PREDICTING COVID-19 CASES IN BRITISH COLUMBIA

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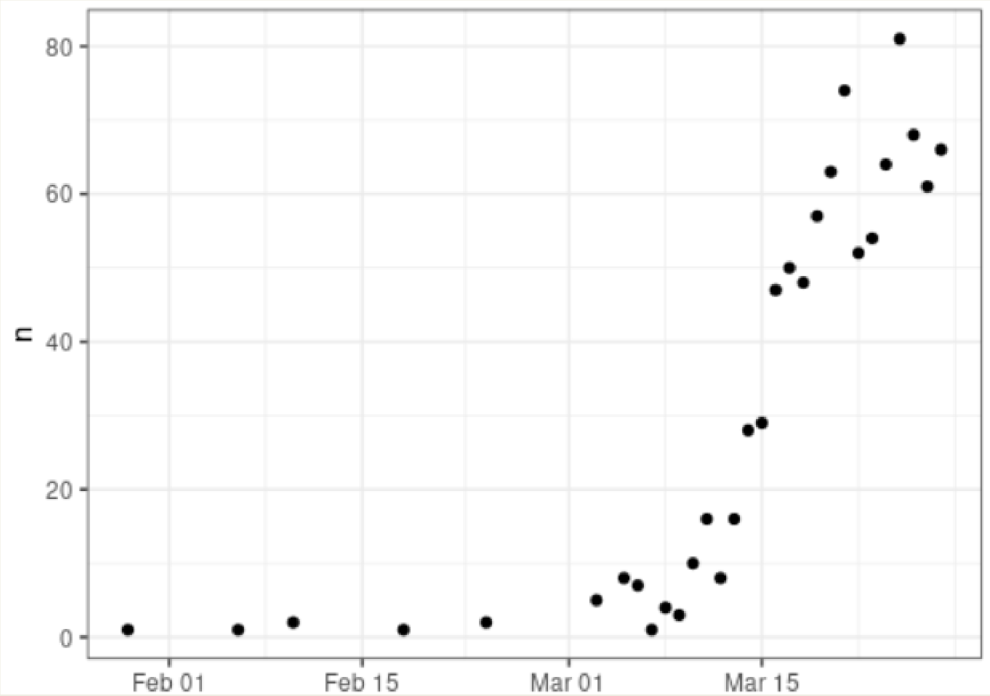
FIELDS

Background

- First confirmed case in Canada on 25 January, 2020
- WHO pandemic declaration on 11 March, 2020
- British Columbia:
- First case on January 28, 2020
- Public health emergency declared on 17 March



Background

- Masking mandates have the potential to decrease transmission of the virus
- Viable public health measure, mostly in the early stages of the pandemic
  - *Little evidence on effective treatment*
  - *Overload to Health Care systems*
  - *No available vaccine*
  - *Essential workers*
- Governments must make decisions quickly, based on available information

Decision-maker/Research question

- How many COVID-19 cases can be prevented from 29 March – 28 April in BC with introduction of mandatory masking?
- Compared to current trends in cases with no masking mandates
- Mandatory masking introduced 1 week after last day of available data
- Short time horizon:
  - *Increasing uncertainty into future*
  - *Continuous data generation*
  - *Growing body of evidence*

Methods

ODE model with 4 states (SEIR)

