Report: COVID19 Bayesian Epidemiological Model

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Contents

Summary / Take Away

New take-aways

- The hierarchical model with no pooling is much easier to fit with fewer divergences. It is also clear that that model better captures the Rt. Especially in the case of Finland and Sweden.

Previous take-aways

- Using the increased number of covariates seems to be better, model-wise compared to the baseline Imperial model. I think in many situations, our models now perform better than Imperial College Londons baseline.
- Mobility on the transit station seems to be a good covariate to use.
- The regression coefficients are sensitive. They need to be bounded on R^+ for the model not to explode.

Current flaws to be fixed

- The infection to fatality ratio (IFR) for Finland now set to the IFR for Sweden.

Potential ways forward

- Introduce a dynamic component in the effect of Rt to smooth out the development over time.
- Use hospitalizations in addition to deaths.
- Focus on Finland and Sweden at the county level, although data may be missing to do this currently.
- Include serological studies to better estimate general prevalence over time.

Model descriptions

- Model 1: The Imperial College model v3, with partial pooling of lockdown variable
- Model 2: Google Mobility and Stringency Index. Regression coefficients are assumed common for all countries (pooled alpha).
- Model 3: Google Mobility and Stringency Index. Regression coefficients are hierarchical and inform each other between countries. (hierarchical alpha)
- Model 4: Google Mobility and Stringency Index. Regression coefficients are estimated for each country. (local alpha)
- Model 5: Google Mobility and Stringency Index and b-spline. Regression coefficients are hierarchical and the b-spline is a local spline over t per country.

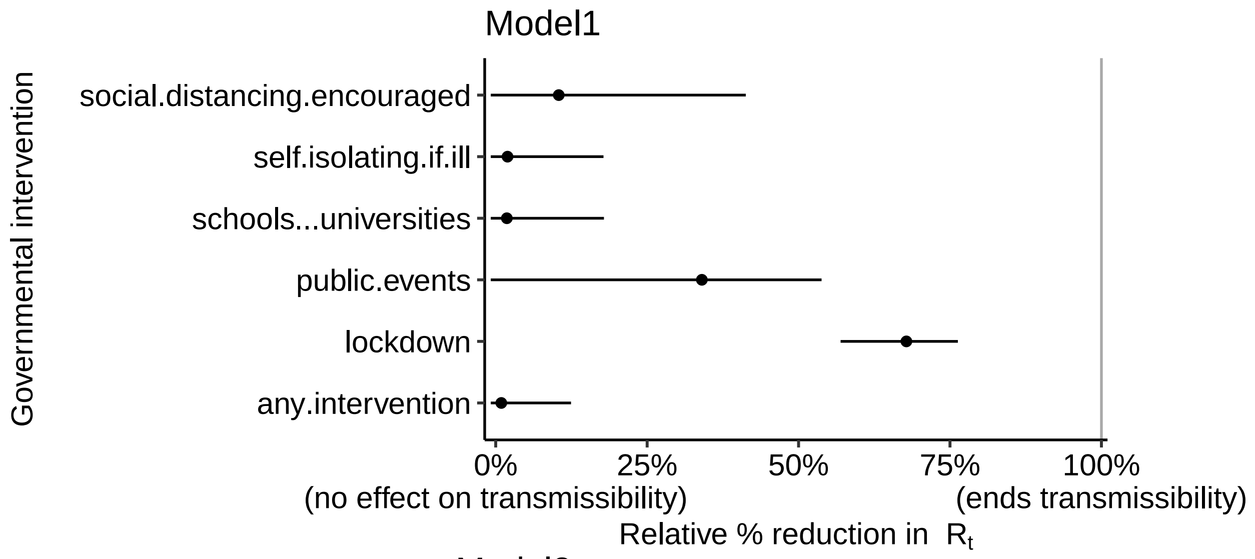
Oxford covariate descriptions

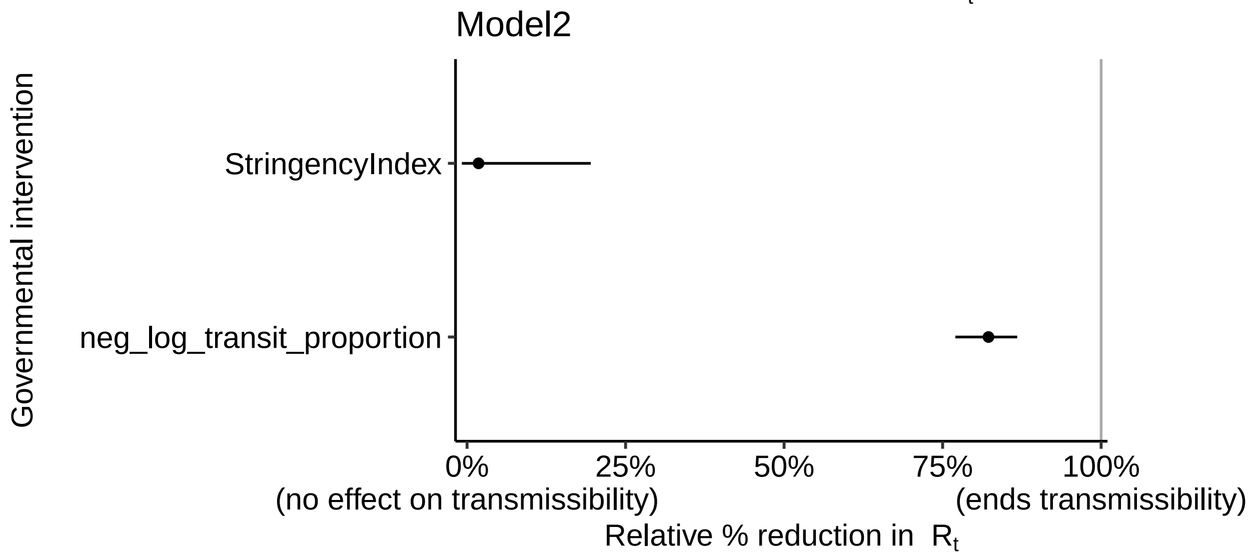
- C1: School closing
- C2: Workplace closing
- C3: Cancel public events
- C4: Restrictions on Gatherings
- C5: Close public transport
- C6: Stay at home requirements
- H2: Testing policy

Case study: The Sweden, Finland and Italy

All other countries are included in the Appendix.

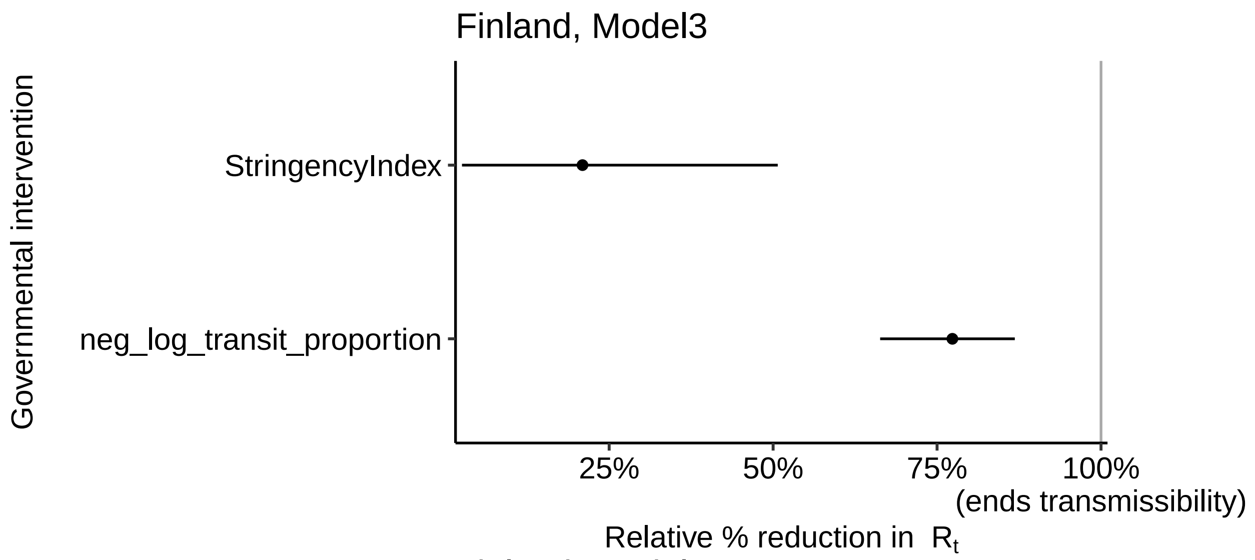
Global covariate effects (model 1 and 2)

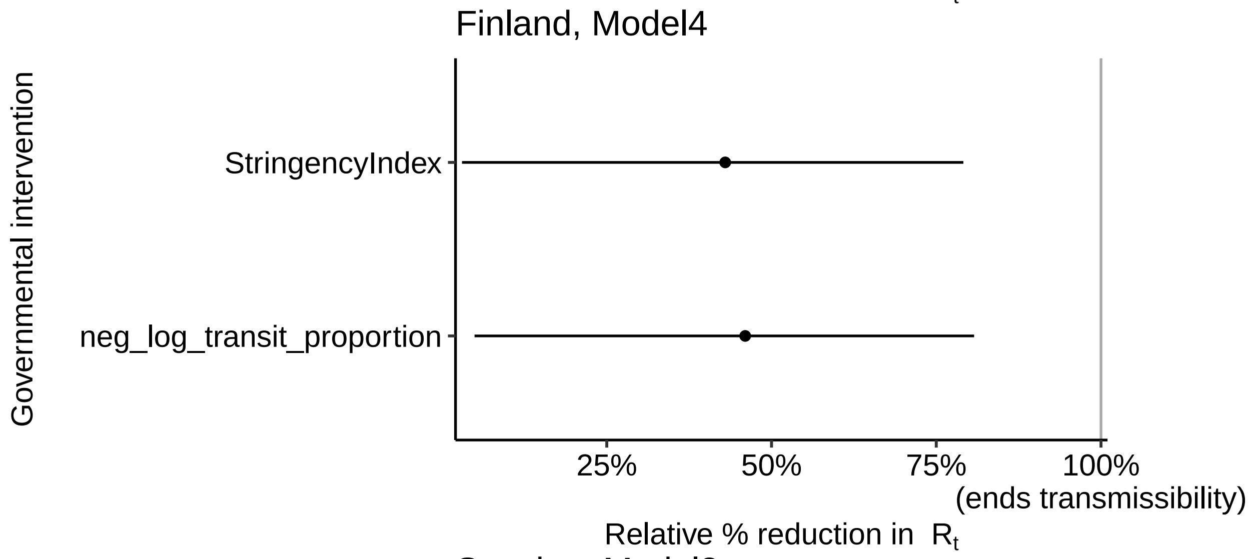


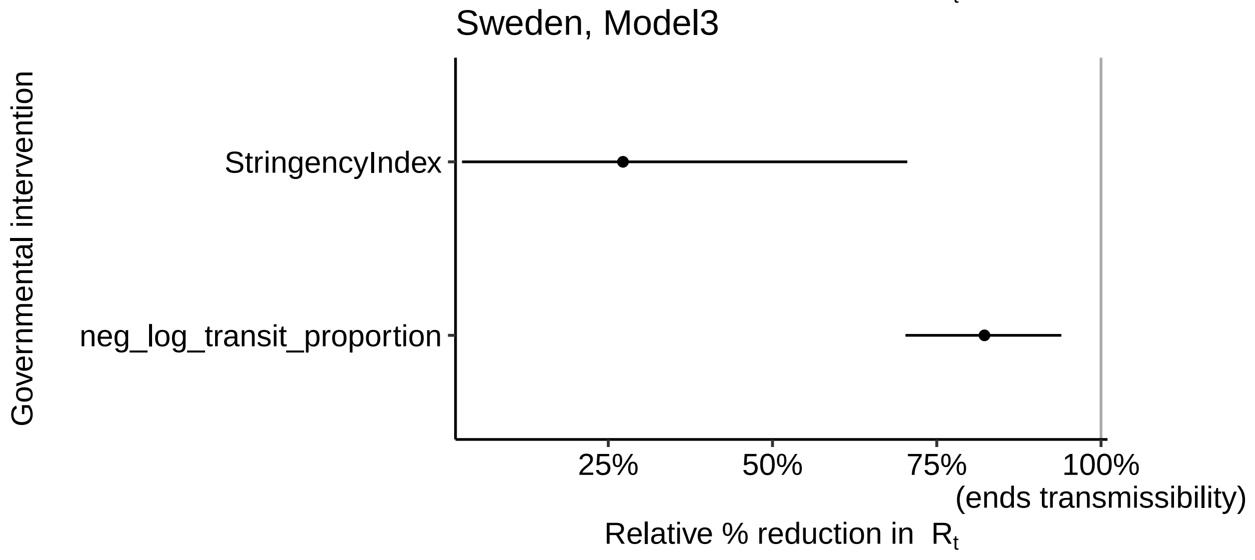


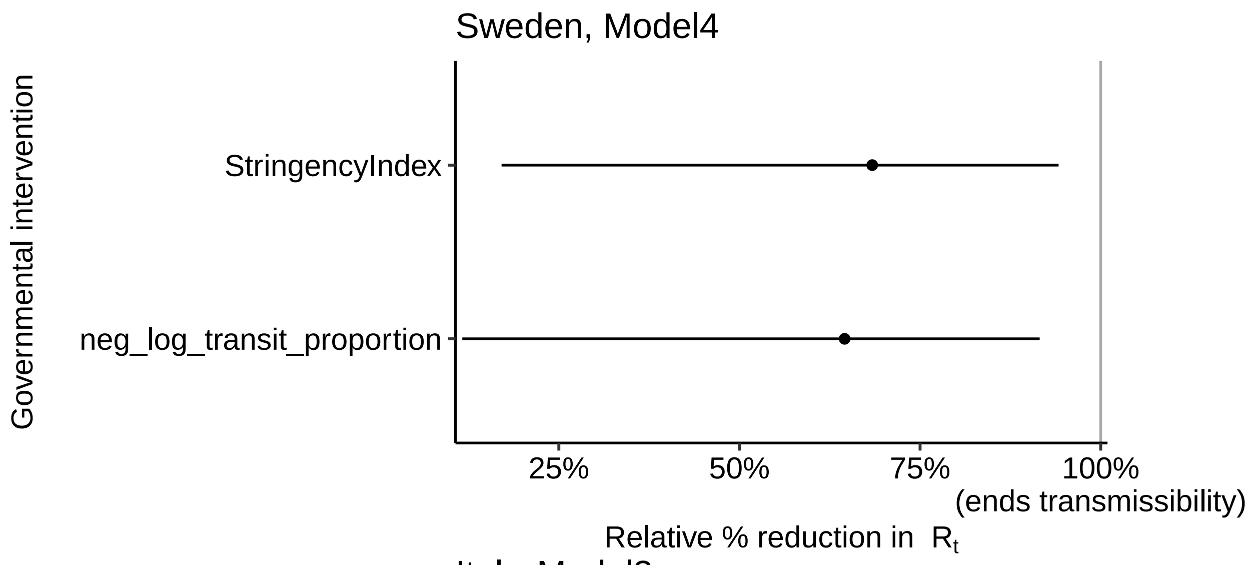
Country specific effects (model 3 and 4)

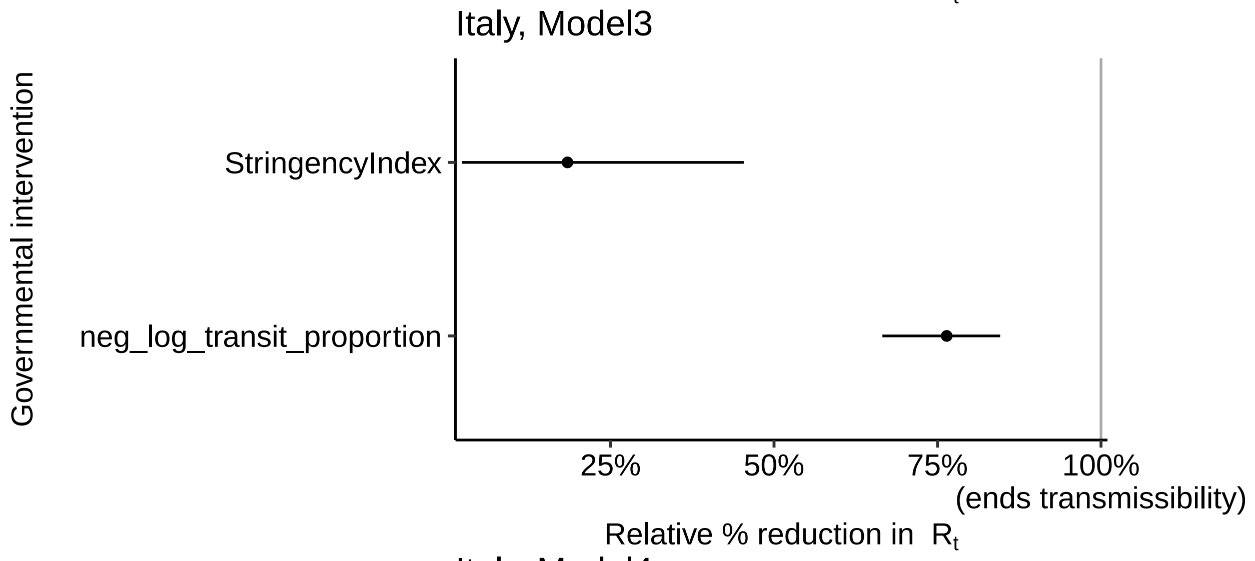
We see that the hierarchical model has an easier time to capture the general effect that mobility has a larger effect than the stringency index. Hence the actual mobility affects R_t more than the interventions.

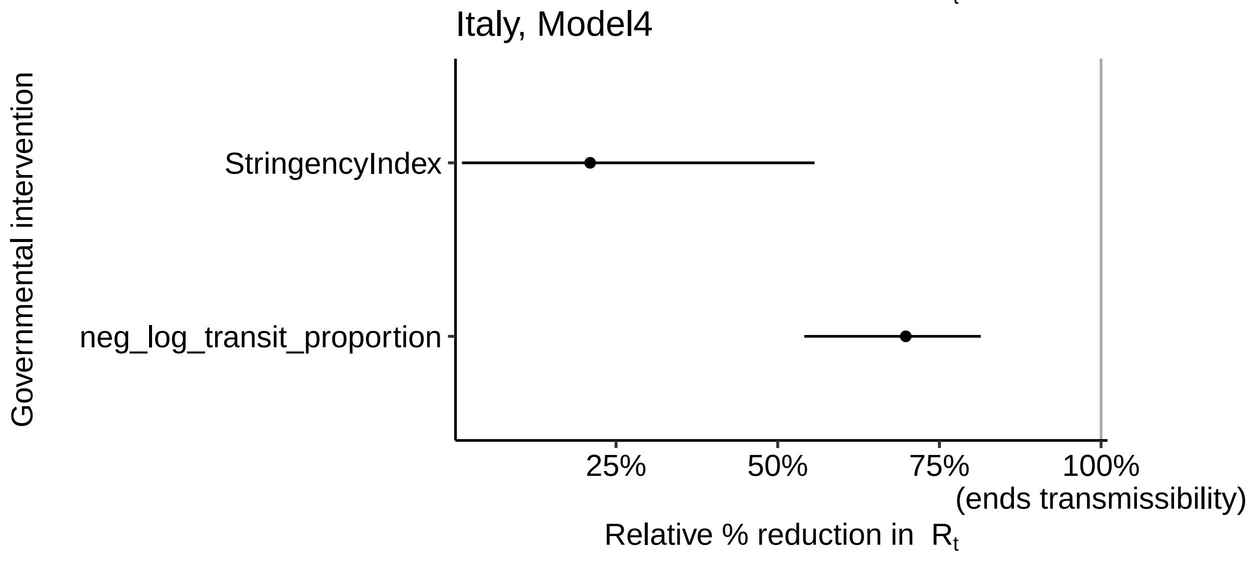

Finland, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Finland, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Sweden, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Sweden, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

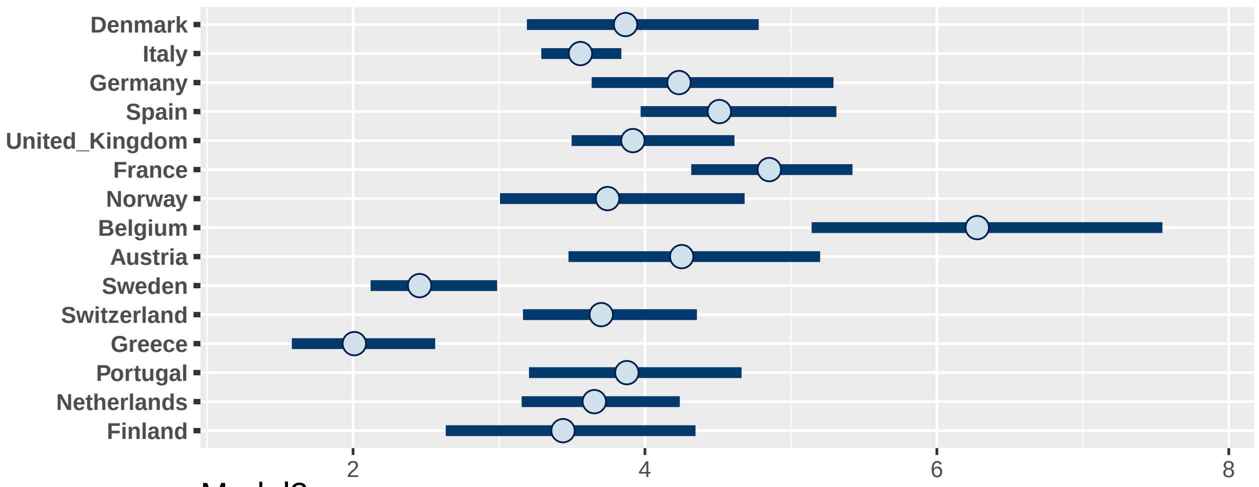

Italy, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Italy, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

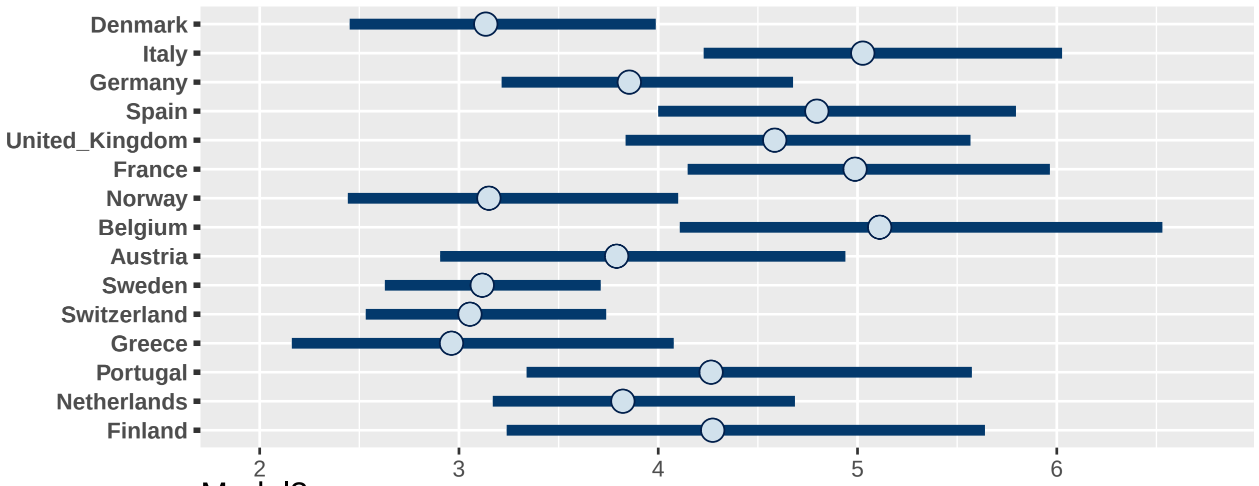
R0 for different countries

We can see that the different values for R0 vary much more between the countries when we use models with common regression coefficients.

