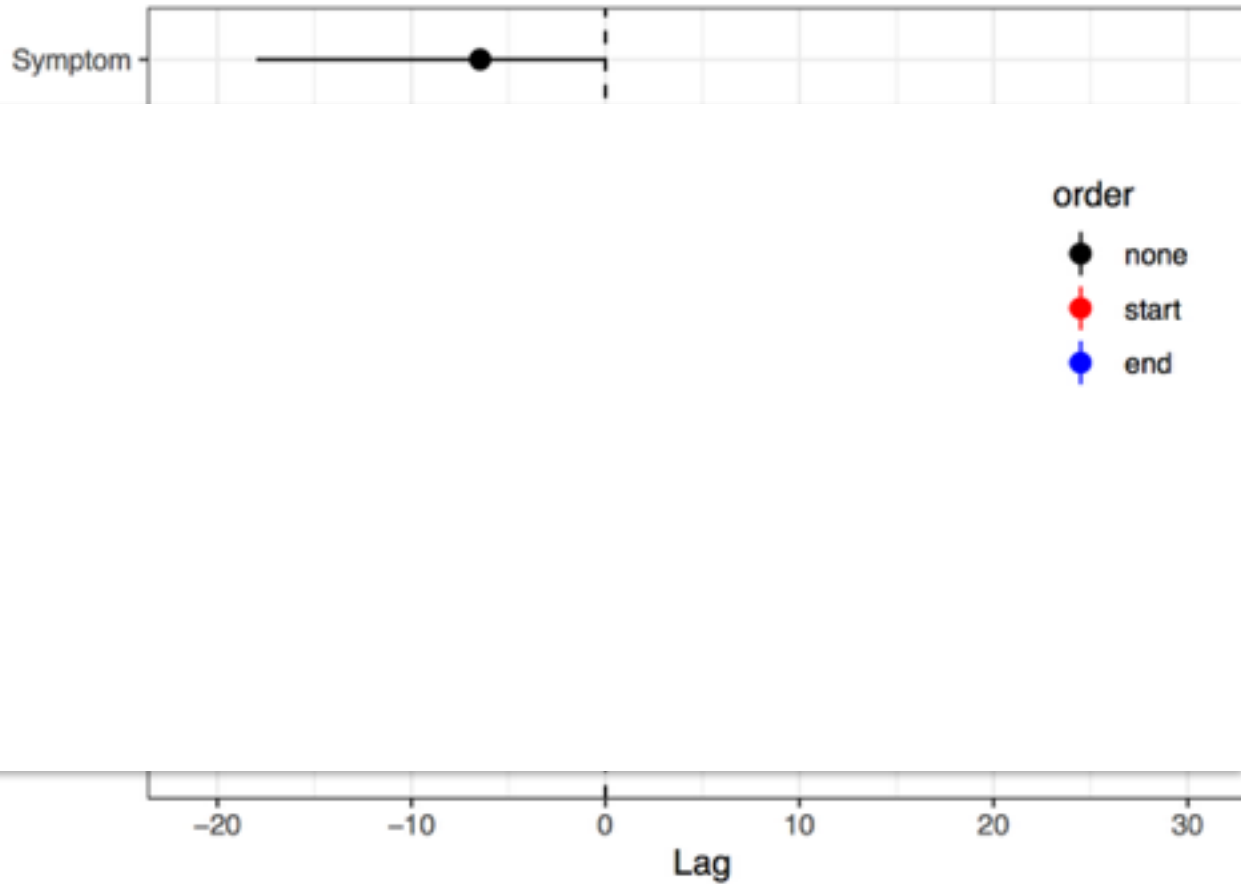
Time intervals



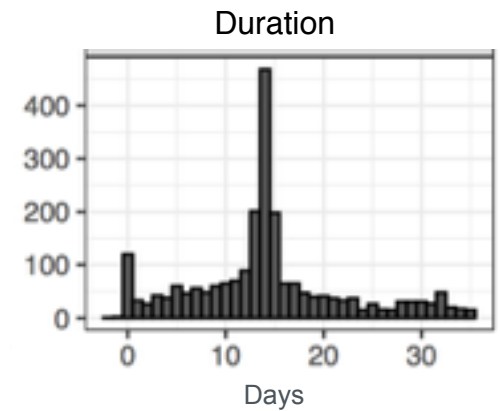
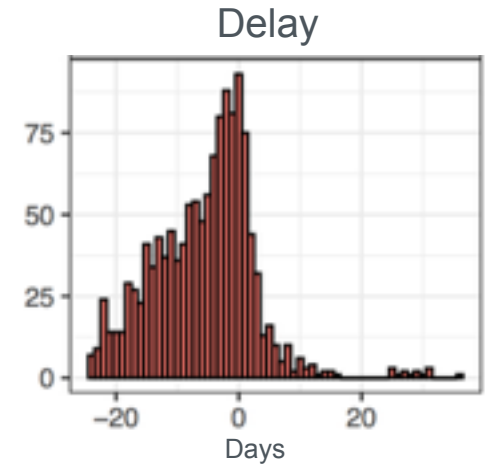
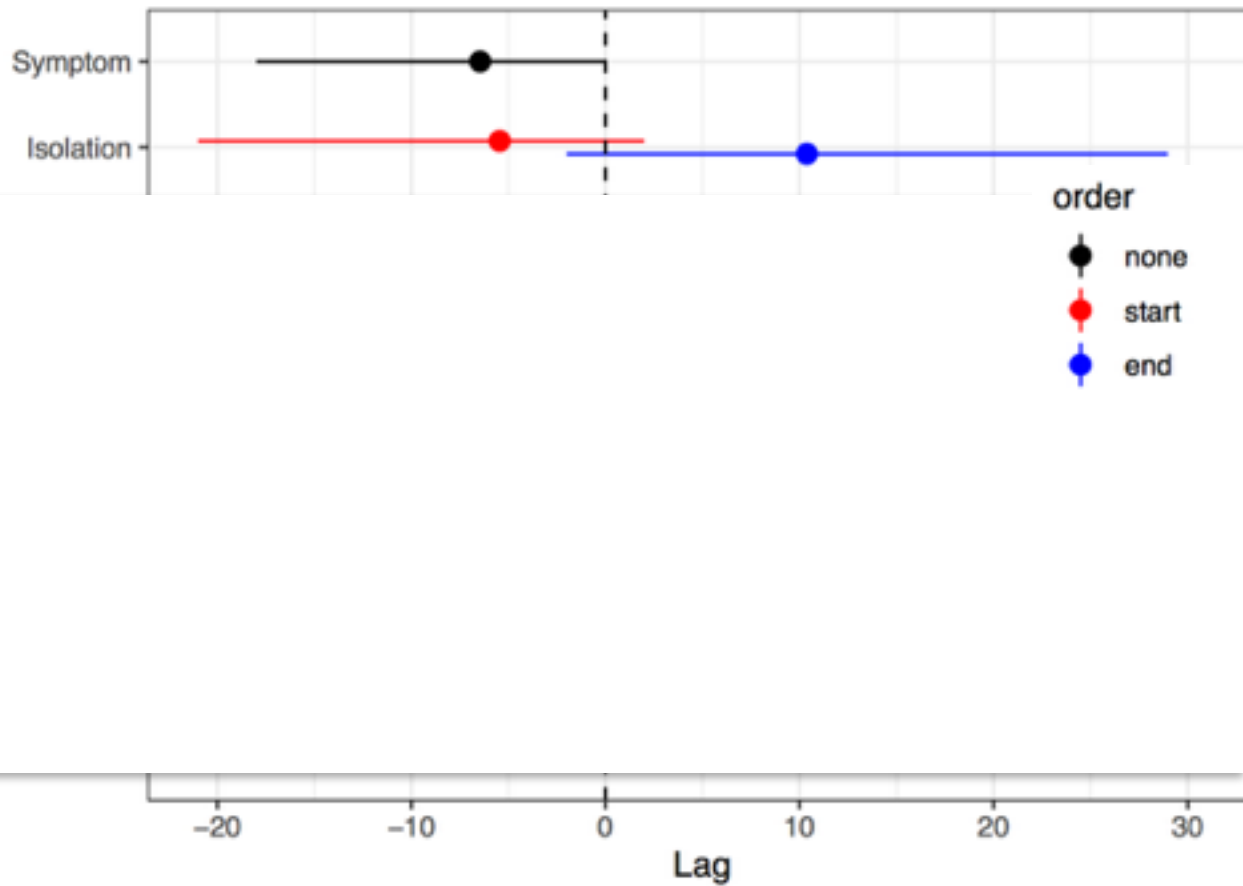
Isolation time
Specimen collection time
Reporting time