$$\frac{dS}{dt} = -\beta \cdot S \cdot \frac{I}{N}$$

$$\frac{dE}{dt} = \beta \cdot S \cdot \frac{I}{N} - \sigma \cdot E$$

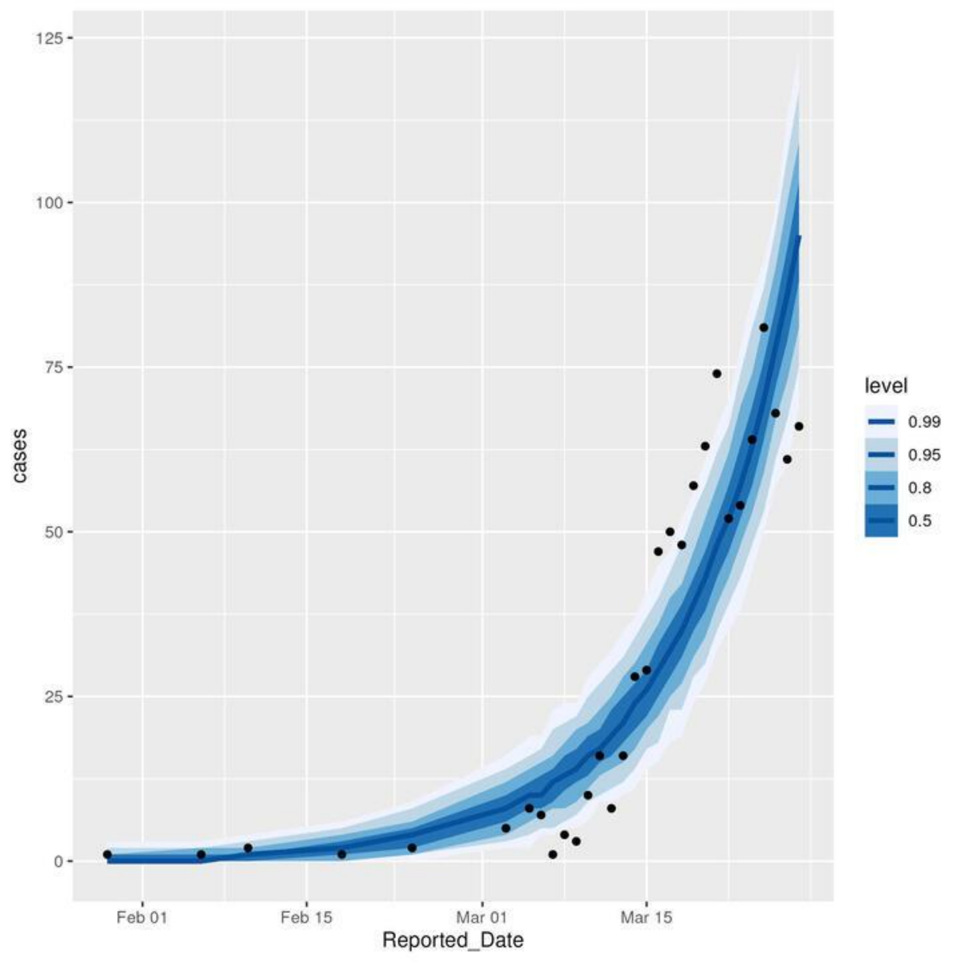
$$\frac{dI}{dt} = \sigma \cdot E - \gamma \cdot I$$

