COVID Testing Bias and Influence on Projected Testing metrics

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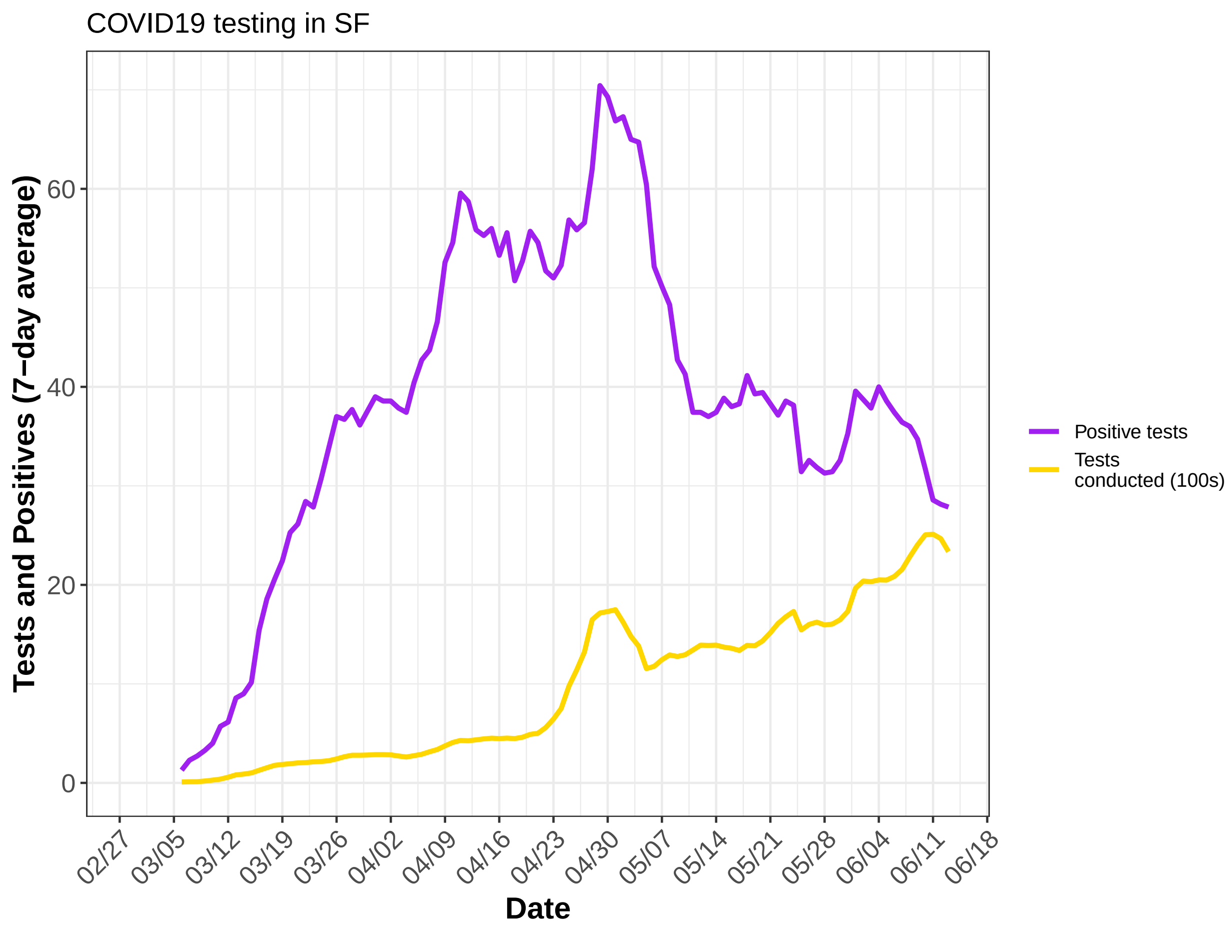
6/4/2020

Purpose

Estimate bias in COVID19 testing in SF and incorporate into near-term projections to determine influence on testing metrics such as %+ tests.

Testing



Model

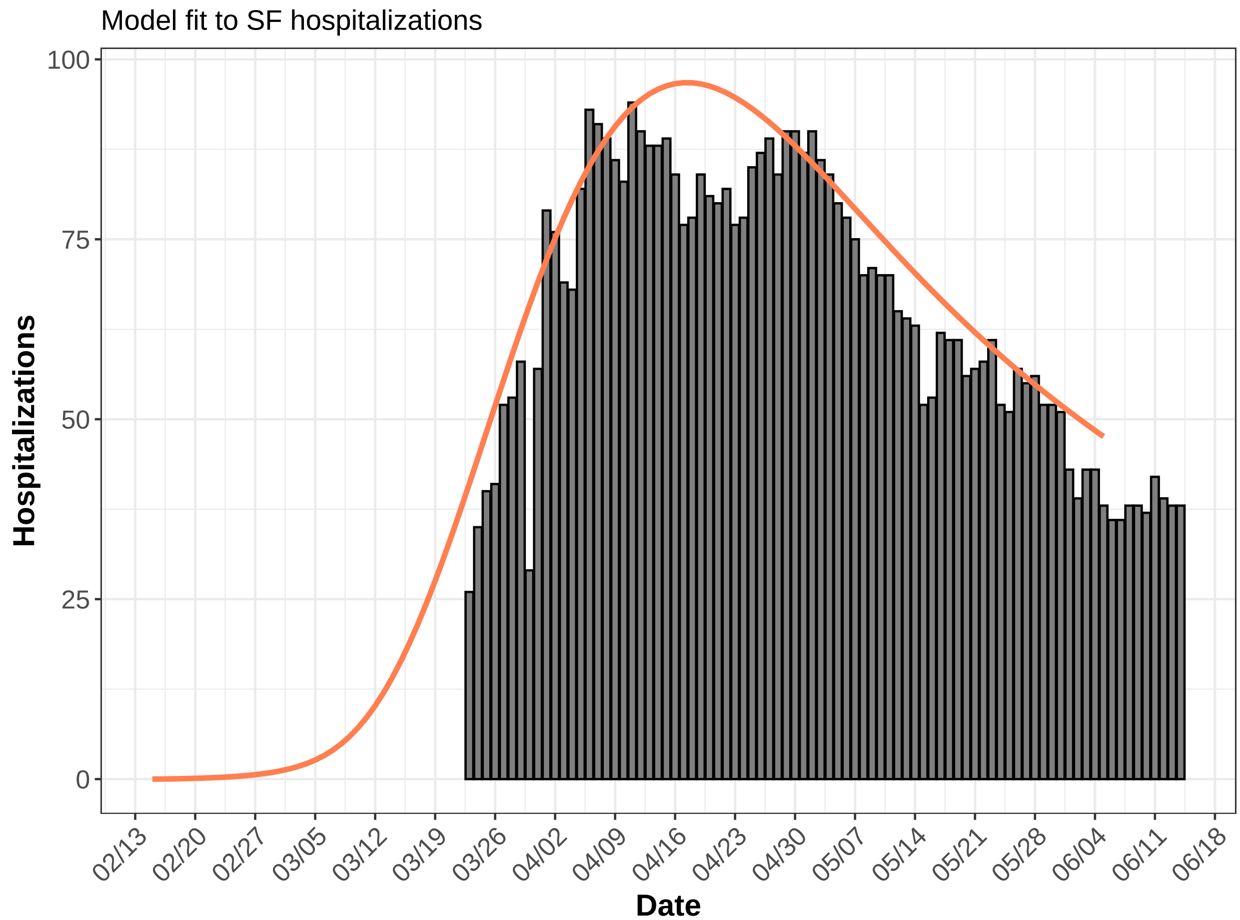
We use a slight tweak to LEMMA to add an explicit deaths compartment in order to fit to deaths data in addition to hospitalizations