ER time
Hospital admission time
ICU time

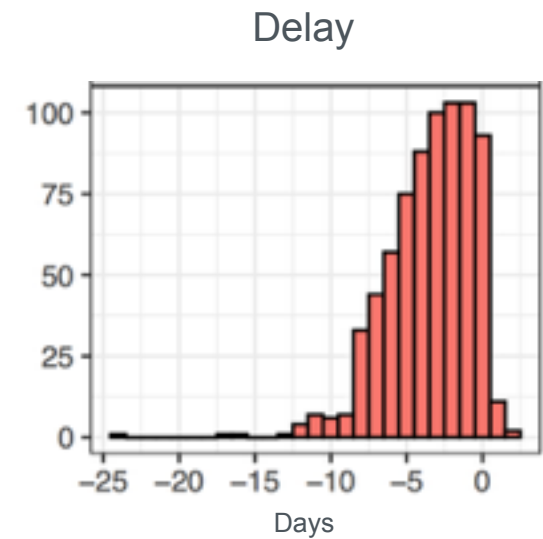
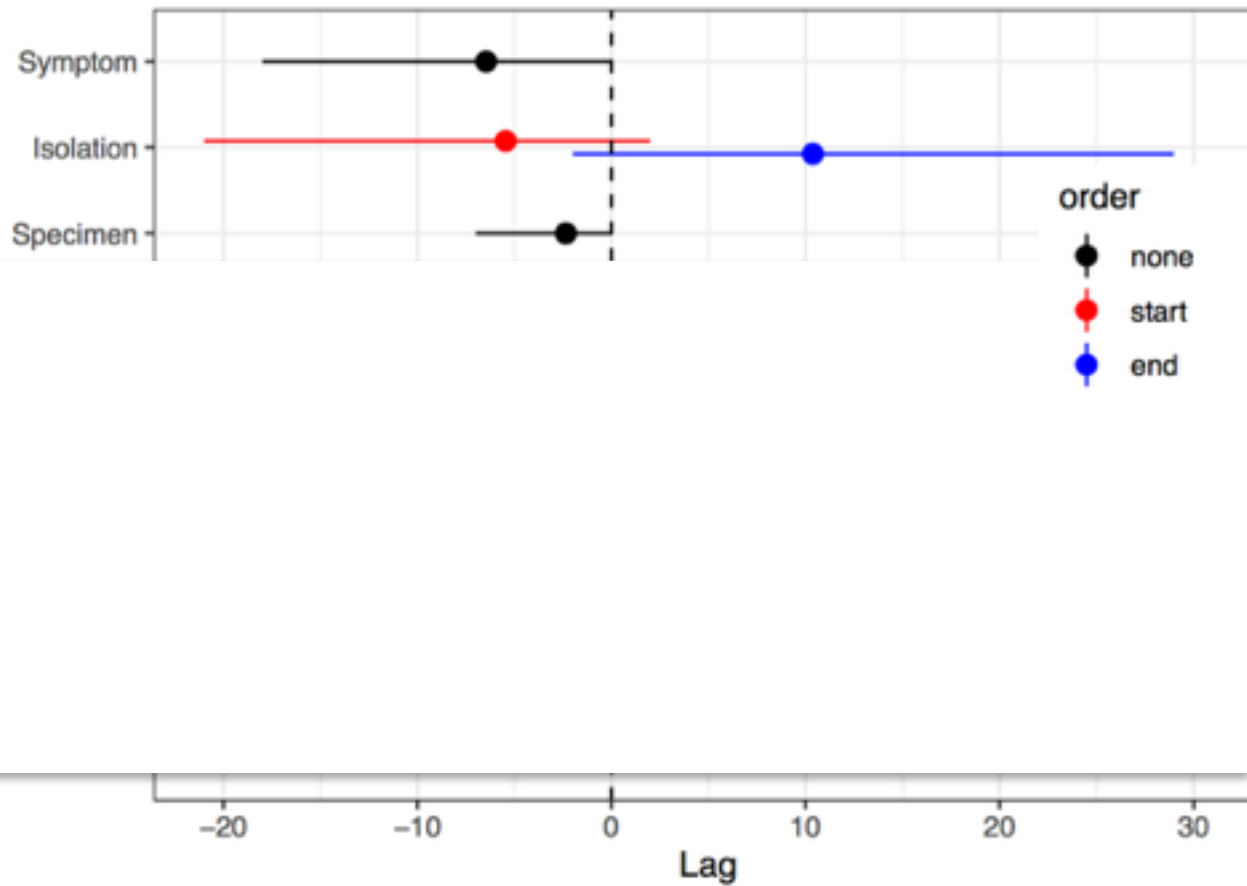
Chronological Episodes (Symptom onset)



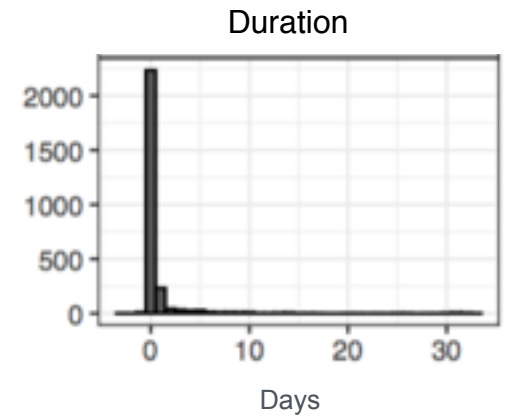
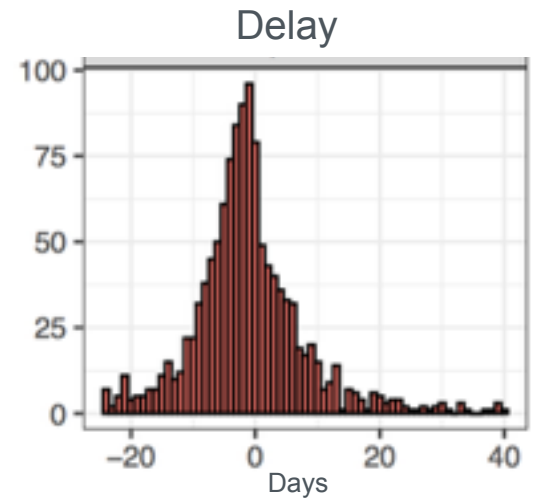
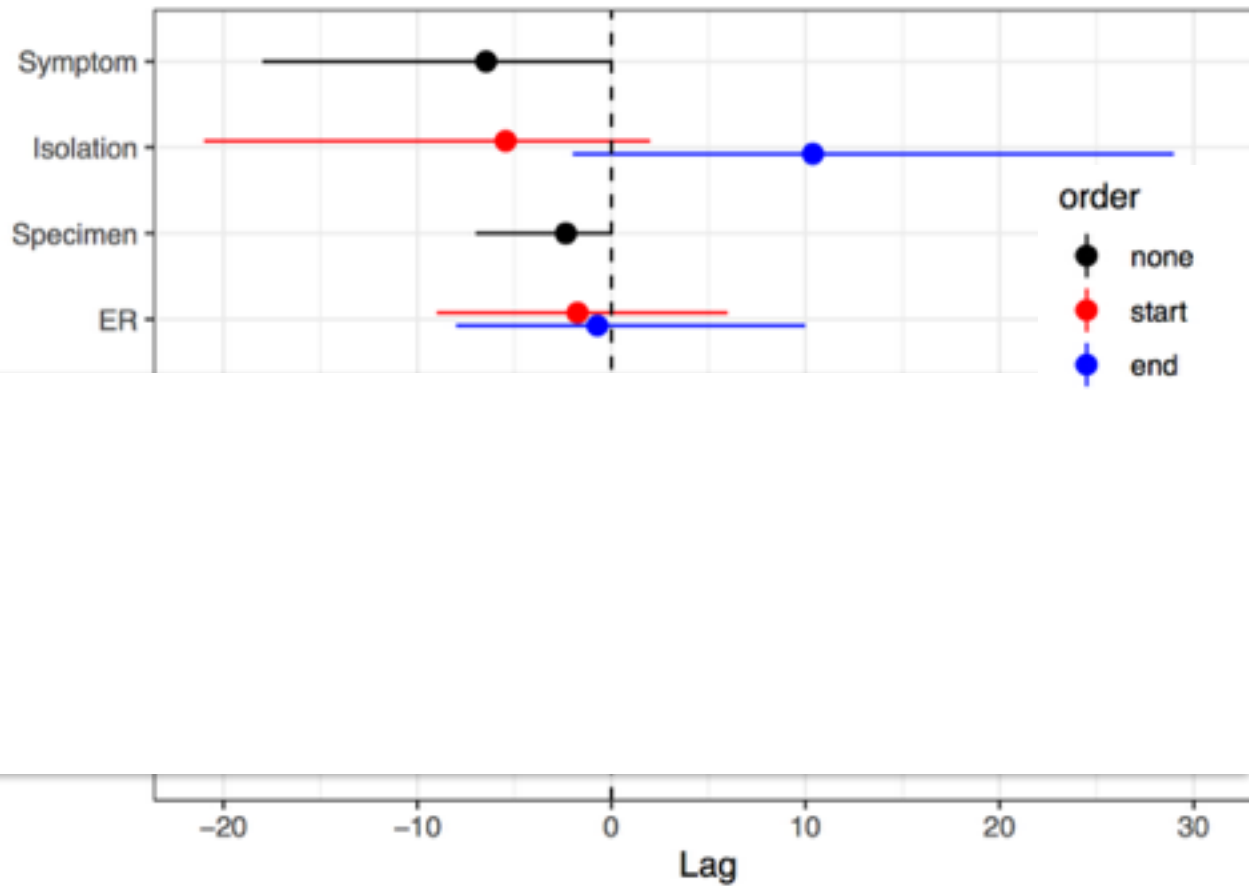
Chronological Episodes (Isolation)



