# Modeling school closures across 35 countries

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**Abstract**

COVID-19 continues to spread around the world and modeling plays an important role in informing policy. An individual-based model called Covasim has recently been fit to data regarding confirmed cases and deaths experience in the United Kingdom during the first half of 2020, and then used it to evaluate alternative intervention strategies there[1]. We extend this methodology to consider data from 35 other countries, and use a database of international intervention specifics called the COVID-19 CONTROL STRATEGIES LIST to retrospectively model interventions employed in these countries. Because the age distribution of populations is a key feature of the COVID-19 pandemic and contacts among young people are often age-stratified and may play an especially important role, we focus here on school closure interventions.

Individual countries varied considerably in both the dates on which they imposed school closings, and in the levels (kindergarten, primary, secondary, university) specified. Critically, the age-stratified sub-populations supported by Covasim allow fine-grained specification of just those individuals affected by school closures at each educational level. Across the 35 countries the model was calibrated to the country's epidemic, simulations were first run without the intervention, and data on confirmed cases and deaths was used to fit key Covasim parameters. Next, specific intervention strategies employed by each country were converted into specifications for Covasim, and the same simulation parameters fit to a second model with the interventions considered. In the 10 countries where there was a significant difference between models, those incorporating school closures were considerably better fits than those without. Since both models' parameters are optimized and evaluated using the same criterion, improved fit with the intervention model may be taken as evidence that the modeled interventions were useful, at least in these 10 countries, in describing observed data.

# 1 Introduction

### Comparisons between countries are essential for the control of COVID-19[2]

> Although international comparisons are often disparaged because of different data quality and fears of the 'ecological fallacy', if done carefully they can play a major role in our learning what works best for controlling COVID-19.[3]
>
> ... the COVID-19 epidemic shows the need for epidemiology to go back to its roots—thinking about populations. Studying disease occurrence by person, place and time (often referred to as 'descriptive epidemiology') is usually taught in introductory courses, even if this approach is then paid little attention subsequently. COVID-19 is a striking example of how we can learn a great deal from comparing countries, states, regions, time trends and persons, despite of all the difficulties.[3]

With travel restrictions as they were in the spring and summer of 2020, levels of migration across national borders are considerably smaller than that across state or provincial boundries. In some countries, school closures were ordered only within particular states. For these reasons, and given the data currently available, only models at the level of individual countries and interventions ordered nationally are considered here.

> Predictive models for large countries, such as the US, are even more problematic because they aggregate heterogeneous subepidemics in local areas.... Models should also seek to use the best possible data for local predictions.[2]

The goal of this *post hoc* analysis of historical data is to understand the limits of our modeling tools as we move forward to use them for predictive tasks.

# 2 Results

## 2.1 Incorporating school closure interventions

The goal of Covasim optimization, with respect to each individual country, is to minimize the difference between the model and data about the number of diagnosed cases of, and deaths caused by, COVID. The objective measure used for optimization is to minimize sum-squared-difference (SSD) "fit value" between both of these. As data regarding deaths is believed to generally more accurate than that about positive tests, SSD over death rates is weighted twice that of diagnoses. In the experiments reported in this section, model calibration was allowed to vary three parameters: the number of initial infectsion, beta, and in some experiments, also testing rate.

The basic experiment is to contrast runs with and with the intervention of school closures modeled. As a first example, Figure 1 shows the curves for New Zealand, Singapore and Malaysia, three countries with large improvements in model fit. In the case of New Zealand, fit with both death and diagnosis data was improved considerably; in Singapore and Malaysia the improvement was primarily with respect to death data. The New Zealand model with school closures uses a similar value for beta but a much smaller initial infected (1161 vs.

11450) and a much larger testing rate (0.063 vs. .001); Singapore reduced beta slightly (2.64e-3 vs. 4.19e-3), a much smaller initial infected (1048 vs. 10825), and less testing (0.247 vs. 0.386). The Malaysian model with school closures was able to fit much better with quite similar values for all three parameters.

Figure 2 provides complete statistics for all 35 countries. The countries have been sorted on the difference in fit value between the two models, one incorporating school closure interventions and one without these. Taiwain has proven a difficult country to model, under many experimental conditions. With this exception, New Zealand, Singapore and Malaysie are at the top of the list. Several cells have been highlighted with orange when they are at maximal bounded values, and with yellow when they are at minimum bounds. These will be discussed further in Section 2.2.4.

Figure 3 shows the range of differences in fit value between these two conditions. The model for Taiwan is very poor in both conditions. For 14 countries, the difference between the two modesl was small, $< 100$. Of the remaining 20 countries where there was a significant difference between models, in 16 cases those incorporating school closures were better fits than those without.

Figure 4 shows the pairs of models for three other countries of potential interest: Romania had an improvement in fit with the incorporation of school closures that is just better than 100. The Lithuanian model had very good fit without school closures and was poorer when this was included. Again, no successful models of Taiwan were found in either case.

## 2.2 Model calibration

### 2.2.1 Stochastic repliction

The question of how stochastic factors within Covasim vary the results of simulations is an important first question, because no optimizer can do well if it is based on noisy results.

A series of n=8 replications of the same simulation were run with the same parameters. Happily, the range of results across multiple runs shown in Figure 5 shows very tight bounds across the mean value. (The standard deviation bars around diagnoses is so small has to be barely visible.)

Figure 6 shows the results across all simulation measures . Again, very consistent results across runs are shown in every measure.

#### 2.2.2 Global optimization

Many modeling efforts now depend on an optimization component that identifies best values for key parameters. This means that there is no guarantee of finding the actual optimal value[4].

All such optimizations generate several new questions:

- How much effort should be put into the search? Ie, how much value is there in extending computational effort towards improved results? What sort of reward is given for deeper search?
- Conversely, what makes a solution “good enough”?
- Since we may have multiple criteria for good solutions, how can we determine the Pareto-optimal combination? For example caring to match both death data and diagnosis data, how do we determine the Pareto optimal combination?

#### 2.2.3 Search dynamics

**The value surface** In the experiments reported here we will generate a sample of 2500 trials of particular parameter pairs of initial infection and beta. The samples were generated by a CMAES search initiated with the bounds shown and initialized at the location of the red plus sign.

On the left is a plot showing all sample points with darker blues indicating better fit values, a red plus sign showing the initial search parameter, and a green X showing the labeled best value found.You need to look closely but you can see several good value “ridges” that have been sampled more densely. On the right is a more detailed contour plot showing an interpolated surface across these samples. It shows a highly texturued, multi-modal region near the discovered optimum.

The cells highlighted in the table of Figure 2 correspond to values at or very near bounds imposed on the search, orange for values of beta or initial infection near the upper bound, and yell for values near their lower bound.

**Convergence to value optimum** The samples were generated adaptively, towards better solutions across "populations" of size 100, in a series of 25 "generations." The progression of this search process can be tracked according to several key statistics as they vary over generations.

A first statistic is the model fit value parameter shown In Figure 8. This shows fit value average, together with standard deviation bars. The later generations 10-25 have been broken out in an inset graph, the better to see the smaller values. After dramatic early improvements, model fit does not improve much after about 12 generations.

Beta leads initialInfections

Figure 9 considers the values of beta and initial infection independently. Values of beta converge more quickly and have stabilized by about generation 10. Values of initial infection continue to increase throughout all generations. Note in Figure 8, however, that increasing initial infections does not change model fit much.

Deaths dominate diagnoses

Figure 10 looks at the component measures on which model fits is evaluated: match with death data and match with diagnosis data. As expected, because it is weighted more heavily, matching death data drives the search. It is interesting to note that improvement with respect to in the two separate values (diagneses and death) is well correlated across the generations of the search.