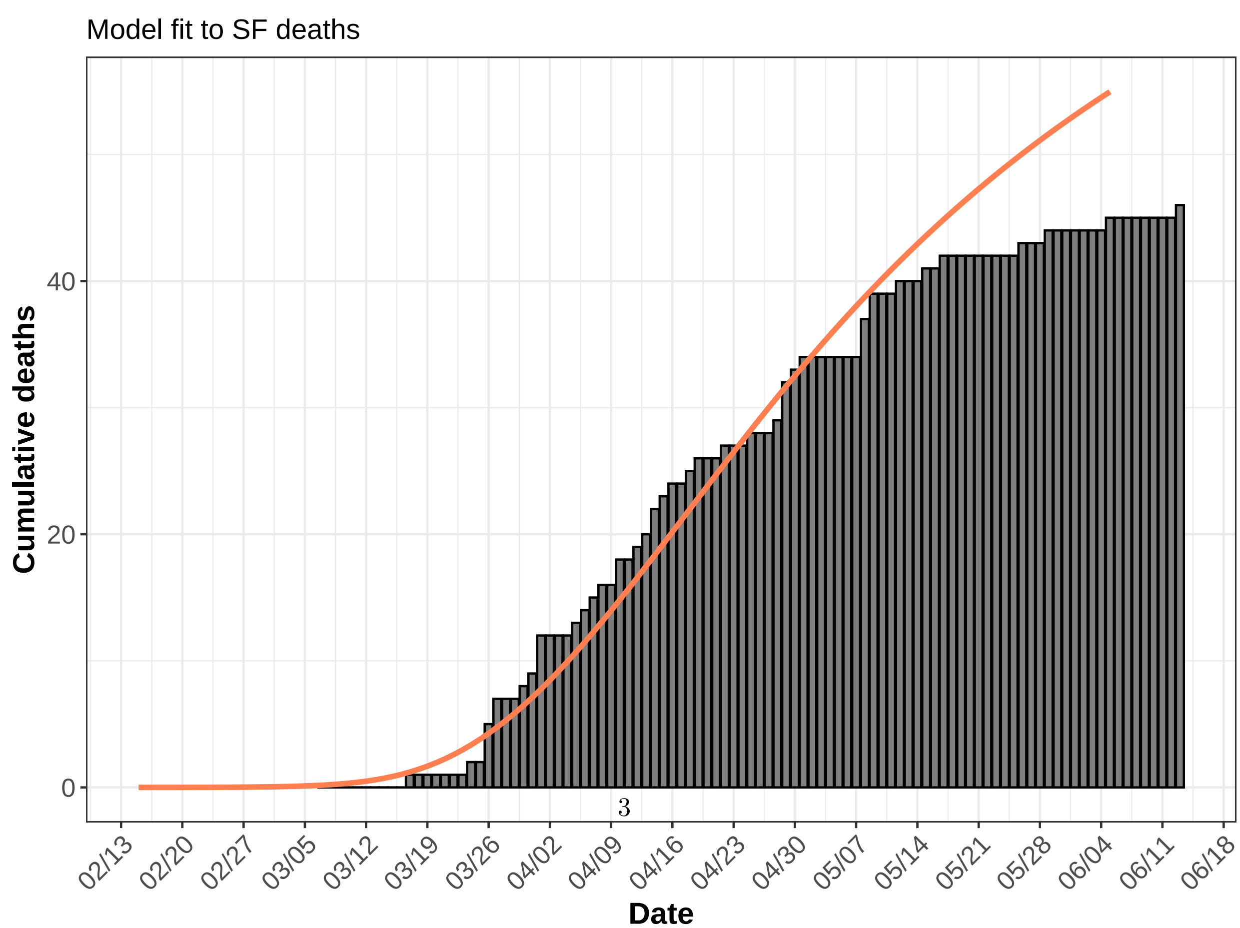
Table 1: Best fit model parameters

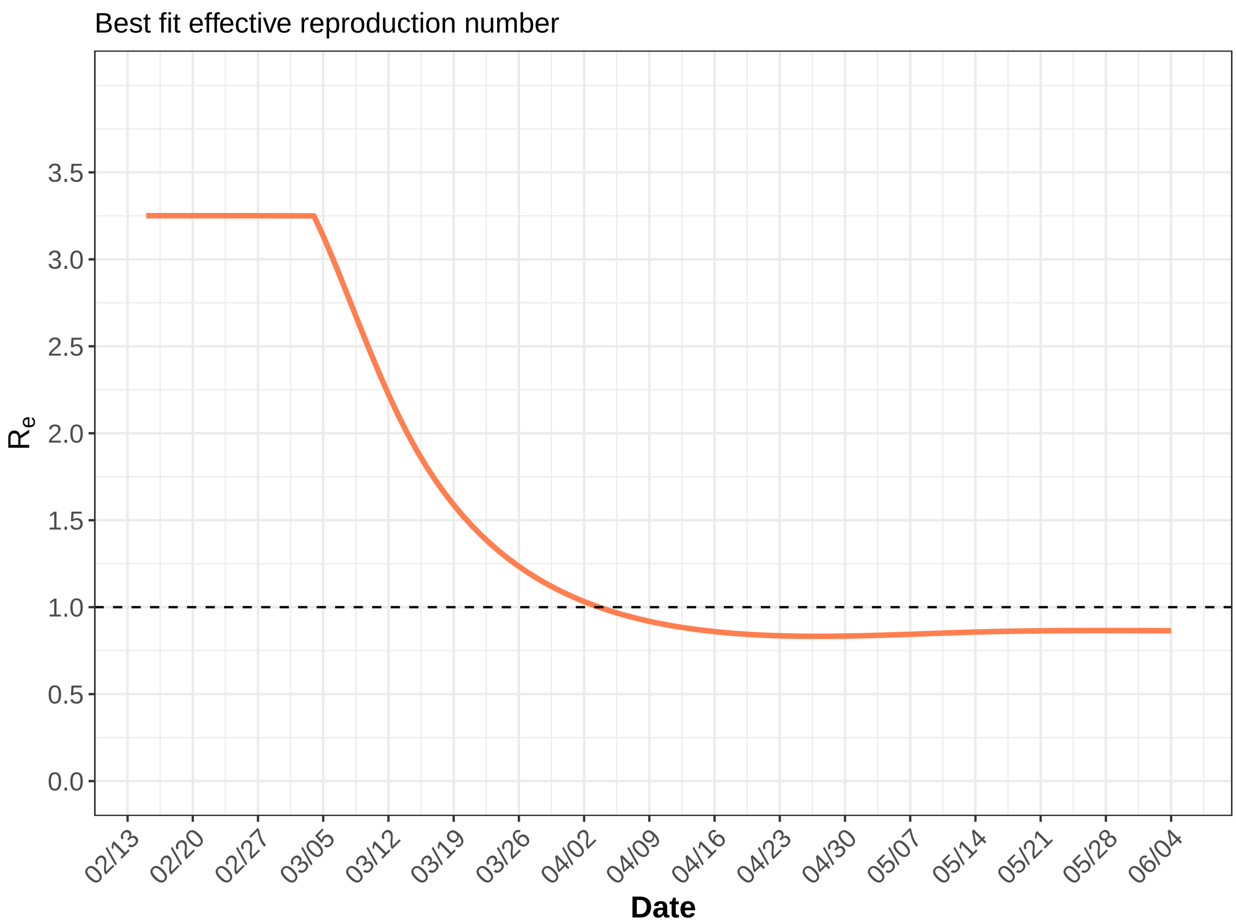
	Value	Definition
N	883305	population size
t.sim	112	time to run simulation
E_0	6	starting number of exposed
c_r	1	Relative contact rate between S and Ir
c_h	1	Relative contact rate between S and Ih
σ	0.333	1/serial interval
α	0.033	proportion severely symptomatic (will be hospitalized)
ρ	0.25	time between symptom onset and hospitalization
γ_r	0.2	1/time to recovery (non-infectiousness) for mildly symptomatic
γ_h	0.083	1/time hospitalized
μ	0.113	proportion of hospitalized cases who die

$$
\begin{aligned}
\dot{S} &= -\beta S(I_R + I_H)/N \\
\dot{E} &= \beta S(I_R + I_H)/N - \sigma E \\
\dot{I_R} &= \sigma(1-\alpha)E - \gamma_R I_R \\
\dot{I_H} &= \sigma\alpha E - \rho I_H \\
\dot{H} &= \rho I_H - \gamma_H H \\
\dot{D} &= \gamma_H \mu H \\
\dot{R} &= \gamma_R I_R \gamma_H (1-\mu) H
\end{aligned}
$$

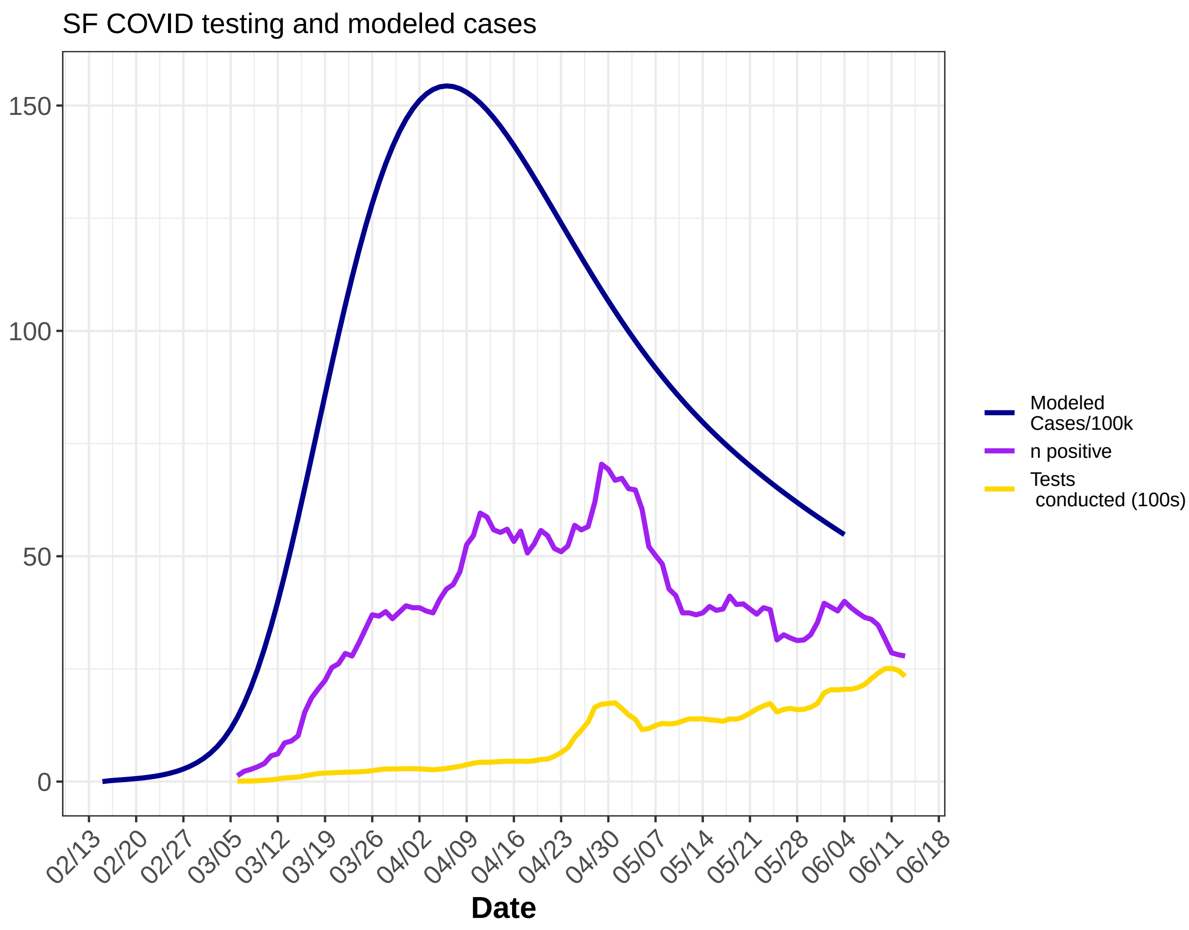
Model fit

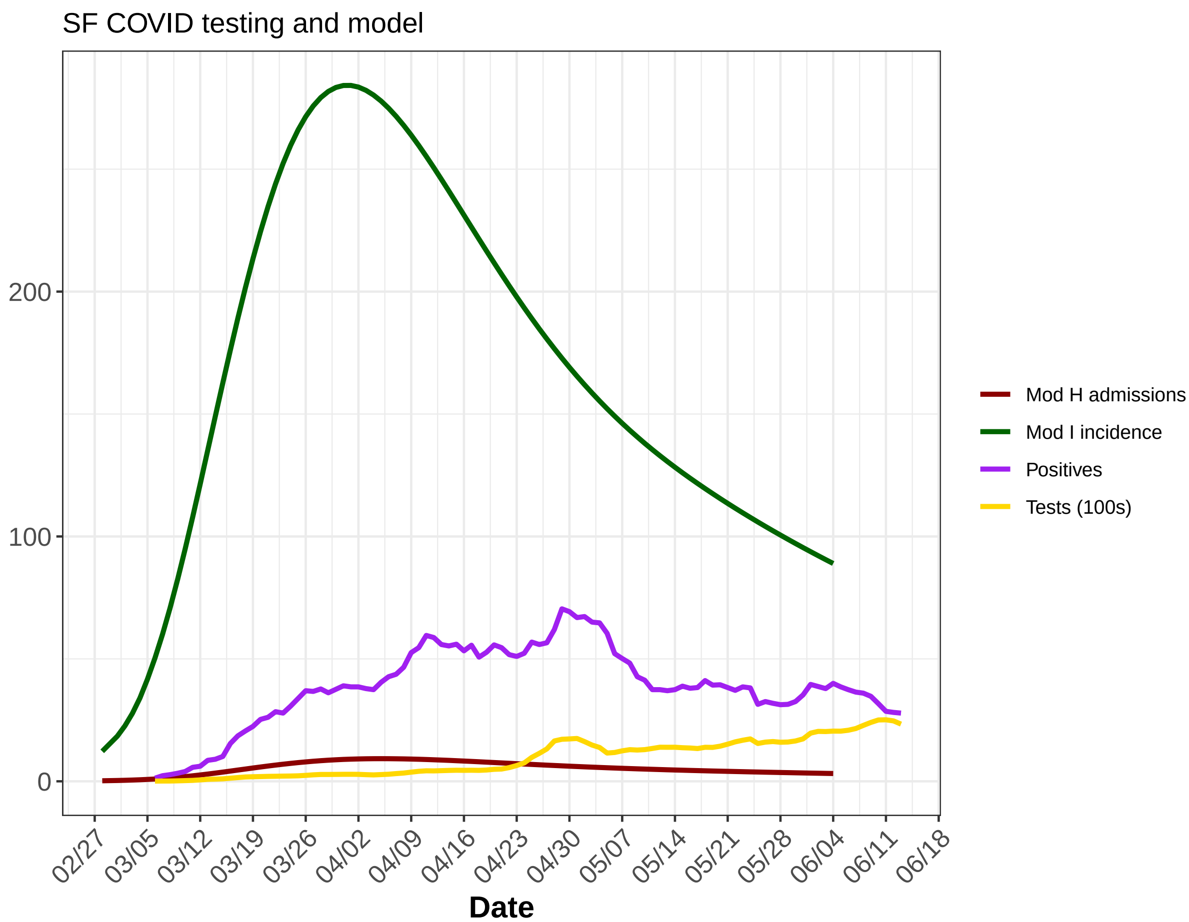

Model fit to SF hospitalizations
Hospitalizations
100
75
50
25
0
02/13
02/20
02/27
03/05
03/12
03/19
03/26
04/02
04/09
04/16
04/23
04/30
05/07
05/14
05/21
05/28
06/04
06/11
06/18
Date