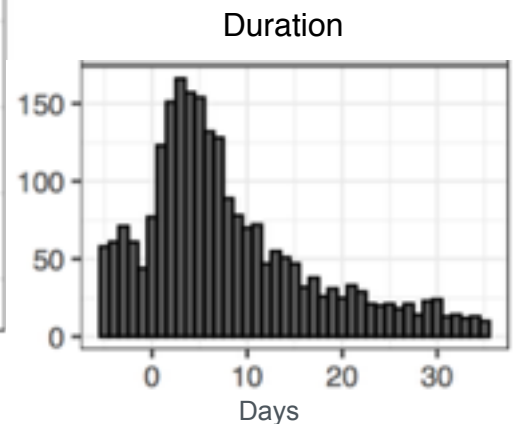
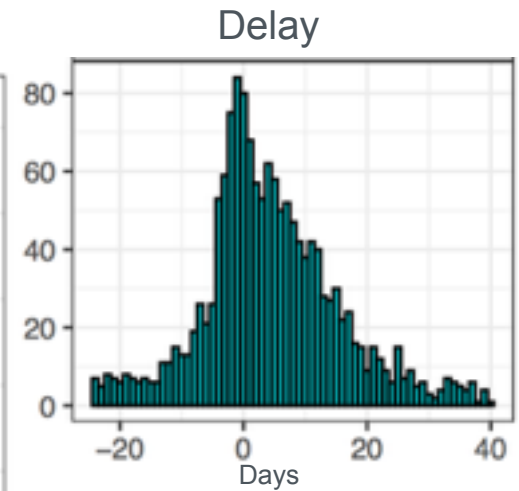
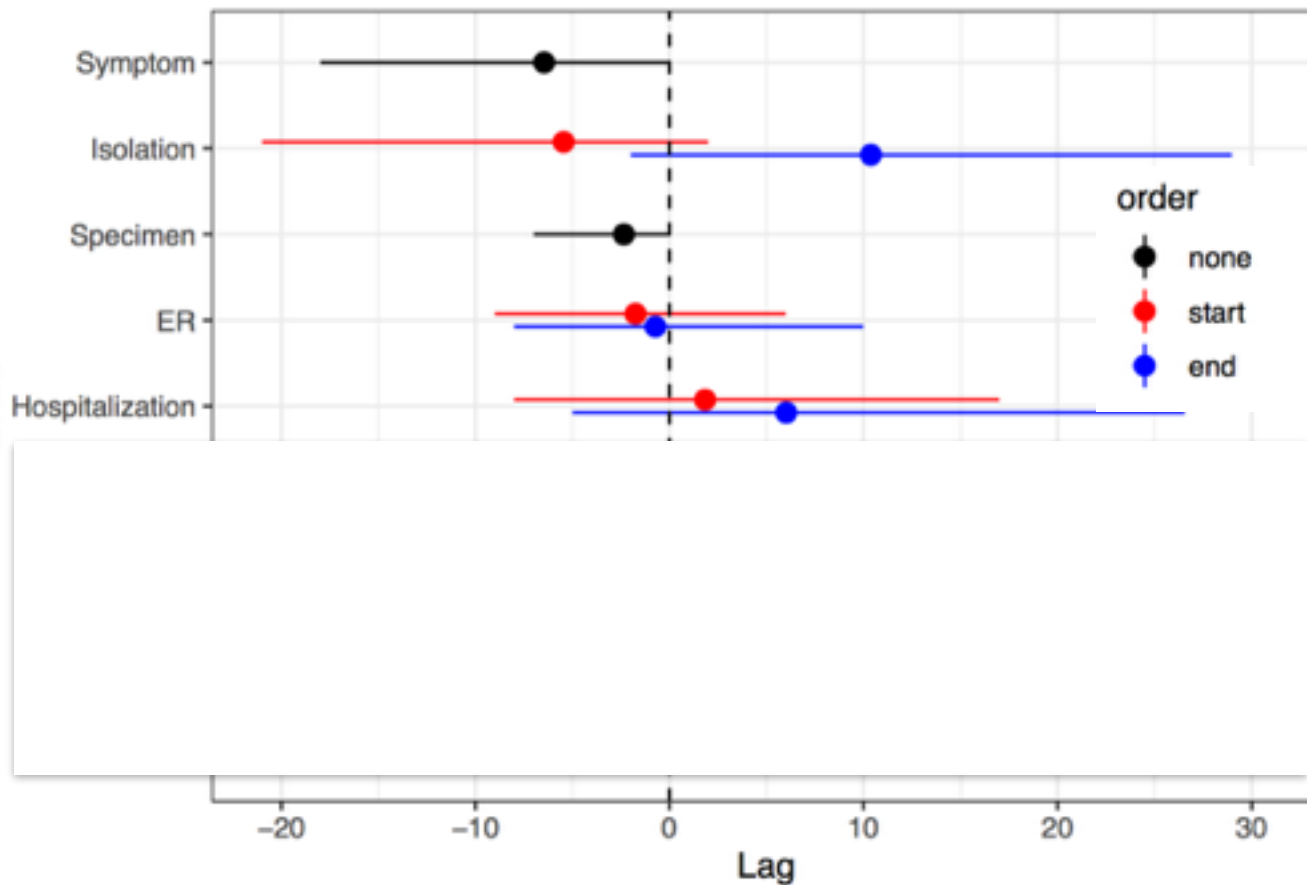
Chronological Episodes (Specimen collection)



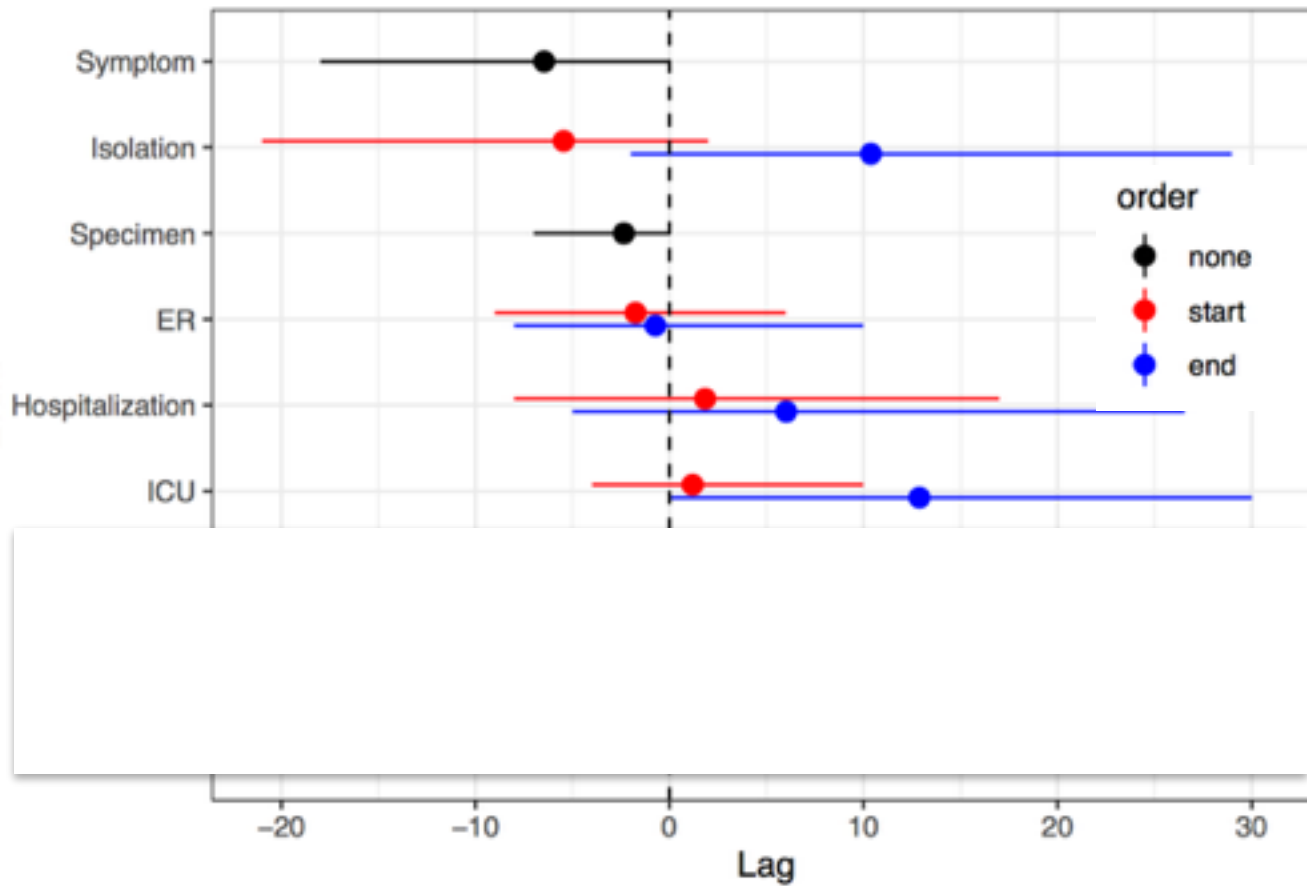
Chronological Episodes (ER)



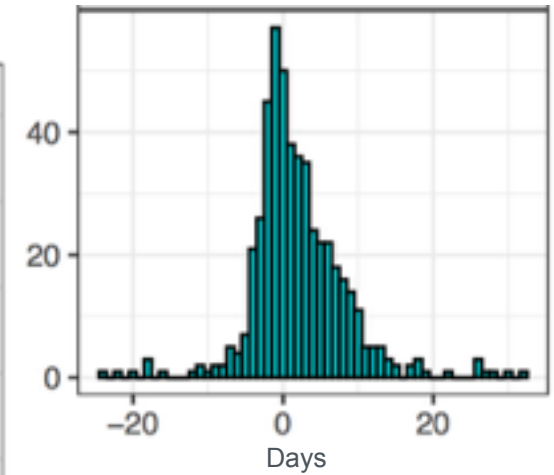
Chronological Episodes (Hospitalization)



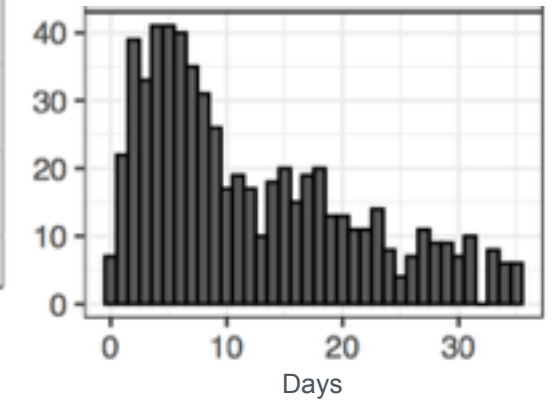
Chronological Episodes (ICU)