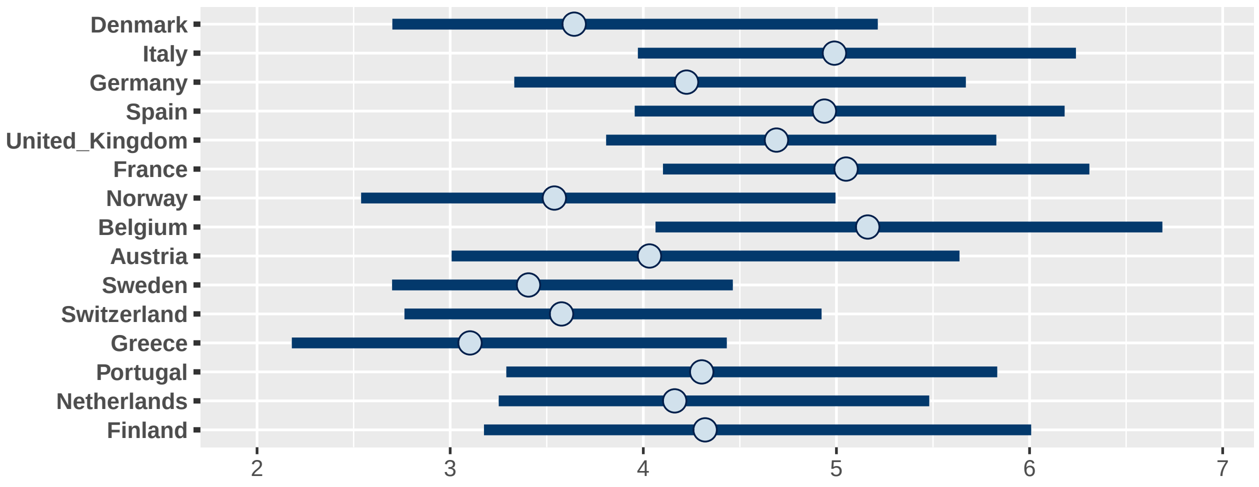
Model1



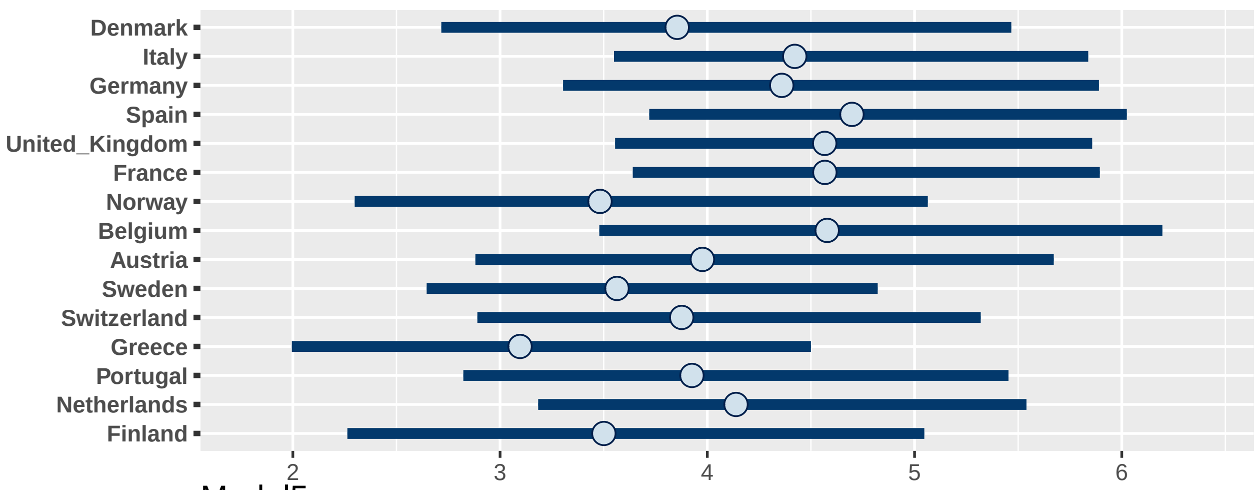
Model2



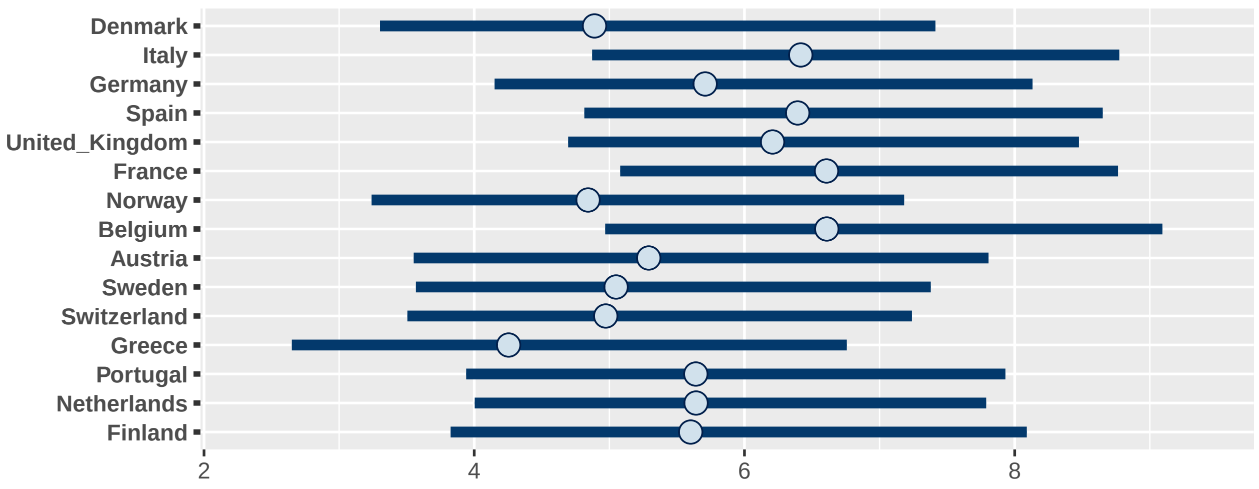
Model3



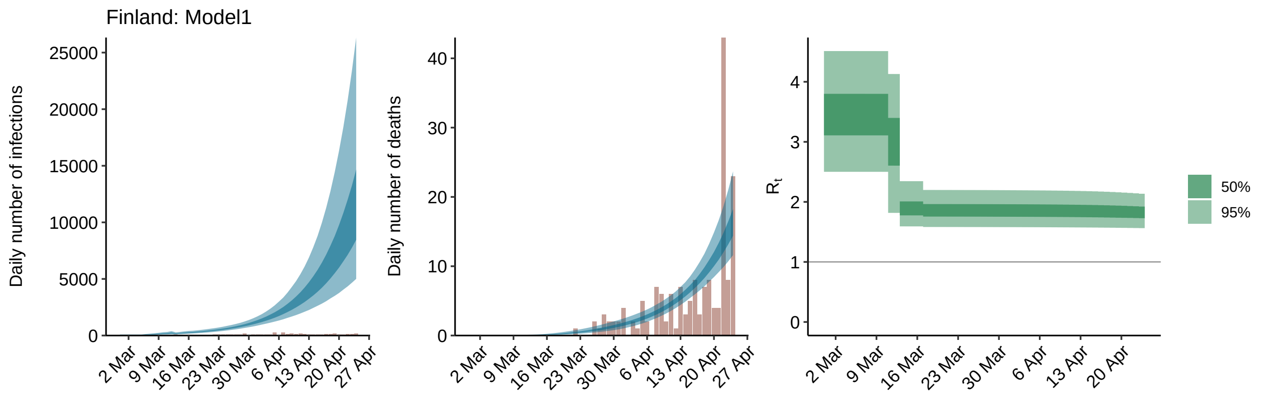
Model4

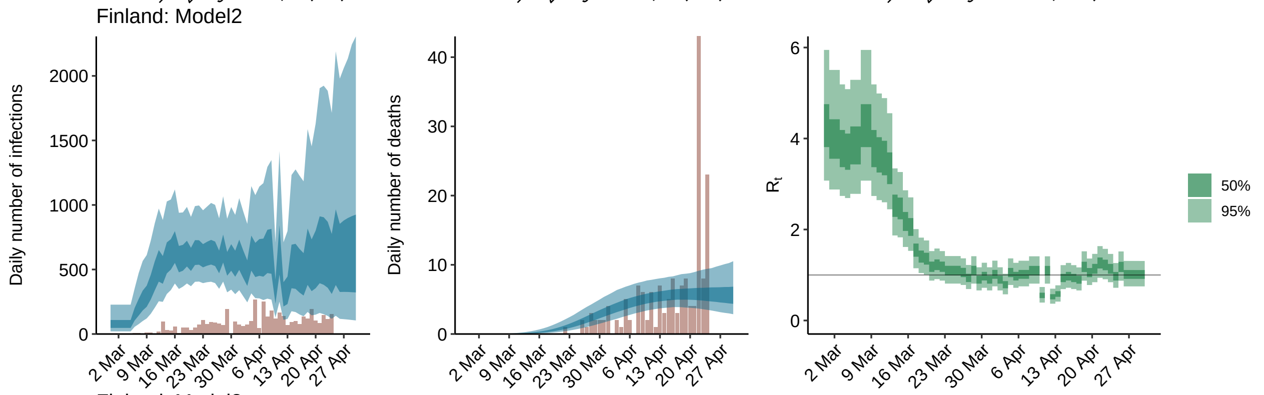


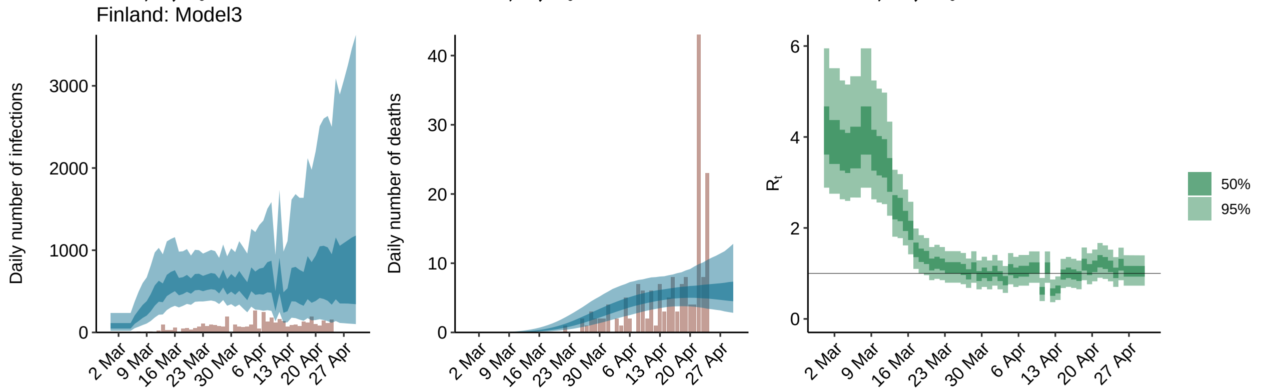
Model5

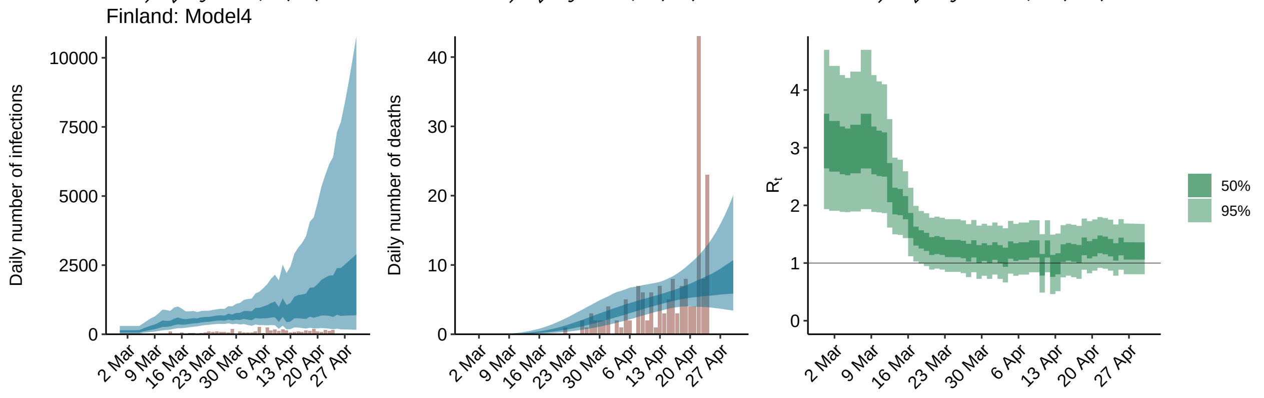


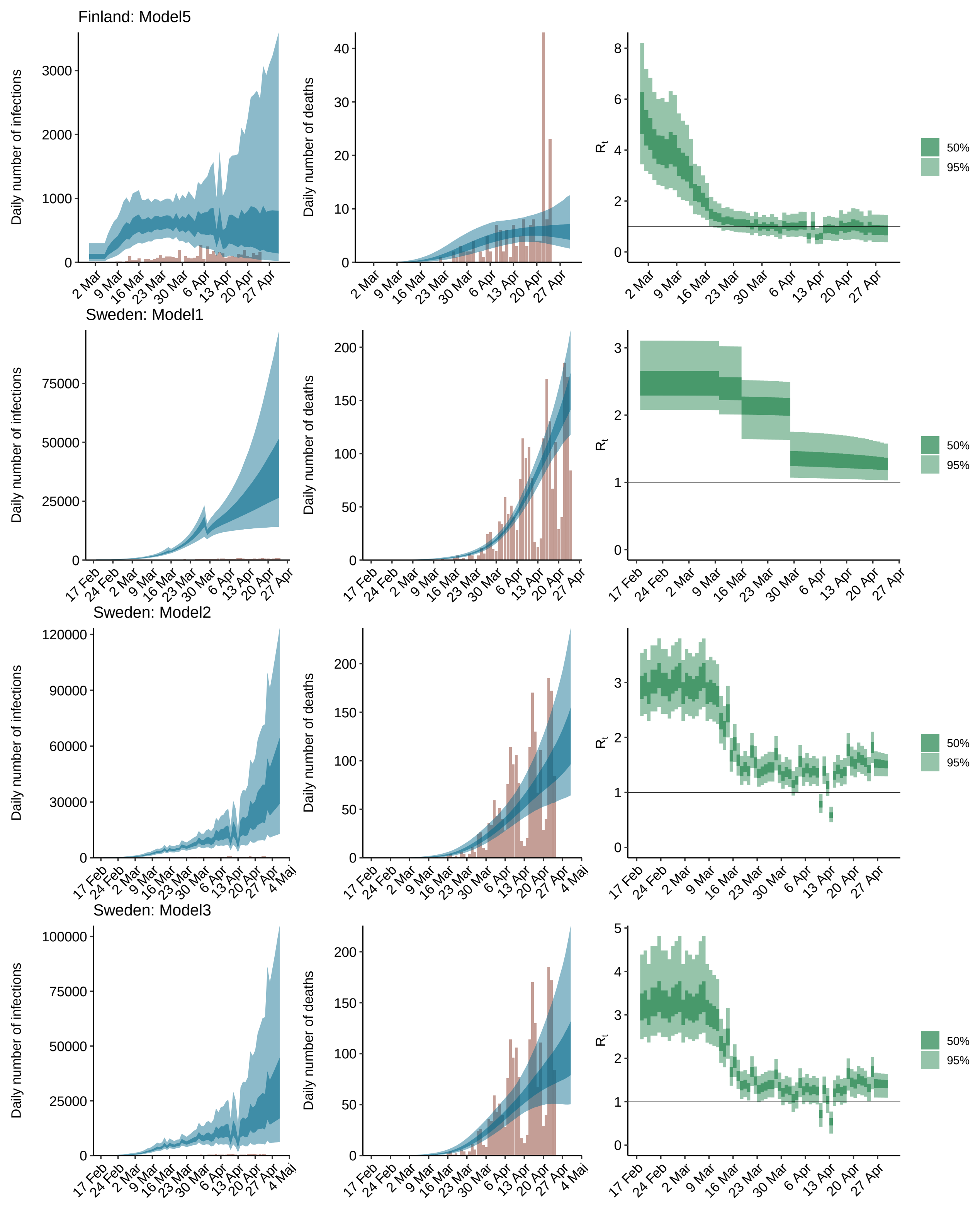
Infections, cases, deaths and Rt by country and model

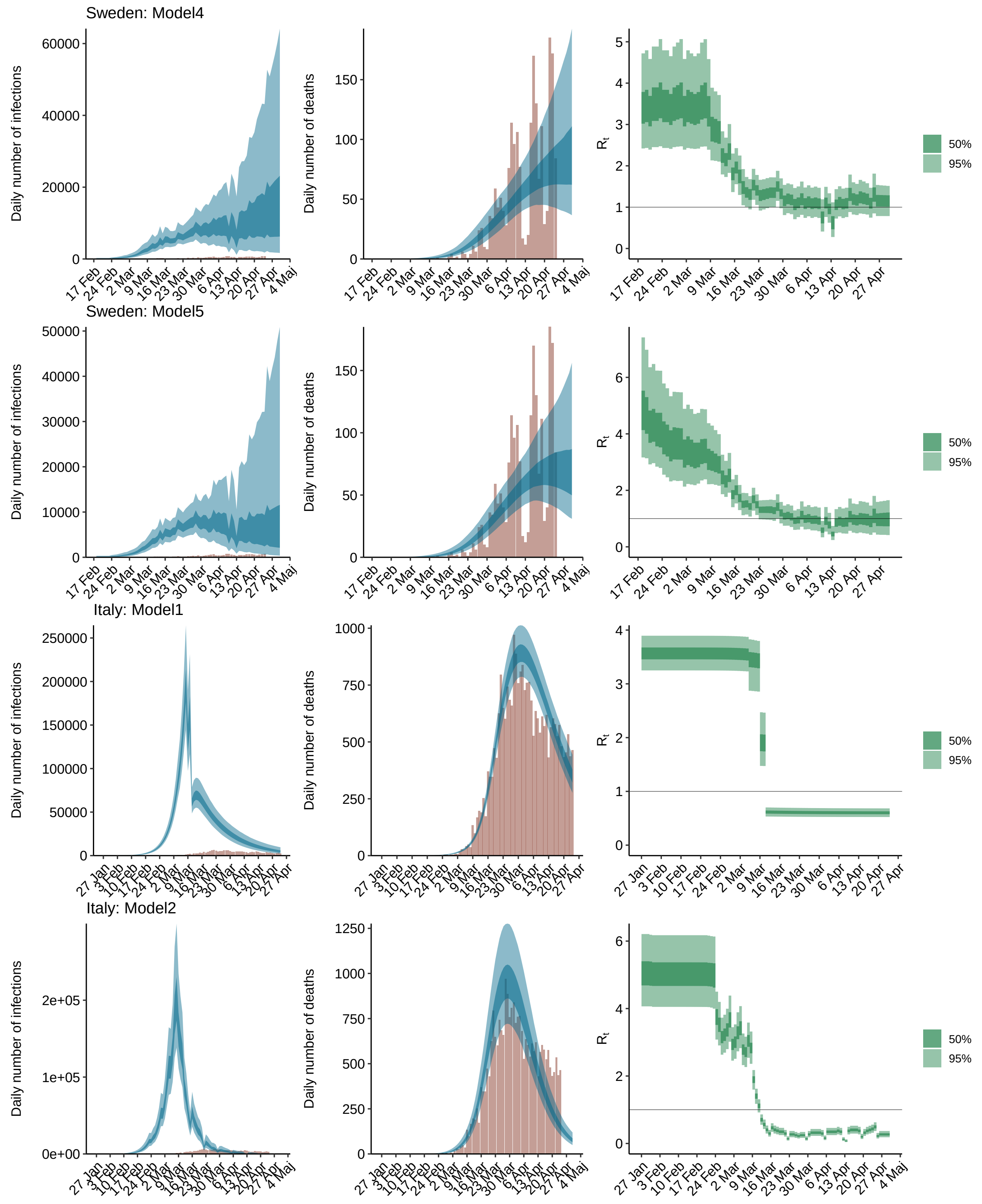


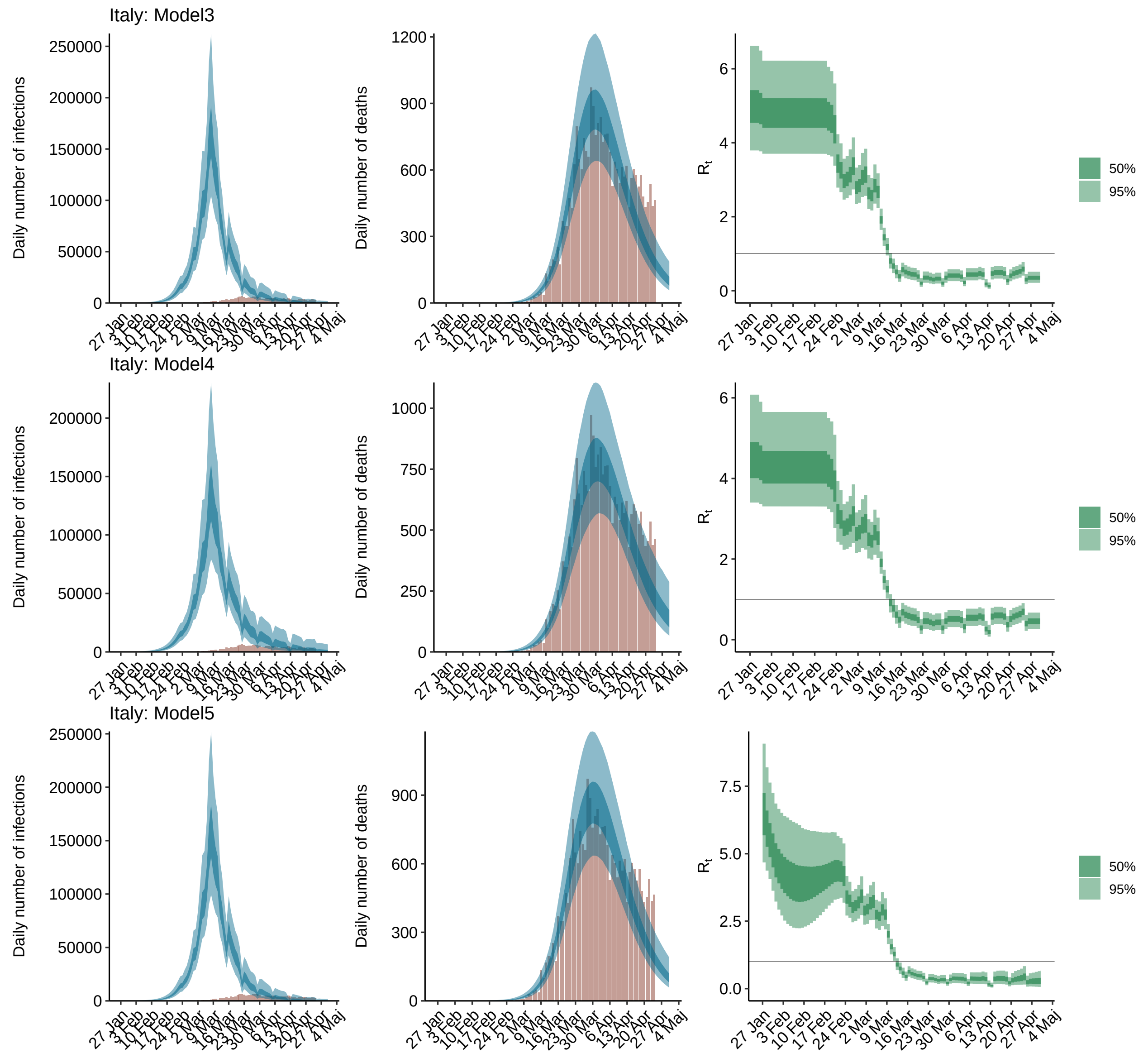







Finland: Model5
Sweden: Model1
Sweden: Model2
Sweden: Model3
Daily number of infections
Daily number of deaths
R_t
50%
95%
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj


Sweden: Model4
Sweden: Model5
Italy: Model1
Italy: Model2
Daily number of infections
Daily number of deaths
R_t
50%
95%
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
27 Jan
3 Feb
10 Feb

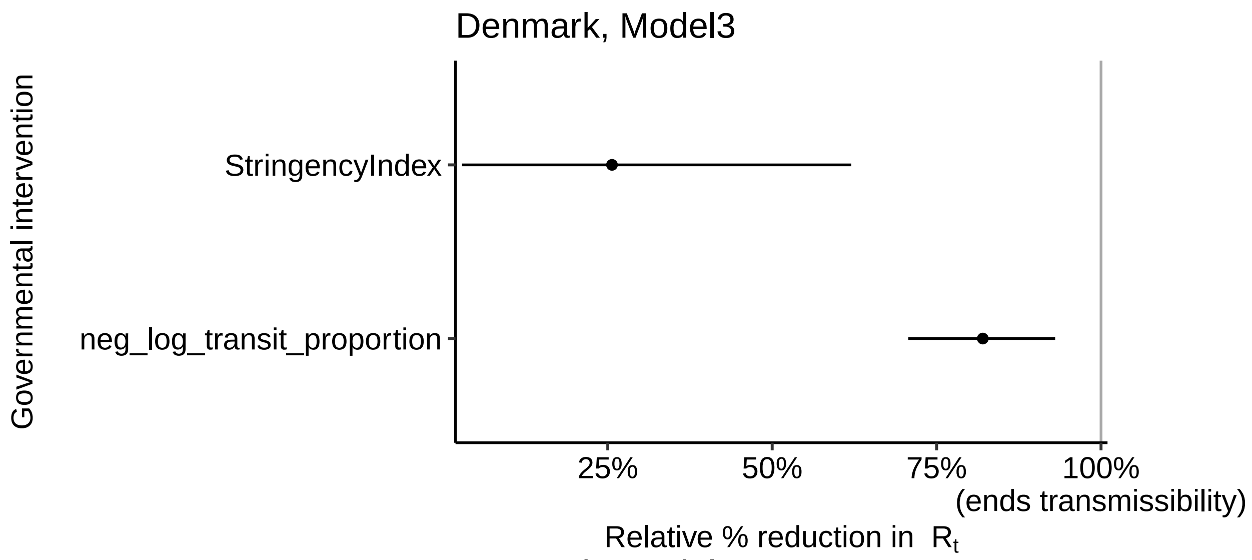


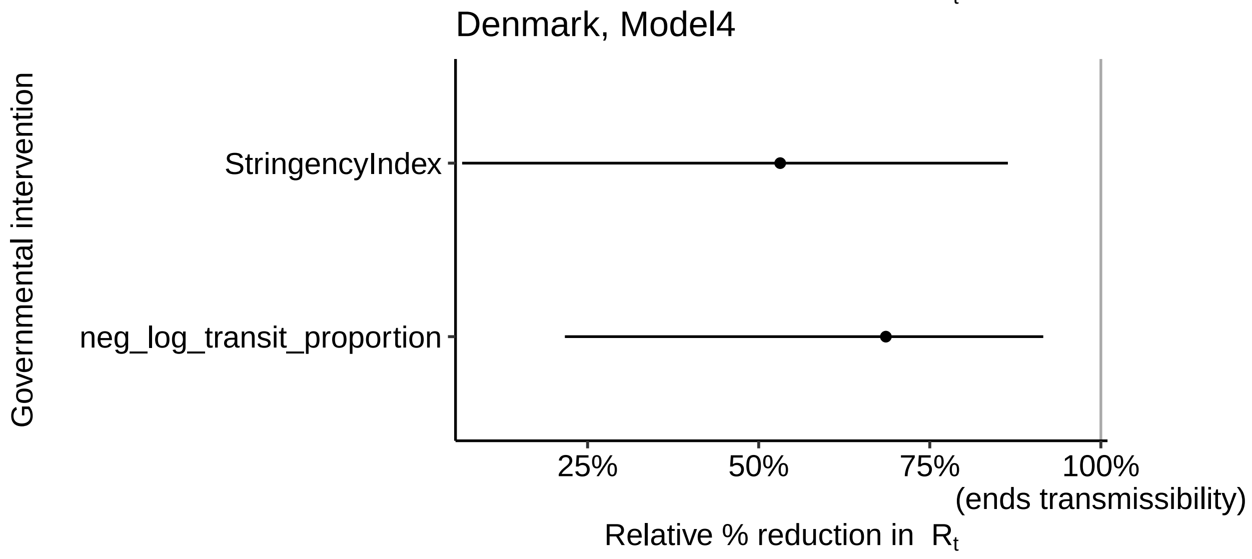
Stan code

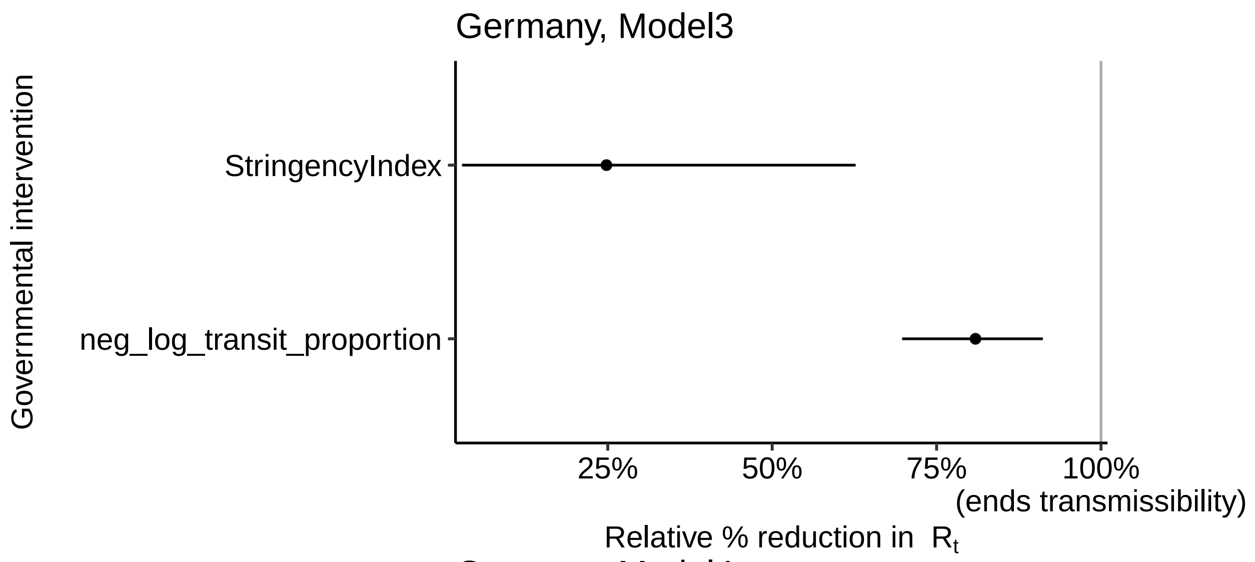
```
## S4 class stanmodel 'base' coded as follows:
## data {
##   int <lower=1> M; // number of countries
##   int <lower=1> P; // number of covariates
##   int <lower=1> N0; // number of days for which to impute infections
##   int<lower=1> N[M]; // days of observed data for country m. each entry must be <= N2
##   int<lower=1> N2; // days of observed data + # of days to forecast
##   int cases[N2,M]; // reported cases
##   int deaths[N2, M]; // reported deaths -- the rows with i > N contain -1 and should be ignored
##   matrix[N2, M] f; // h * s
##   matrix[N2, P] X[M]; // features matrix
##   int EpidemicStart[M];
##   real pop[M];
##   real SI[N2]; // fixed pre-calculated SI using emprical data from Neil
## }
##
## transformed data {
##   vector[N2] SI_rev; // SI in reverse order
##   vector[N2] f_rev[M]; // f in reversed order
##
##   for(i in 1:N2)
##     SI_rev[i] = SI[N2-i+1];
##
##   for(m in 1:M){
##     for(i in 1:N2) {
##      f_rev[m, i] = f[N2-i+1,m];
##     }
##   }
## }
##
##
## parameters {
##   real<lower=0> mu[M]; // intercept for Rt
##   real<lower=0> alpha_hier[P]; // sudo parameter for the hier term for alpha
##   real<lower=0> gamma;
##   vector[M] lockdown;
##   real<lower=0> kappa;
##   real<lower=0> y[M];
##   real<lower=0> phi;
##   real<lower=0> tau;
##   real <lower=0> ifr_noise[M];
## }
##
## transformed parameters {
##     vector[P] alpha;
##     matrix[N2, M] prediction = rep_matrix(0,N2,M);
##     matrix[N2, M] E_deaths  = rep_matrix(0,N2,M);
##     matrix[N2, M] Rt = rep_matrix(0,N2,M);
##     matrix[N2, M] Rt_adj = Rt;
##
##     {
##       matrix[N2,M] cumm_sum = rep_matrix(0,N2,M);
##       for(i in 1:P){
##         alpha[i] = alpha_hier[i] - ( log(1.05) / 6.0 );
##       }
##       for (m in 1:M){
##         prediction[1:N0,m] = rep_vector(y[m],N0); // learn the number of cases in the first N0 days
##         cumm_sum[2:N0,m] = cumulative_sum(prediction[2:N0,m]);
##
##         Rt[,m] = mu[m] * exp(-X[m] * alpha - X[m][,5] * lockdown[m]);
##         Rt_adj[1:N0,m] = Rt[1:N0,m];
##         for (i in (N0+1):N2) {
##           real convolution = dot_product(sub_col(prediction, 1, m, i-1), tail(SI_rev, i-1));
##           cumm_sum[i,m] = cumm_sum[i-1,m] + prediction[i-1,m];
##           Rt_adj[i,m] = ((pop[m]-cumm_sum[i,m]) / pop[m]) * Rt[i,m];
##           prediction[i, m] = Rt_adj[i,m] * convolution;
##         }
##         E_deaths[1, m]= 1e-15 * prediction[1,m];
##         for (i in 2:N2){
##           E_deaths[i,m] = ifr_noise[m] * dot_product(sub_col(prediction, 1, m, i-1), tail(f_rev[m], i
##         }
##       }
##     }
## }
## model {
##   tau ~ exponential(0.03);
##   for (m in 1:M){
##       y[m] ~ exponential(1/tau);
##   }
##   gamma ~ normal(0,.2);
##   lockdown ~ normal(0,gamma);
##   phi ~ normal(0,5);
##   kappa ~ normal(0,0.5);
##   mu ~ normal(3.28, kappa); // citation: https://academic.oup.com/jtm/article/27/2/taaa021/5735319
##   alpha_hier ~ gamma(.1667,1);
##   ifr_noise ~ normal(1,0.1);
##   for(m in 1:M){
##     deaths[EpidemicStart[m]:N[m], m] ~ neg_binomial_2(E_deaths[EpidemicStart[m]:N[m], m], phi);
##    }
## }
##
## generated quantities {
##     matrix[N2, M] prediction0 = rep_matrix(0,N2,M);
##     matrix[N2, M] E_deaths0  = rep_matrix(0,N2,M);
##
##     {
##       matrix[N2,M] cumm_sum0 = rep_matrix(0,N2,M);
##       for (m in 1:M){
##          for (i in 2:N0){
##           cumm_sum0[i,m] = cumm_sum0[i-1,m] + y[m];
##         }
##         prediction0[1:N0,m] = rep_vector(y[m],N0);
##         for (i in (N0+1):N2) {
##           real convolution0 = dot_product(sub_col(prediction0, 1, m, i-1), tail(SI_rev, i-1));
##           cumm_sum0[i,m] = cumm_sum0[i-1,m] + prediction0[i-1,m];
##           prediction0[i, m] = ((pop[m]-cumm_sum0[i,m]) / pop[m]) * mu[m] * convolution0;
##         }
##         E_deaths0[1, m]= 1e-15 * prediction0[1,m];
##         for (i in 2:N2){
##           E_deaths0[i,m] = ifr_noise[m] * dot_product(sub_col(prediction0, 1, m, i-1), tail(f_rev[m]
##         }
##       }
##     }
## }
##
```

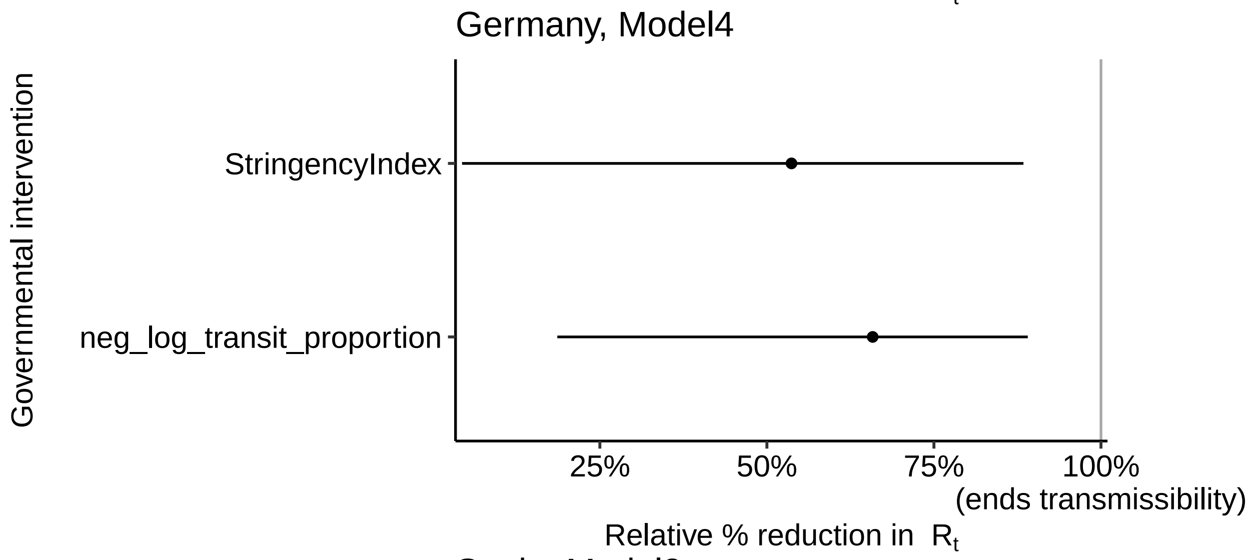
Appendix

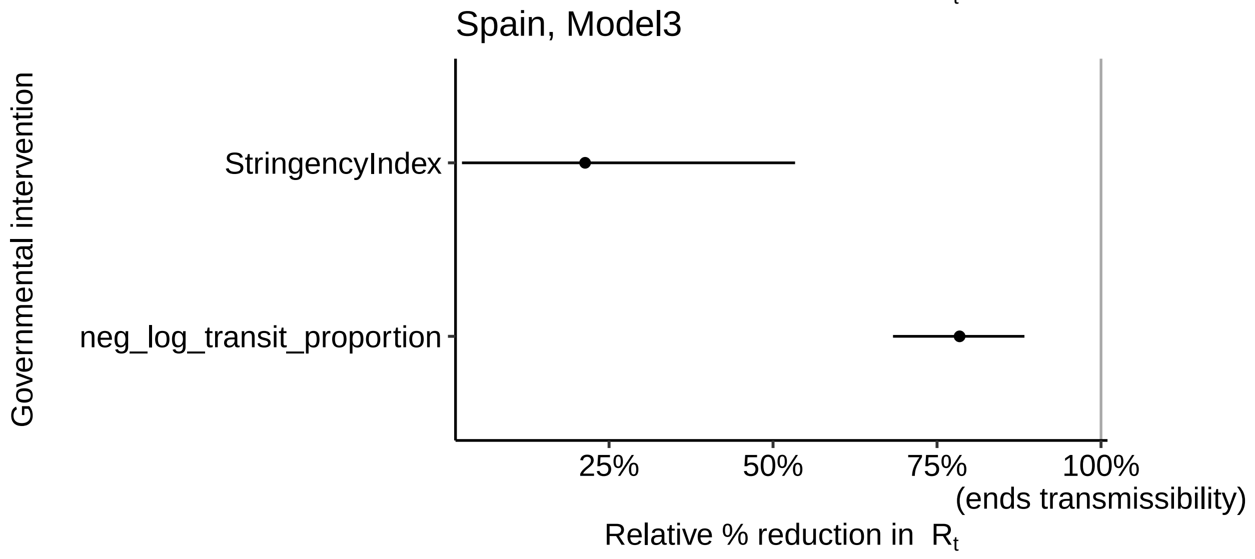
Country specific effects (model 3 to 4)

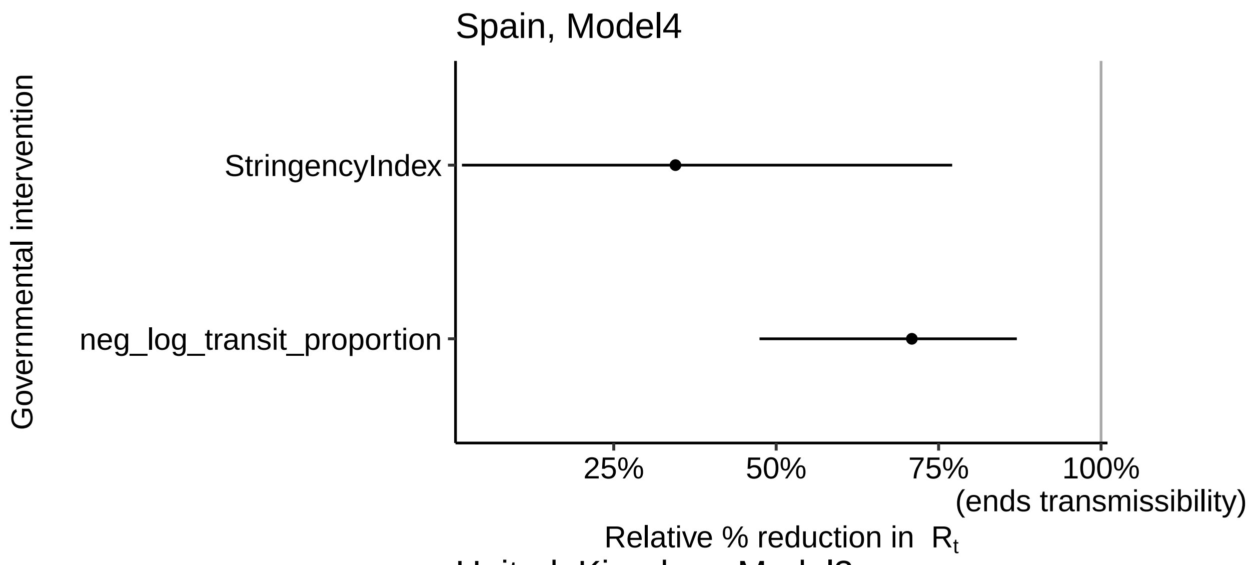




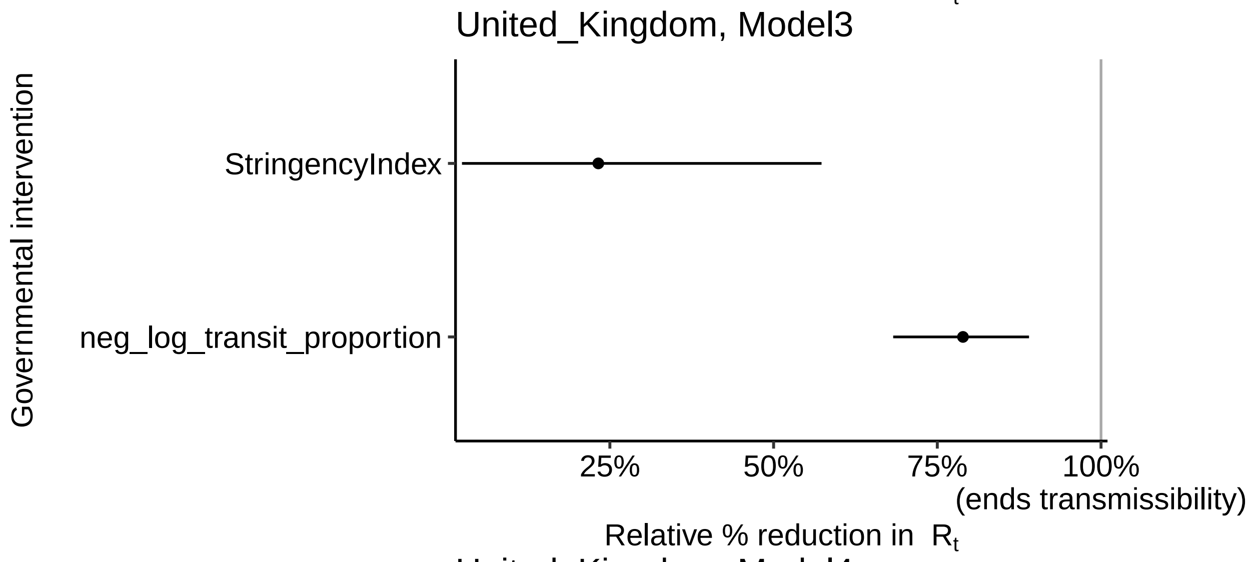

Germany, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Germany, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