Model fit to SF deaths
Cumulative deaths
40
20
0
02/13
02/20
02/27
03/05
03/12
03/19
03/26
04/02
04/09
04/16
04/23
04/30
05/07
05/14
05/21
05/28
06/04
06/11
06/18
Date


Best fit effective reproduction number
R_e
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
02/13
02/20
02/27
03/05
03/12
03/19
03/26
04/02
04/09
04/16
04/23
04/30
05/07
05/14
05/21
05/28
06/04
Date

Comparison to testing data





Match modeled testing to observed testing

Assume all new hospitalized cases are tested and confirmed positive, then assume remaining tests are allocated to non-hospitalized population. In the model, this is equivalent to a sample of S, E, and $I_r + I_h$. In reality, lots of nuance in the E and R compartments with regard to testing, but for simplicity, we'll assume positive tests from this sample only come from $I_r + I_h$ and Rs are not tested. So want to solve for sampling bias, $\mathcal{B}$, from:

$$\frac{+Tests - H_{new}}{Tests - H_{new}} = \frac{\mathcal{B}(I_r + I_h)}{S + E + I_r + I_h}$$

where $\mathcal{B}$ can be roughly interpreted as the enhanced probability of infectious individuals being tested

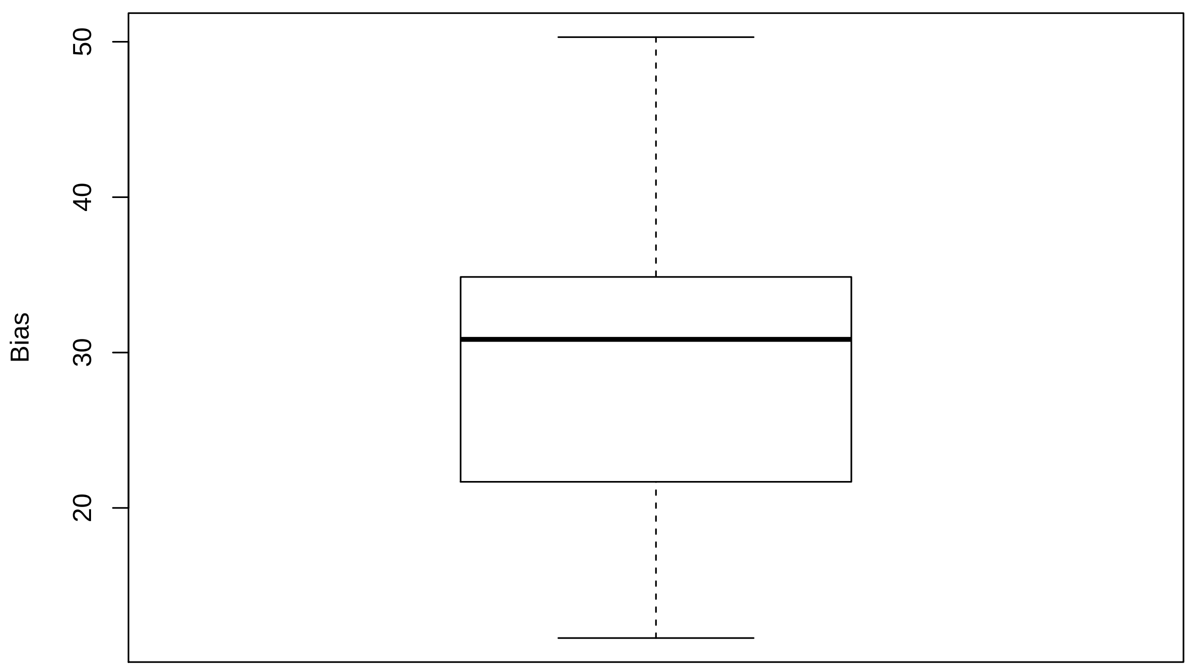
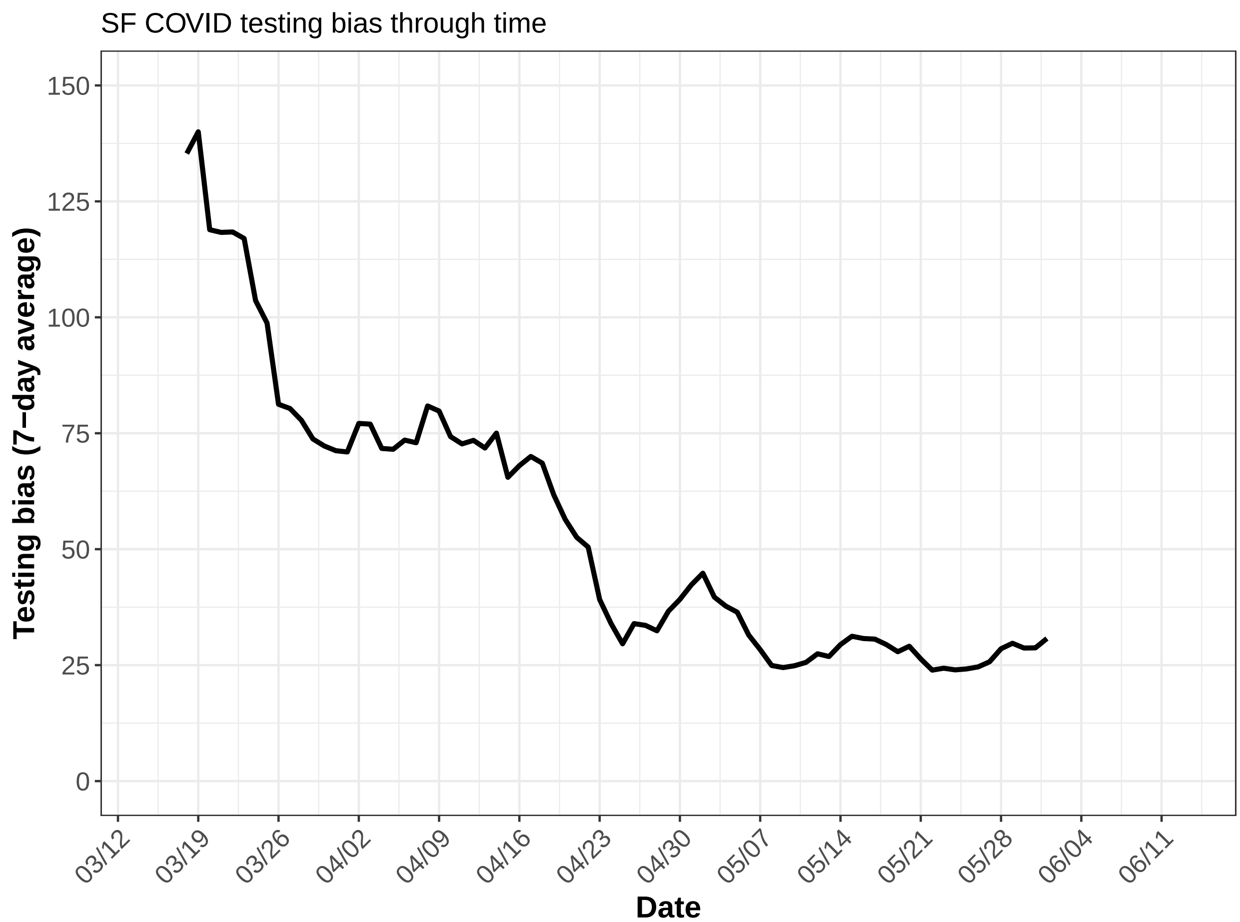
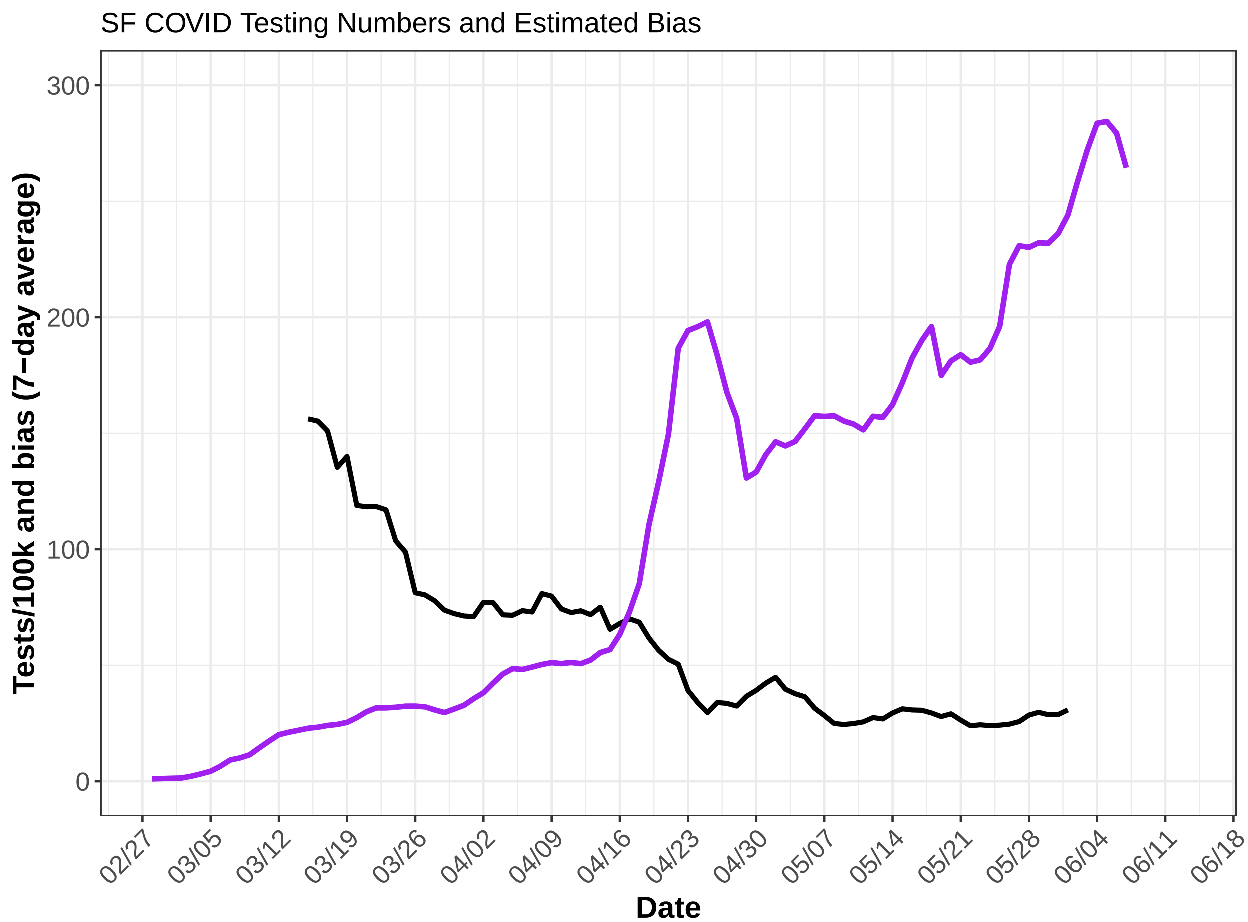
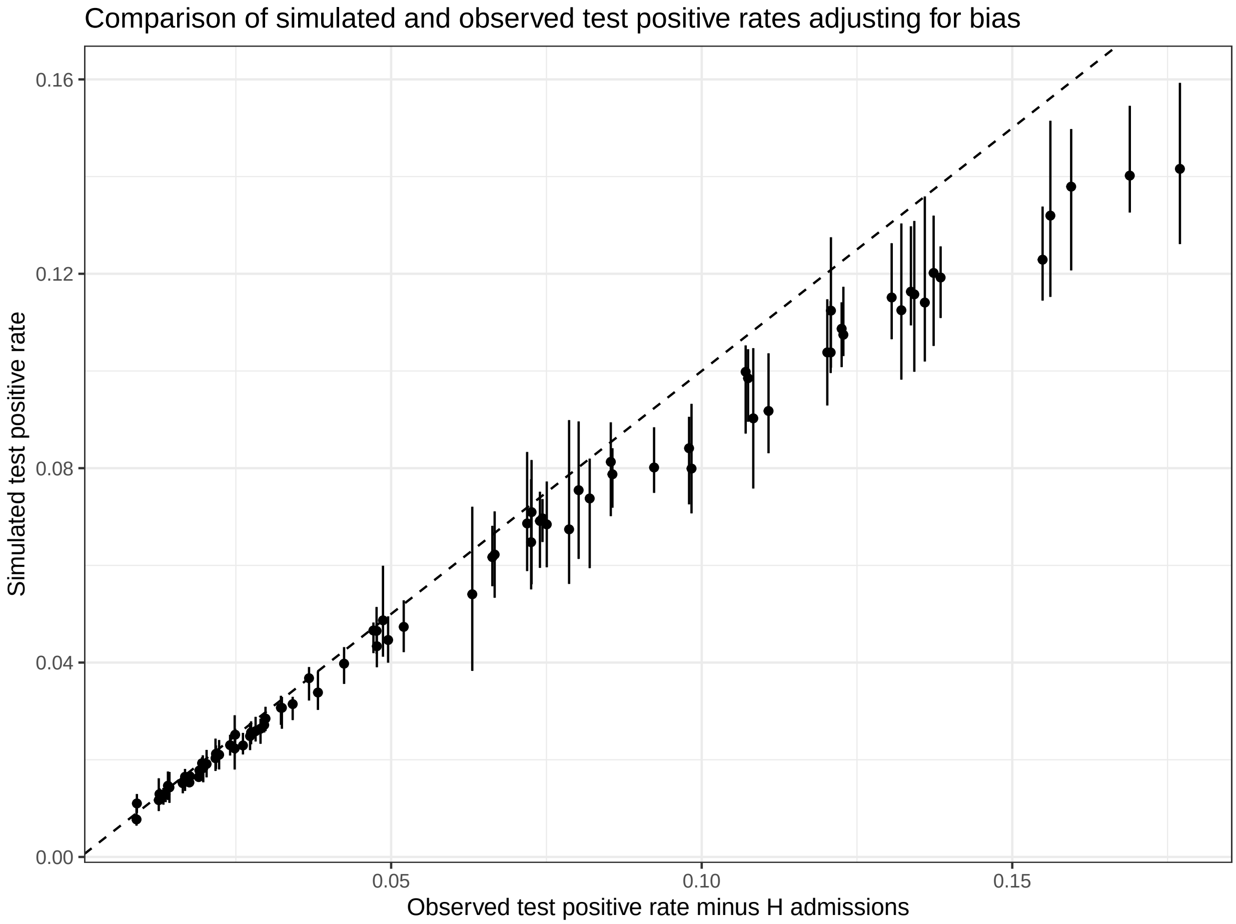