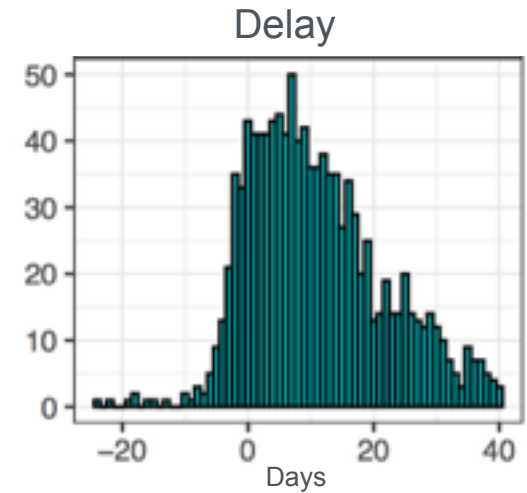
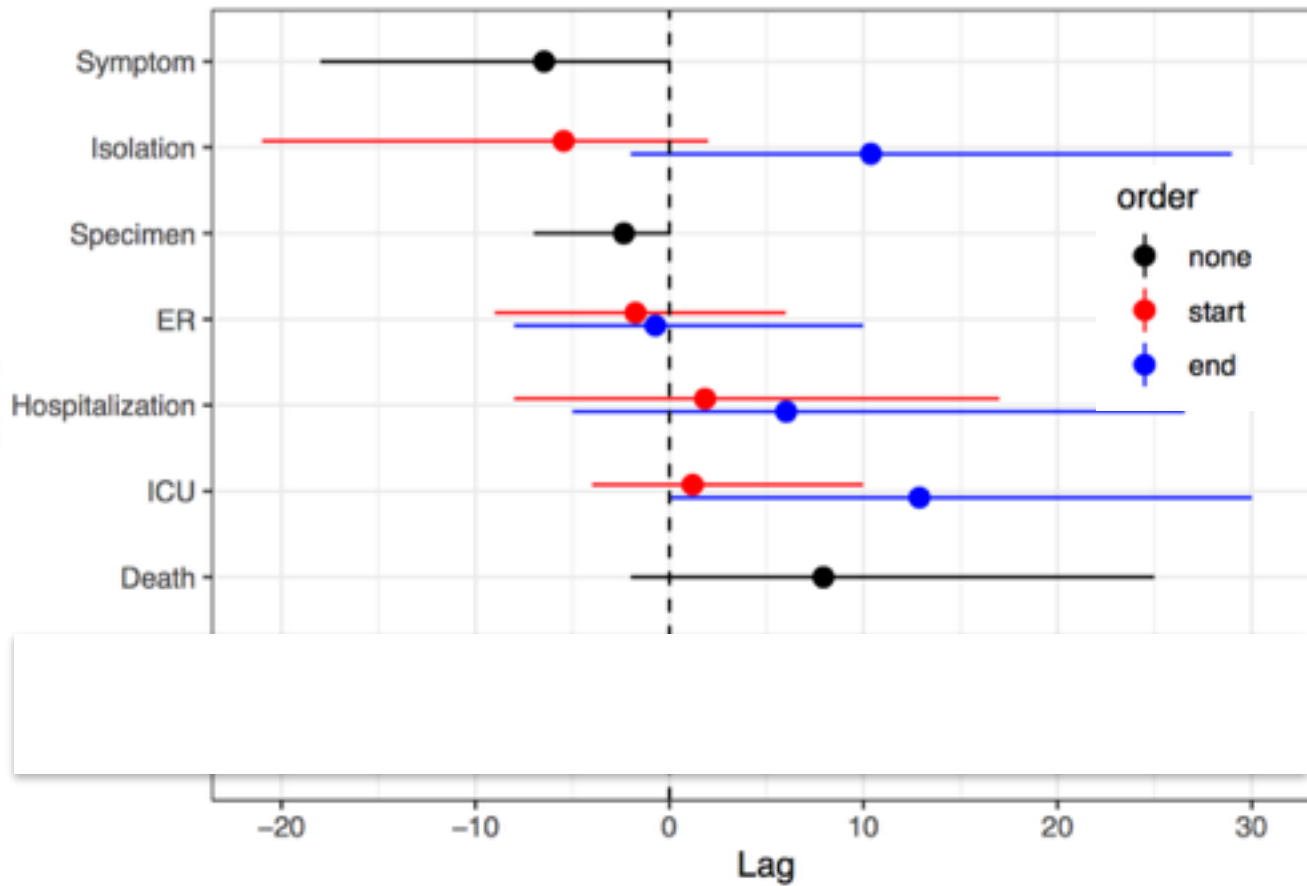
Delay



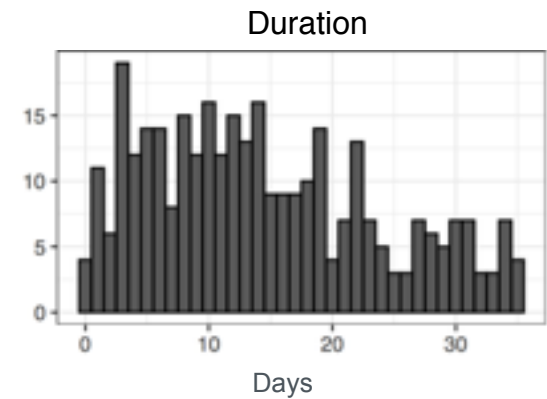
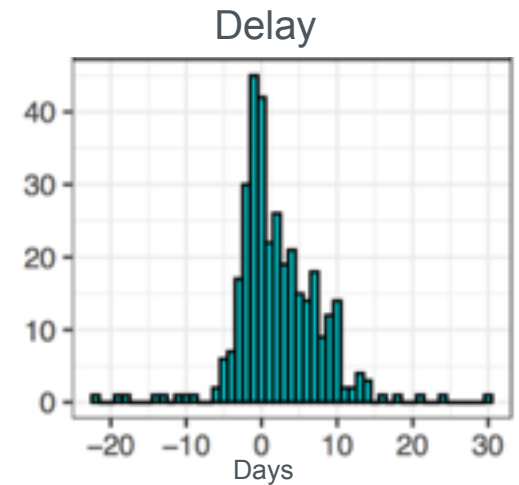
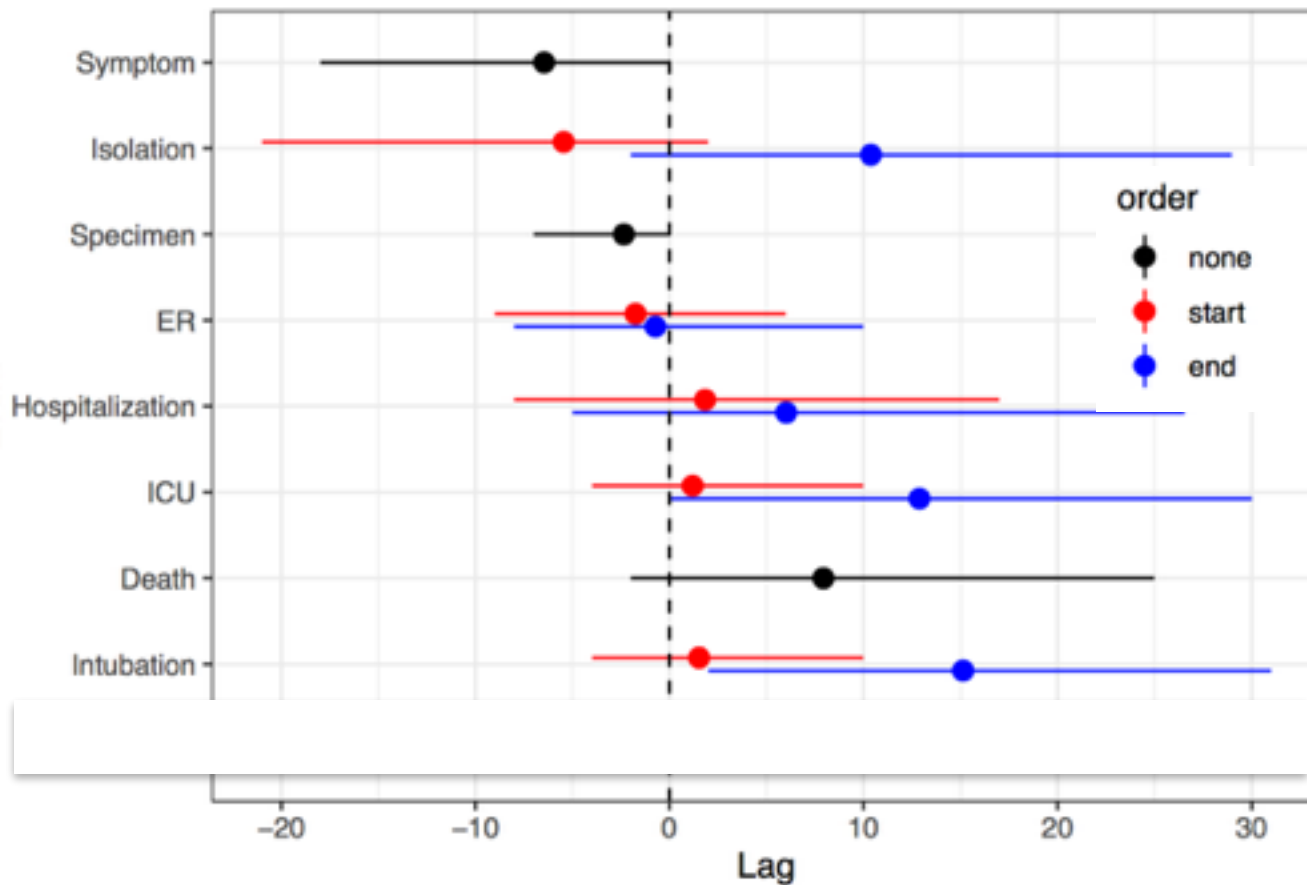
Duration