### 2.2.4 Bounding search

As mentioned earlier, global optimization procedures generally require bounds within which they are to search. Figure 11 can be compared to that originally shown in Figure 7. Here a range of initial infection sizes twice as large (50000 vs 25000) was allowed in the search. Again, the first plot shows similar ridges leading from the initial starting value, to an optima with about the same number of initial infections but a smaller beta. A second, vertical ridge is indicated leading to the very top boundary imposed by the a priori constraint.

Back-of-the-envelope calculations regarding possible values for initial infections[1] suggests that the second, upper attractor containing the optimum in this experiment should be discounted as implausible. [2]

There is a clear bifurcation shown in the second contour plot. The lower upper bound on initial infection (25000) was selected to force search to include only the lower attractor.

## 2.3 Using data for testing rate

Rather than asking the optimization process to select a best testing rate, data from OWID can be used instead.

Experiments alternating the two possible sources for testing rates, data or search, are summarized in Figure 12. In all cases, allowing search to establish the parameter value produced better fitting models. This is to be expected, as a new free parameter has been allowed.

Figure 13 shows contrasting results for the case of New Zealand using search versus data for testing rate. The optimized value for testing rate shows an enormous number of tests performed, relative to available data.

Note that the improvement allowed with testing rate as free parameter is despite the error with respect to available data having no consequence in Pareto-optimum calculation,

[1] r0 = number of contacts * days infectious * infection probability per contact per day so if we assume r0 = 2, 20 contacts, 8 days infectious, we get beta = 0.0125 [Cliff, 3 Oct]

[2] That's why the primary experiments that are the focus of the results above!

since it is given a zero weight.

# 3 Methods

## 3.1 Data sources

- OurWorldInData[5]
- Covid-19 Control Strategies List, developed by Amélie Desvars-Larrive and colleagues [Complexity Science Hub Vienna]

## 3.2 Covasim

Covasim[6]

Optuna[7]

Tree-Structured Parzen Estimator[8]

CMAEvolution[9]

Did not make use of SynthPop

## 3.3 Key details

- `self.weights = sc.mergedicts({'cum_deaths':10, 'cum_diagnoses':5}, weights)`
- `educLevelSize = {'h':4, 'w':20, 'c':20, 'sk': 20, 'sp': 20, 'ss': 40 , 'su': 80}`
- Only countries with populations > 1e6 were considered.
- Only countries with educational interventions coming after at least one week of diagnoses and death data were considered. For example, while both Ghana and Mauritius had school closures, but data on diagnoses and deaths was not available for a week before the dates of their closures.

- Simulation start date picked when number of infections becomes $> 50$
- Each educational level (kindergarten, primary, secondary, university) was treated as a separate "layer" by Covasim and captured into separate age ranges within the total population. This allows interventions at different educational levels to be treated independently.
- Each school closure at any educational level is modeled as a simple on/off: school closings start on a specified date, infection rate was set very low (`ClosedSchoolBeta = 0.02`) for children in each age group associated with the educational level, and are assumed to be in effect until an end-of-closure date.
- In a small number (6 of 35) of cases, the Covid-19 Control Strategies List contained a specific *end* for the school closure; for these countries that date was used to end the intervention. Otherwise, a default `SchoolOutDate = 2020-06-01` was used.

### 3.3.1 Age distribution

- `educLevel_ages = {'sk': [4,5], 'sp': [6,10], 'ss': [11,18], 'su': [19,24]}`

The distinguished age cohorts associated with school levels is shown in Figure

## 3.4 Model calibration

An outer-loop of software based on Optuna exists to allow "calibration" of Covasim models with respect to key parameters. It supports both TFE and CMAES optimization techniques.

Population size is a convenient way to broaden the search so as to reduce sampling error. The CMA library has a "tell-ask" interface that allows easy bundling of parallel executions.

We optimize over two parameters, $\beta$ and the number of initial infections, and in some cases a third, the assumed testing rate.

NTrial=100 trials were allocated to find the search for parameter values causing the model to best fit the data.

# 4 Next steps

## 4.1 Model validation

1. {lauerReich20}: Infectious Disease Forecasting for Public Health[10]

2. {bergmeir18}:A note on the validity of cross-validation for evaluating autoregressive time series prediction[11]

3. {bergmeirBenitez12}: On the use of cross-validation for time series predictor evaluation[12]

## 4.2 Integration of genomic data: molecular epidemiology

- Rockett[13]

    1. examine the added value of near real-time genome sequencing of SARS-CoV-2 in a subpopulation of infected patients during the first 10 weeks of COVID-19 containment in Australia and compare findings from genomic surveillance with predictions of a computational agent-based model (ABM)
    2. based on AceMOD
    3. 21 January and 28 March 2020, 1,617 cases of COVID- 19 were diagnosed and reported to the NSW Ministry of Health. All patients resided in metropolitan Sydney.

# 5 Conclusions

## 5.1 Honest priors

- Bounds; bounded optimization

- testing rates

- What accuracy can we claim for model parameter estimation?

## 5.2 Scientific sharing, publishing and open source models

- The expressive power of agent-based models allows evaluation of many intervention strategies
- Open source modeling systems like Covasim allow independent model components to be investigated and incorporated separately
- The publishing of full model implementation, like that included with the [Panovska-Griffiths] publication is an excellent example
- Fast-paced scientific sharing like that demanded by COVID-19 is catalyzed by such interactions