Figure 1: Distribution of estimated sampling bias since end of April



SF COVID testing bias through time
Testing bias (7−day average)
150
125
100
75
50
25
0
03/12
03/19
03/26
04/02
04/09
04/16
04/23
04/30
05/07
05/14
05/21
05/28
06/04
06/11
Date


SF COVID Testing Numbers and Estimated Bias
Tests/100k and bias (7−day average)
300
200
100
0
02/27
03/05
03/12
03/19
03/26
04/02
04/09
04/16
04/23
04/30
05/07
05/14
05/21
05/28
06/04
06/11
06/18
Date



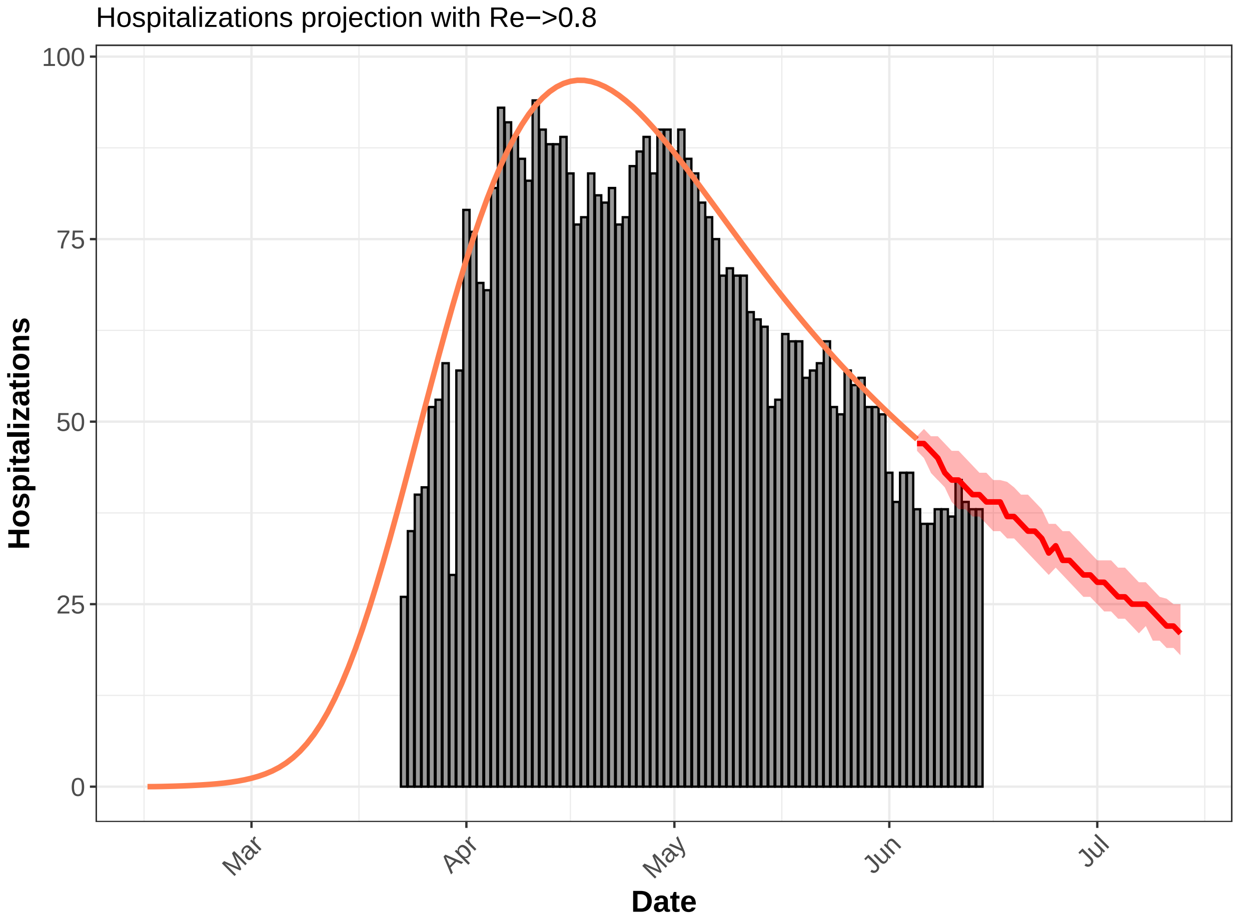
This is ok as the most recent test positive rates (which are lower) are in the lower left of this plot where the simulation and observed match better. Higher observed test positive rates were earlier in the outbreak when less tests were avaialble and testing bias was probably even more sporadic.