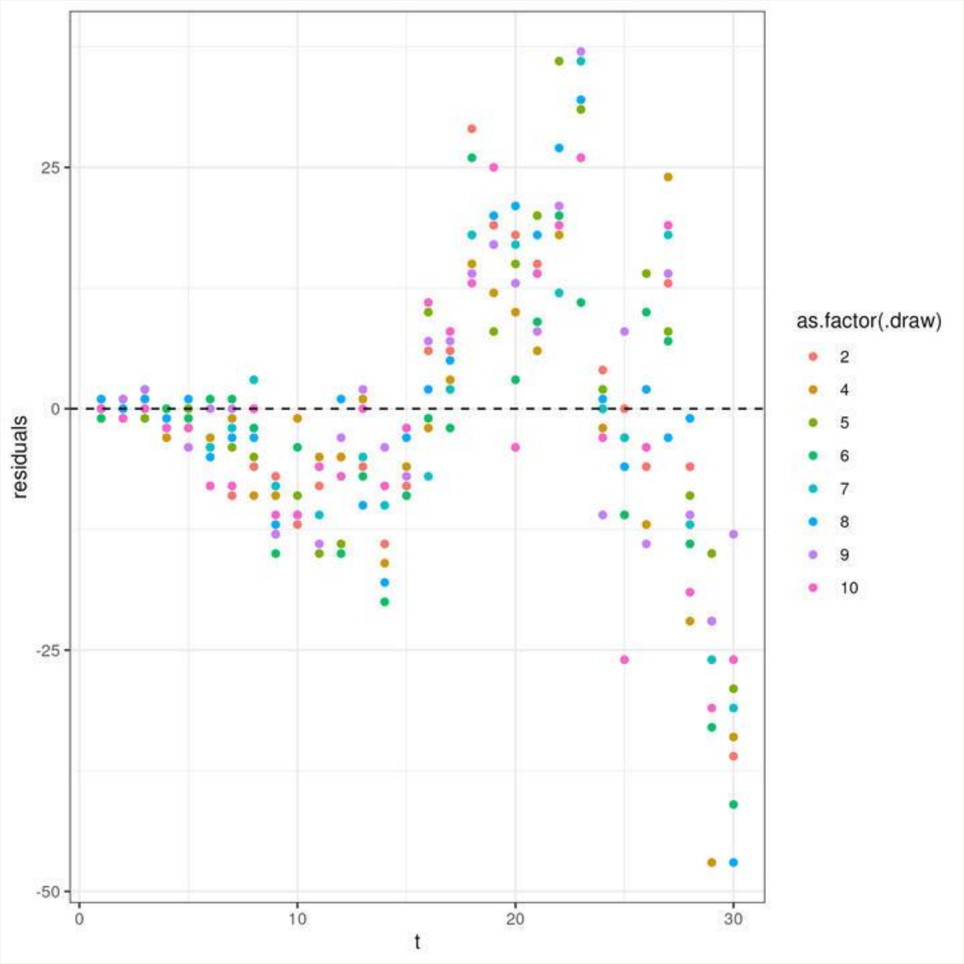
$$\frac{dR}{dt} = \gamma \cdot I$$

Initial Model

```
// define parameters.
// any non-fixed parameters are in the theta array. Any fixed
// parameters are in the x_r array
real R0 = theta[1];
real sigma = x_r[1];
real gamma = x_r[2];
real pop_size = x_r[3];

real lambda = (R0 * gamma * y[3]) / pop_size;

// S
dydt[1] = - lambda * y[1];
// E
dydt[2] =  lambda * y[1] - sigma * y[2];
// I
dydt[3] =  sigma * y[2] - gamma * y[3];
// R
dydt[4] =  gamma * y[3];

return dydt;
```

Initial Model





Modified model

```
// define parameters.
// any non-fixed parameters are in the theta array. Any fixed
// parameters are in the x_r array
real logR0_baseline = theta[1];
real logpan_impact = theta[2];


real sigma = x_r[1];
real gamma = x_r[2];
real pop_size = x_r[3];
real time_masking = x_r[4];
real logmask_impact = x_r[5];
real time_start_of_pandemic = x_r[6];

real R0 = exp(logR0_baseline - (t > time_masking) * logmask_impact -
(t > time_start_of_pandemic) * logpan_impact);
real lambda = (R0 * gamma * y[3]) / pop_size;

// S
dydt[1] = - lambda * y[1];
// E
dydt[2] =  lambda * y[1] - sigma * y[2];
// I
dydt[3] =  sigma * y[2] - gamma * y[3];
// R
dydt[4] =  gamma * y[4];

return dydt;
```

Modified model

- Developed by Dr Michael Irvine
- Additional parameters/data:
  - *Masking effect: relative rate = 0.7*[1]
  - *Decreased social interactions after pandemic declaration: Day 15*[2]

Table. Studies of the Effect of Mask Wearing on SARS-CoV-2 Infection Risk[a]

Source	Location	Population studied	Intervention	Outcome
Hendrix et al	Hair salon in Springfield, Missouri	139 Patrons at a salon with 2 infected and symptomatic stylists	Universal mask wearing in salon (by local ordinance and company policy)	No COVID-19 infections among 67 patrons who were available for follow-up
Payne et al	USS Theodore Roosevelt, Guam	382 US Navy service members	Self-reported mask wearing	Mask wearing reduced risk of infection by 70% (unadjusted odds ratio, 0.30 [95% CI, 0.17-0.52])