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# List of Figures

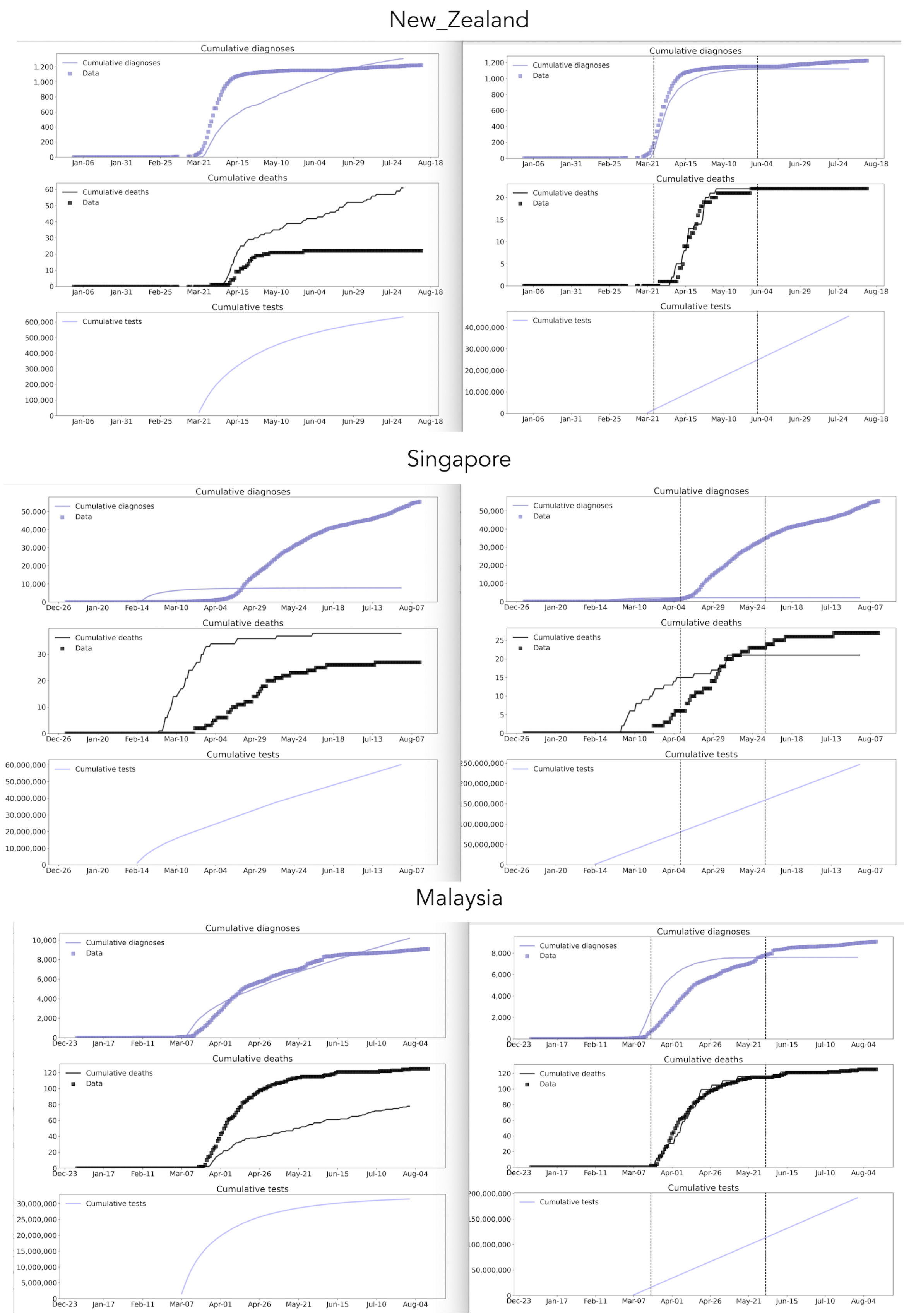


Figure 1: Sample countries

| | No intervention | | | | Difference: Non - intervention | | | | Intervention modeled | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Value** | **Beta** | **InitInfect** | **TestRate** | **Value** | **Beta** | **InitInfect** | **TestRate** | **Value** | **Beta** | **InitInfect** | **TestRate** |
| Taiwan | 6828 | 2.000E-3 | 8787 | 0.000 | 5557 | -5.200E-5 | 7778 | -0.687 | 1272 | 2.052E-3 | 1009 | 0.687 |
| New_Zealand | 1284 | 2.022E-3 | 11450 | 0.001 | 1209 | 1.300E-5 | 10289 | -0.063 | 75 | 2.009E-3 | 1161 | 0.063 |
| Singapore | 1258 | 4.193E-3 | 10825 | 0.386 | 643 | 1.552E-3 | 9777 | 0.139 | 615 | 2.641E-3 | 1048 | 0.247 |
| Malaysia | 583 | 2.956E-3 | 9440 | 0.081 | 444 | 9.550E-4 | 63 | 0.049 | 139 | 2.001E-3 | 9377 | 0.031 |
| Germany | 1073 | 2.000E-2 | 24991 | 0.205 | 408 | 1.710E-2 | 13500 | 0.189 | 665 | 2.898E-3 | 11492 | 0.016 |
| Austria | 437 | 5.073E-3 | 22952 | 0.029 | 379 | 2.247E-3 | 12161 | -0.001 | 58 | 2.826E-3 | 10791 | 0.030 |
| Denmark | 462 | 4.454E-3 | 13767 | 0.023 | 378 | 1.675E-3 | 2439 | 0.005 | 85 | 2.779E-3 | 11328 | 0.018 |
| Spain | 1351 | 1.999E-2 | 24963 | 0.245 | 367 | 3.966E-3 | -36 | -0.432 | 984 | 1.602E-2 | 25000 | 0.677 |
| Czechia | 440 | 4.055E-3 | 11178 | 0.037 | 328 | 2.032E-3 | 2143 | 0.011 | 112 | 2.023E-3 | 9035 | 0.026 |
| Norway | 463 | 3.350E-3 | 10219 | 0.035 | 318 | 9.260E-4 | 2743 | 0.008 | 145 | 2.424E-3 | 7476 | 0.028 |
| Finland | 433 | 3.621E-3 | 21188 | 0.021 | 246 | 7.970E-4 | 16012 | -0.008 | 187 | 2.824E-3 | 5176 | 0.029 |
| Italy | 1372 | 1.997E-2 | 23629 | 0.248 | 243 | 1.575E-2 | 13181 | 0.244 | 1129 | 4.221E-3 | 10448 | 0.004 |
| France | 1187 | 2.000E-2 | 24999 | 0.260 | 170 | 1.360E-2 | 14090 | 0.007 | 1017 | 6.402E-3 | 10909 | 0.253 |
| Poland | 224 | 1.090E-2 | 17136 | 0.031 | 130 | 8.497E-3 | 7016 | 0.017 | 94 | 2.400E-3 | 10119 | 0.014 |
| Ecuador | 612 | 1.729E-2 | 9244 | 0.048 | 109 | 1.467E-2 | 851 | 0.046 | 503 | 2.614E-3 | 8394 | 0.002 |
| India | 440 | 1.992E-2 | 9565 | 0.273 | 107 | -6.300E-5 | -4253 | -0.413 | 333 | 1.998E-2 | 13818 | 0.686 |
| Romania | 211 | 1.123E-2 | 11148 | 0.020 | 103 | 8.614E-3 | 1798 | 0.015 | 108 | 2.618E-3 | 9350 | 0.006 |
| Serbia | 224 | 4.307E-3 | 9561 | 0.049 | 88 | 2.186E-3 | 1769 | 0.017 | 136 | 2.121E-3 | 7791 | 0.032 |
| Netherlands | 826 | 1.904E-2 | 9209 | 0.053 | 68 | 1.649E-2 | -9550 | 0.047 | 758 | 2.556E-3 | 18759 | 0.006 |
| Belgium | 925 | 1.940E-2 | 9534 | 0.085 | 65 | 1.676E-2 | -5819 | 0.085 | 861 | 2.642E-3 | 15353 | 0.000 |
| Hungary | 509 | 4.353E-3 | 11365 | 0.000 | 64 | 2.311E-3 | 5199 | 0.000 | 444 | 2.042E-3 | 6166 | 0.000 |
| Mexico | 505 | 1.989E-2 | 1182 | 0.429 | 62 | 1.576E-2 | -11147 | 0.423 | 443 | 4.132E-3 | 12329 | 0.005 |
| Greece | 295 | 2.616E-3 | 14453 | 0.012 | 52 | 6.080E-4 | 9414 | -0.007 | 243 | 2.008E-3 | 5038 | 0.019 |
| Japan | 296 | 5.460E-3 | 10032 | 0.033 | 50 | 3.222E-3 | 1366 | 0.028 | 245 | 2.238E-3 | 8666 | 0.005 |
| Kuwait | 179 | 5.828E-3 | 8510 | 0.077 | 28 | 3.393E-3 | -1423 | 0.057 | 151 | 2.435E-3 | 9933 | 0.020 |
| Estonia | 147 | 2.049E-3 | 11601 | 0.018 | 15 | -4.750E-4 | 9847 | -0.020 | 132 | 2.524E-3 | 1754 | 0.038 |
| Slovenia | 102 | 2.062E-3 | 7852 | 0.012 | 13 | -2.350E-4 | 5081 | -0.001 | 90 | 2.297E-3 | 2771 | 0.013 |
| North_Macedonia | 96 | 3.950E-3 | 2199 | 0.008 | 5 | 1.632E-3 | -382 | 0.006 | 91 | 2.318E-3 | 2581 | 0.002 |
| Kazakhstan | 139 | 4.966E-3 | 8483 | 0.061 | -25 | 1.248E-3 | 6098 | -0.076 | 164 | 3.718E-3 | 2385 | 0.136 |
| Croatia | 99 | 2.481E-3 | 9147 | 0.020 | -43 | 4.630E-4 | 6882 | -0.007 | 141 | 2.018E-3 | 2265 | 0.027 |
| Portugal | 230 | 1.295E-2 | 8880 | 0.043 | -84 | 9.649E-3 | -1535 | 0.031 | 313 | 3.303E-3 | 10415 | 0.012 |
| Senegal | 52 | 4.029E-3 | 9067 | 0.007 | -130 | 1.562E-3 | 7457 | -0.004 | 182 | 2.467E-3 | 1609 | 0.011 |
| Switzerland | 127 | 2.000E-2 | 10107 | 0.030 | -134 | 1.705E-2 | -9570 | 0.021 | 261 | 2.946E-3 | 19677 | 0.009 |
| Ireland | 249 | 1.999E-2 | 12007 | 0.020 | -176 | 1.774E-2 | -3073 | 0.020 | 425 | 2.251E-3 | 15080 | 0.000 |
| Lithuania | 78 | 2.083E-3 | 11230 | 0.014 | -410 | -6.810E-4 | 9585 | -0.448 | 488 | 2.764E-3 | 1645 | 0.461 |