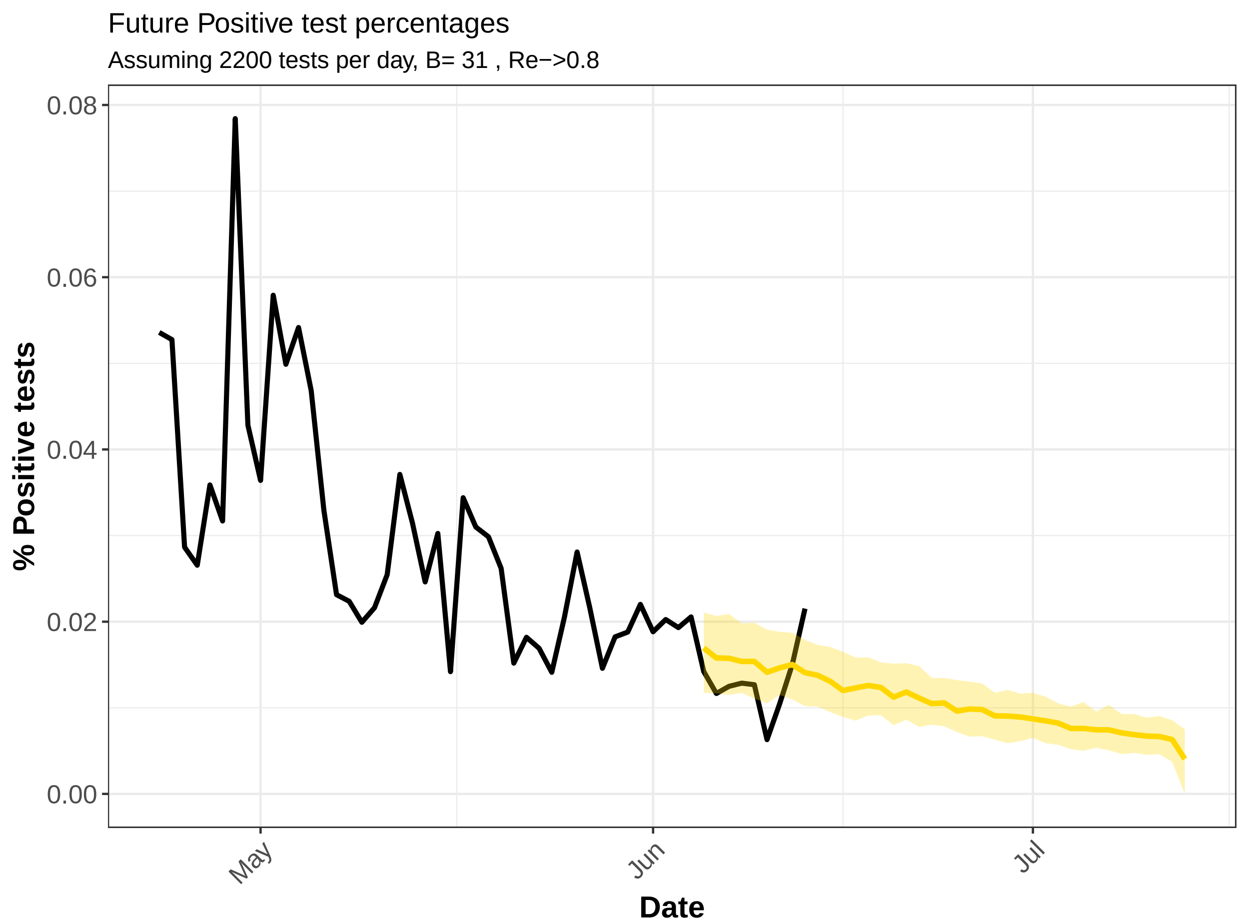
Model forecast

Assuming testing bias and number of tests remain constant, now want to determine what testing (and hospitalizations since that is what model fitting is based on) may look like in the near future under different transmission scenarios. The model was fit through the first week of June (June 5th), and the different transmission scenarios assume:

1. Transmission has remained constant with $\mathcal{R}_e \approx 0.8$
2. Transmission has increased above 1 as of June 15th with $\mathcal{R}_e \approx 1.1$
3. Transmission has increased well above 1 as of June 15th with $\mathcal{R}_e \approx 1.4$

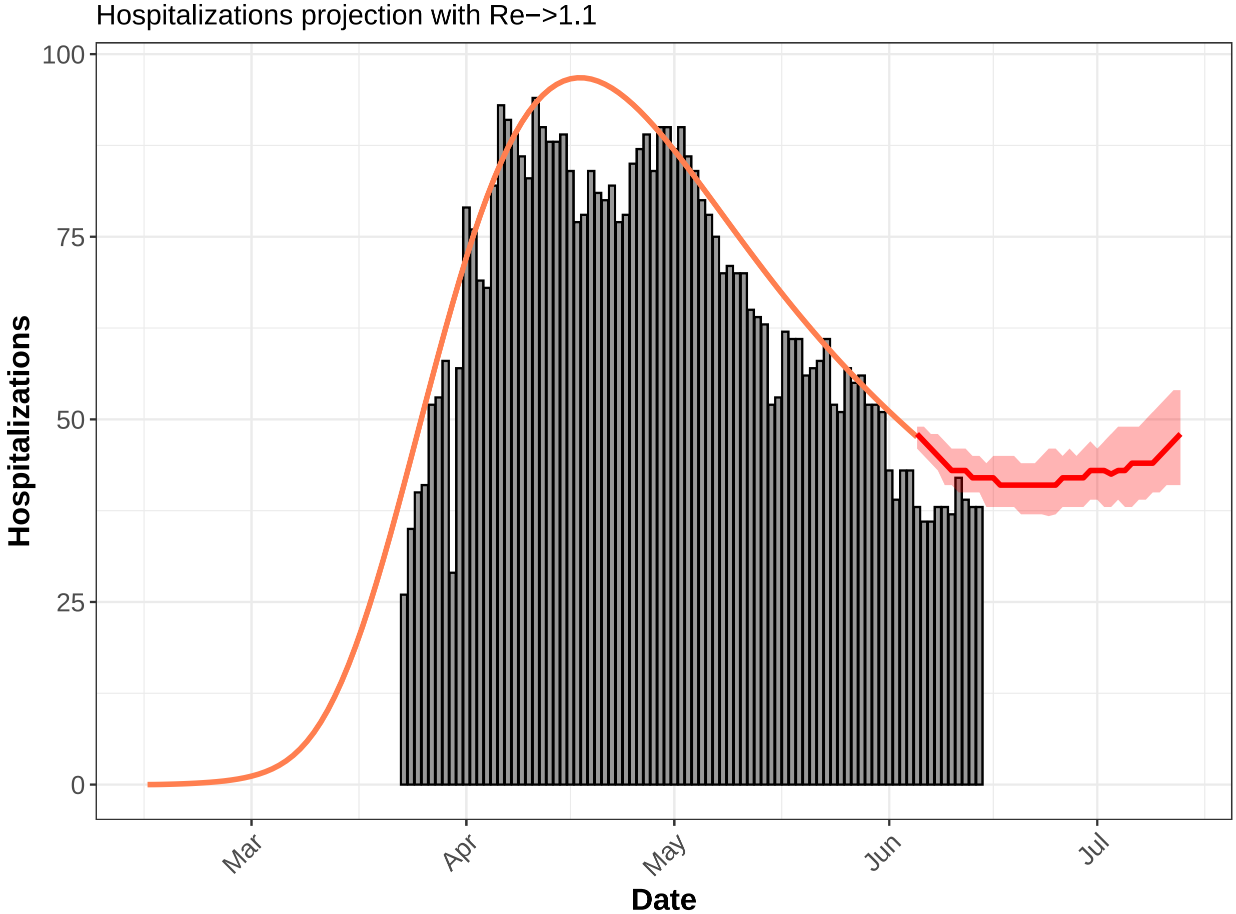
$\mathcal{R}_e \to 0.8$

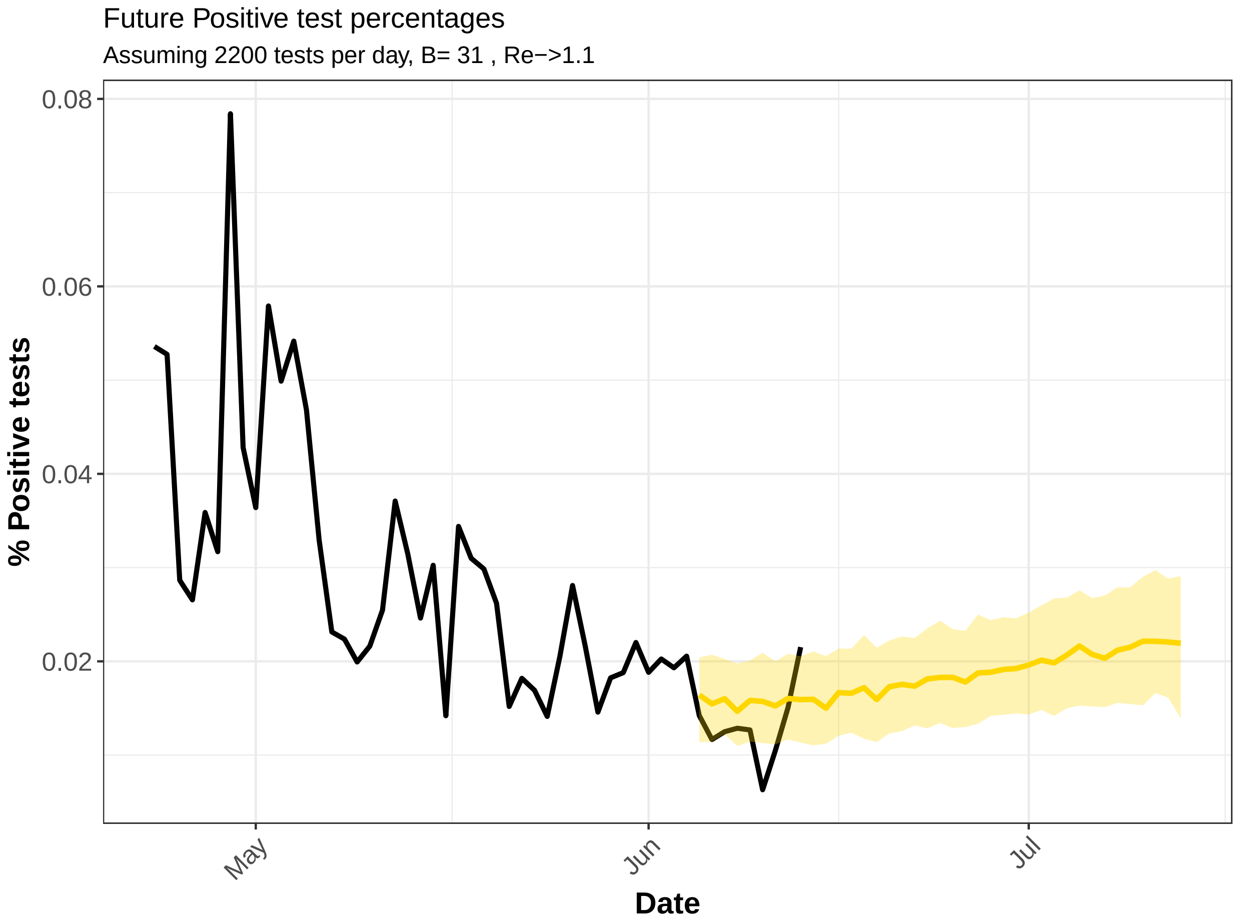




Future Positive test percentages
Assuming 2200 tests per day, B= 31 , Re−>0.8
0.08
0.06
0.04
0.02
0.00
% Positive tests
May
Jun
Jul
Date