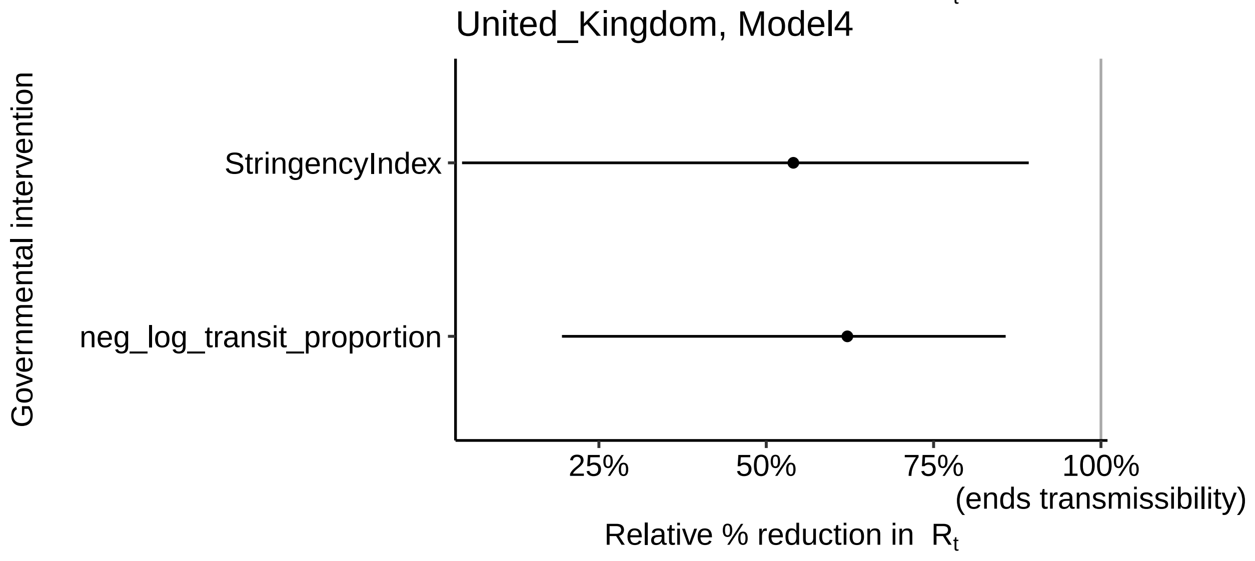

Spain, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t



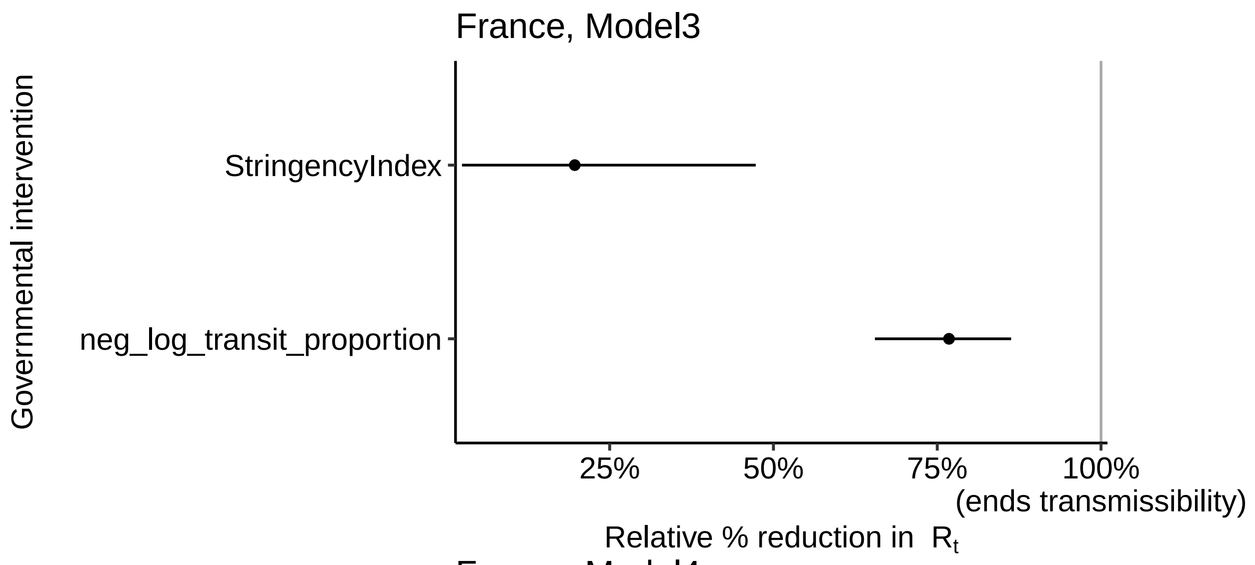
Spain, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

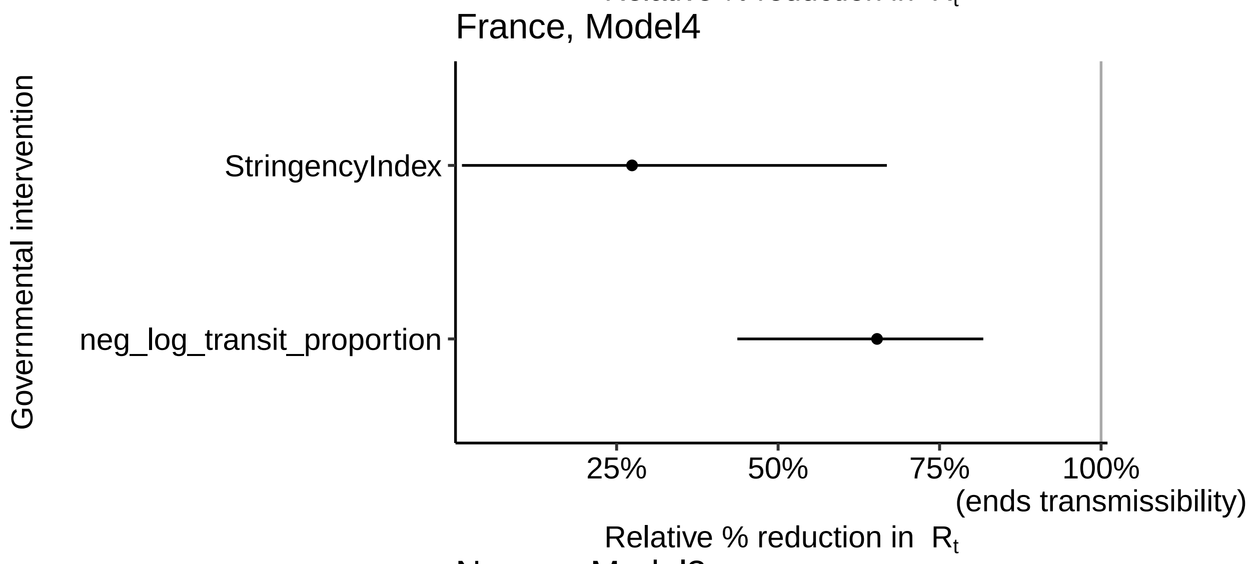


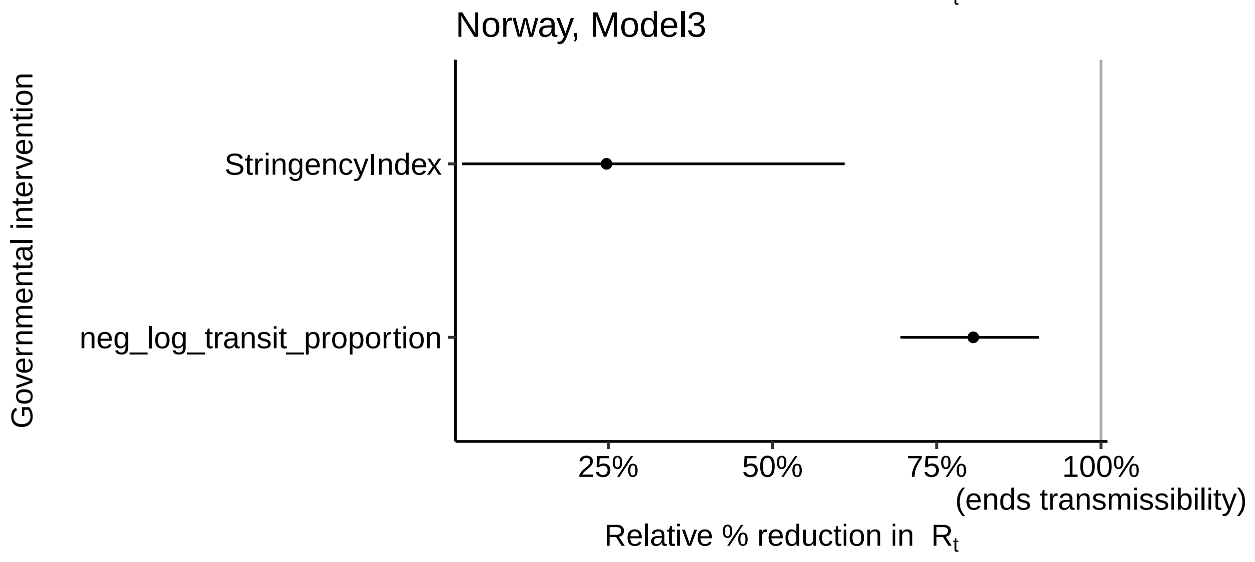
United_Kingdom, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

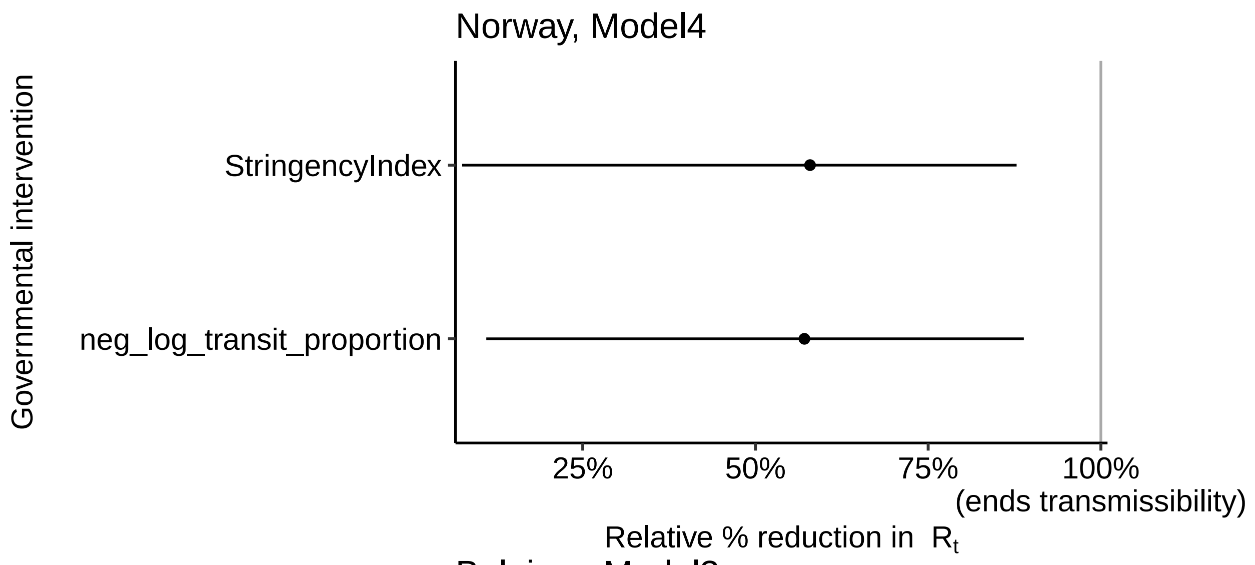


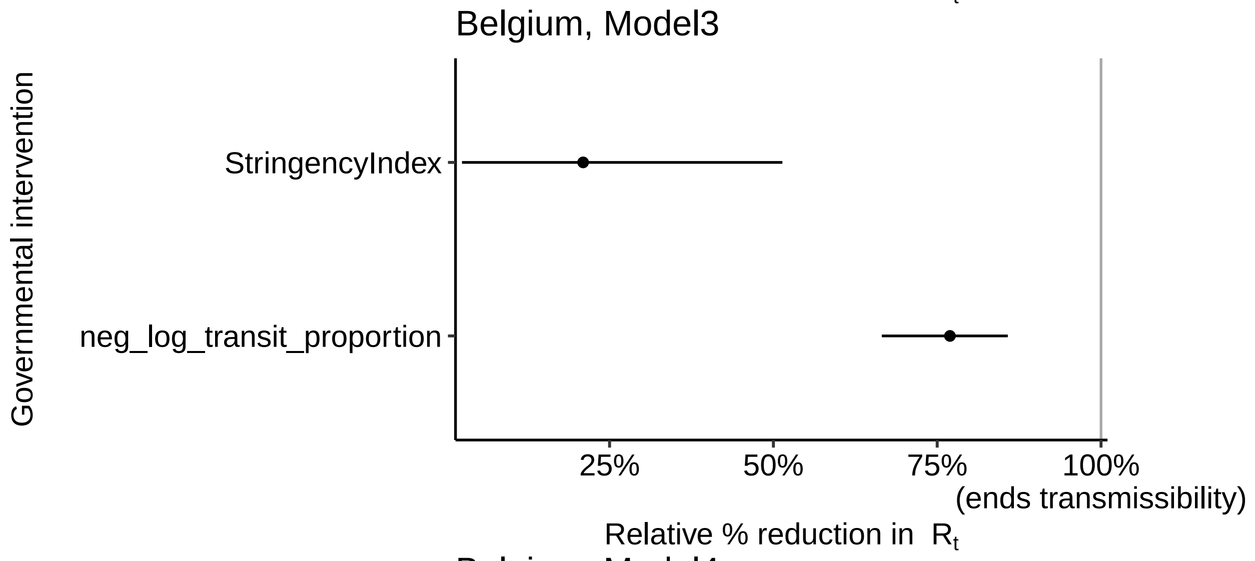
United_Kingdom, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

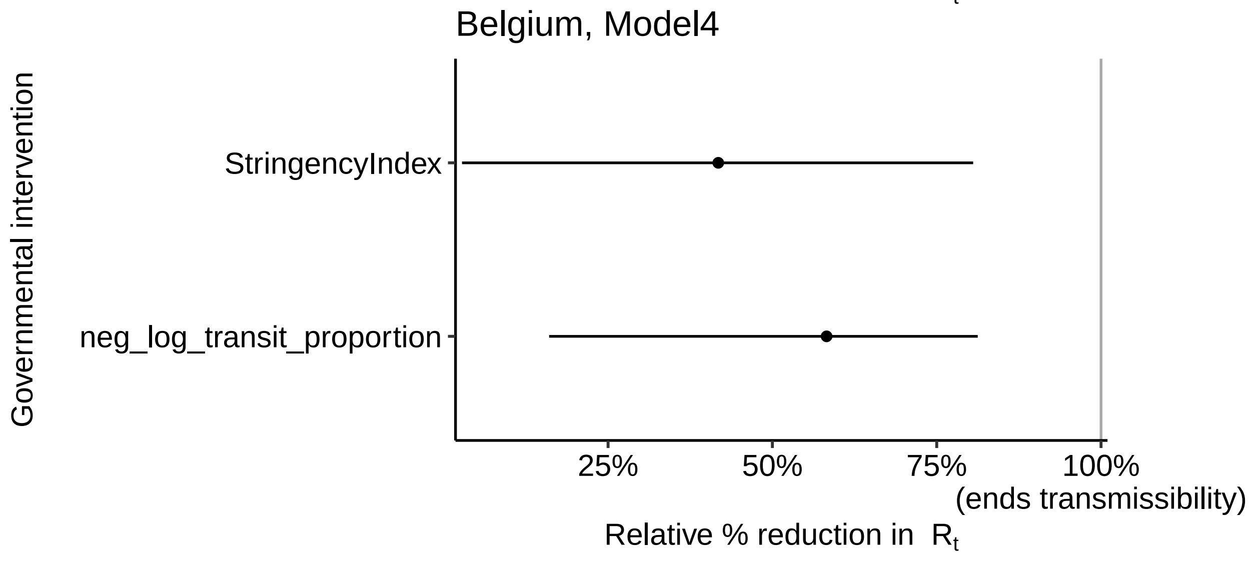

France, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

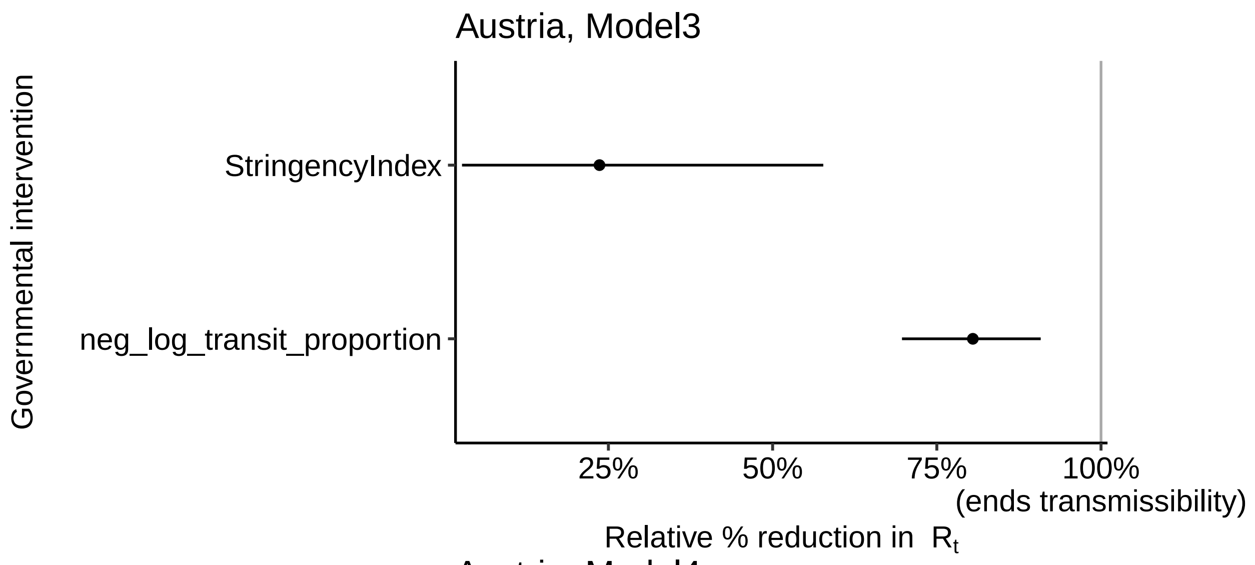

France, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Norway, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

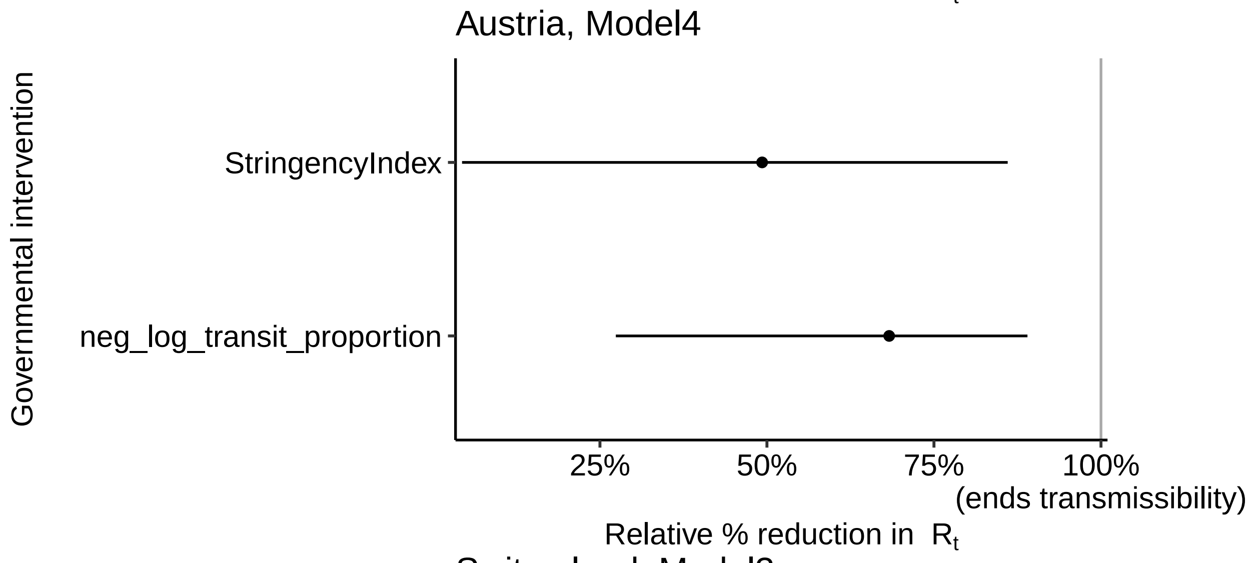

Norway, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Belgium, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

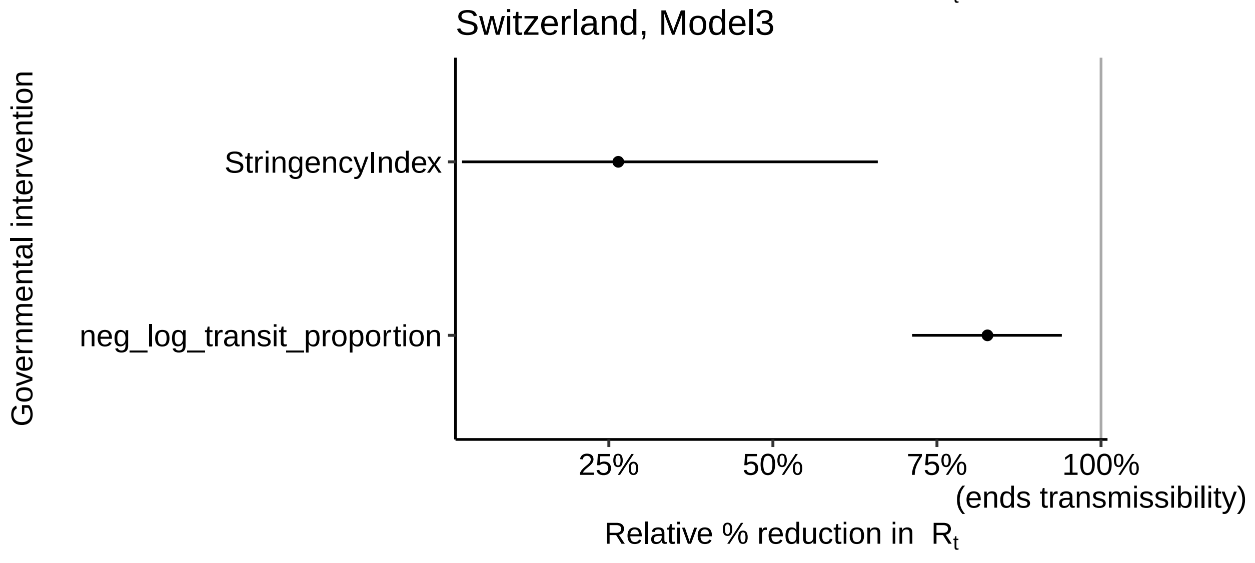

Belgium, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t



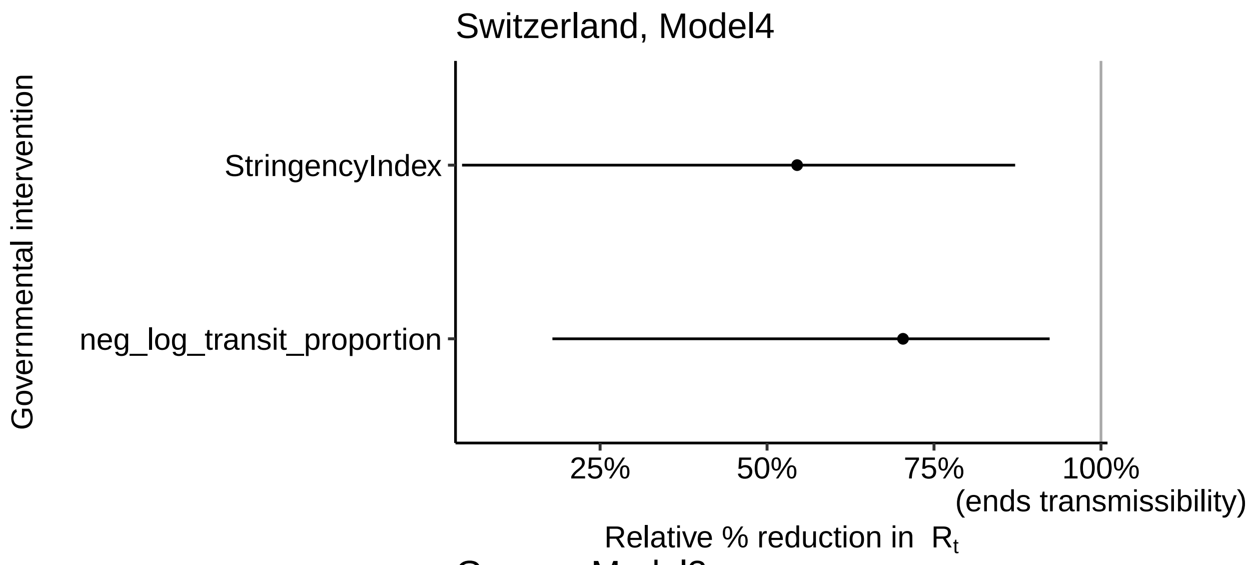
Austria, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