Figure 2: All country statistics

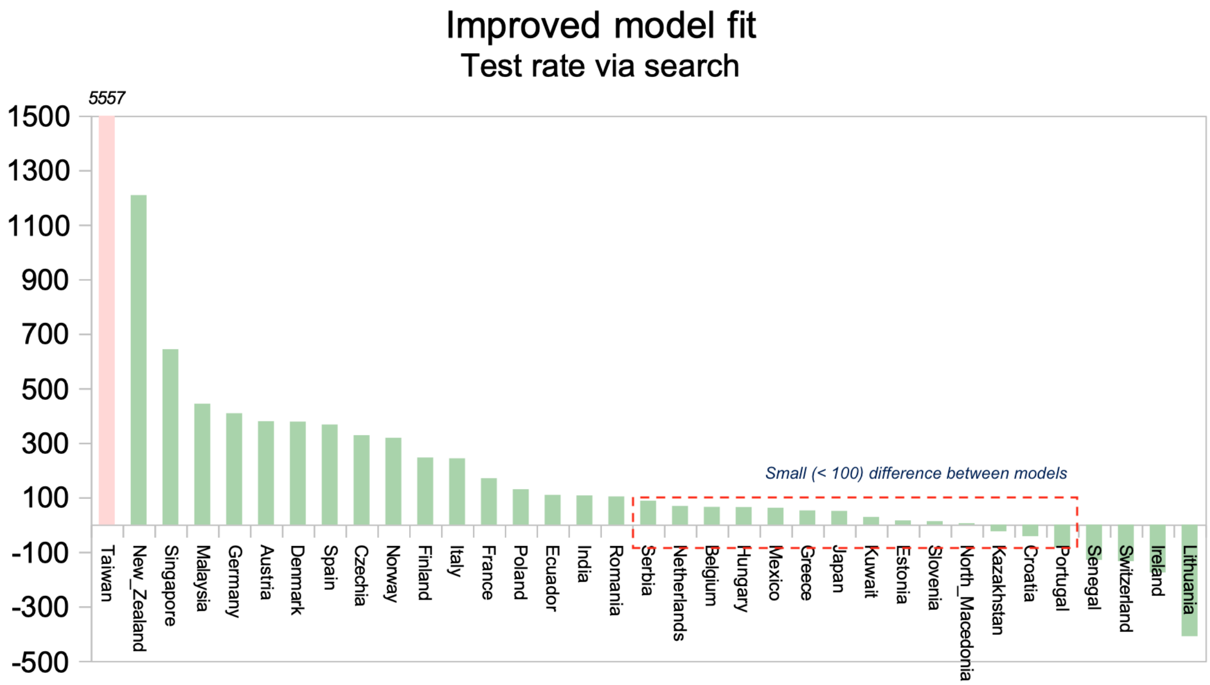


Figure 3: Improved fit

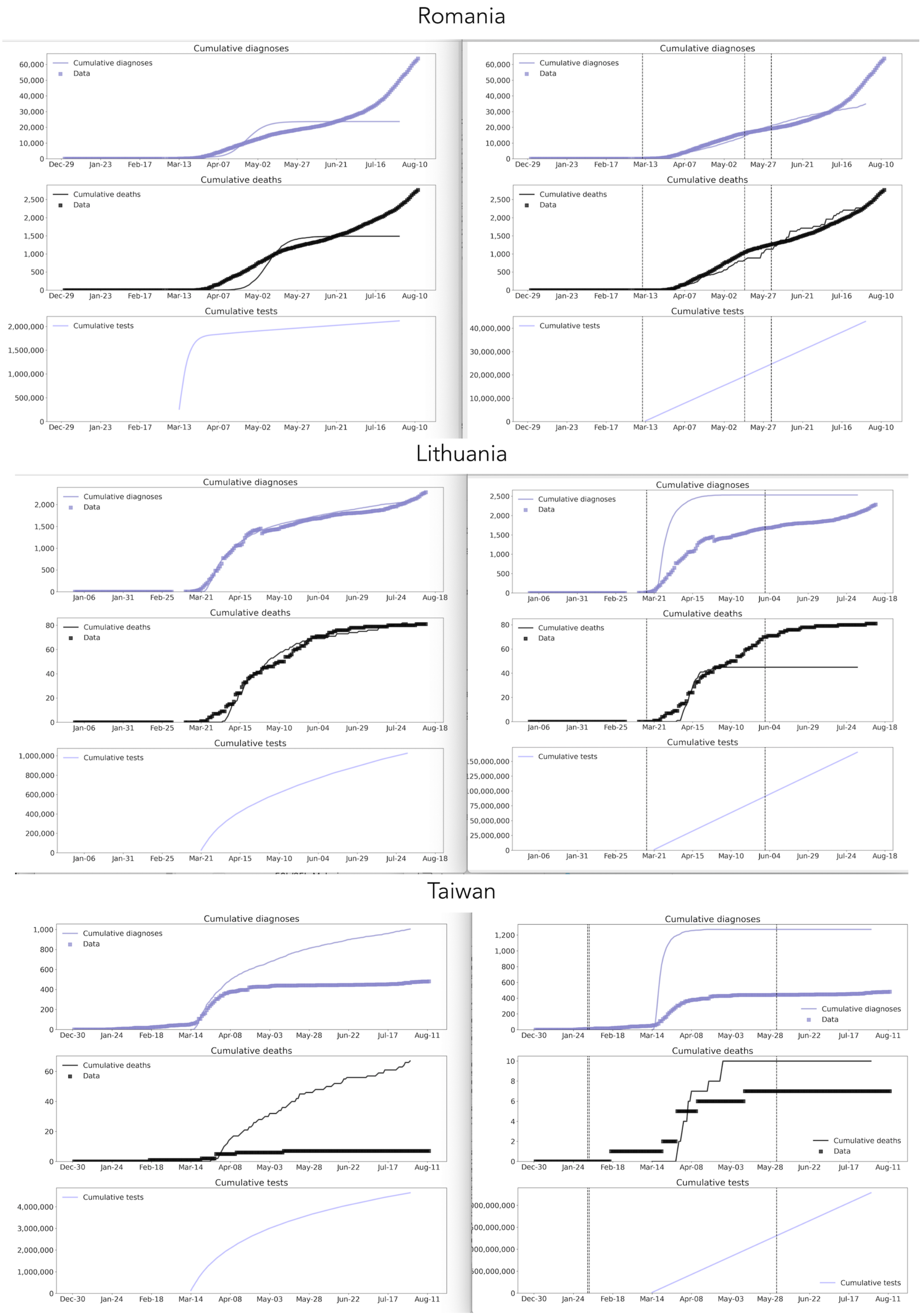


Figure 4: Other countries

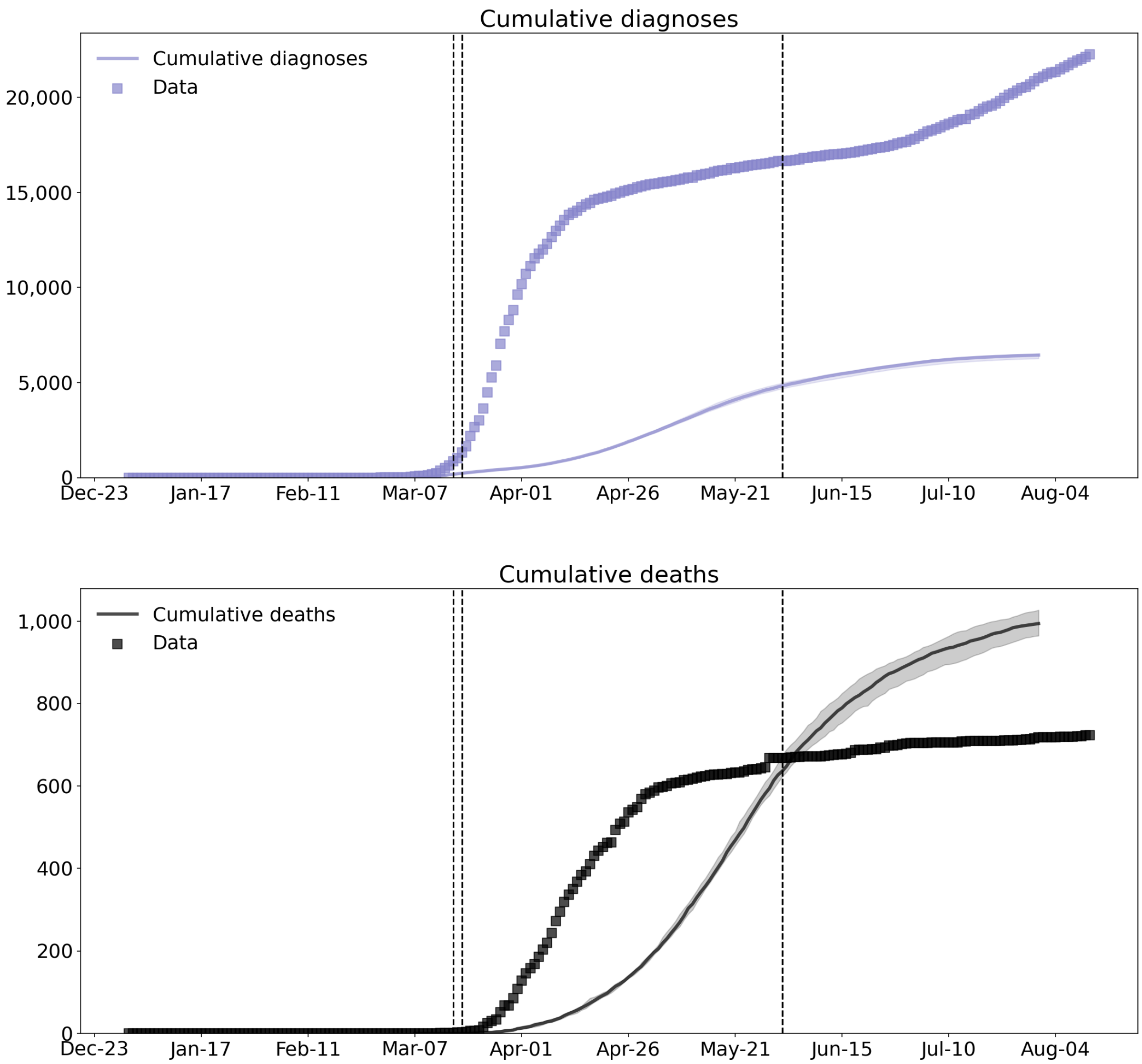


Figure 5: Stochastic replication

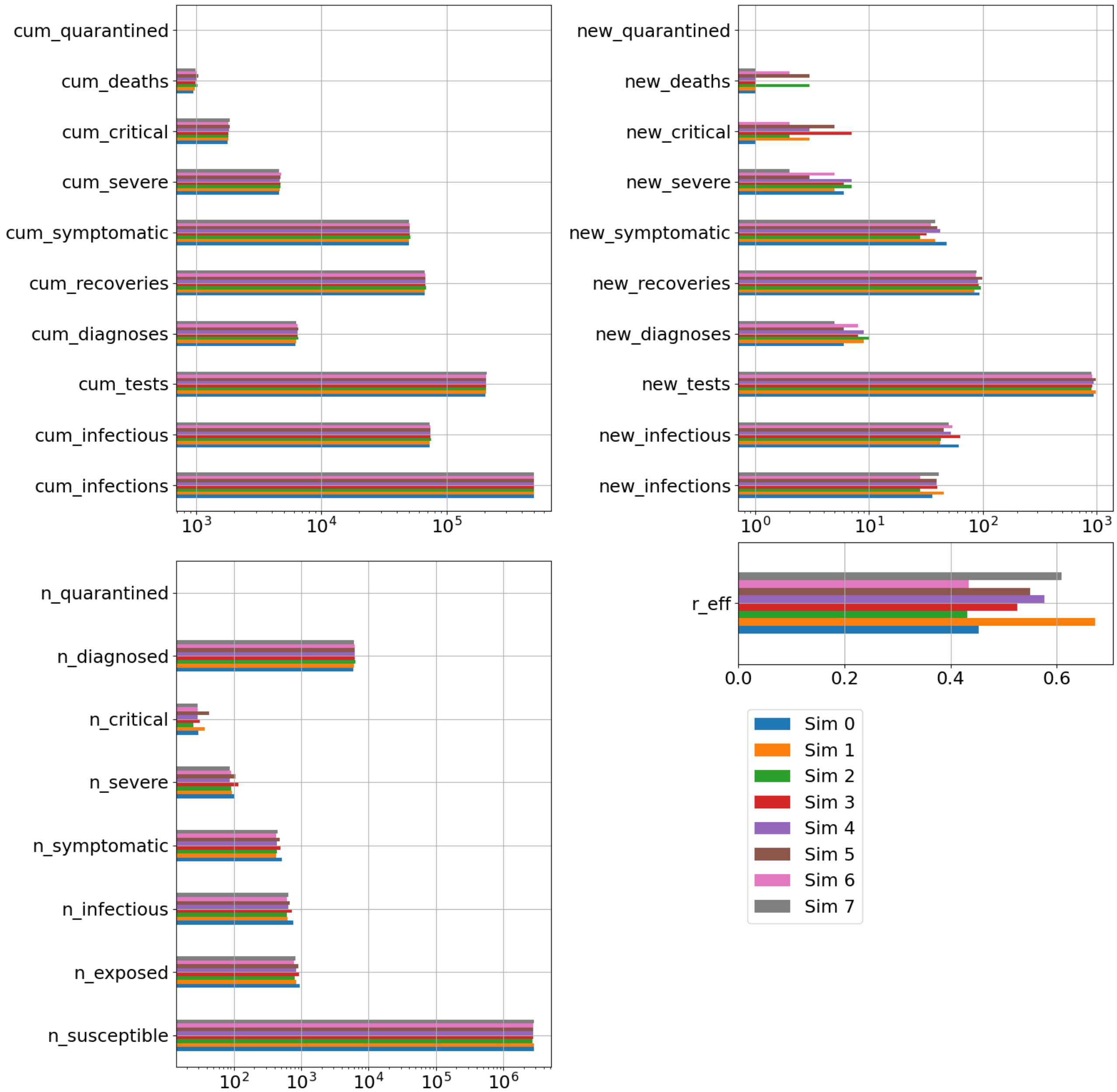


Figure 6: Comparing stochastic results

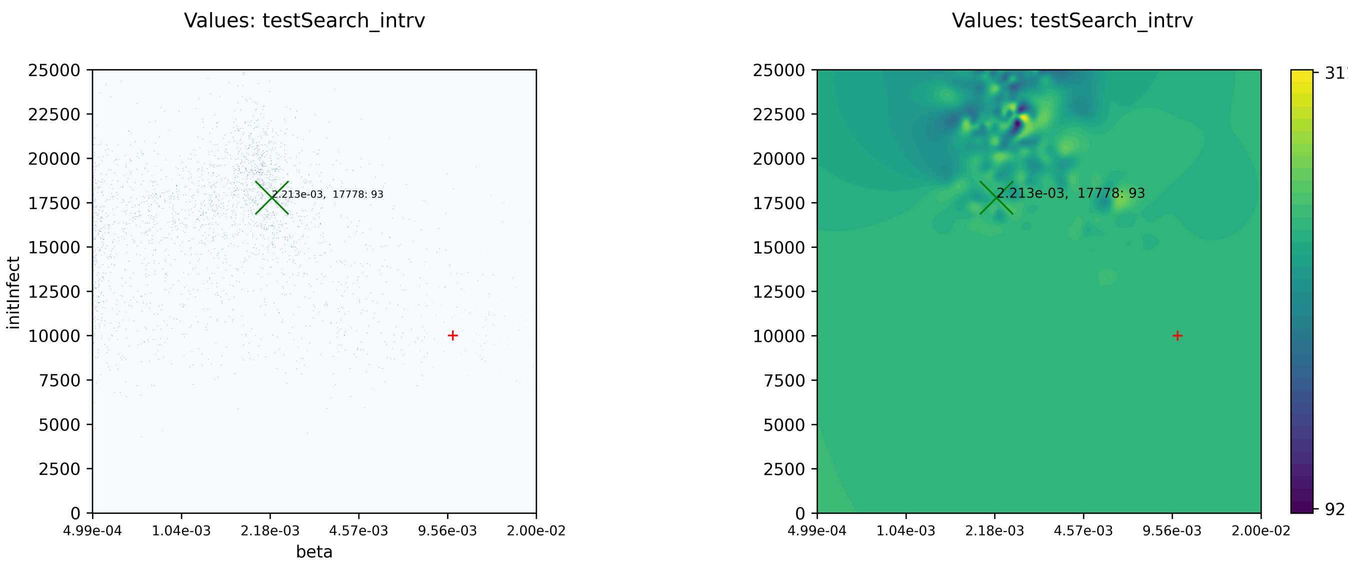


Figure 7: Value surface

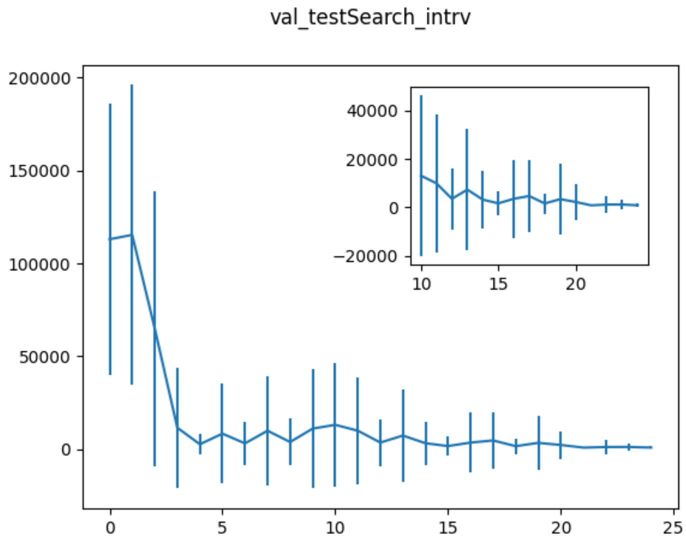


Figure 8: Value convergence

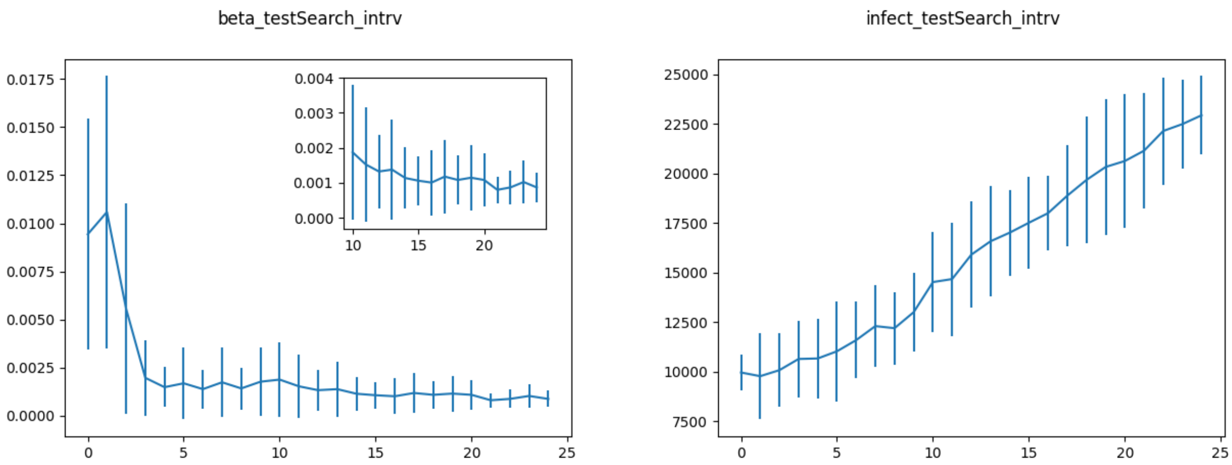


Figure 9: Parameter convergence