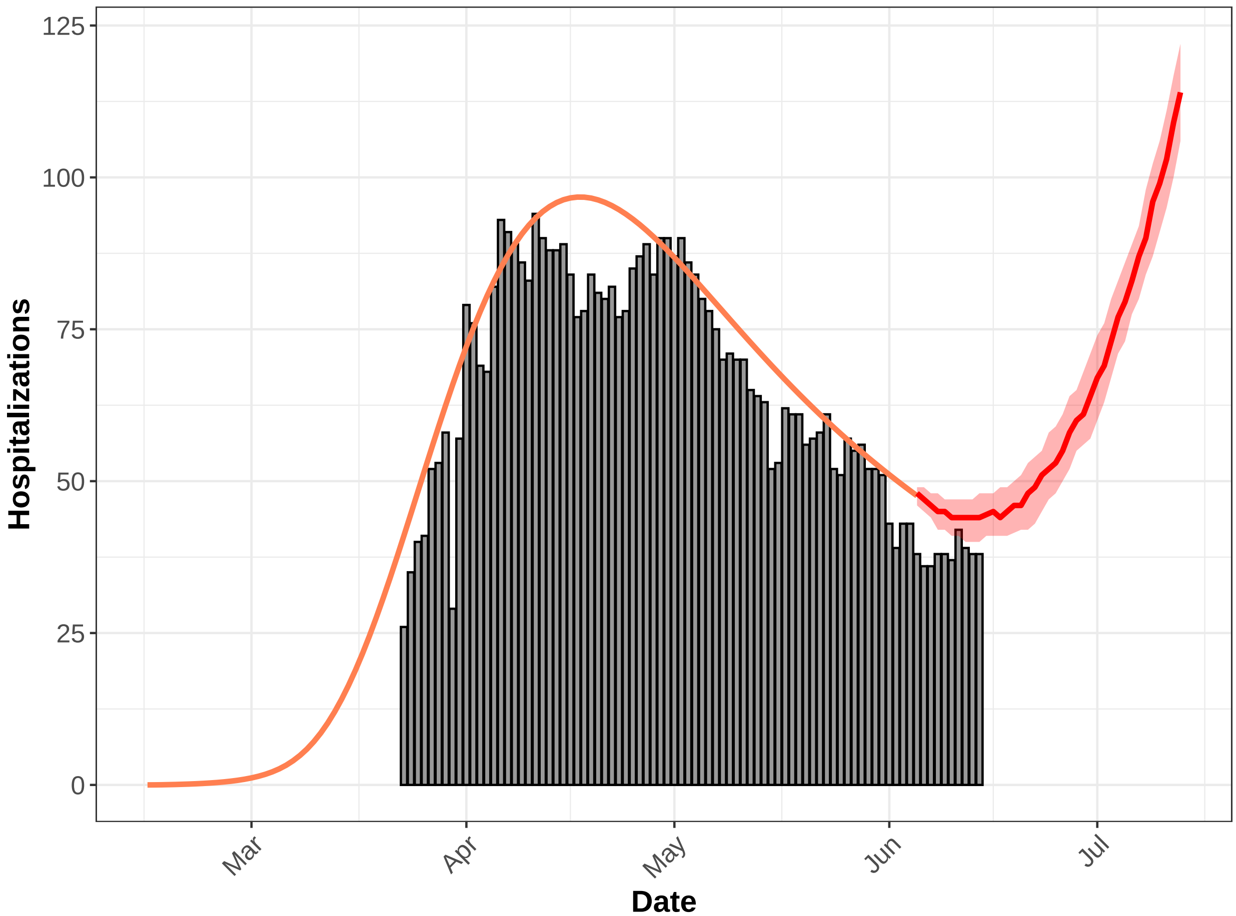
$\mathcal{R}_e \to 1.1$

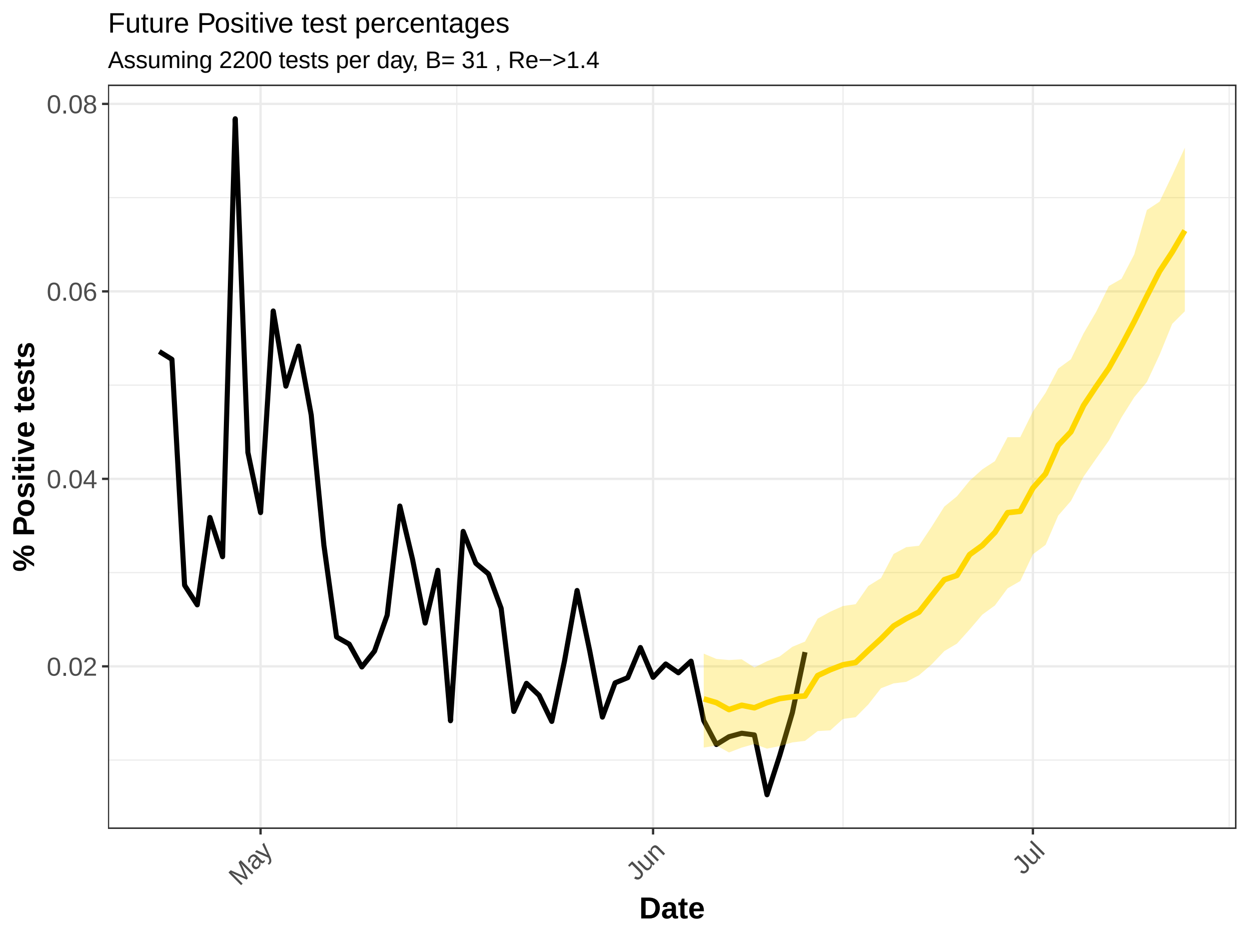




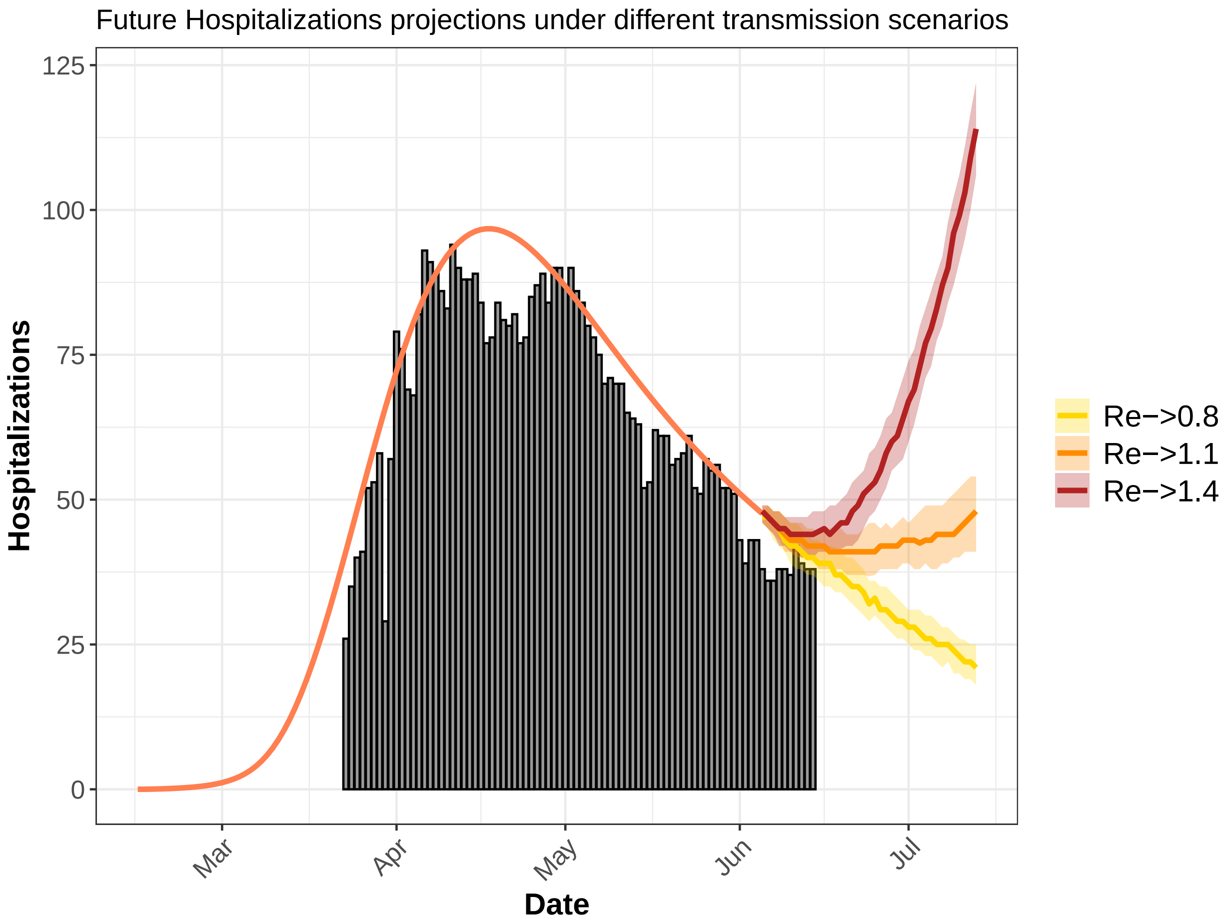
Future Positive test percentages
Assuming 2200 tests per day, B= 31 , Re−>1.1
0.08
0.06
0.04
0.02
% Positive tests
May
Jun
Jul
Date