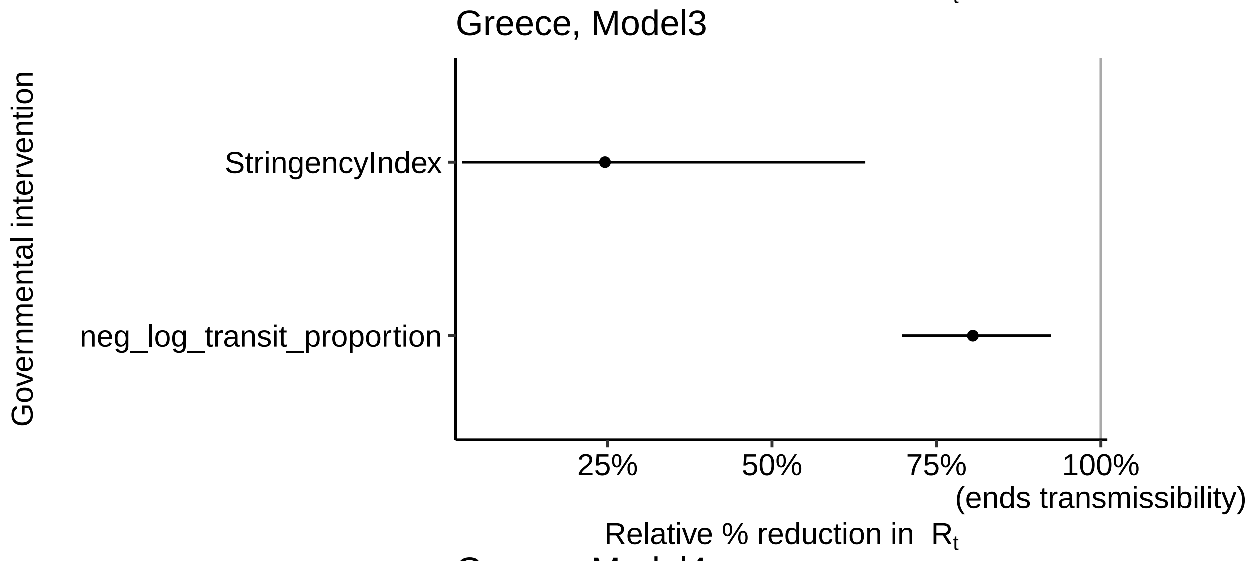


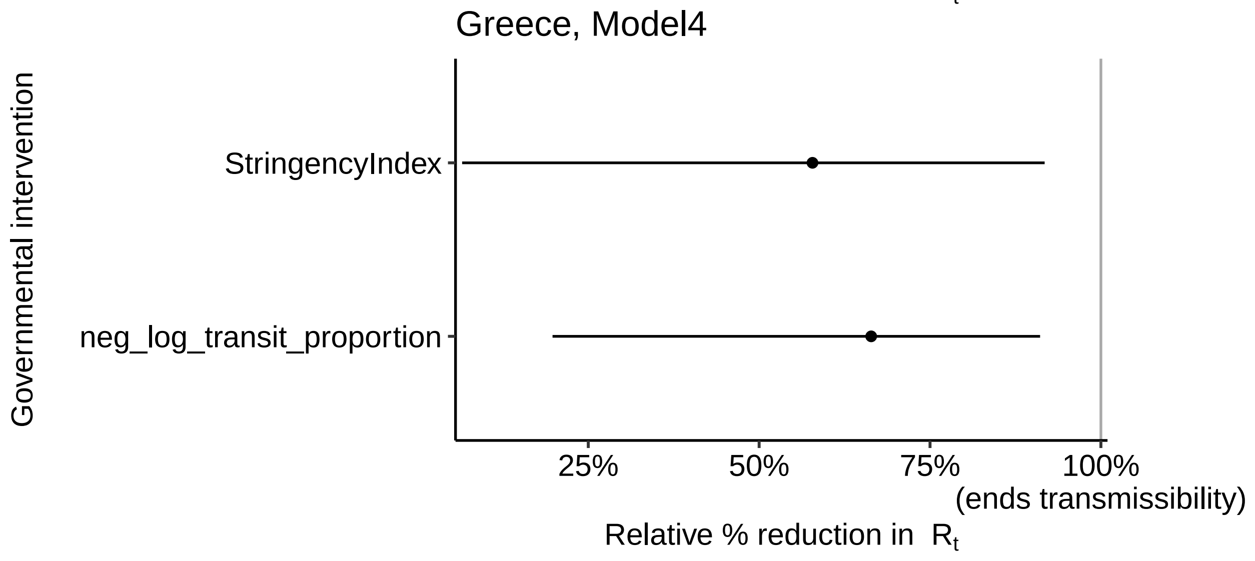
Austria, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

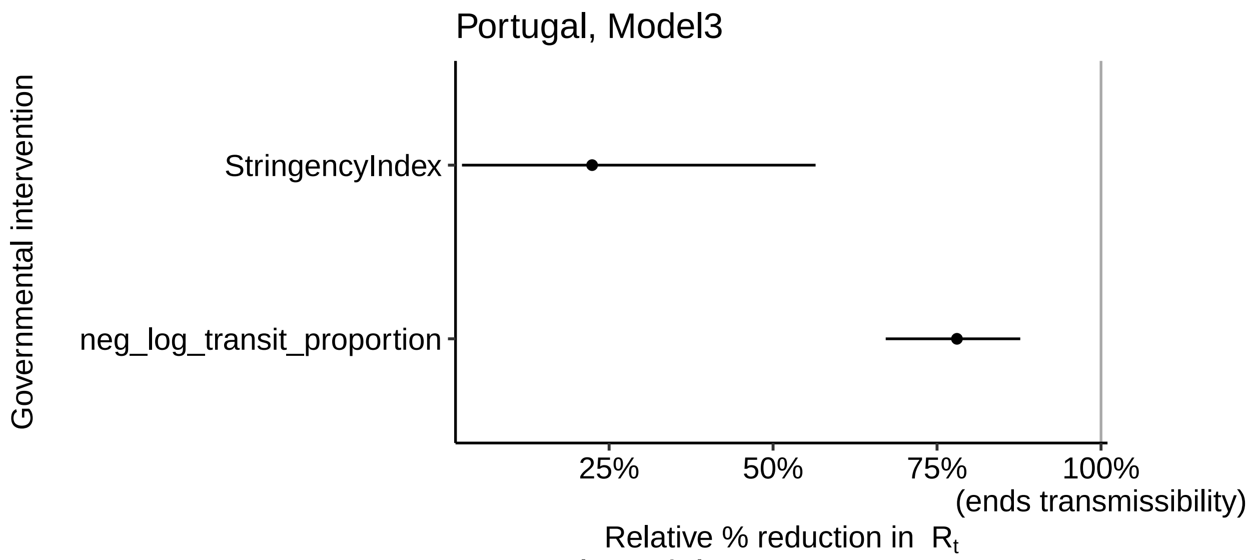


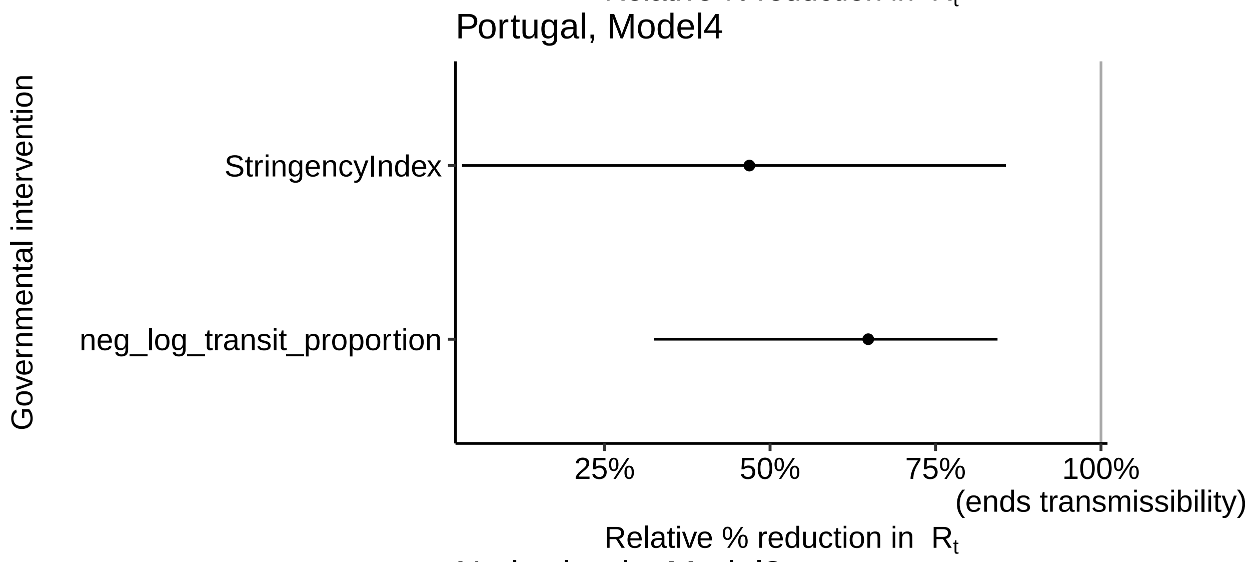
Switzerland, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

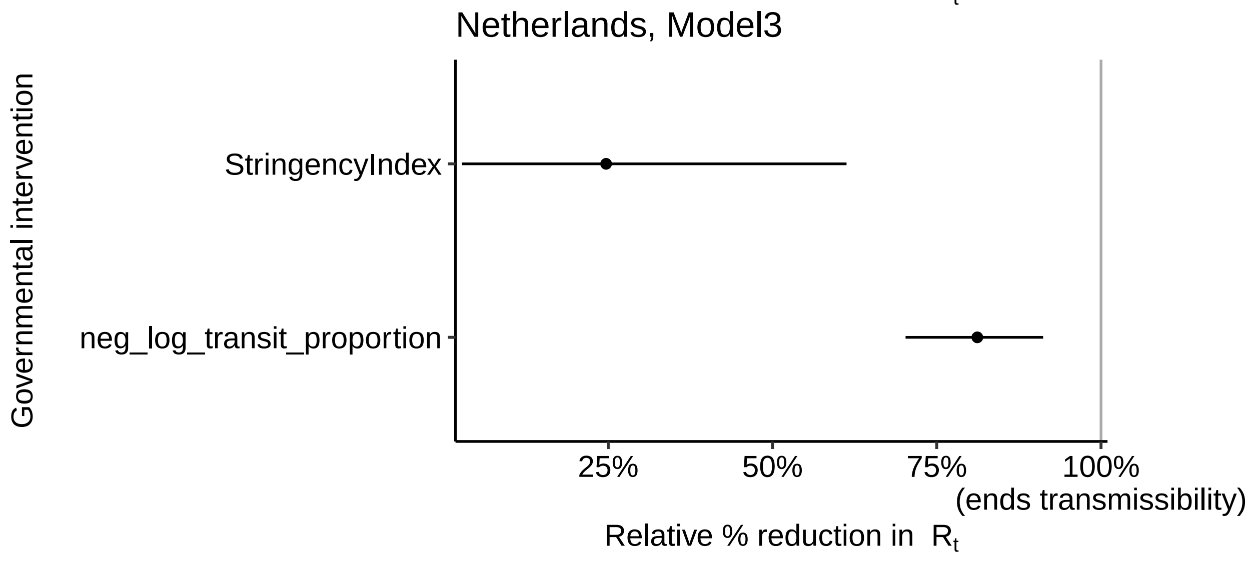

Switzerland, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

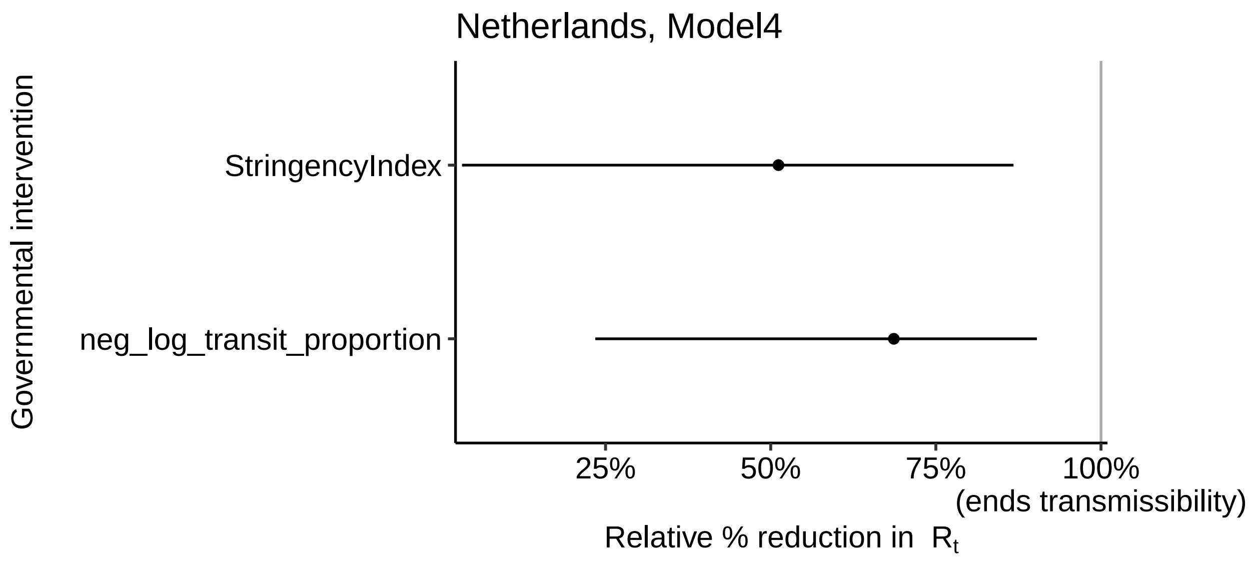

Greece, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t


Greece, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

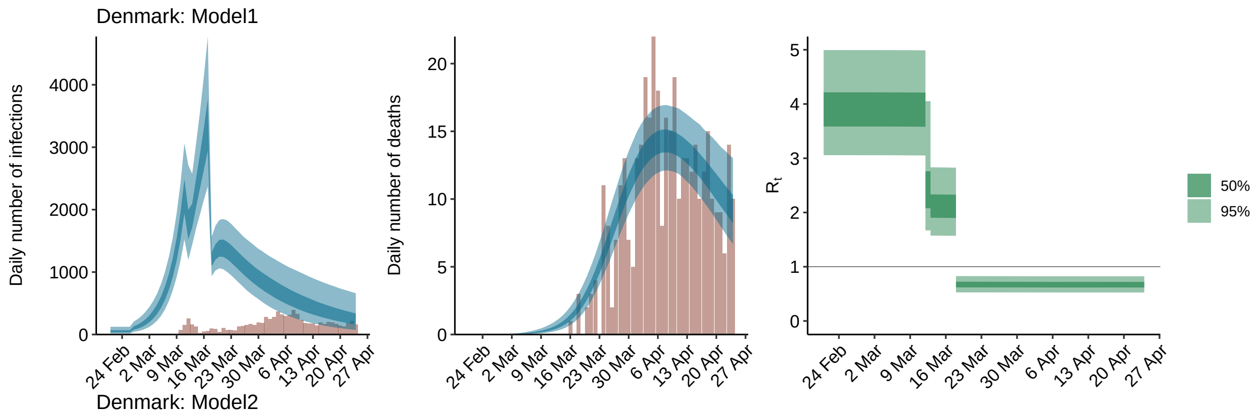

Portugal, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

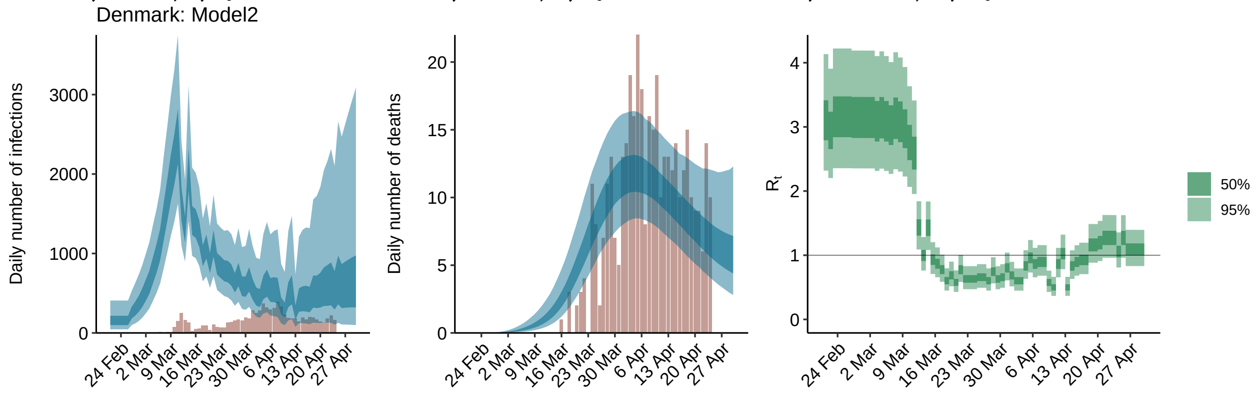

Portugal, Model4
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

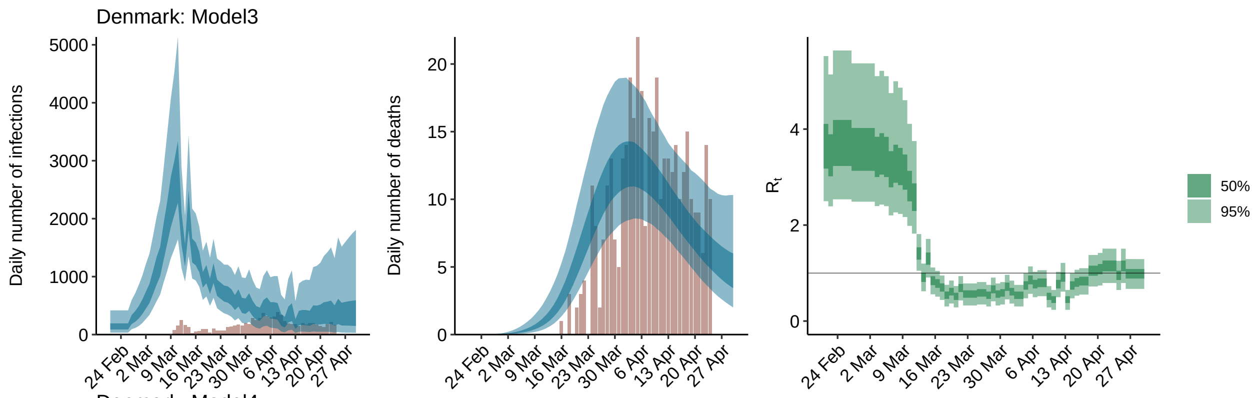

Netherlands, Model3
Governmental intervention
StringencyIndex
neg_log_transit_proportion
25%
50%
75%
100%
(ends transmissibility)
Relative % reduction in R_t

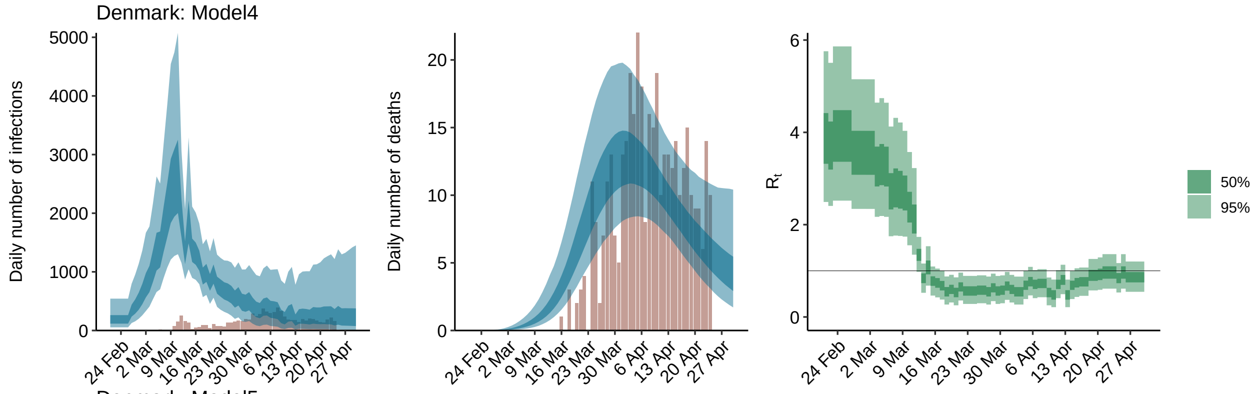


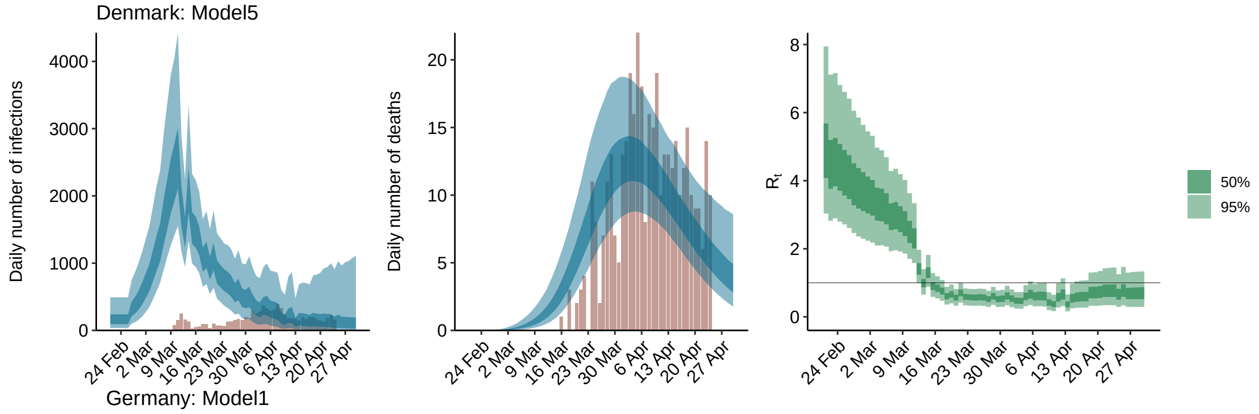
Infections, cases, deaths and Rt by country and model