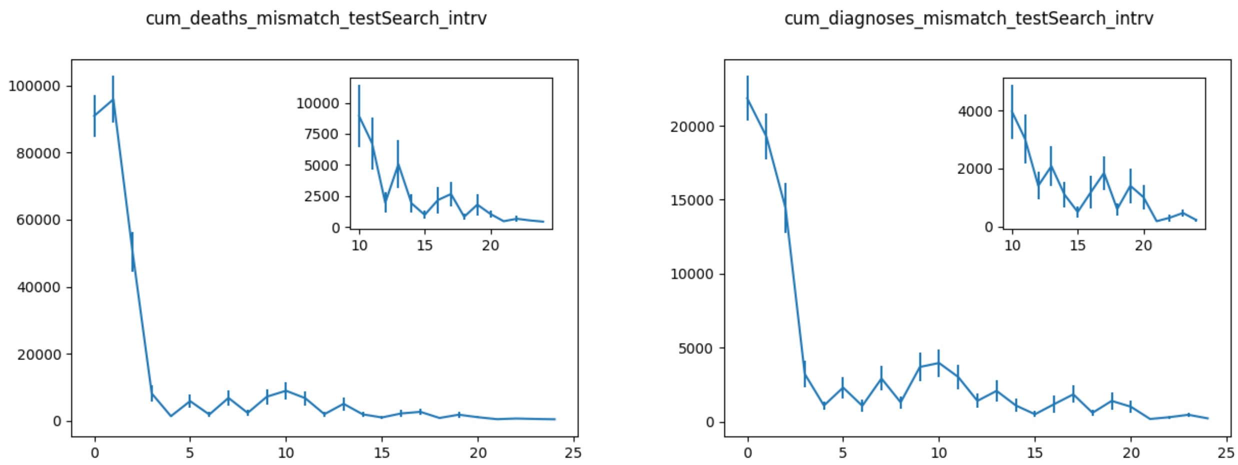


Figure 10: Independent deaths and diagnoses

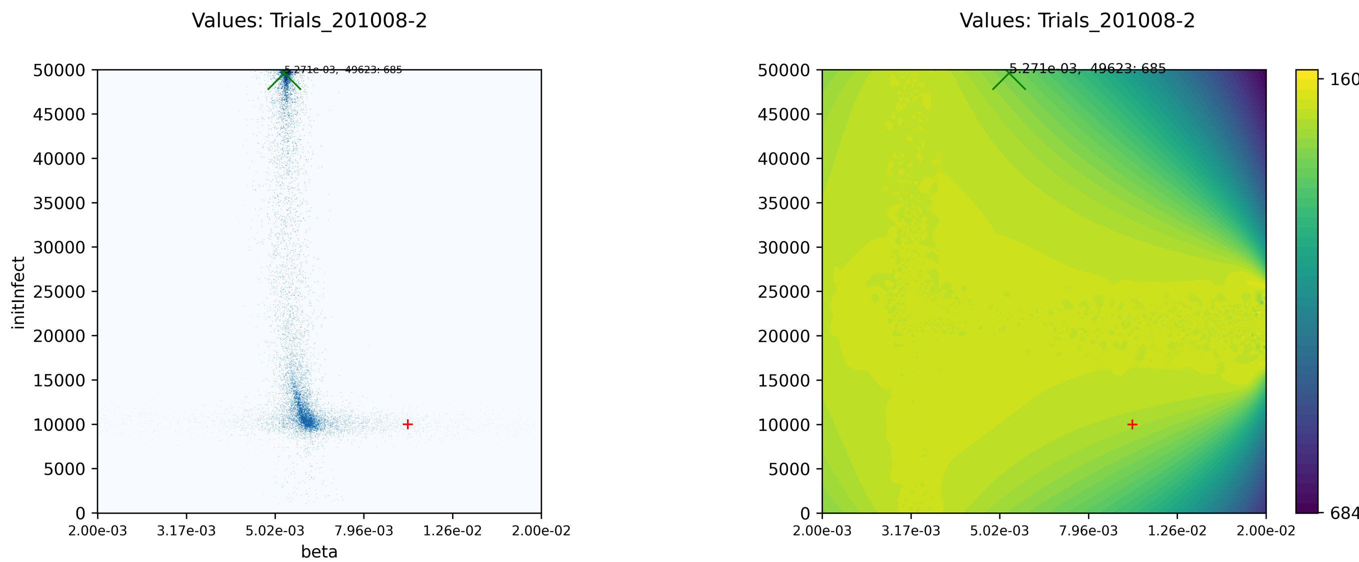


Figure 11: Values across larger bounded region

| Country | Test DATA Value | Test SEARCH Value | Testing rate (via search) | valDiff |
|---|---|---|---|---|
| Austria | 820 | 58 | 0.030 | 762 |
| Belgium | 1374 | 861 | 0.000 | 513 |
| Croatia | 171 | 141 | 0.027 | 30 |
| Czechia | 611 | 112 | 0.026 | 499 |
| Denmark | 656 | 85 | 0.018 | 572 |
| Ecuador | 845 | 503 | 0.002 | 342 |
| Estonia | 218 | 132 | 0.038 | 86 |