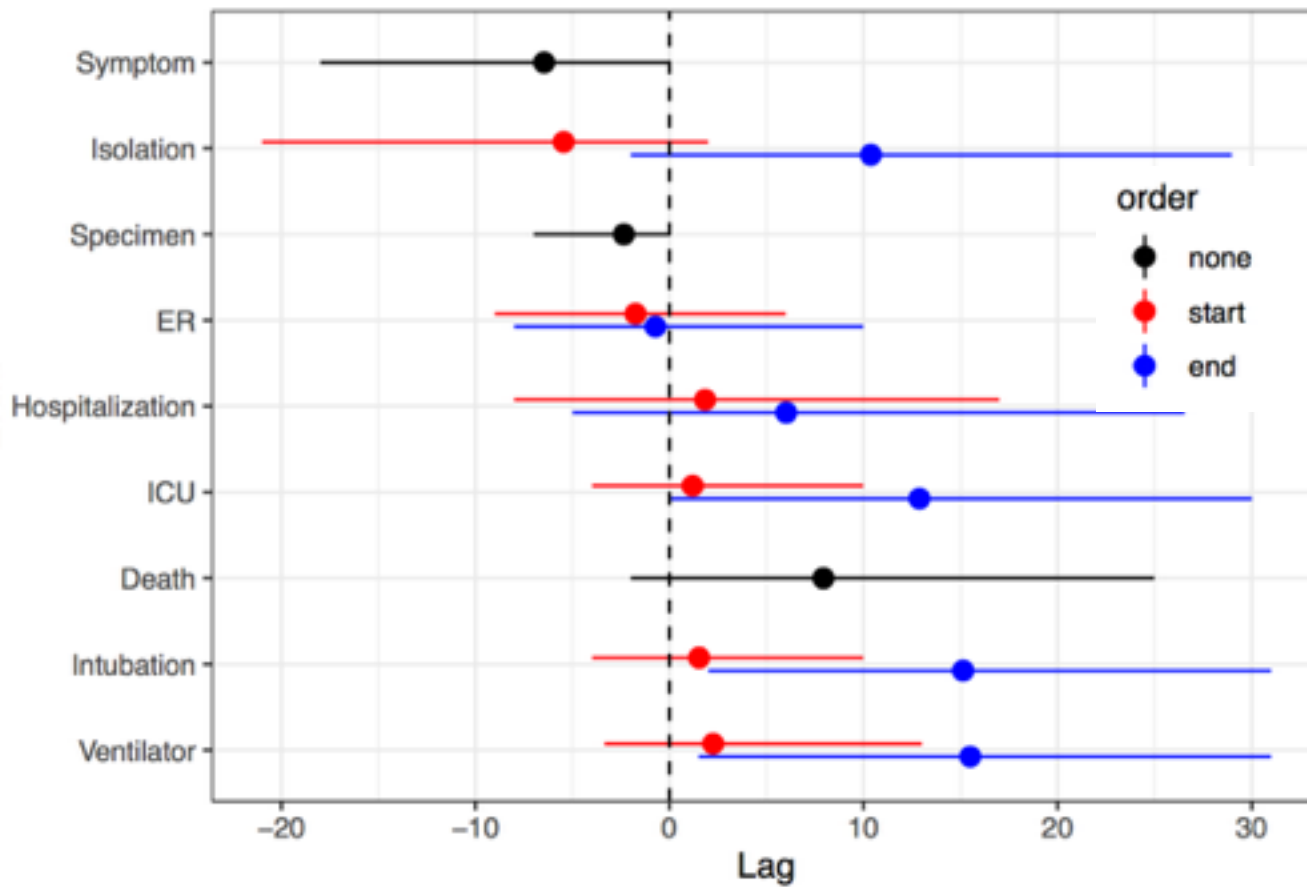
Chronological Episodes (Death)



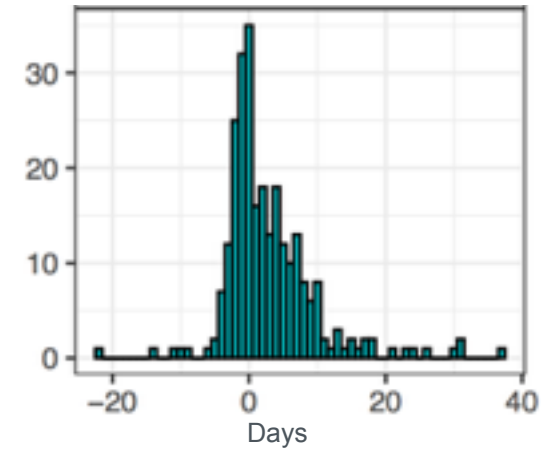
Chronological Episodes (Intubation)



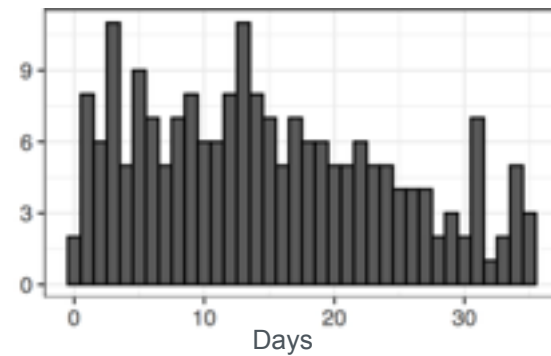
Chronological Episodes (Ventilator)