Wang Y et al	Households in Beijing, China	124 Households of diagnosed cases comprising 335 people	Self-reported mask wearing by index cases or ≥1 household member prior to index case's diagnosis	Mask wearing reduced risk of secondary infection by 79% (adjusted odds ratio, 0.21 [95% CI, 0.06-0.79])
Doung-ngern et al	Bangkok, Thailand	839 Close contacts of 211 index cases	Self-reported mask wearing by contact at time of high-risk exposure to case	Always having used a mask reduced infection risk by 77% (adjusted odds ratio, 0.23 [95% CI, 0.09-0.60])
Gallaway et al	Arizona	State population	Mandatory mask wearing in public	Temporal association between institution of mask wearing policy and subsequent decline in new diagnoses
Rader et al	US	374 021 Persons who completed web-based surveys	Self-reported mask wearing in grocery stores and in the homes of family or friends	A 10% increase in mask wearing tripled the likelihood of stopping community transmission (adjusted odds ratio, 3.53 [95% CI, 2.03-6.43])
Wang X et al	Boston, Massachusetts	9850 Health care workers (HCWs)	Universal masking of HCWs and patients in the Mass General Brigham health care system	Estimated weekly decline in new diagnoses among HCWs of 3.4% after full implementation of the mask wearing policy
Mitze et al	Jena (Thuringia), Germany	City population aged ≥15 y	Mandatory mask wearing in public spaces (eg, public transport, shops)	Estimated daily decline in new diagnoses of 1.32% after implementation of the mask mandate
Van Dyke et al	Kansas	State population	Mandatory mask wearing in public spaces	Estimated case rate per 100 000 persons decreased by 0.08 in counties with mask mandates but increased by 0.11 in those without
Lyu and Wehby	15 US states and Washington, DC	State populations	Mandatory mask wearing in public	Estimated overall initial daily decline in new diagnoses of 0.9% grew to 2.0% at 21 days following mandates
Karaivanov et al	Canada	Country population	Mandatory mask wearing indoors	Estimated weekly 25%-40% decline in new diagnoses following mask mandates