| Finland | 587 | 187 | 0.029 | 399 |
| France | 1496 | 1017 | 0.253 | 479 |
| Germany | 1331 | 665 | 0.016 | 666 |
| Greece | 361 | 243 | 0.019 | 118 |
| Hungary | 500 | 444 | 0.000 | 56 |
| India | 495 | 333 | 0.686 | 162 |
| Ireland | 634 | 425 | 0.000 | 210 |
| Italy | 1636 | 1129 | 0.004 | 507 |
| Japan | 553 | 245 | 0.005 | 308 |
| Kazakhstan | 220 | 164 | 0.136 | 56 |
| Kuwait | 296 | 151 | 0.020 | 145 |
| Lithuania | 505 | 488 | 0.461 | 17 |
| Malaysia | 863 | 139 | 0.031 | 724 |
| Mexico | 623 | 443 | 0.005 | 180 |
| Netherlands | 1271 | 758 | 0.006 | 513 |
| New_Zealand | 1838 | 75 | 0.063 | 1763 |
| North_Macedonia | 275 | 91 | 0.002 | 184 |
| Norway | 642 | 145 | 0.028 | 497 |
| Poland | 477 | 94 | 0.014 | 383 |
| Portugal | 482 | 313 | 0.012 | 169 |
| Romania | 408 | 108 | 0.006 | 300 |
| Senegal | 300 | 182 | 0.011 | 118 |
| Serbia | 382 | 136 | 0.032 | 245 |
| Singapore | 1458 | 615 | 0.247 | 844 |
| Slovenia | 303 | 90 | 0.013 | 214 |
| Spain | 1570 | 984 | 0.677 | 586 |
| Switzerland | 596 | 261 | 0.009 | 334 |
| Taiwan | 6539 | 1272 | 0.687 | 5268 |