Delay

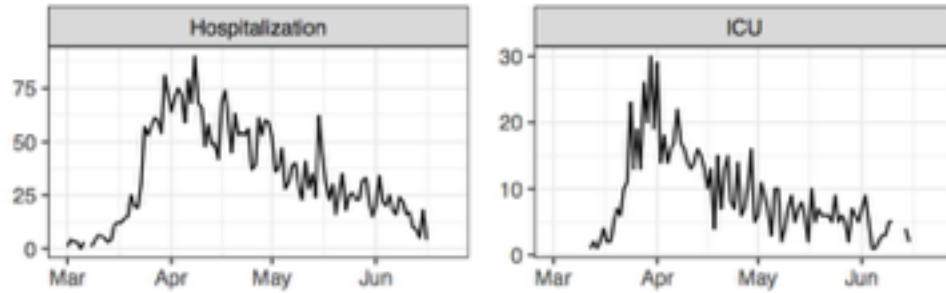


Duration



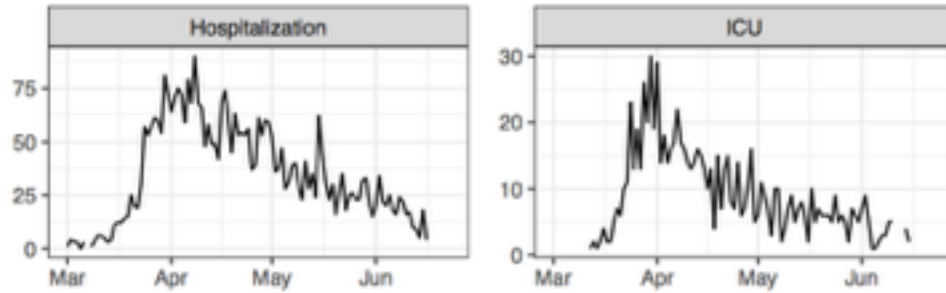
Admissions, Durations and Occupancies

Daily Admissions

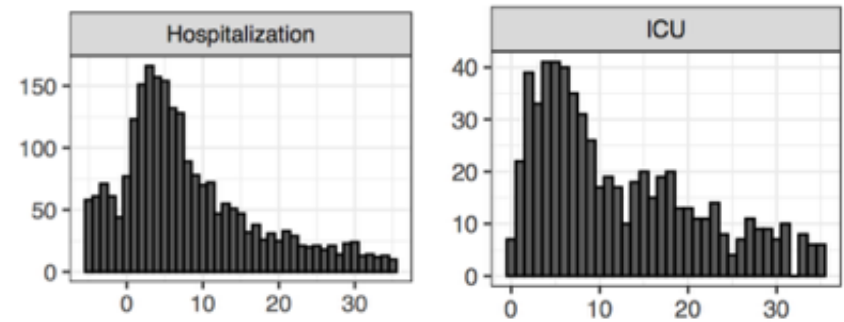


Admissions, Durations and Occupancies

Daily Admissions

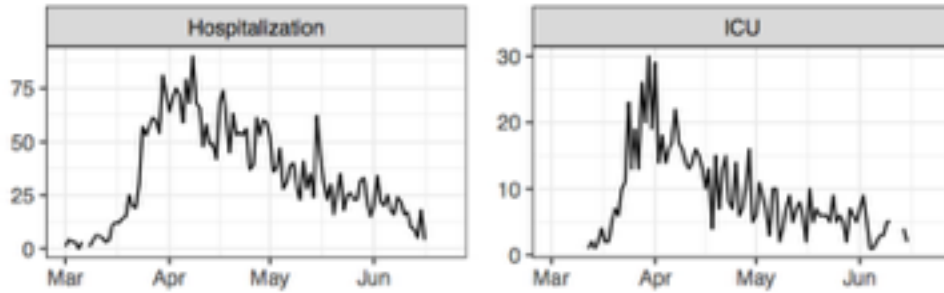


Durations

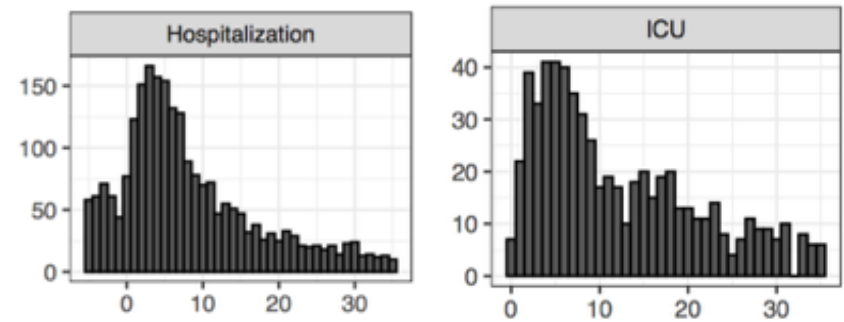


Admissions, Durations and Occupancies

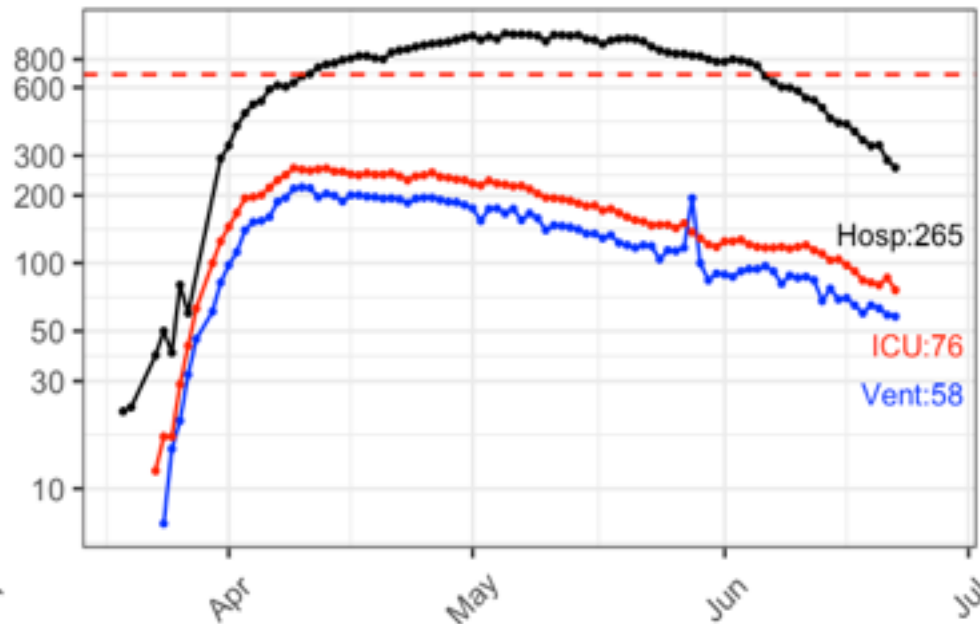
Daily Admissions



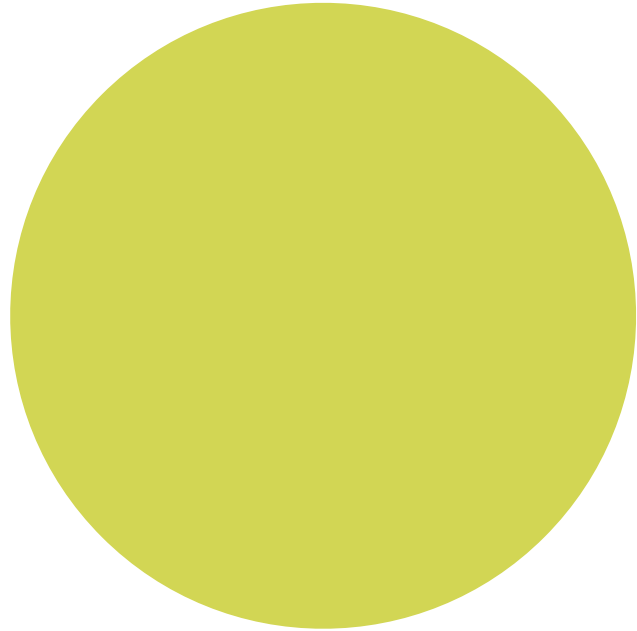
Durations



Occupancy



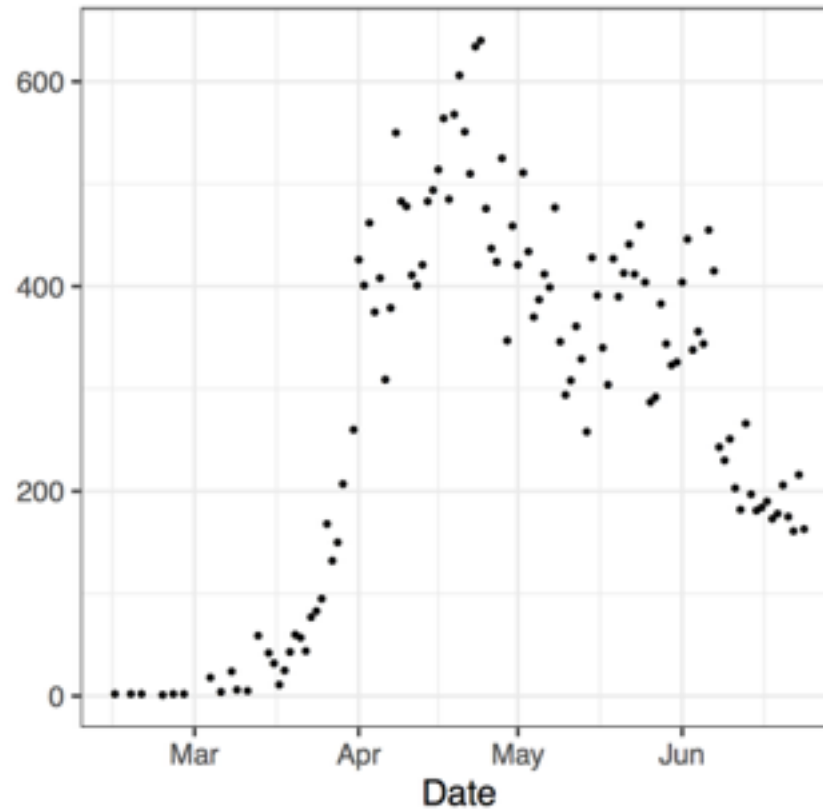
Distributions of delays associated with COVID-19 healthcare in Ontario, Canada