[a] See the Supplement for the complete table.

Modified model

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- Additional parameters/data:
  - *Masking effect: relative rate = 0.7*[1]
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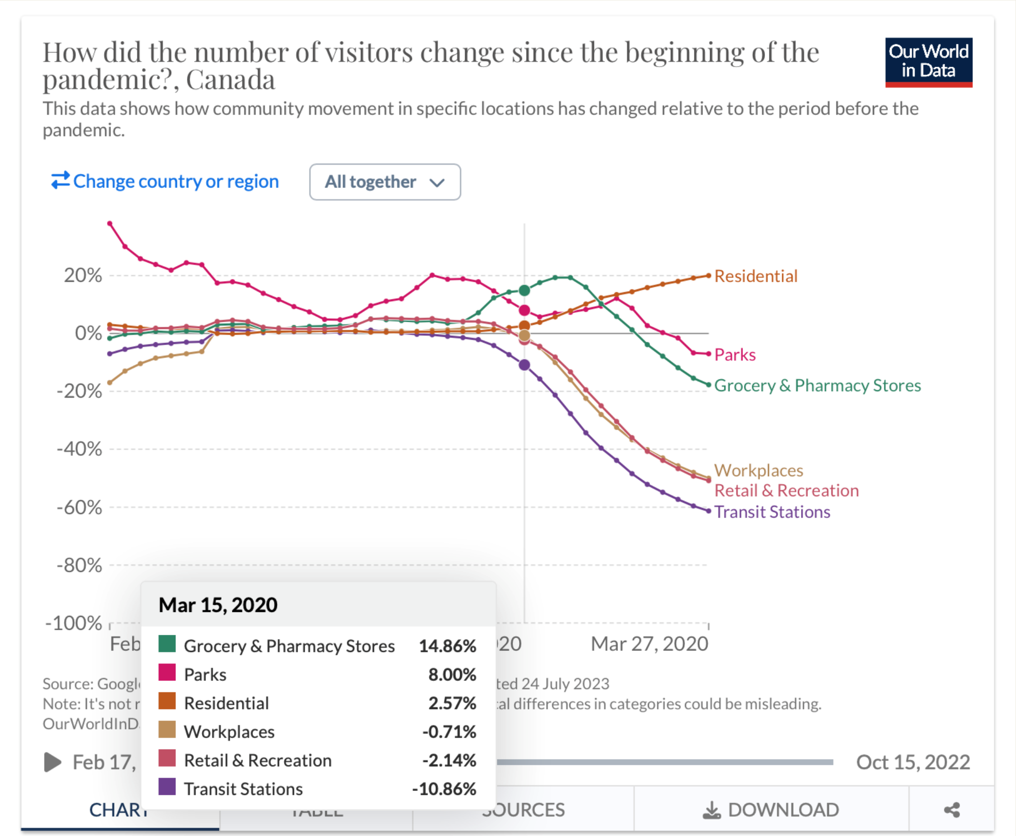
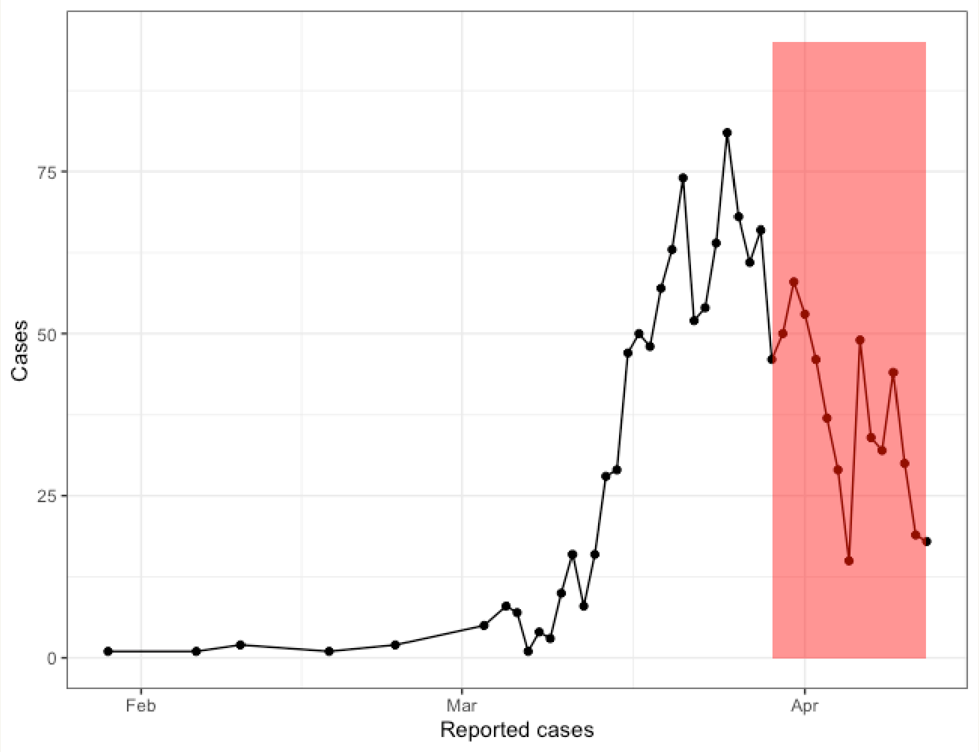