Figure 12: Testing rate via search vs. data

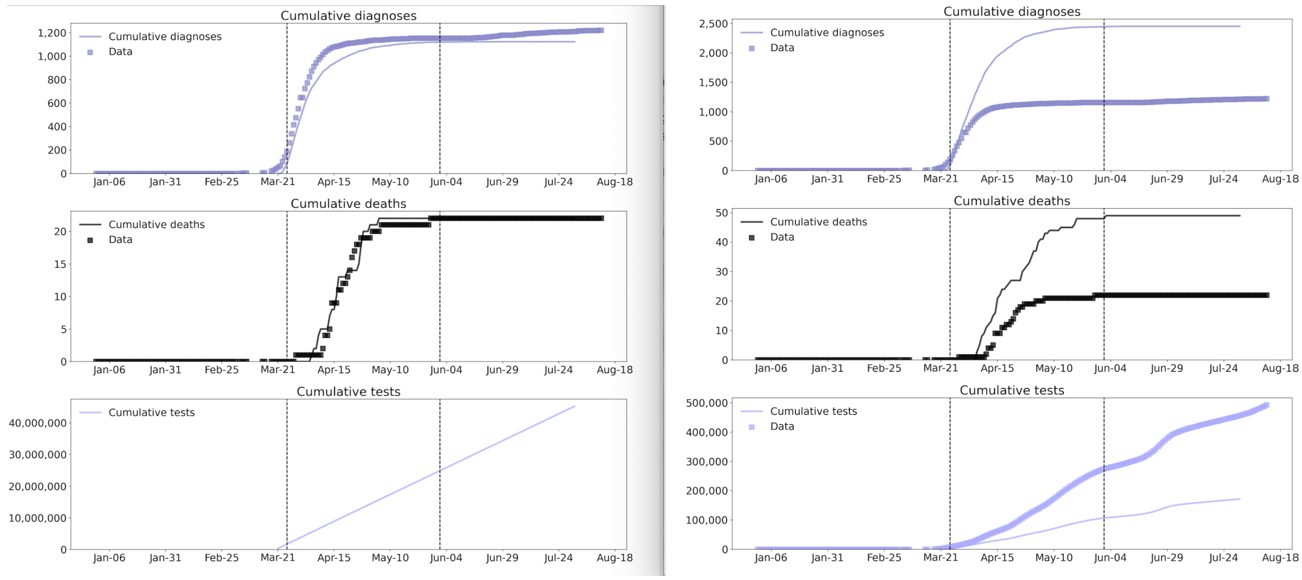


Figure 13: Testing search vs. data in New Zealand

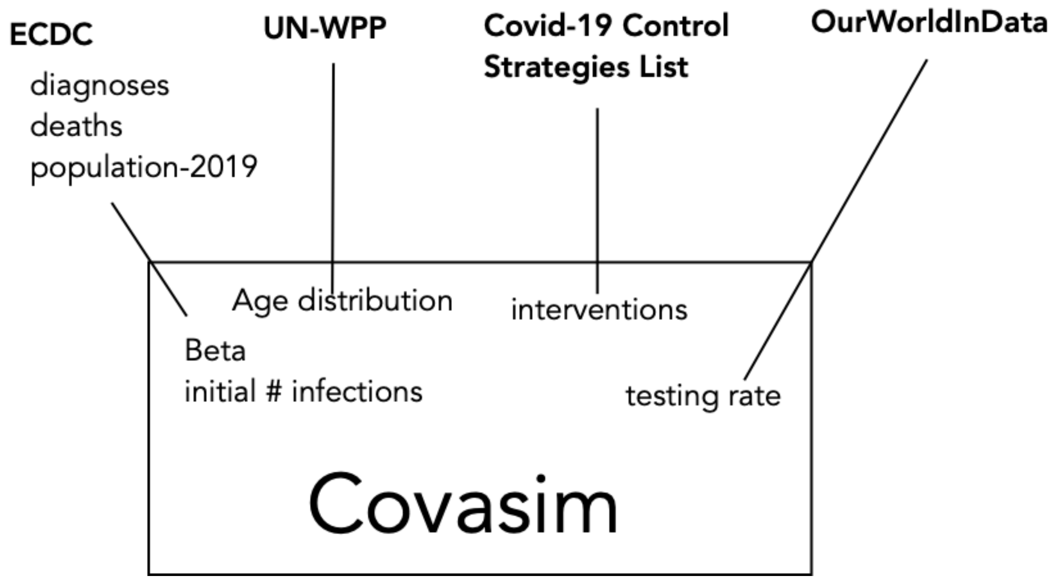


Figure 14: Data sources

| CName | Date | Levels | CName | Date | Levels |
|---|---|---|---|---|---|
| Albania | 03/08/20 | k, p, s, u | Italy | 03/05/20 | k, p, s, u |
| Austria | 03/16/20 | u | Japan | 03/02/20 | p, s |
| Austria | 03/18/20 | k, p, s | Kazakhstan | 04/06/20 | p, s |
| Belgium | 03/13/20 | p, s | Kuwait | 03/01/20 | k, p, s, u |
| Switzerland | 03/16/20 | k, p, s, u | Lithuania | 03/16/20 | k, p, s, u |
| Czechia | 03/11/20 | u, p, s | Mexico | 03/20/20 | k, p, s, u |
| Czechia | 04/20/20 | u | North_Macedo | 03/10/20 | k, p, s, u |
| Germany | 03/17/20 | k, p, s | Mauritius | 03/18/20 | k, p, s, u |
| Denmark | 03/13/20 | u, s | Malaysia | 03/18/20 | k, p, s, u |
| Denmark | 03/16/20 | k, p | Netherlands | 03/16/20 | k, p, s |
| Ecuador | 03/13/20 | p, s | Norway | 03/12/20 | u, p, s |
| Ecuador | 03/14/20 | u | New_Zealand | 03/25/20 | k, p, s, u |
| Spain | 03/17/20 | k, p, s, u | Poland | 03/11/20 | k, p, s, u |
| Estonia | 03/16/20 | k, p, s, u | Portugal | 03/12/20 | k, p, s, u |
| Finland | 03/18/20 | u, p, s | Romania | 03/11/20 | k, p, s |
| France | 03/16/20 | u, p, k, s | Romania | 05/15/20 | u |
| Ghana | 03/16/20 | k, p, s, u | Senegal | 03/16/20 | k, p, s, u |
| Greece | 03/10/20 | k, p, s, u | Singapore | 04/08/20 | k, p, s |
| Honduras | 03/12/20 | k, p, s, u | El_Salvador | 03/11/20 | k, p, s, u |
| Croatia | 03/13/20 | k, p, s, u | Serbia | 03/15/20 | k, p, s, u |
| Hungary | 03/12/20 | u | Slovakia | 03/12/20 | k, p, s, u |
| Hungary | 03/16/20 | p, s | Syria | 03/14/20 | k, p, s, u |
| India | 03/16/20 | k, p, s, u | Taiwan | 02/02/20 | k, p, s |
| Ireland | 03/12/20 | k, p, s, u | Taiwan | 02/03/20 | u |

Figure 15: Intervention dates and educational levels

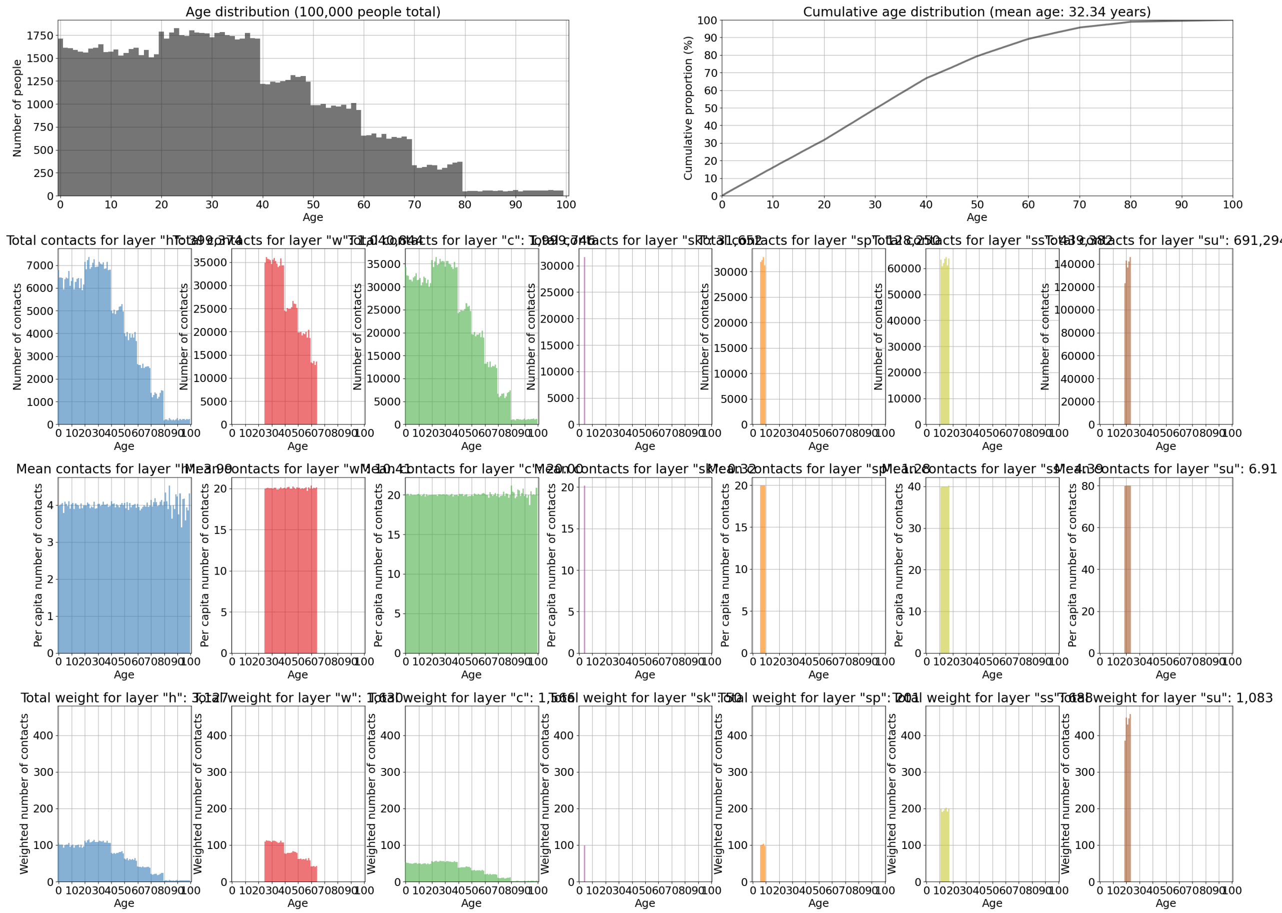


Figure 16: Population age distribution