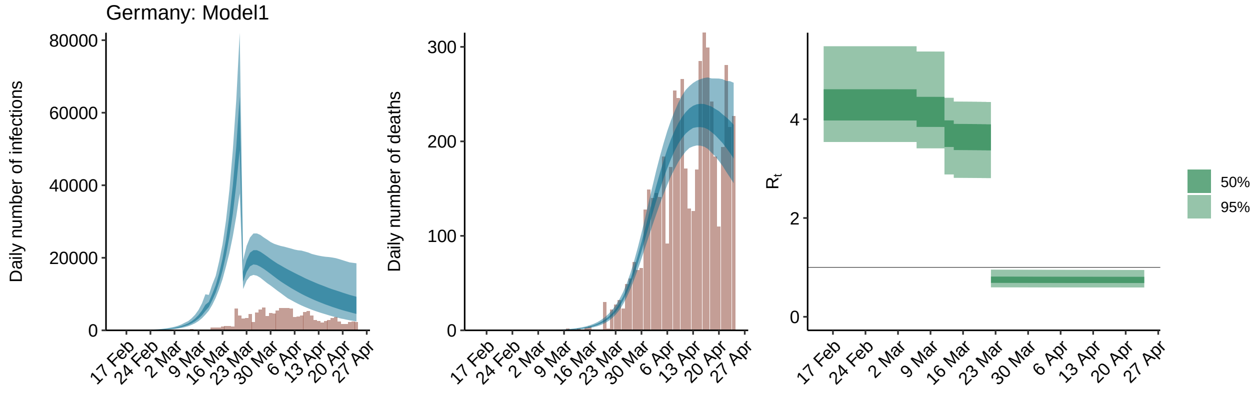


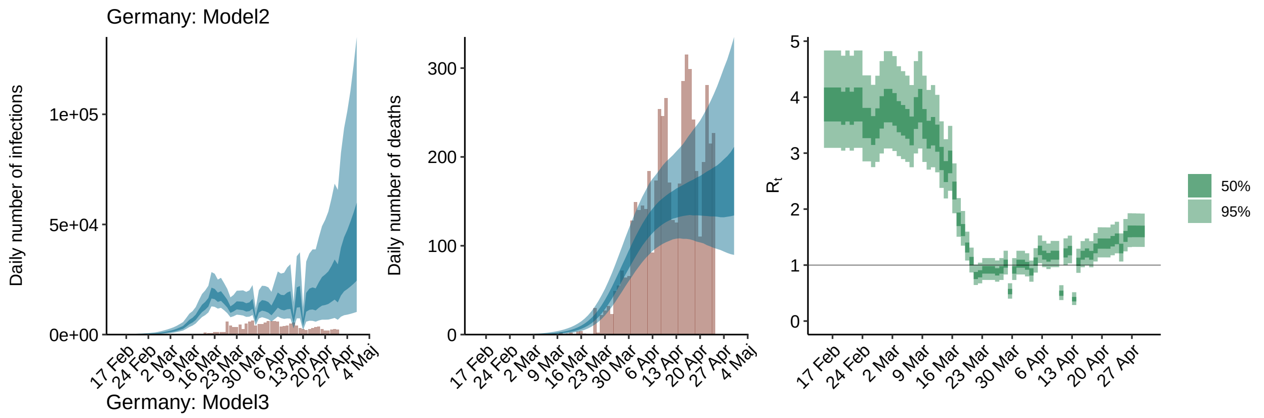


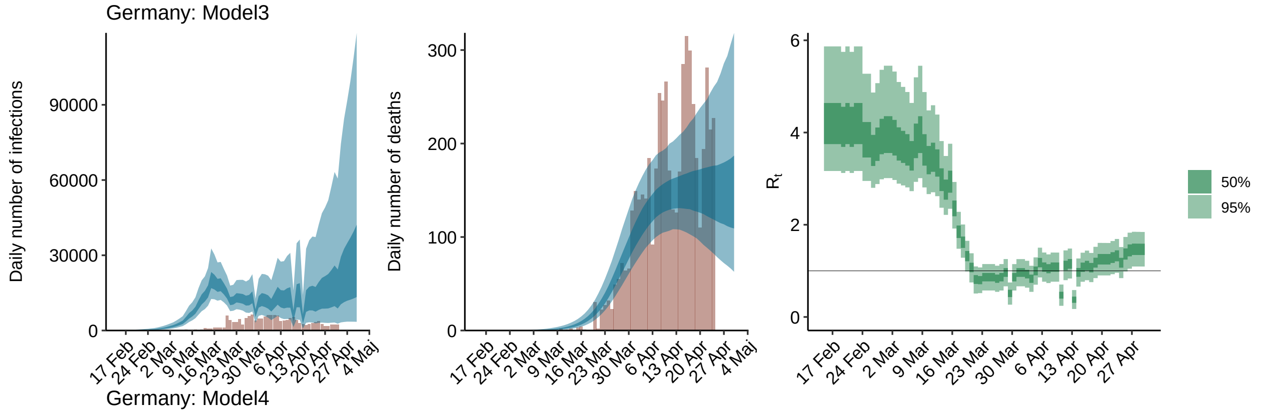

Denmark: Model3
Daily number of infections
0
1000
2000
3000
4000
5000
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
Daily number of deaths
0
5
10
15
20
R_t
0
2
4
50%
95%

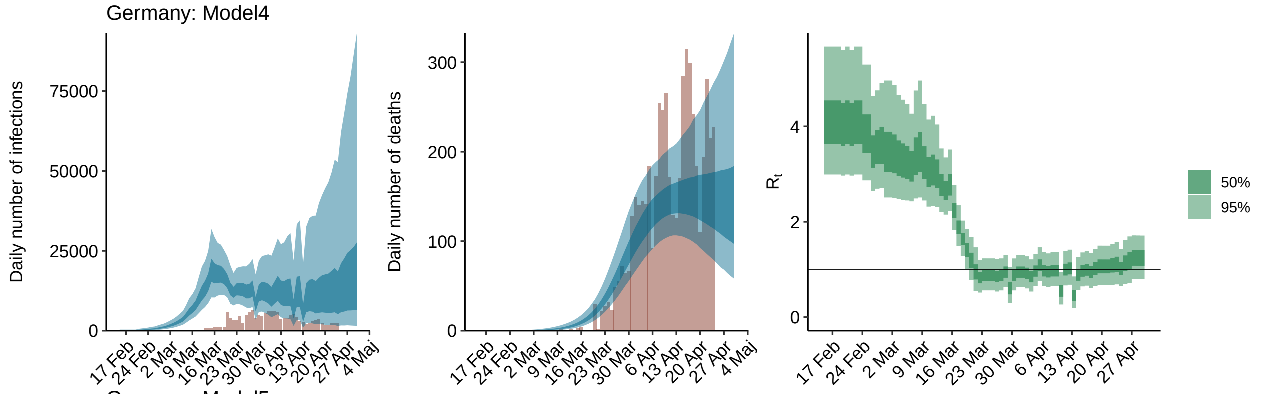

Denmark: Model4
Daily number of infections
0
1000
2000
3000
4000
5000
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
Daily number of deaths
0
5
10
15
20
R_t
0
2
4
6
50%
95%

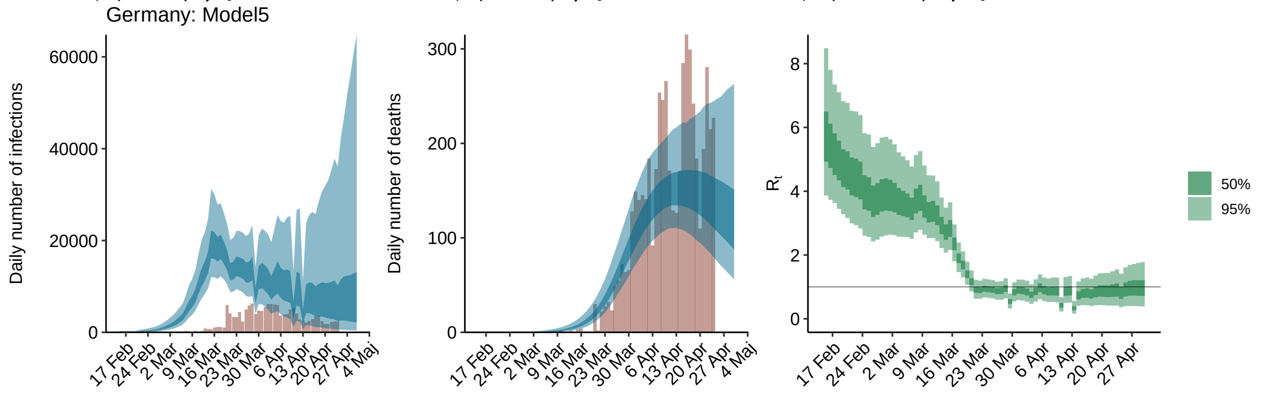

Denmark: Model5
Daily number of infections
0
1000
2000
3000
4000
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
Daily number of deaths
0
5
10
15
20
R_t
0
2
4
6
8
50%
95%

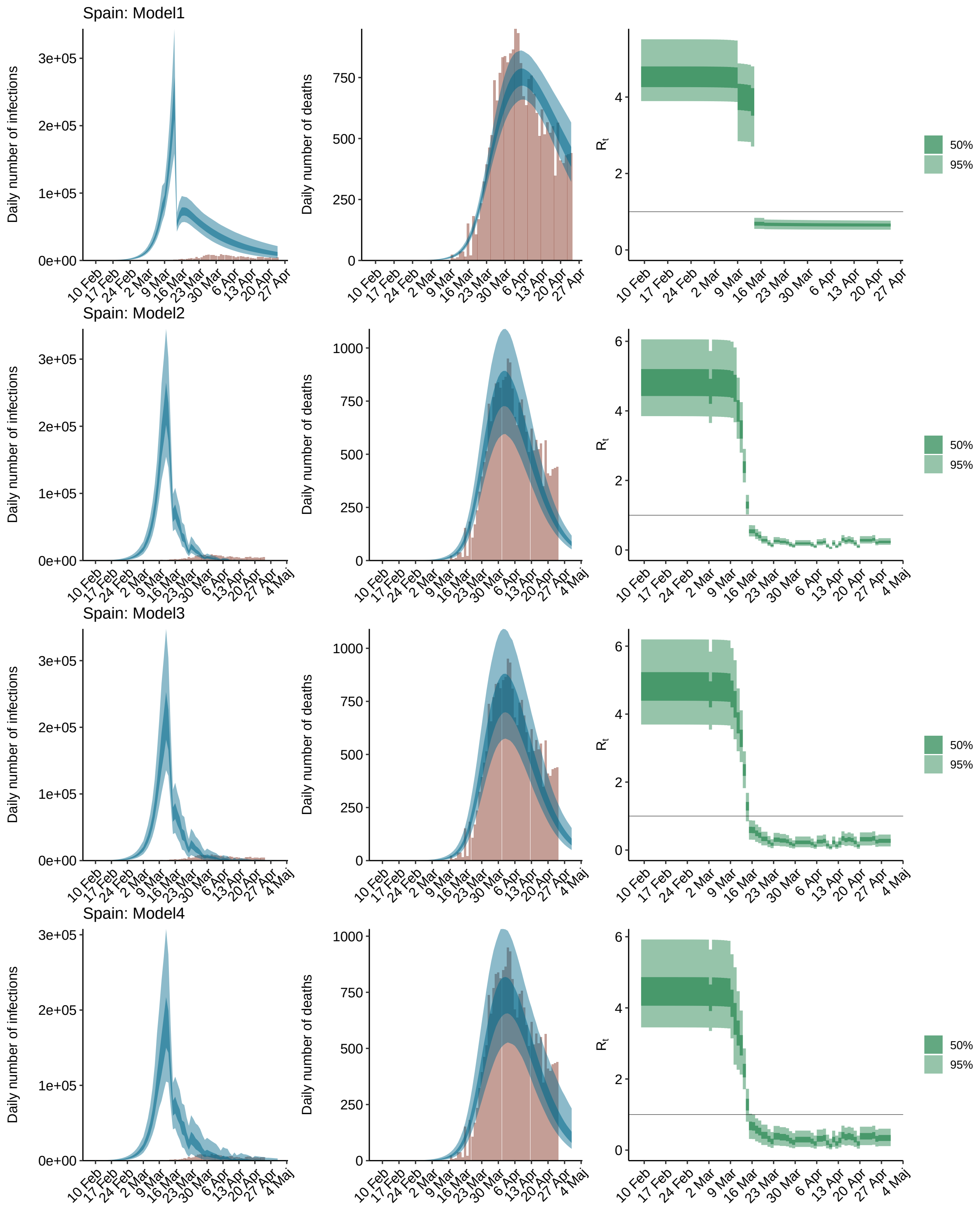

Germany: Model1
Daily number of infections
0
20000
40000
60000
80000
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
Daily number of deaths
0
100
200
300
R_t
0
2
4
50%
95%


Germany: Model2
Daily number of infections
0e+00
5e+04
1e+05
Daily number of deaths
0
100
200
300
R_t
0
1
2
3
4
5
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
50%
95%

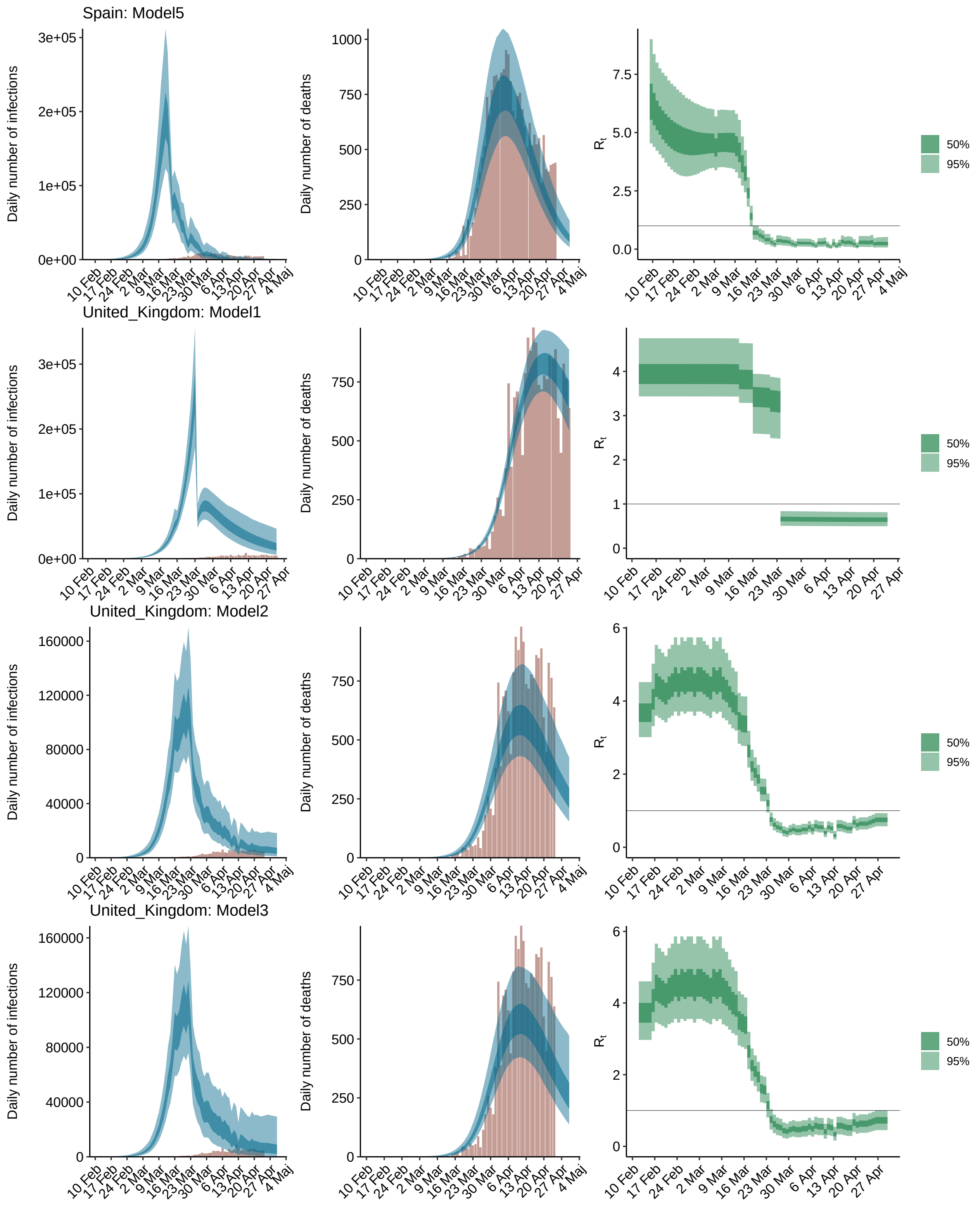

Germany: Model3
Daily number of infections
0
30000
60000
90000
Daily number of deaths
0
100
200
300
R_t
0
2
4
6
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
50%
95%

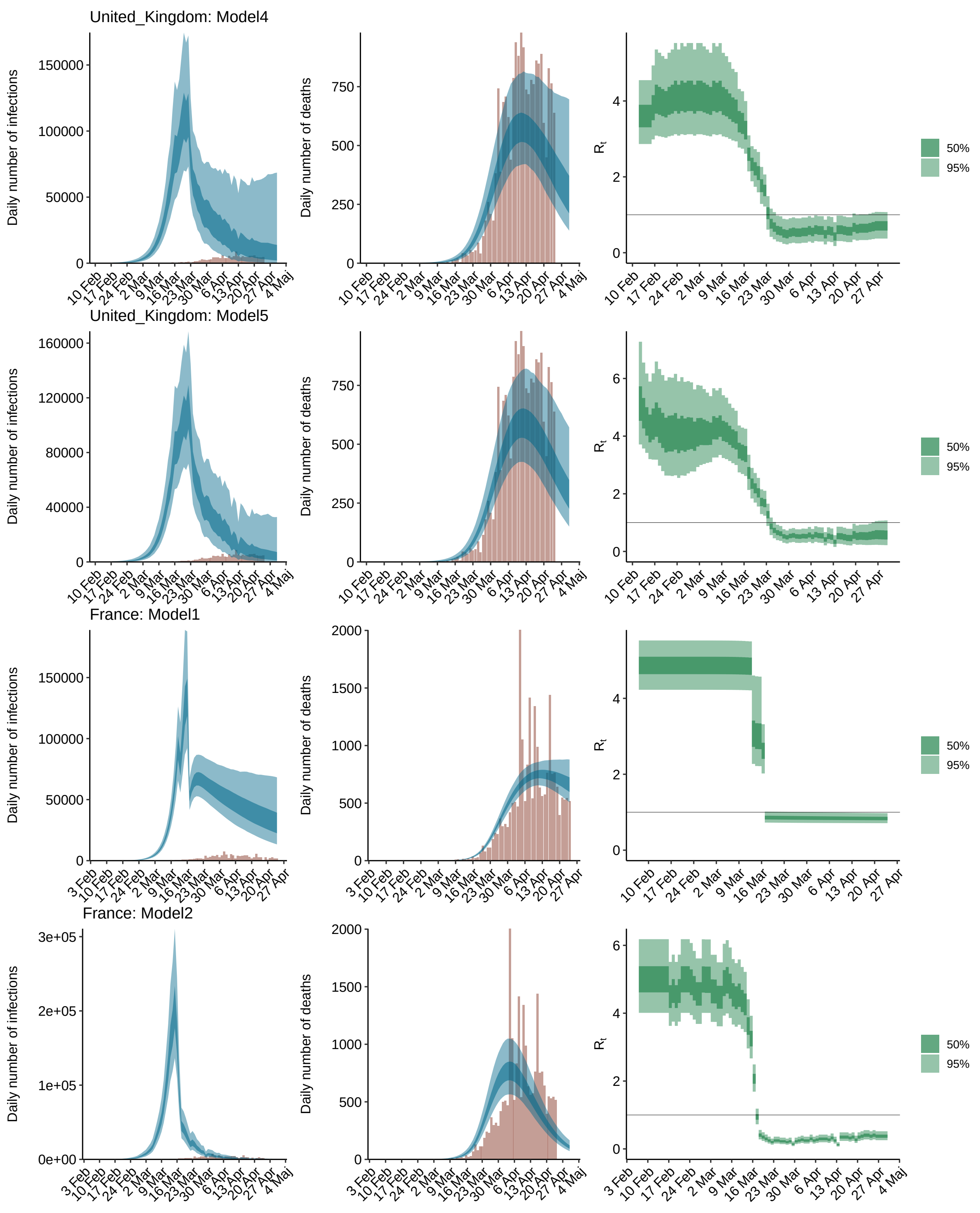

Germany: Model4
Daily number of infections
0
25000
50000
75000
Daily number of deaths
0
100
200
300
R_t
0
2
4
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
50%
95%

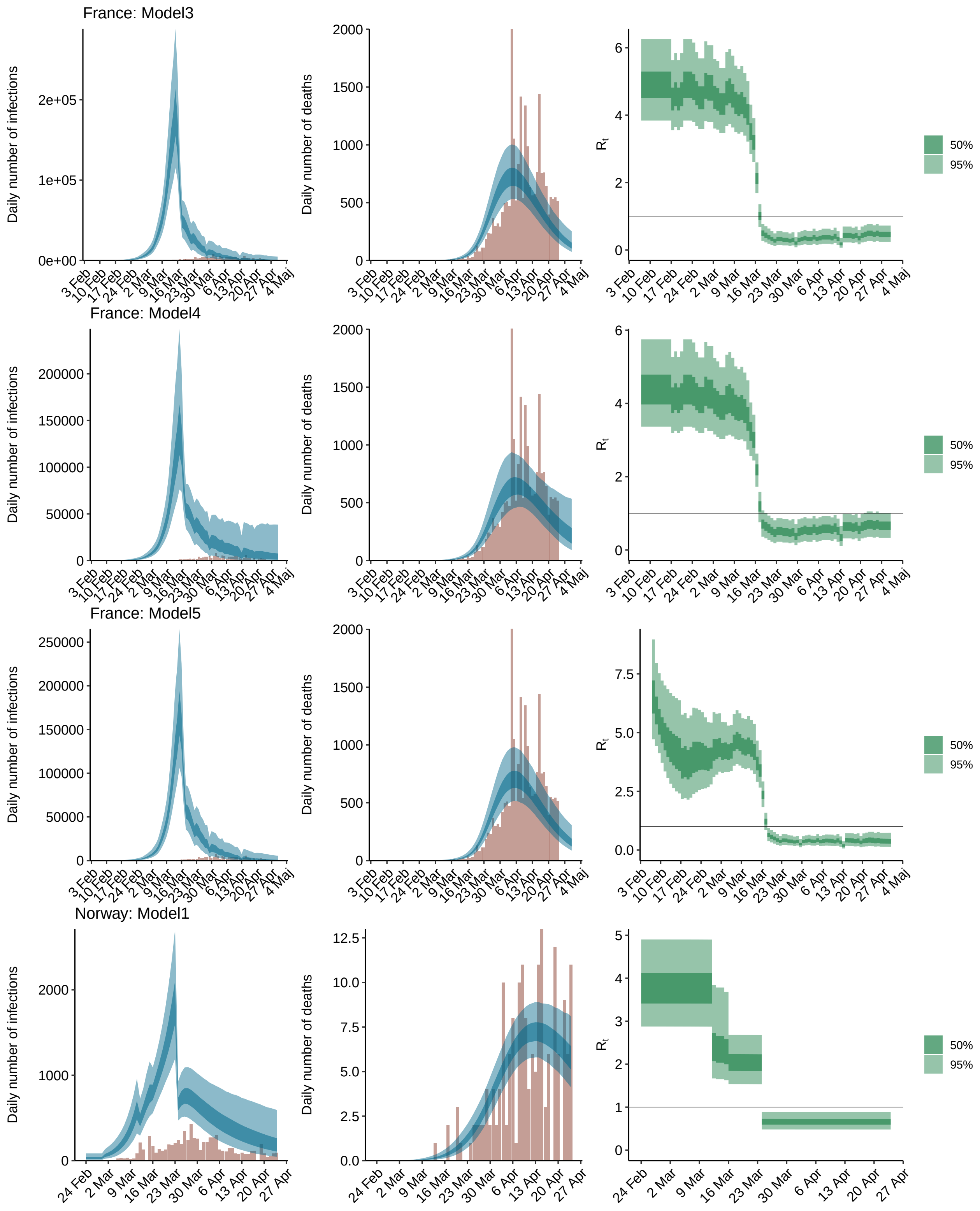

Germany: Model5
Daily number of infections
0
20000
40000
60000
Daily number of deaths
0
100
200
300
R_t
0
2
4
6
8
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
50%
95%