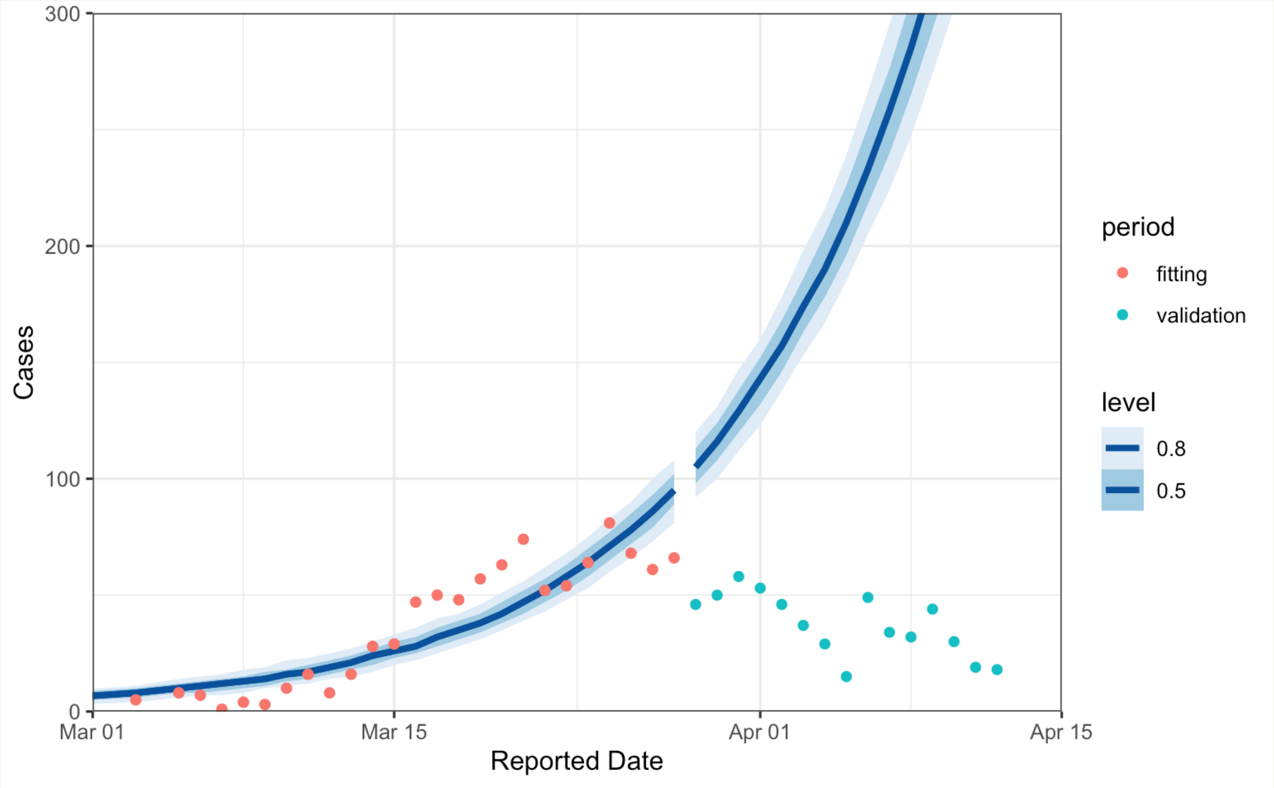
```r
stan_data_extended <- list(
  T = length(fitting_time_points), # number of data points
  y = fitting_cases, # observed infection cases
  ts = fitting_time_points, # Time points
  forecast_T = length(forecast_time_points), # number of forecast points
  forecast_ts = forecast_time_points, # Forecast time points
  R0_prior = c(log(2.5), 0.2), # log Mean and std for R0
  i0_prior = c(log(8), 1.0), # log Mean and std for i0
  gamma = 1 / 7, # recovery rate
  sigma = 1 / 5, # incubation rate
  pop_size = 5e6, # population of BC
  t0 = -1,
  logmask_impact = log(0.5),
  time_masking = 52,
  time_start_of_pandemic = 15
)
```