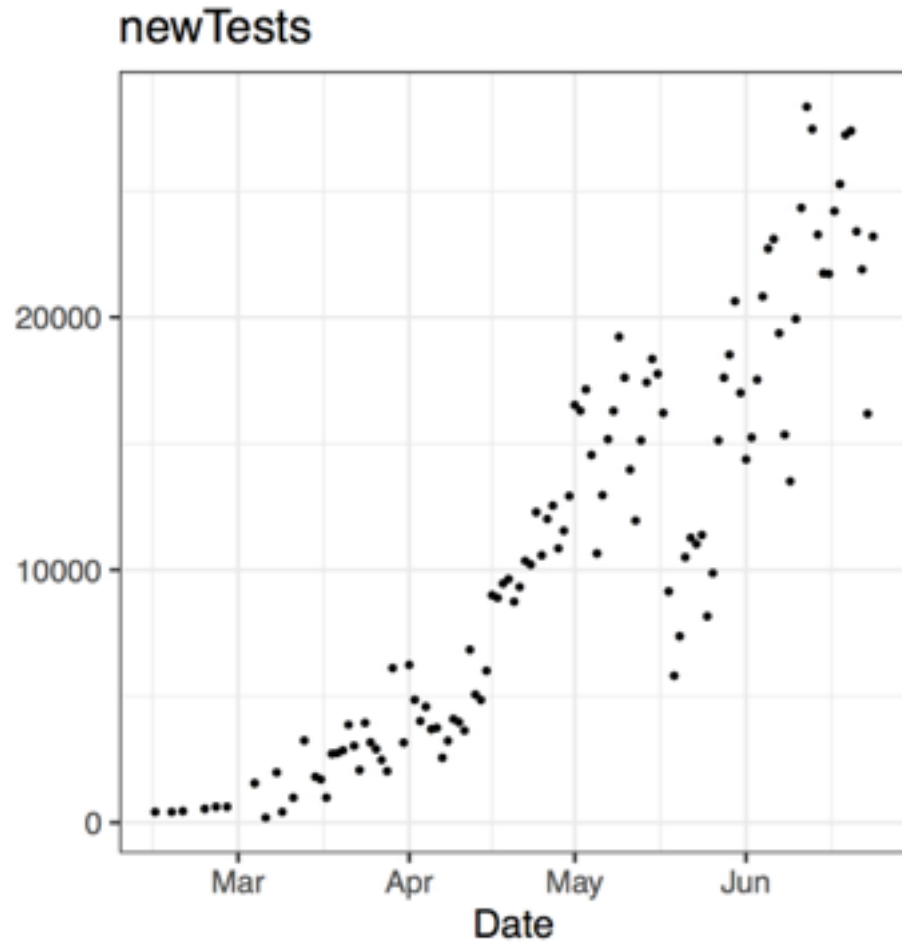
Changes over time

New Confirmations

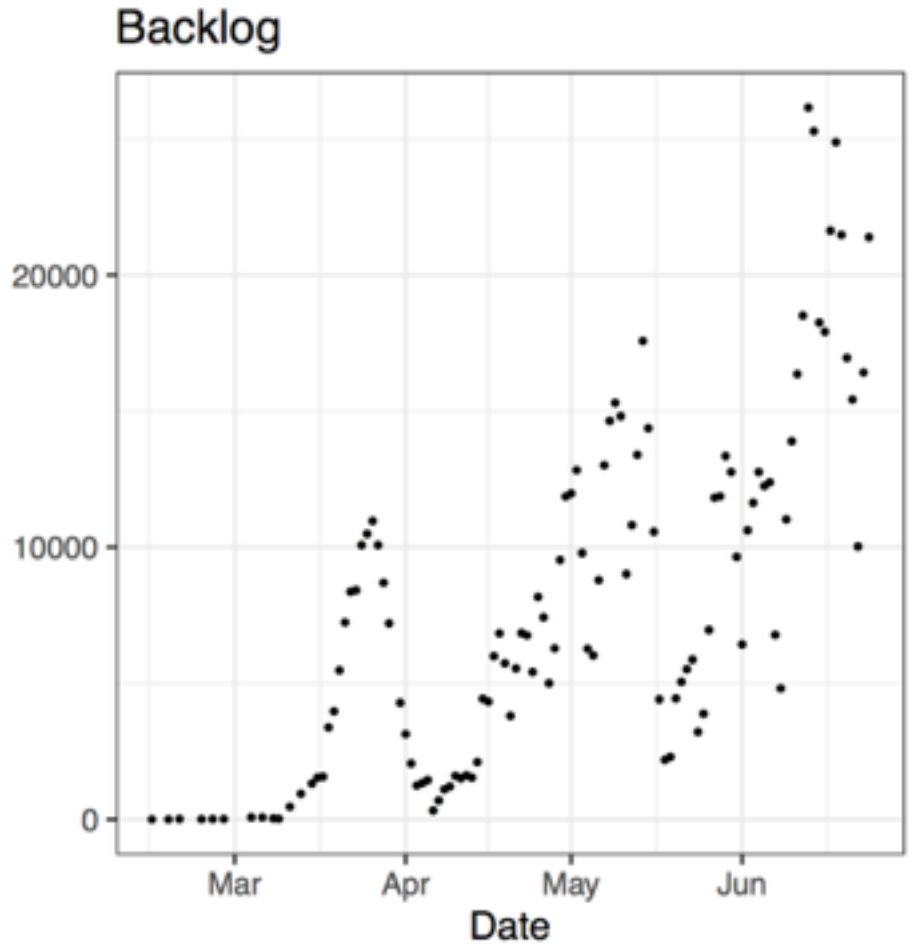
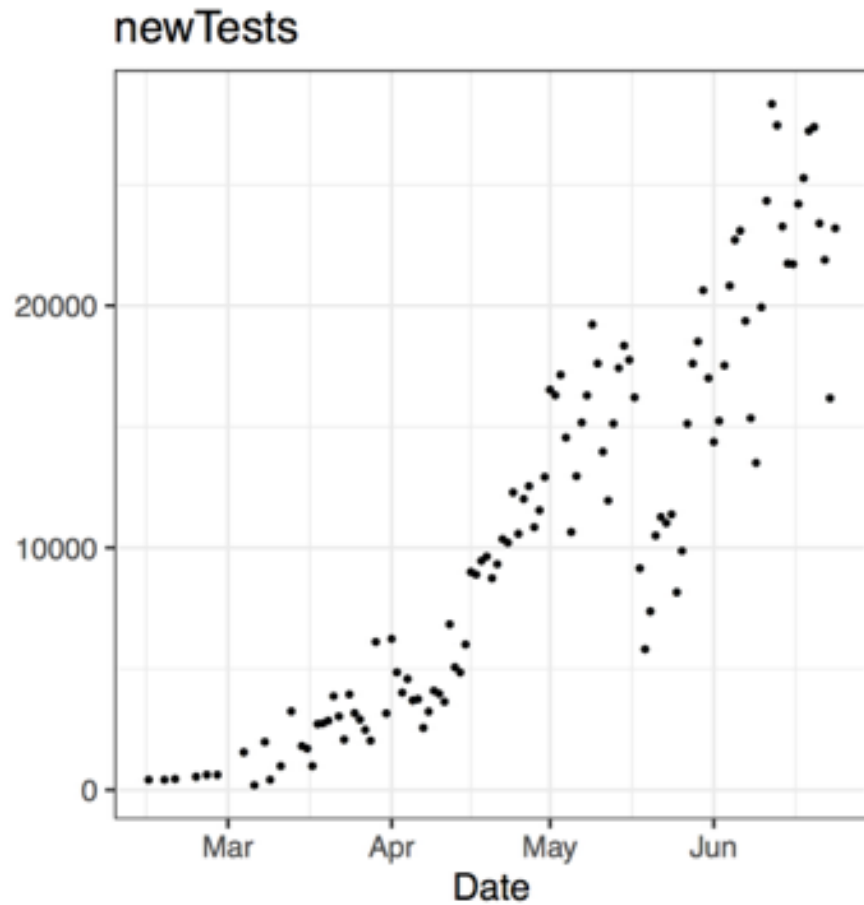
Ontario, Canada



Testing capacity

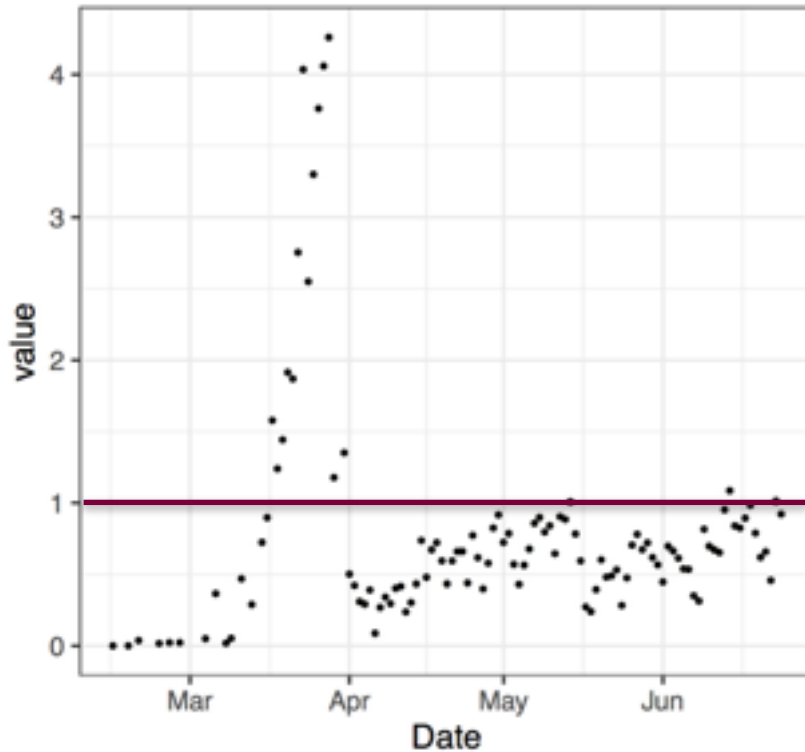


Testing capacity



Backlog ratio

Backlog ratio

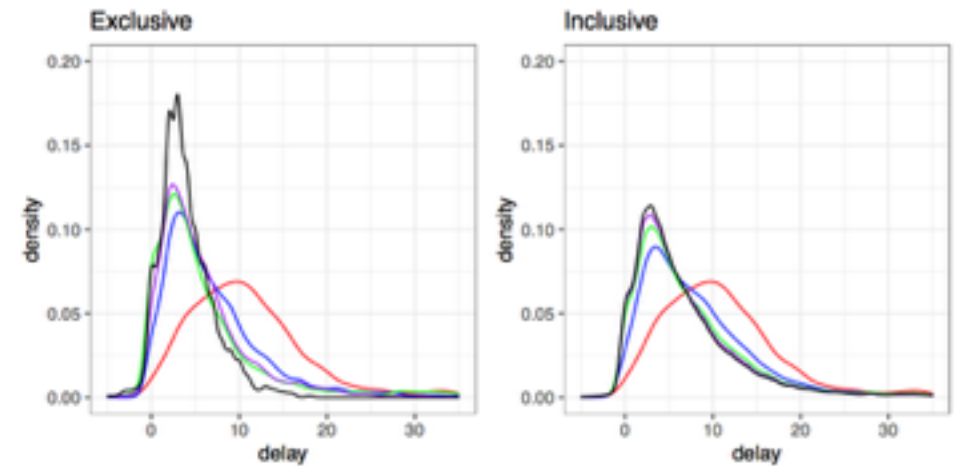
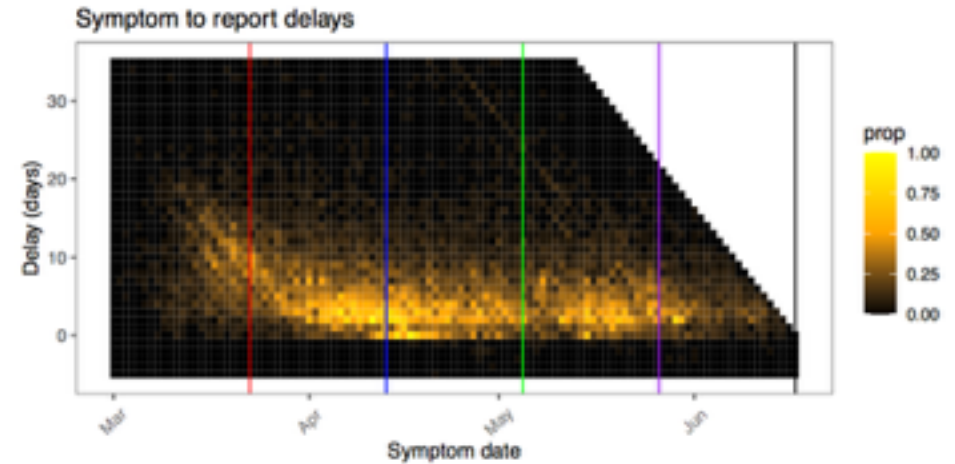
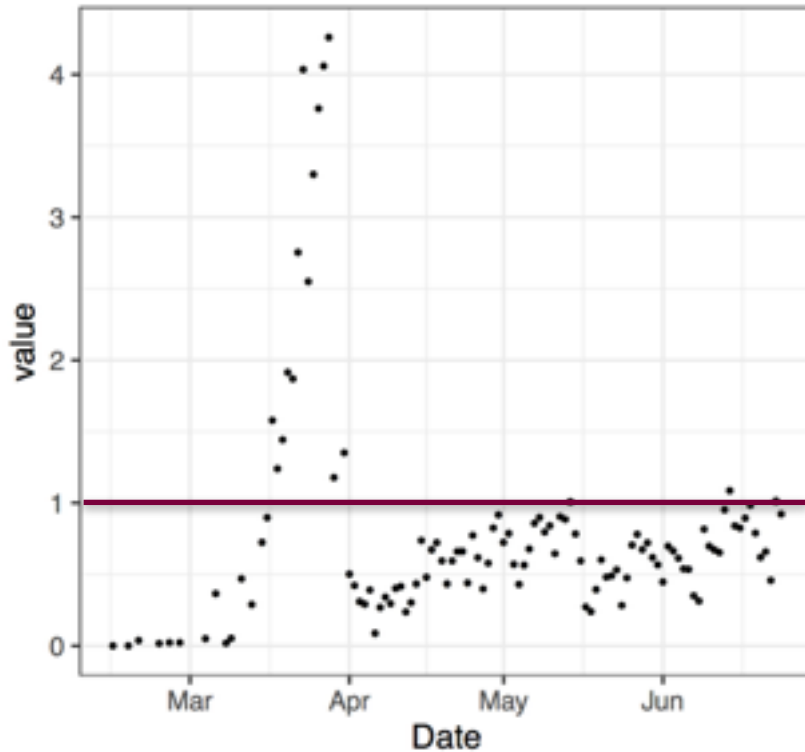