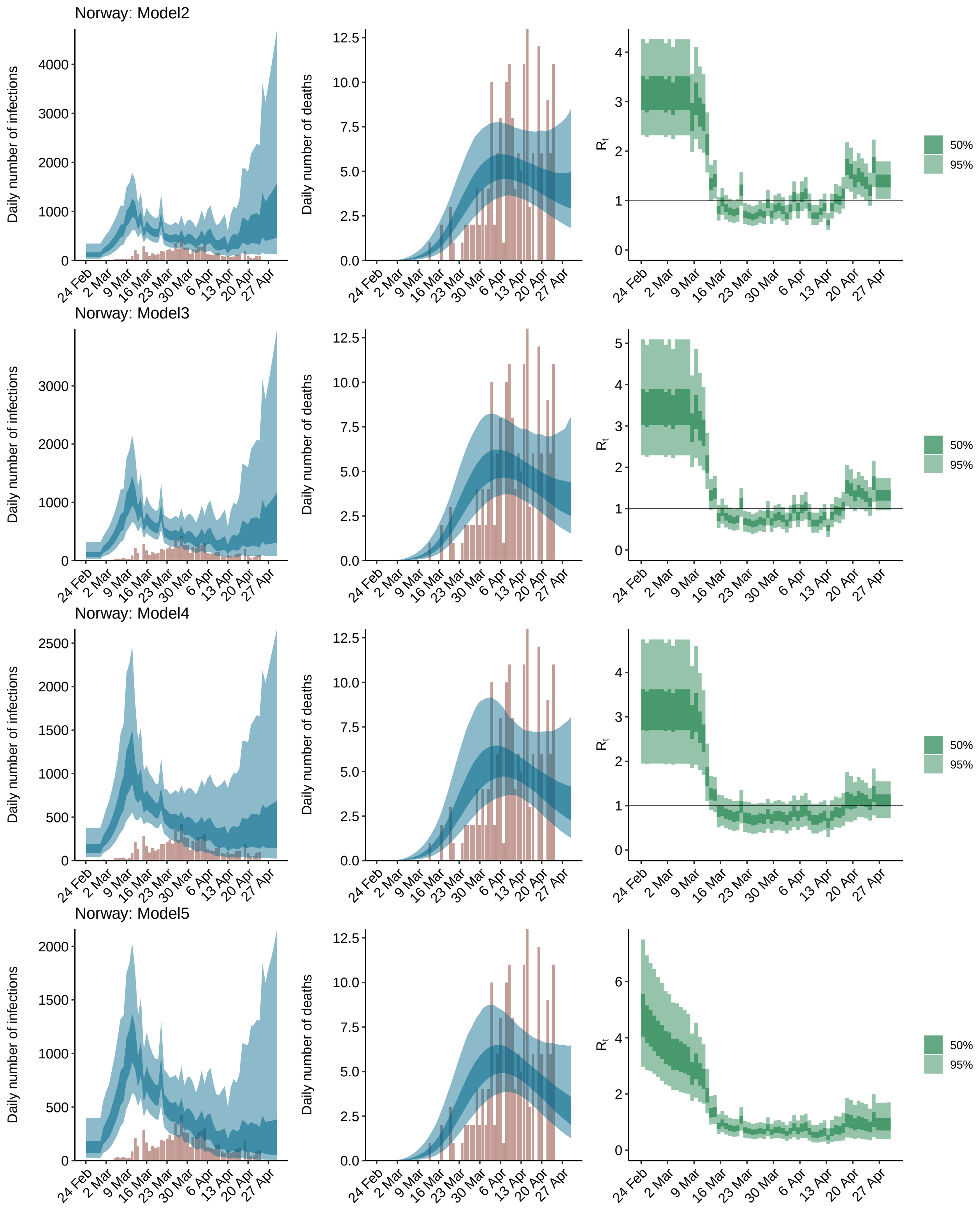
Spain: Model1
Spain: Model2
Spain: Model3
Spain: Model4
Daily number of infections
Daily number of deaths
R_t
0e+00
1e+05
2e+05
3e+05
0
250
500
750
1000
0
2
4
6
50%
95%
10 Feb
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj

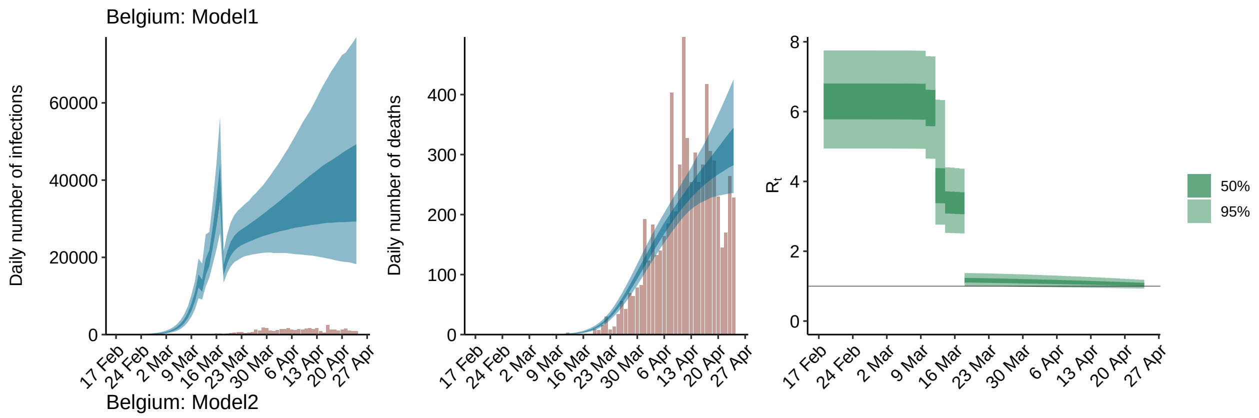

Spain: Model5
United_Kingdom: Model1
United_Kingdom: Model2
United_Kingdom: Model3
Daily number of infections
Daily number of deaths
R_t
50%
95%
10 Feb
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj

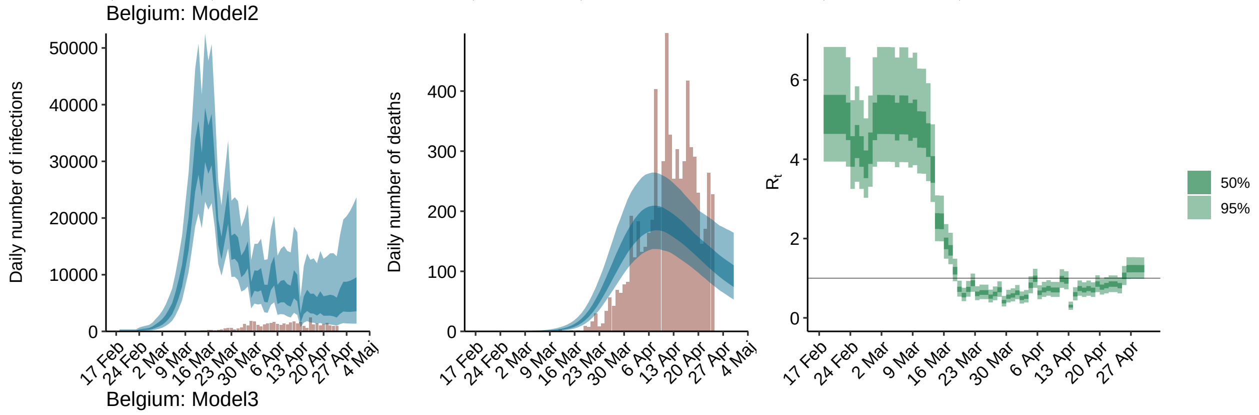

United_Kingdom: Model4
United_Kingdom: Model5
France: Model1
France: Model2
Daily number of infections
Daily number of deaths
R_t
50%
95%
10 Feb
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
3 Feb

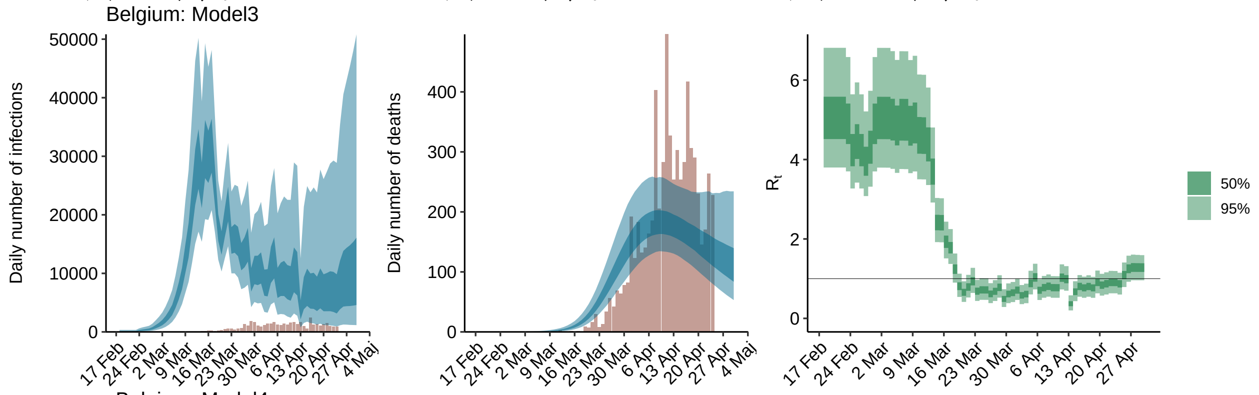


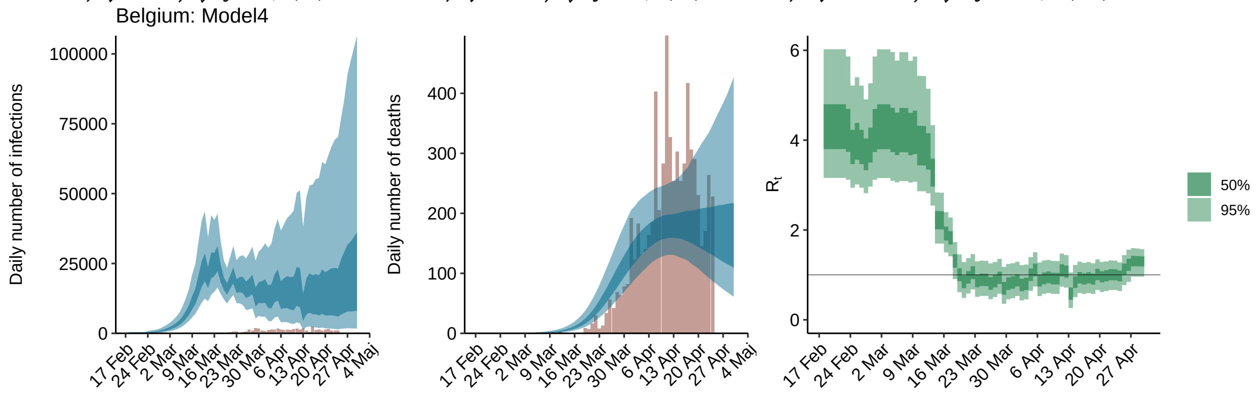
France: Model3
France: Model4
France: Model5
Norway: Model1
Daily number of infections
Daily number of deaths
R_t
50%
95%

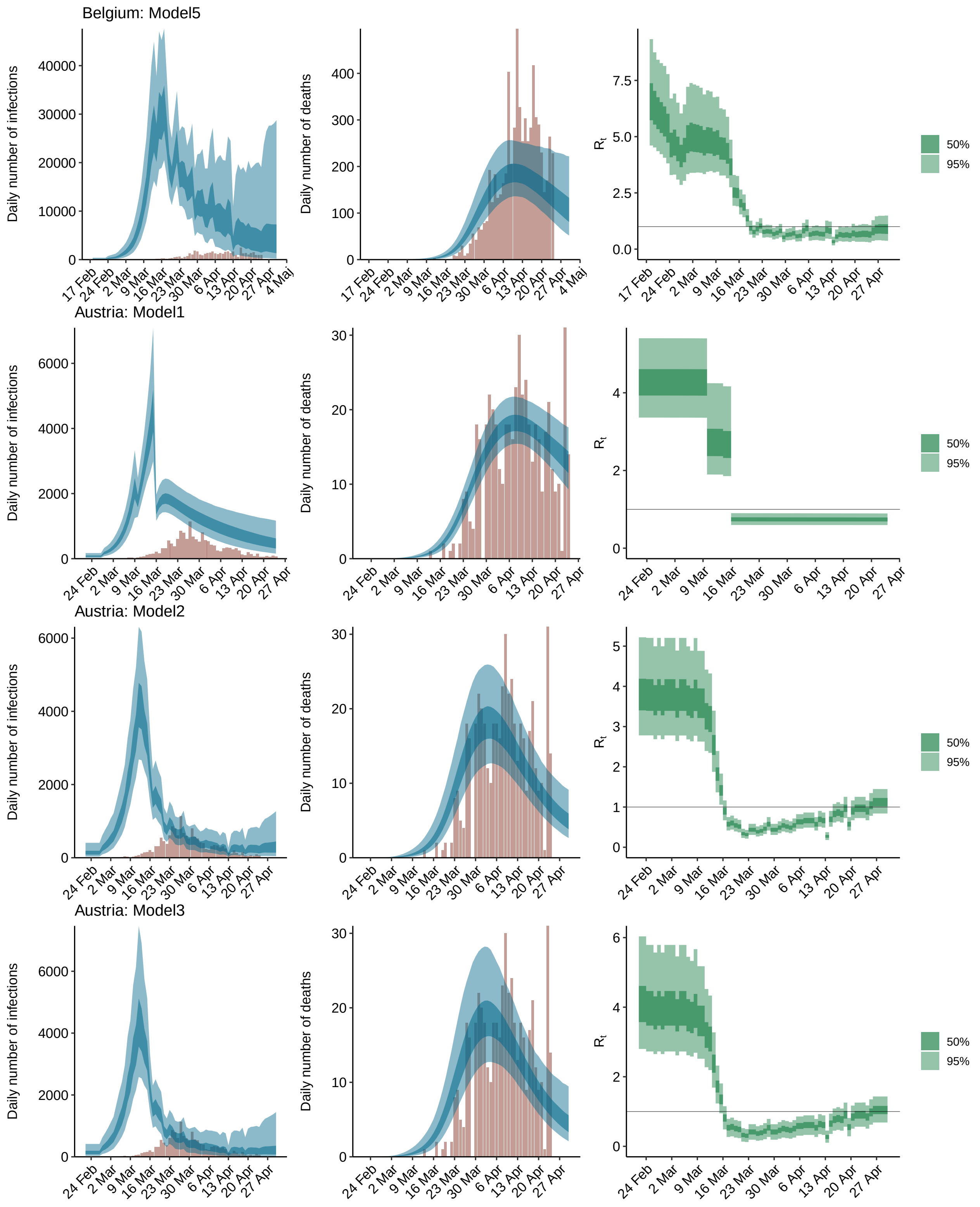

Norway: Model2
Norway: Model3
Norway: Model4
Norway: Model5
Daily number of infections
Daily number of deaths
R_t
50%
95%
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr

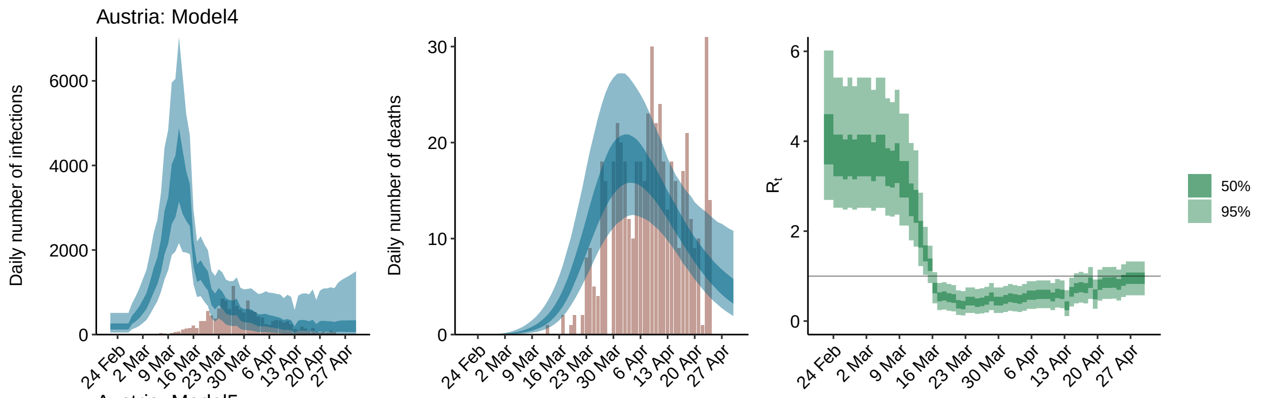

Belgium: Model1
Daily number of infections
0
20000
40000
60000
Daily number of deaths
0
100
200
300
400
R_t
0
2
4
6
8
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
🟩 50%
🟩 95%

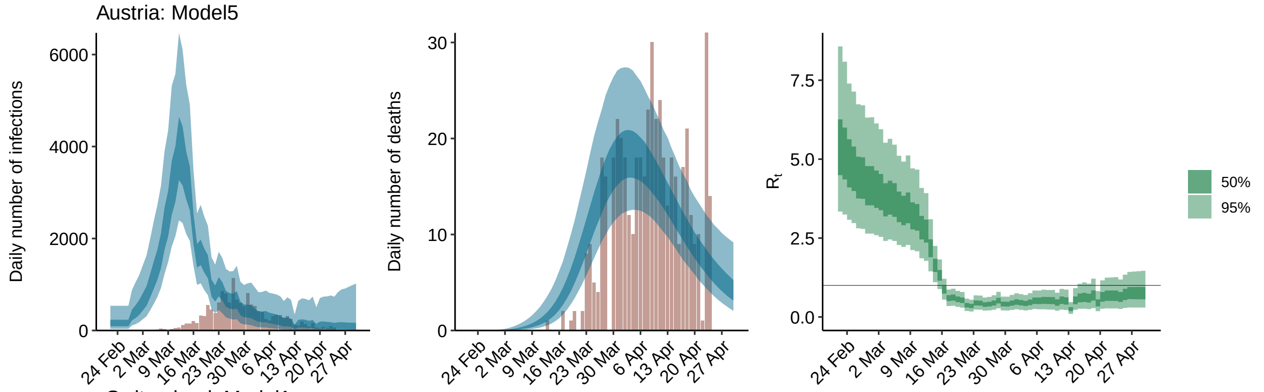

Belgium: Model2
Daily number of infections
0
10000
20000
30000
40000
50000
Daily number of deaths
0
100
200
300
400
R_t
0
2
4
6
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
🟩 50%
🟩 95%

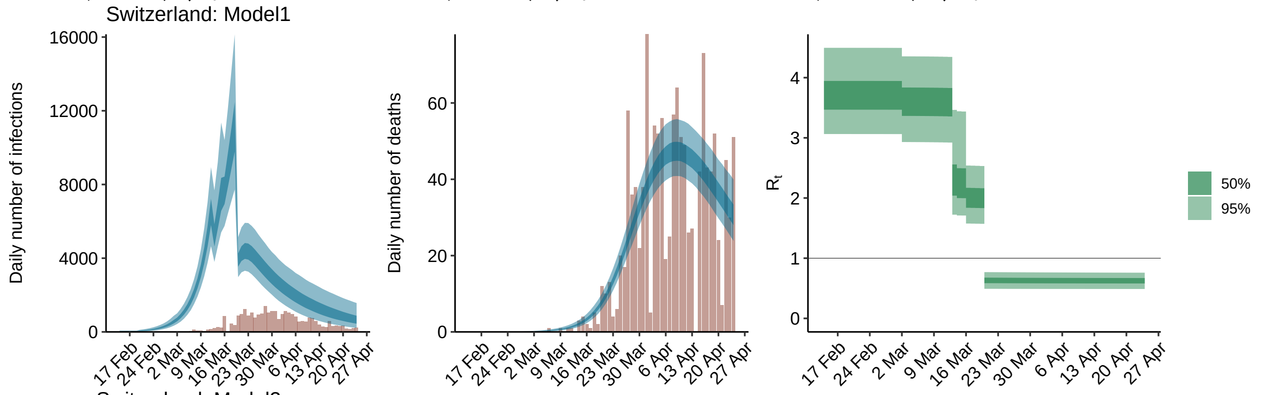

Belgium: Model3
Daily number of infections
0
10000
20000
30000
40000
50000
Daily number of deaths
0
100
200
300
400
R_t
0
2
4
6
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
🟩 50%
🟩 95%

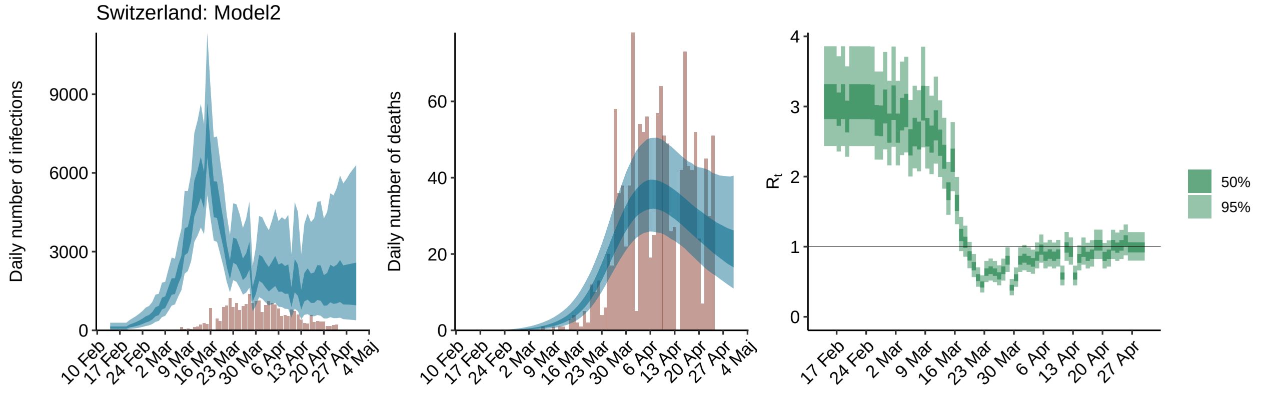

Belgium: Model4
Daily number of infections
0
25000
50000
75000
100000
Daily number of deaths
0
100
200
300
400
R_t
0
2
4
6
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj
🟩 50%
🟩 95%


Belgium: Model5
Austria: Model1
Austria: Model2
Austria: Model3
Daily number of infections
Daily number of deaths
R_t
50%
95%
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj

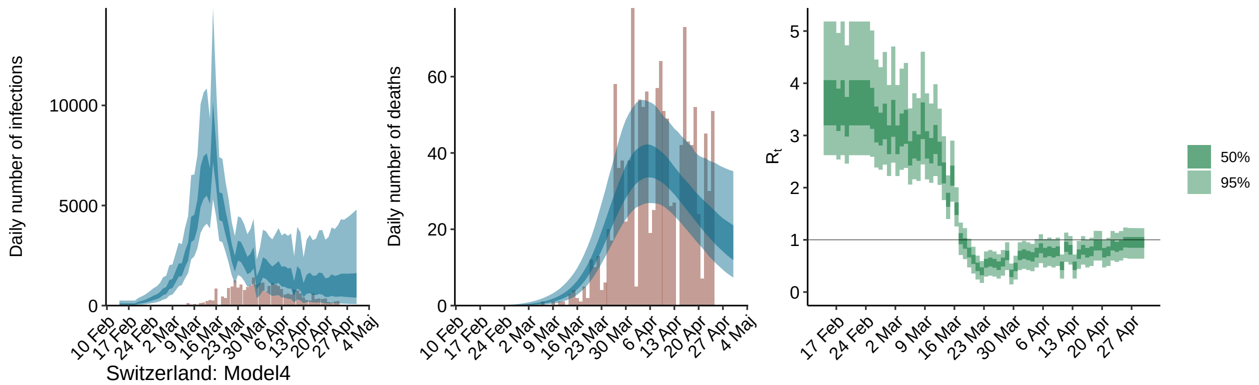

Austria: Model4
Daily number of infections
Daily number of deaths
R$_t$
50%
95%
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr


Austria: Model5
Daily number of infections
Daily number of deaths
R$_t$
50%
95%
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr

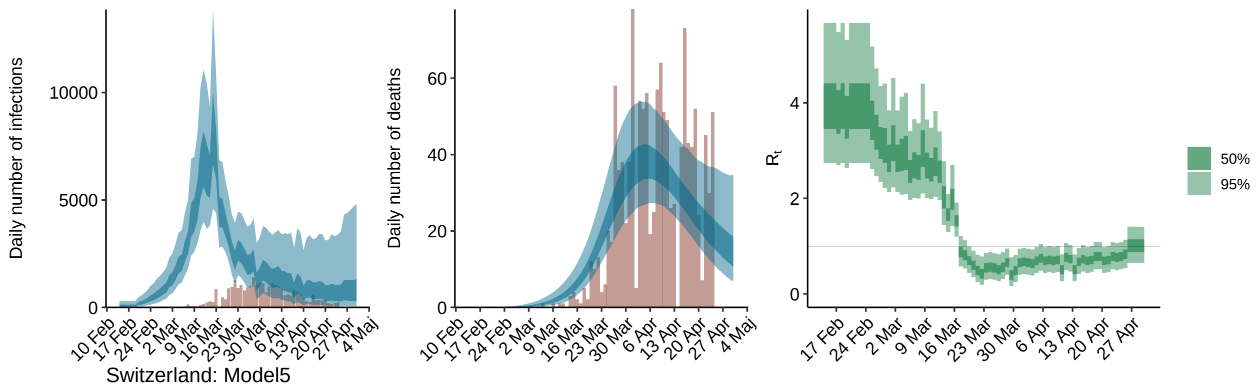

Switzerland: Model1
Daily number of infections
Daily number of deaths
R$_t$
50%
95%
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr


Switzerland: Model2
Daily number of infections
Daily number of deaths
R$_t$
50%
95%
10 Feb
17 Feb
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr
4 Maj

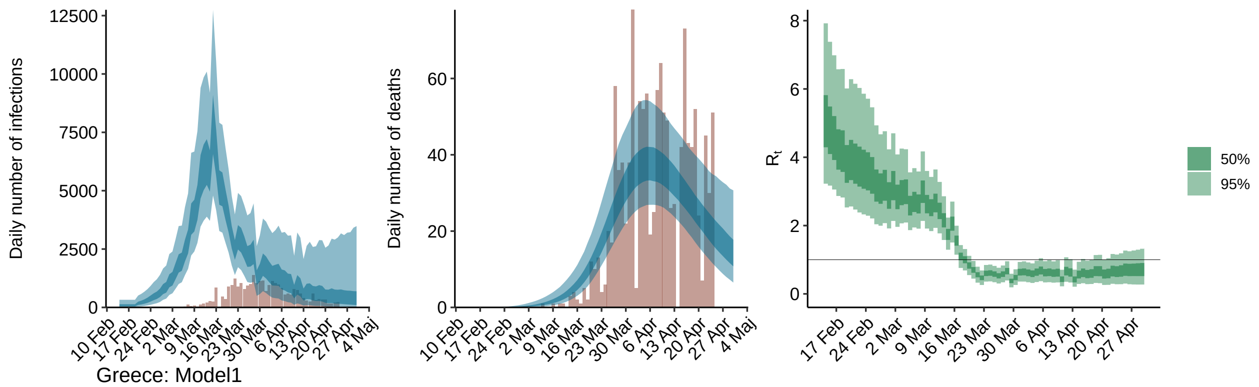
Switzerland: Model3



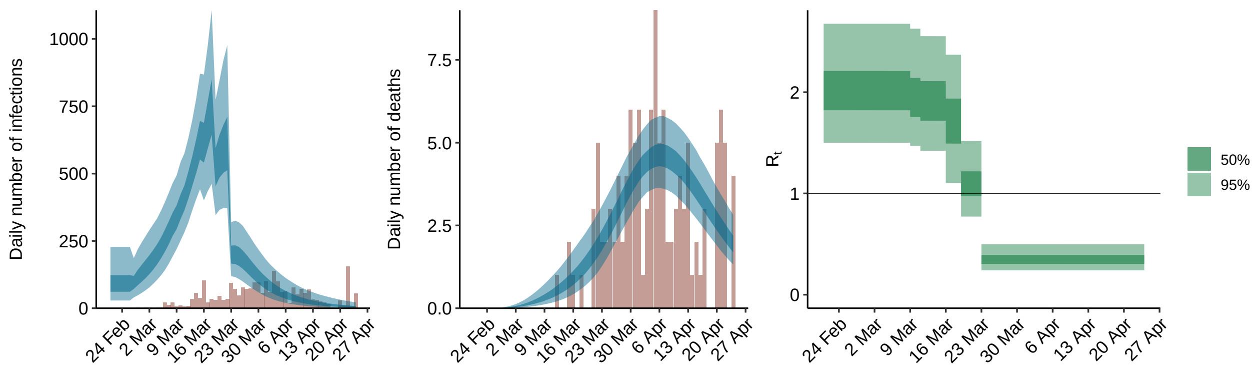
Switzerland: Model4

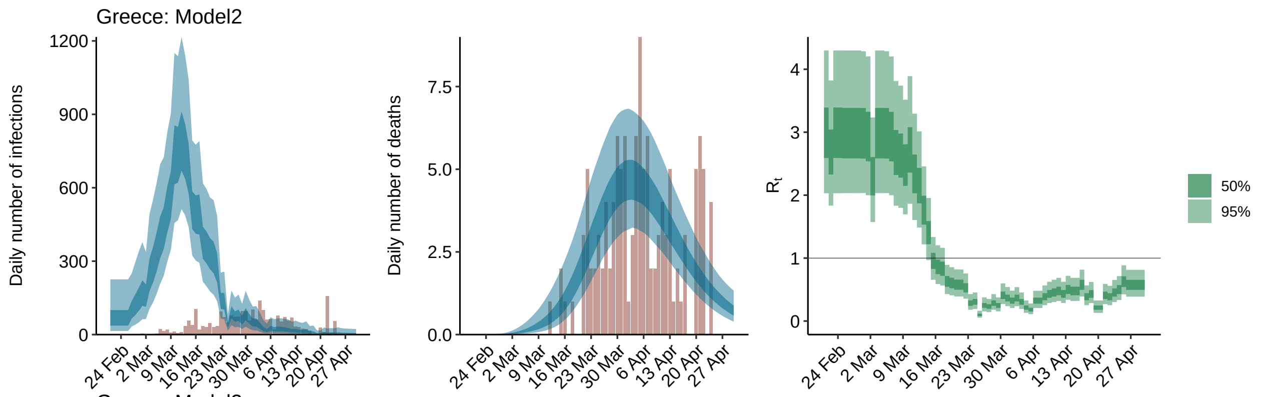


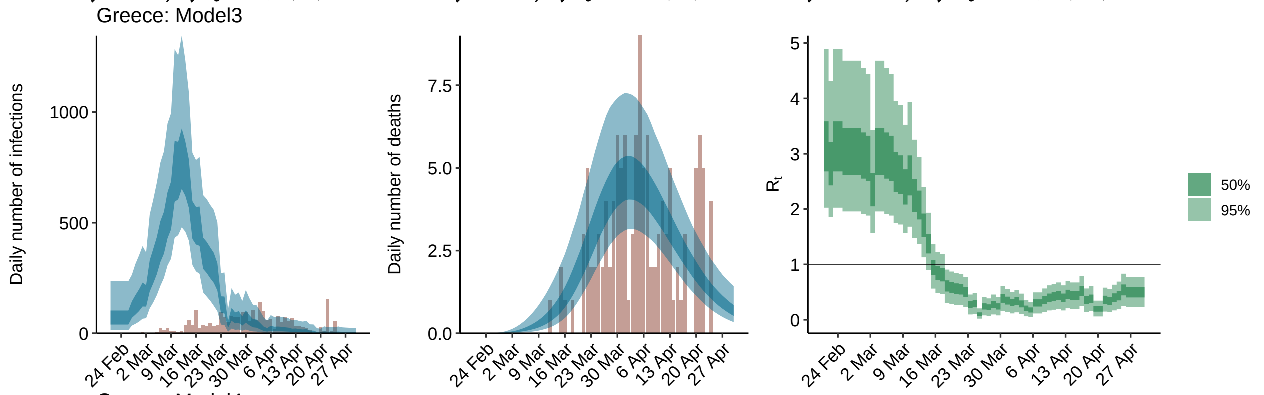
Switzerland: Model5

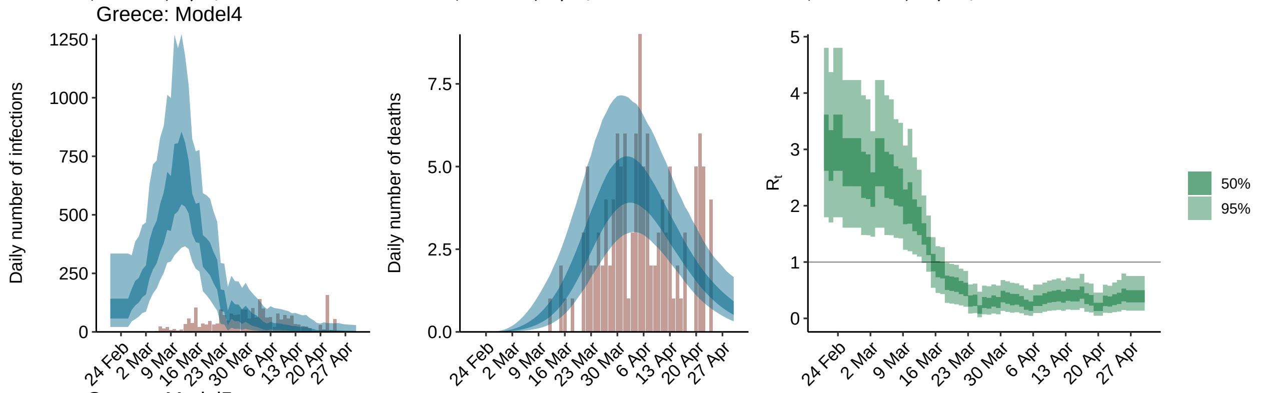


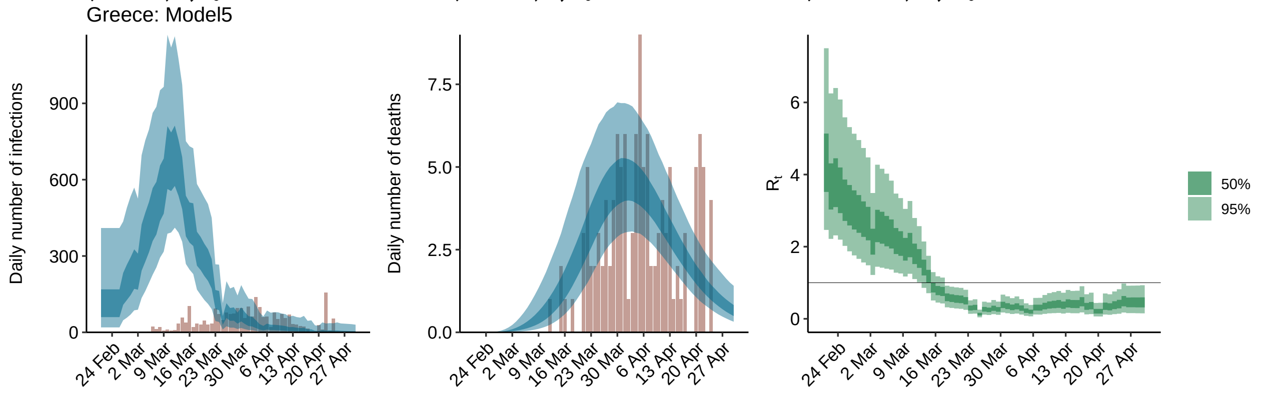
Greece: Model1

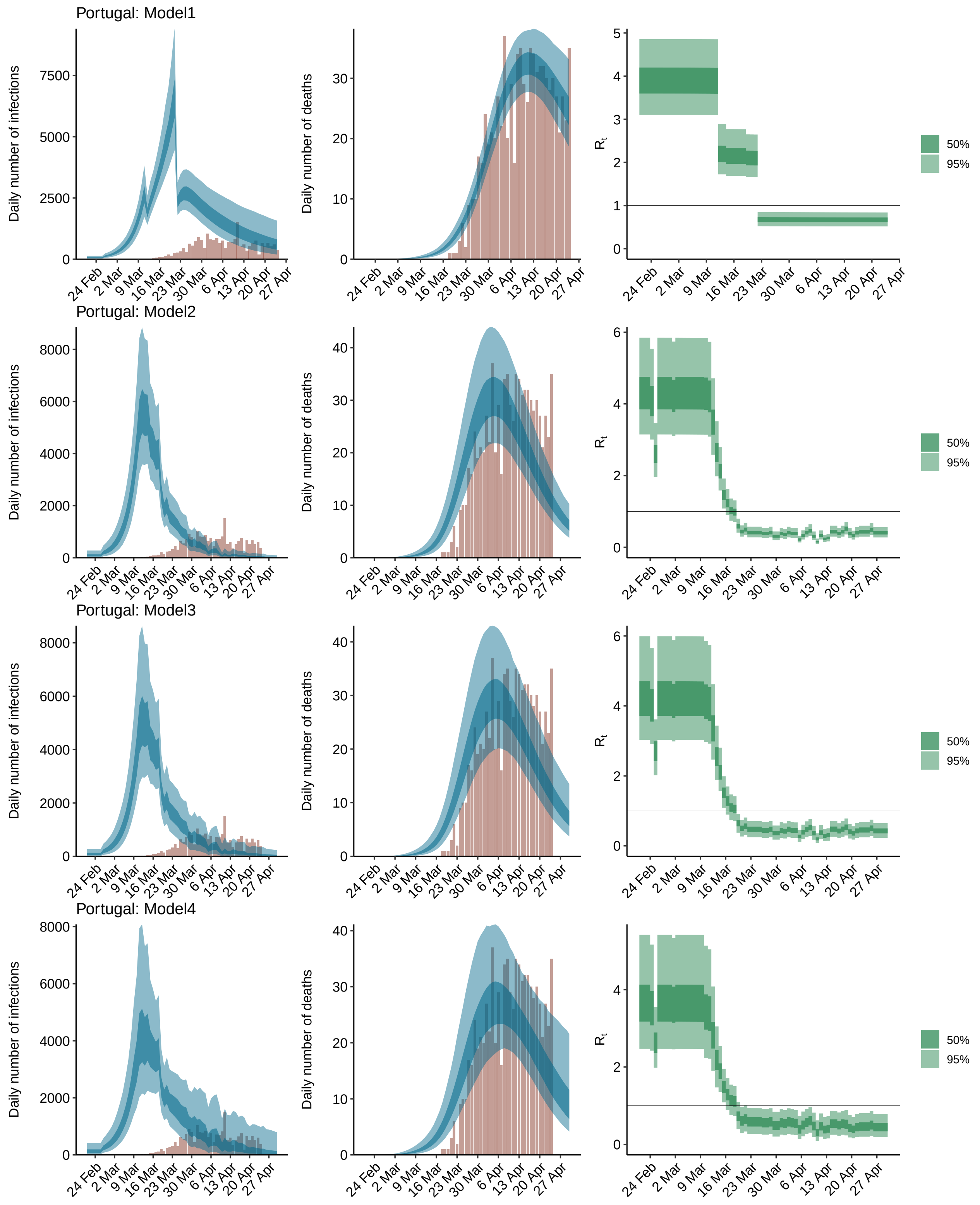


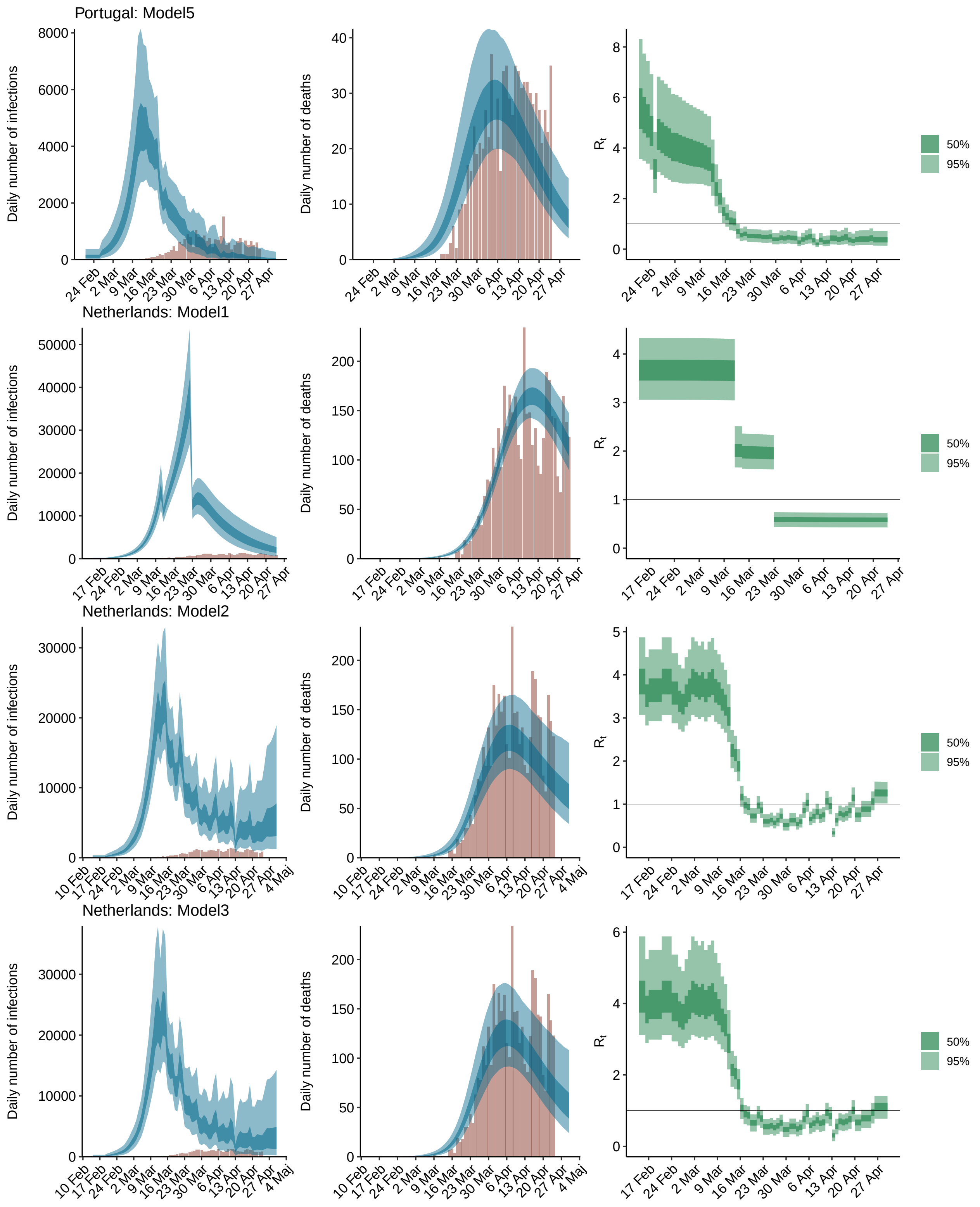

Greece: Model2
Daily number of infections
Daily number of deaths
R_t
50%
95%
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr

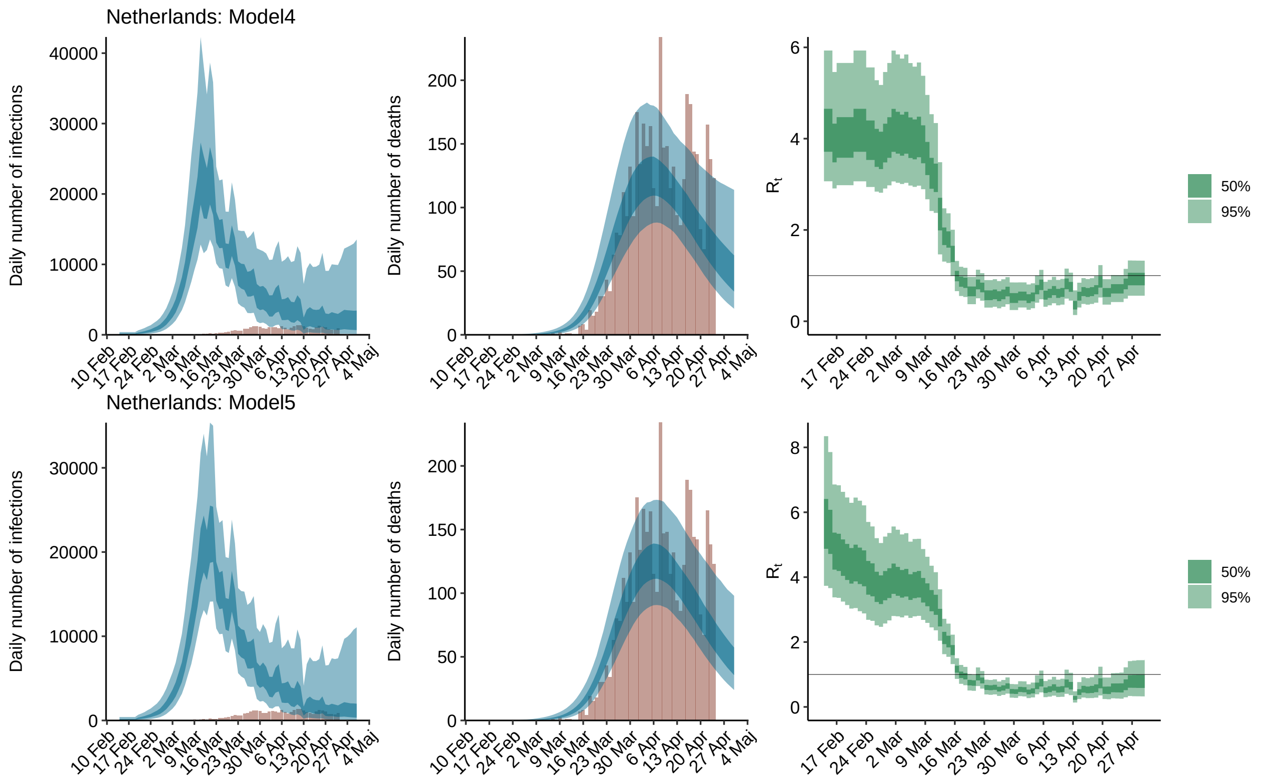

Greece: Model3
Daily number of infections
Daily number of deaths
R_t
50%
95%


Greece: Model4
Daily number of infections
Daily number of deaths
R_t
50%
95%


Greece: Model5
Daily number of infections
Daily number of deaths
R_t
50%
95%


Portugal: Model1
Portugal: Model2
Portugal: Model3
Portugal: Model4
Daily number of infections
Daily number of deaths
R_t
50%
95%
24 Feb
2 Mar
9 Mar
16 Mar
23 Mar
30 Mar
6 Apr
13 Apr
20 Apr
27 Apr


Portugal: Model5
Netherlands: Model1
Netherlands: Model2
Netherlands: Model3
Daily number of infections
Daily number of deaths
R_t
50%
95%



Reproducibility

Report git hash:

```
## 4473e0191f3b40756192ec0cf1bac62b027dbc78
```