Validation data



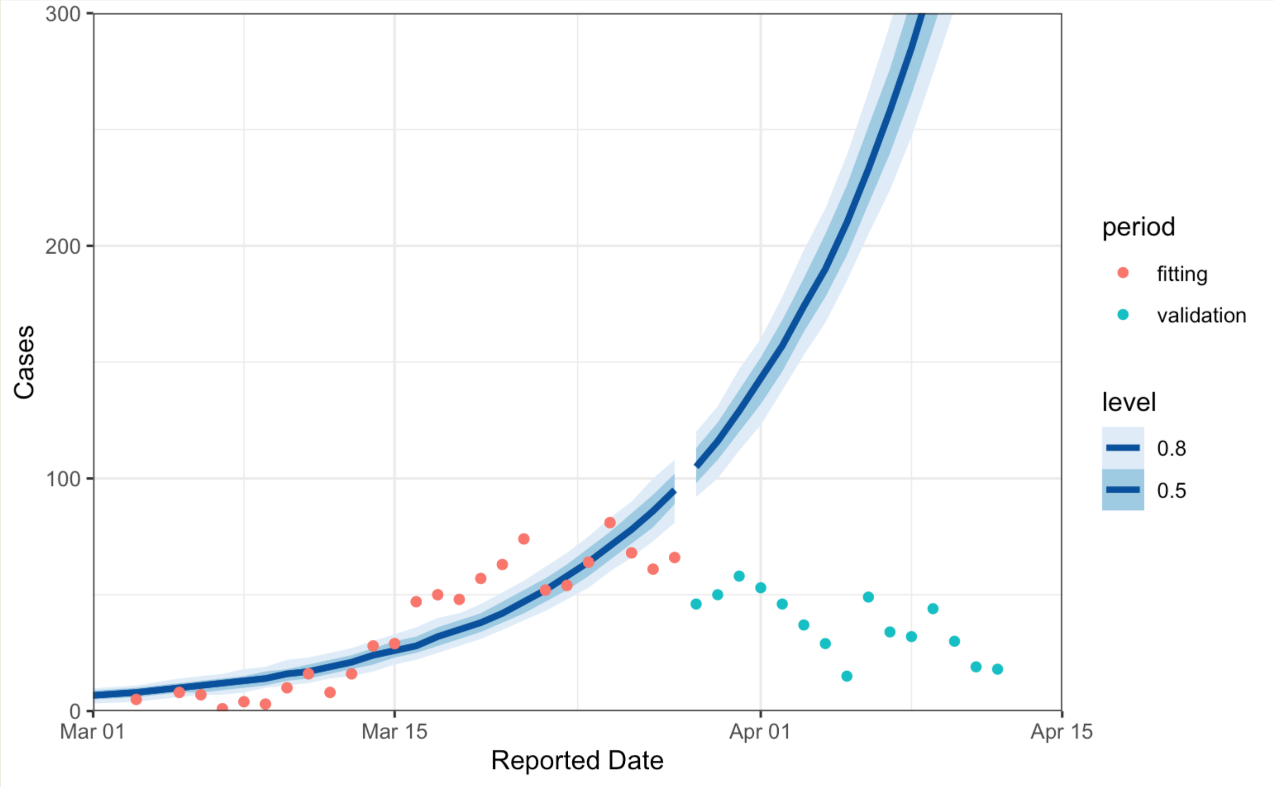
Observations

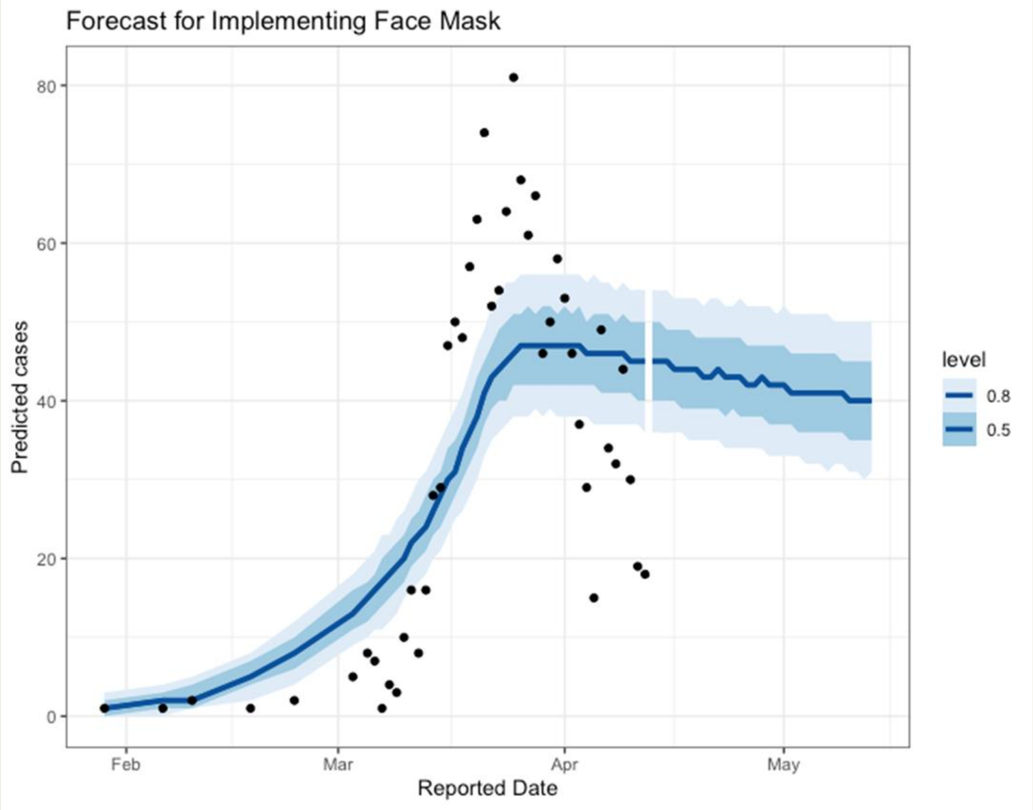
Comparing forecast to validation data



Original data and validation data

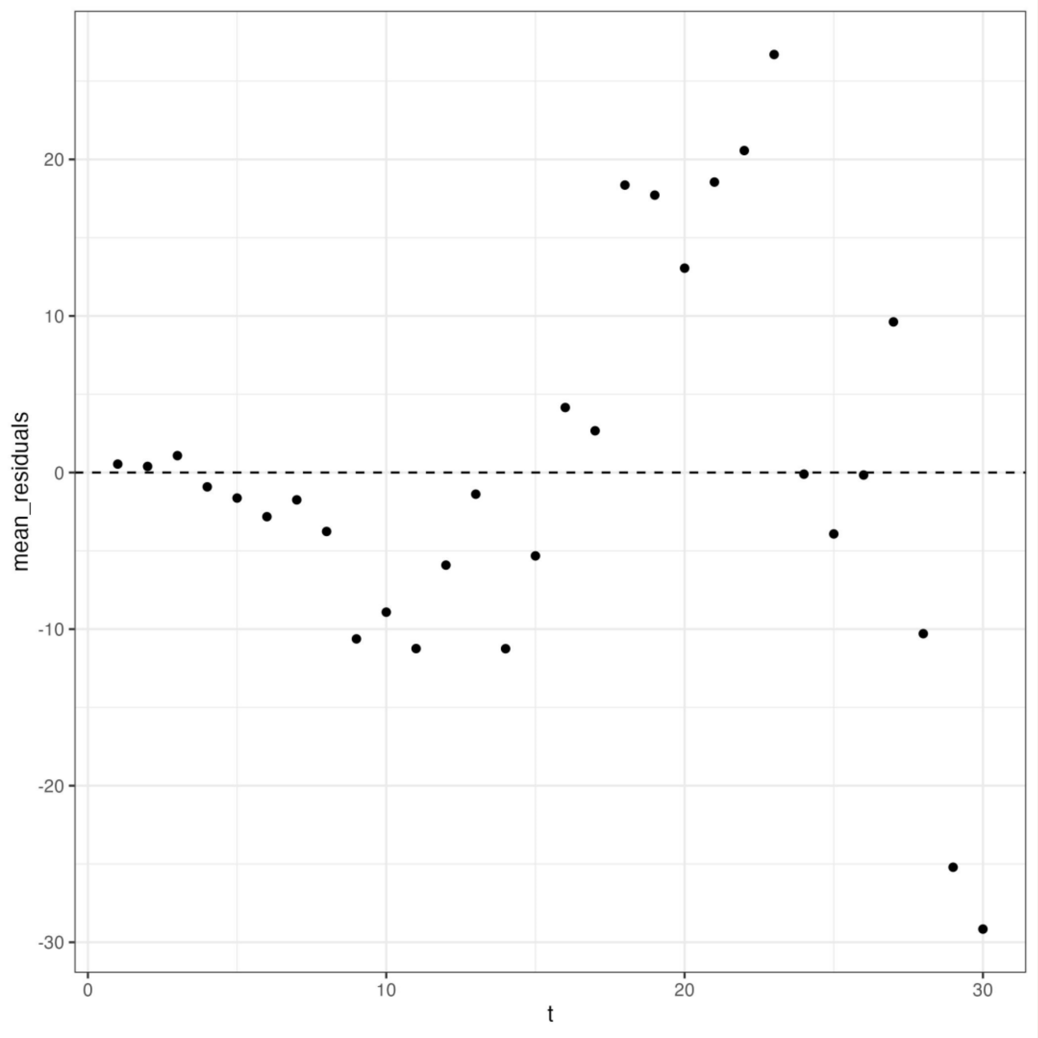
Comparing model forecast : Masking vs non masking effect





Original data and validation data

Residuals (Masking effect model)



Conclusions

- Our model:

- Limited for predicting future cases in spite of the modifications that accounted for a possible effect of masking ad general behavioural changes in the population at the beginning of the pandemic
- Improvements could be:
  - *Modify the beginning of the "pandemic start" and "masking start"*
  - *Using a negative binomial instead of a Poisson to estimate the number of cases or use another framework to account for changes in the system.*
- Several parameters influence over the transmission.

References

1. Brooks JT, Butler JC. Effectiveness of Mask Wearing to Control Community Spread of SARS-CoV-2. JAMA.2021;325(10):998–999. doi:10.1001/jama.2021.1505
2. Edouard Mathieu, Hannah Ritchie, Lucas Rodés-Guirao, Cameron Appel, Charlie Giattino, Joe Hasell, Bobbie Macdonald, Saloni Dattani, Diana Beltekian, Esteban Ortiz-Ospina and Max Roser (2020) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/coronavirus' [Online Resource]