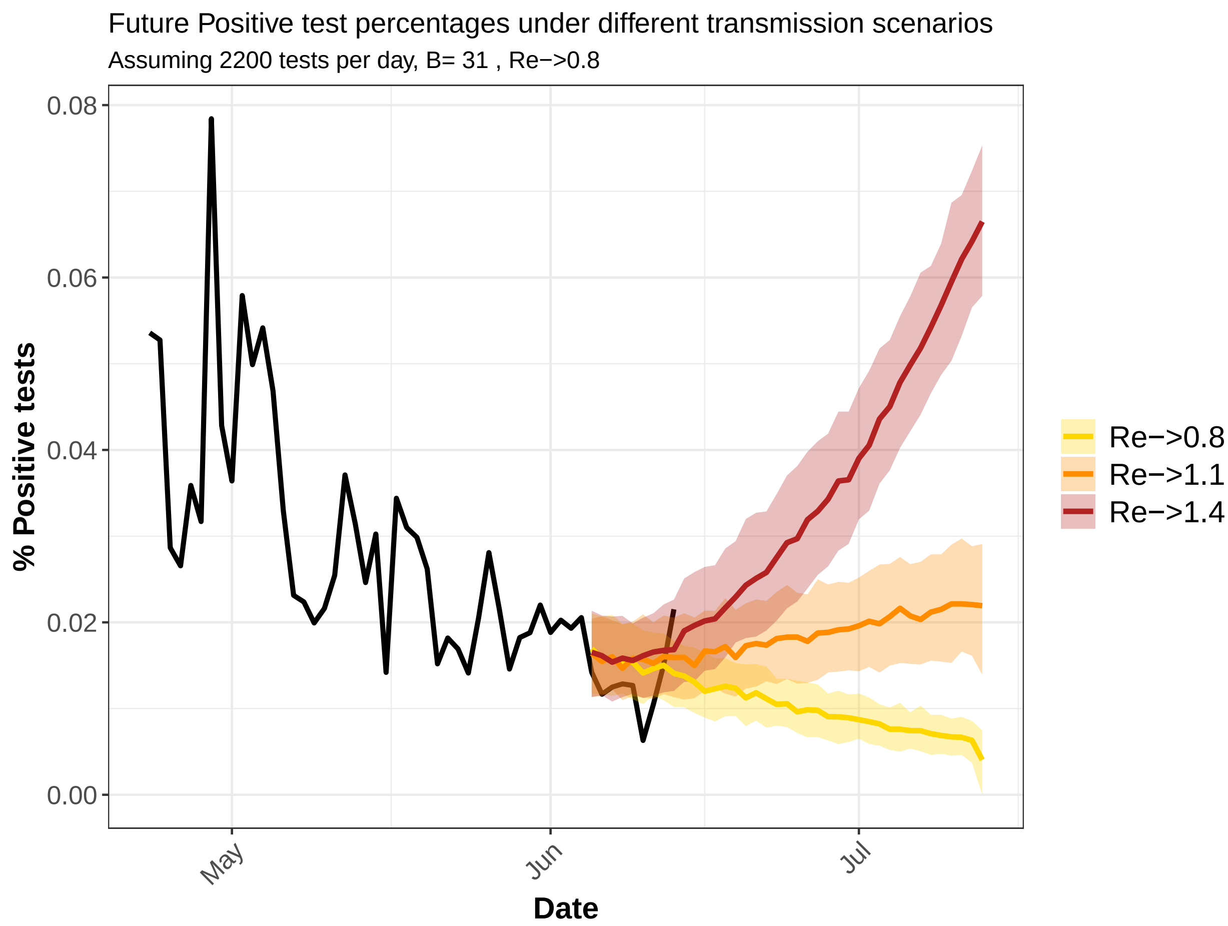
$\mathcal{R}_e \to 1.4$

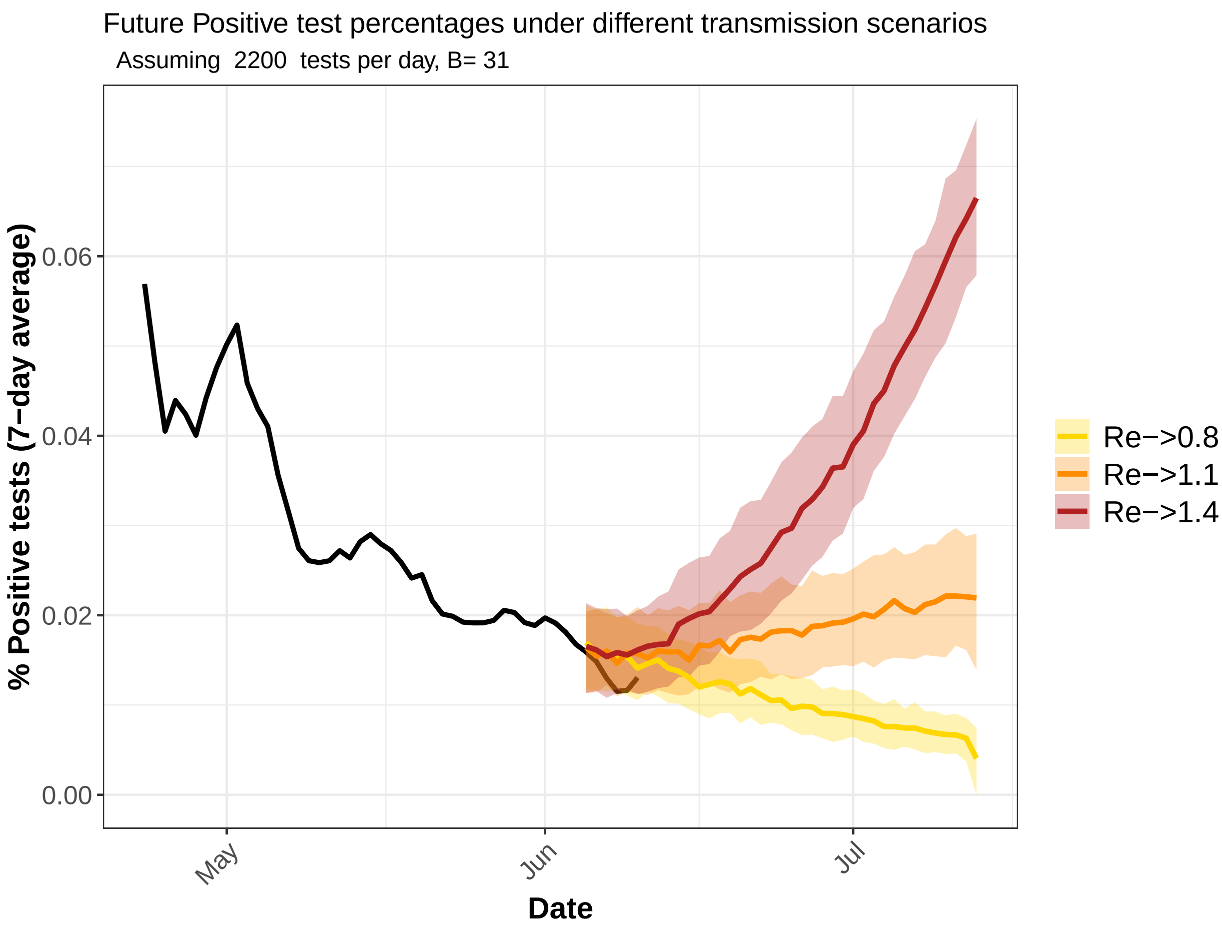



Future Positive test percentages
Assuming 2200 tests per day, B= 31 , Re−>1.4
0.08
0.06
0.04
0.02
% Positive tests
May
Jun
Jul
Date

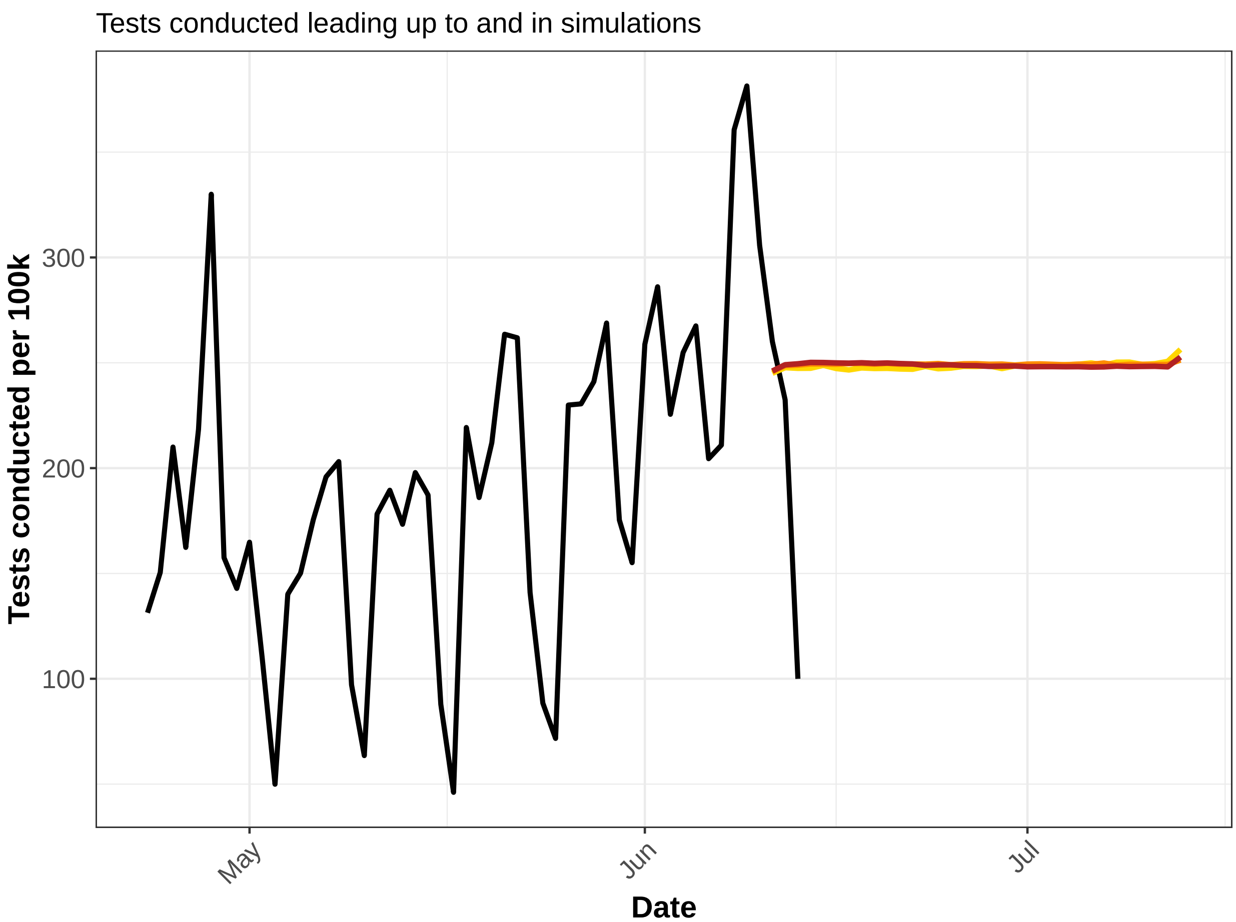
Compare tests, hospitalizations in different future transmission scenarios