$$\frac{\text{Backlog (test)}}{\text{newTests (test/day)}}$$

~ X days to clear the backlogs

Changes in Delays over time

Backlog ratio



```
#> [1] "2020-03-01" "2020-03-22" "2020-04-13" "2020-05-04" "2020-05-26"  
#> [6] "2020-06-17"
```

Summary

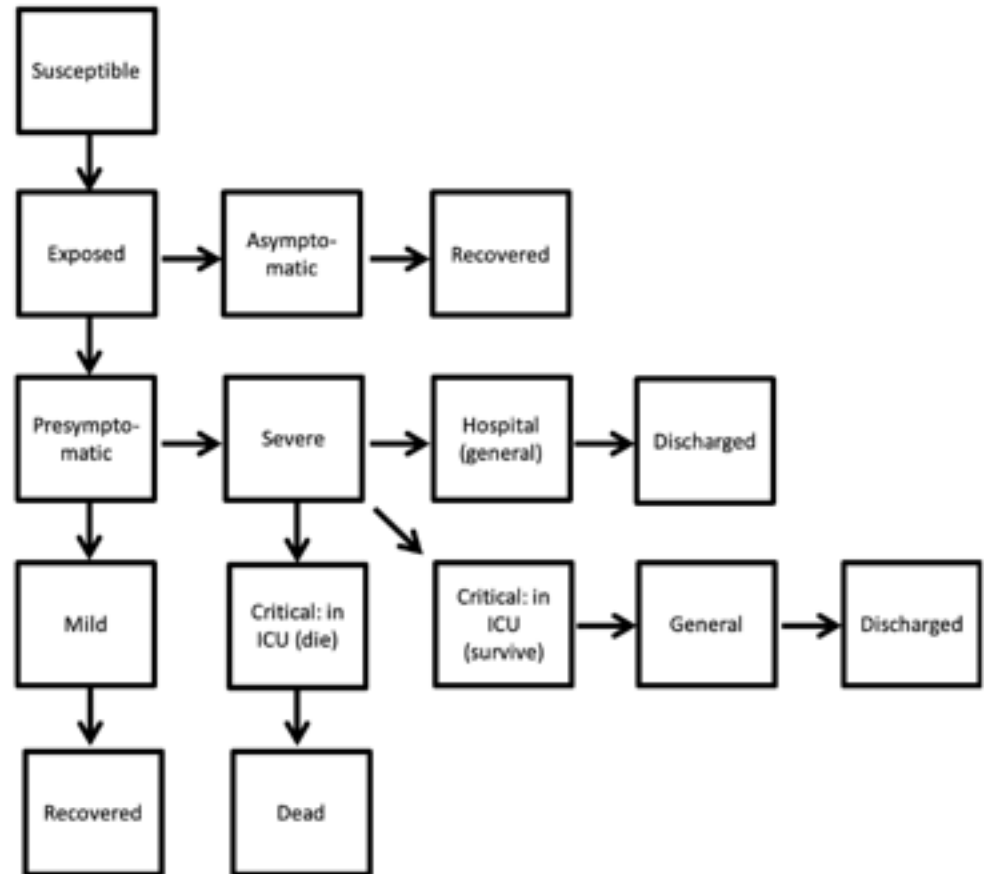
- Early detection is key in controlling the spread of covid
 - Reduce delay -> earlier isolation/treatment
- What components we can take back to the modelling world to improve models
 - e.g. Hospitalization data
 - Duration spent in treatment
- Combining different data streams to model

McMaster Pandemic

- SEIR model
 - Including Hospitalization time series
 - Using empirical delay/duration distributions to parameterize the flow of the compartments

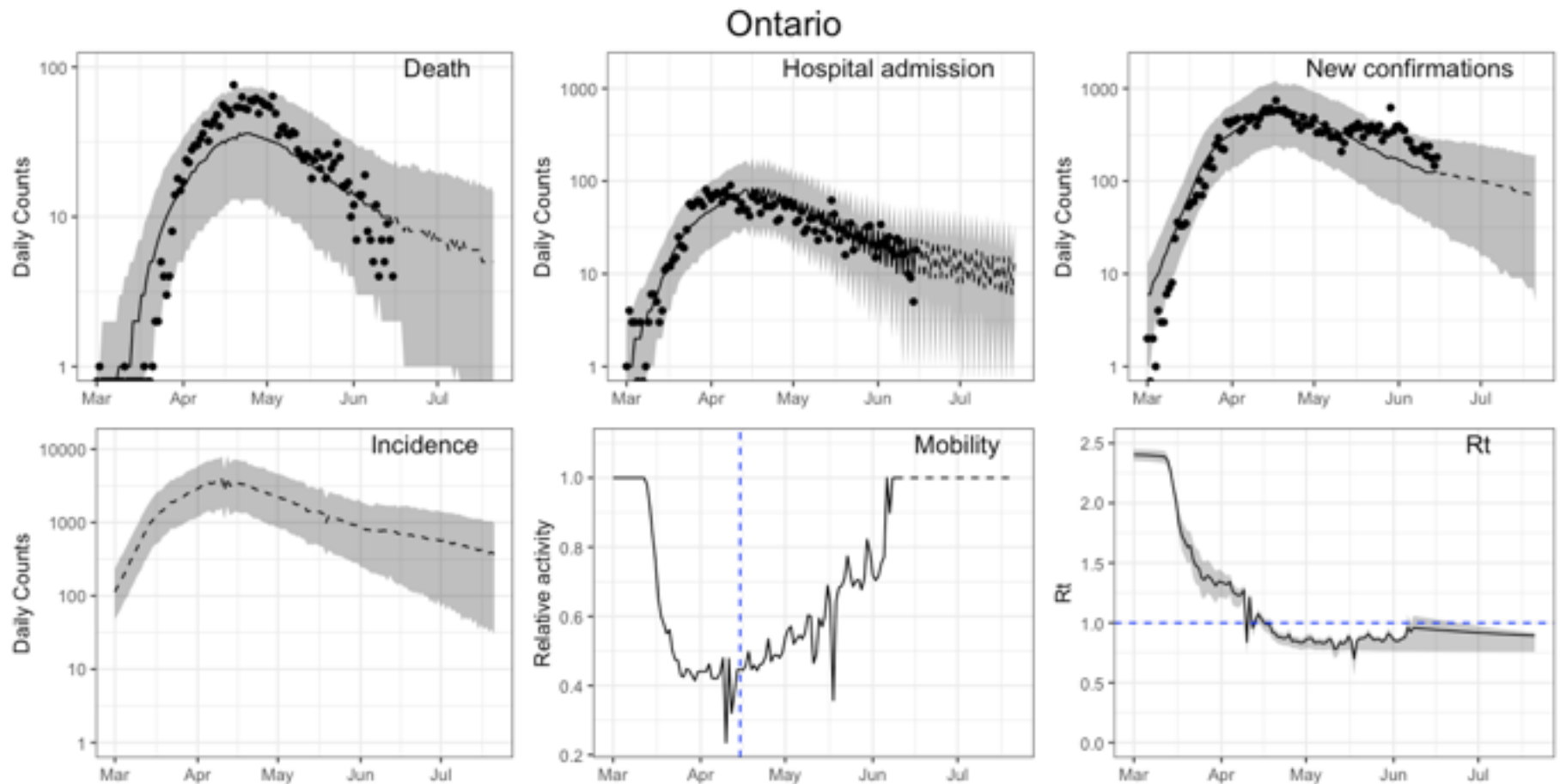
Additional features

- mobility from google and apple



<https://github.com/bbolker/McMasterPandemic>

Distributions of delays associated with COVID-19 healthcare in Ontario, Canada



Final remarks

- Easy to be tunnel visioned in the model world
- Important to get a sense what is happening in reality
- Bridging the knowledge gap in both directions (Public Health and Modelling)

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 - Important to get a sense what is happening in reality
 - Bridging the knowledge gap in both directions (Public Health and Modelling)
-
- Small piece of the pie



Acknowledgments

MacTheoBio

Steve Cygu

Chyun Shi

Martin Stelmach



Dr. Jonathan Dushoff



Dr. Ben Bolker



Dr. David Earn

Sang Woo Park (Princeton University)

David Champerdon (University of Western Ontario)

Morgan Kain (Stanford University)

Irena Papst (Cornell University)

McMaster University

CIHR

IIDR @ McMaster U

PHAC

PHO