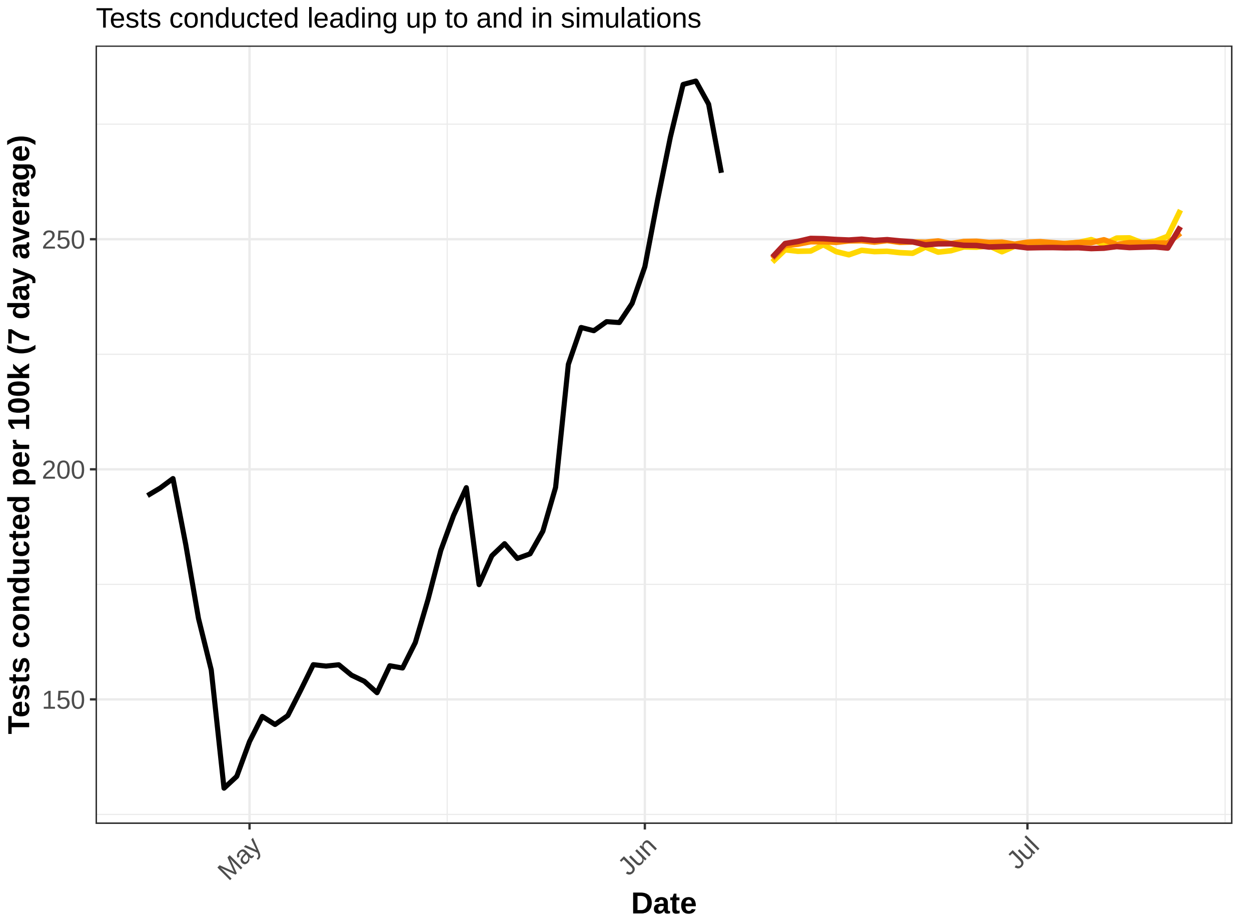

Future Positive test percentages under different transmission scenarios
Assuming 2200 tests per day, B= 31 , Re−>0.8
% Positive tests
0.08
0.06
0.04
0.02
0.00
May
Jun
Jul
Date
Re−>0.8
Re−>1.1
Re−>1.4



Future Positive test percentages under different transmission scenarios
Assuming 2200 tests per day, B= 31
% Positive tests (7−day average)
0.06
0.04
0.02
0.00
May
Jun
Jul
Date
Re−>0.8
Re−>1.1
Re−>1.4

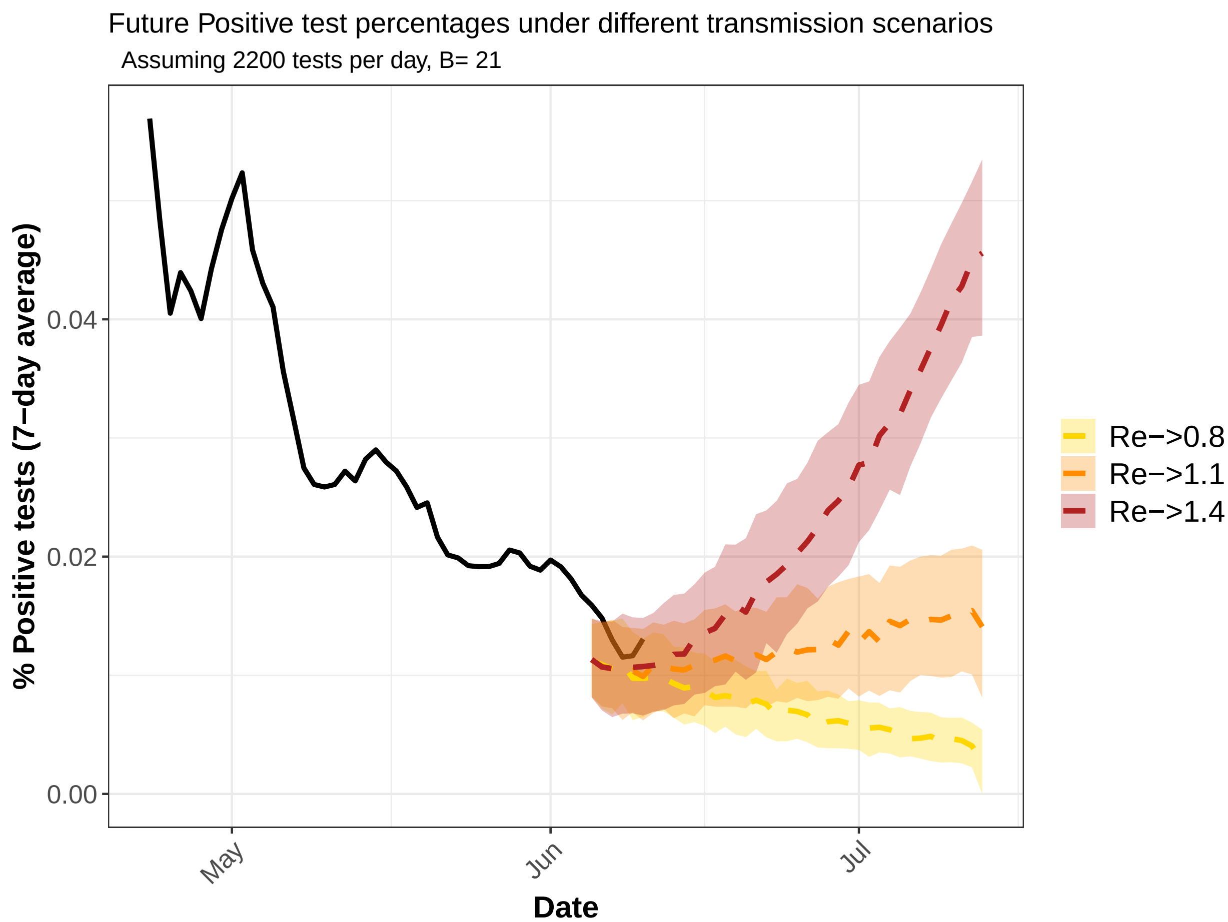


Tests conducted leading up to and in simulations
Tests conducted per 100k
300
200
100
May
Jun
Jul
Date

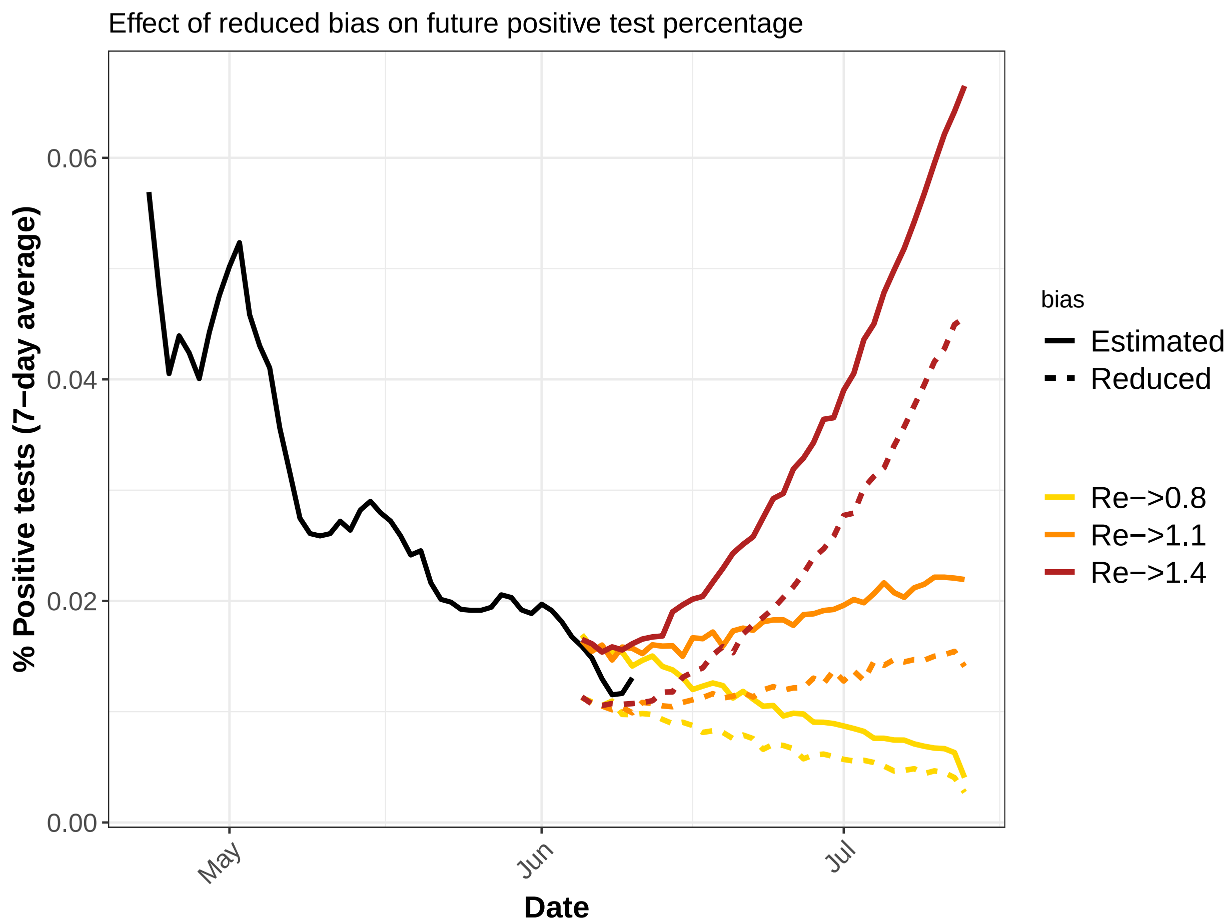


Consequences of unaccounted changes in sampling bias

If sampling bias decreases such that infectious people are less likely to seek testing, our ability to detect an increase in $\mathcal{R}_e$ through testing data is likely to be limited, and may even give a false sense of security: positive % or number of positive tests may appear to be decreasing, even as transmission is increasing, if the sampling bias of infectious people has decreased. Therefore here the assumption that testing bias remains constant in the nearterm projections is changed to an assumption that the testing bias decreases by ~30%. This is feasible to imagine as people may become more complacent/accustomed to COVID and therefore decrease they're test-seeking behavior, especially among mild cases. E.g. someone with a headache and mild cough who would have been very concerned about COVID in April/May no longer seeks out testing or delays testing until more serious symptoms arise or persist.



Future Positive test percentages under different transmission scenarios
Assuming 2200 tests per day, B= 21
% Positive tests (7−day average)
0.04
0.02
0.00
May
Jun
Jul
Date
Re−>0.8
Re−>1.1
Re−>1.4


Effect of reduced bias on future positive test percentage
% Positive tests (7−day average)
0.06
0.04
0.02
0.00
May
Jun
Jul
Date
bias
Estimated
Reduced
Re−>0.8
Re−>1.1
Re−>1.4