GRATTAN Institute

Modelling COVID-19 in a partially-vaccinated Australia

Technical supplement to *Race to 80: our best shot at living with COVID*

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1 The `covidReff` model

The `covidReff` model is an R package used to simulate Covid transmission in a population based on an input effective reproduction number, vaccination rate and effectiveness inputs, population characteristics, and other factors (described in Section 1.4). The package is open source, publicly hosted on Github, and can be found at Mackey and Parsonage (2021).[1]

What the model does

This model uses individual agents – one for each of the resident of the Australian population – to simulate the spread of Covid within a partially vaccinated population.

It uses population demographics of Australia, virus characteristics of the Delta variant and age-based hospitalisation and ICU rates from more than a year of COVID data from Australian ICU units.[2] The model assumes that kids under the age of 16 are less likely to get and transmit COVID.[3]

The simulation process is described in full from Section 1.1 onwards.

What the model does not do

Unlike other agent-based models developed by The University of Melbourne, the Burnet Institute, the University of Sydney, or past models developed by Grattan Institute, this model does not focus on agents' activity or behaviour. It takes transmission without vaccines as an *input* rather than exploring the effect of a reduction in agents' movement or activity on transmission.

Social networks are not explicitlymodelled. The model uses one big interconnected 'network'. This simplification may slightly overestimate the speed with which COVID spreads throughout communities.

Random variables are used to determine individual infection, hospitalisation and ICU need and length of stay, and death. But the dispersion of infectiousness – including super spreader events – are not explicitly modelled.[4] The average infectiousness, described through the input variable `R`, is sufficient for an analysis that uses repeated introductions of Covid infections. Where there are a small number of starting Covid infections, networks and the 'dispersion' of Covid infectiousness are important: some infections can peter out despite high average `R`. But this becomes less likely, and less important, in a simulation that introduces hundreds of cases.

1.1 Iteration `i=0`: starting conditions

Recent Australian population estimates by age are pulled from ABS *National, state and territory population*.[5] The population is then 'uncounted' by age, leaving one row of data per person, with one variable showing their single-digit age.[6]

This population is then scaled down (or up) proportionally by age to the `n_population` variable to create an `aus` dataset that contains `n_population` rows and `1` variable showing each individual's age.

1. The `covidReff` package and post simulation analysis was performed in R: R Core Team (2020); using packages from the `tidyverse`: Wickham (2021); and functions from `data.table`: Dowle and Srinivasan (2021); `magrittr`: Bache and Wickham (2020); and `dqrng`: Stubner (2021).
2. See Table 1.1 on page 8.
3. Danchin et al (2021); and Koirala et al (2021).
4. They are, however, a result of randomness in the model. See Figure 1.4.
5. Table 59 of ABS Cat. 3101.0, accessed using the `readabs` package: Cowgill et al (2020).
6. Given the strong correlation between age and morbidity, this granular level of age detail is necessary.

A proportion of the population is then **fully vaccinated** (having already received two doses) according to the conditions set out in `vaccination_levels`. A person's age is matched with their likelihood of already being vaccinated, and if a random draw is below that level, the person is vaccinated.[7]

For each vaccinated person, a **vaccine type** is generated using their age and the parameters set out in `over60_az_share` and `under60_az_share`. For example, if `over60_az_share = 0.8`, then 80 per cent of the already-vaccinated population over the age of 60 would have an AstraZeneca (AZ) vaccine, and 20 per cent would have a Pfizer (Pf) vaccine.[8]

For each fully-vaccinated person by vaccine type, the implied number of people with only a **first dose** of that vaccine is calculated. This number is based on time between first and second dose for each vaccine (90 days for AZ, 21 days for Pf) and the recent growth rates by vaccine type; i.e. how many people in the past `X` days would have had their first shot. For each person starting the simulation with only a first dose of a vaccine, the days since their first dose is also generated based on their vaccine type.

A number of new infections are then introduced. The `n_start_infected` parameter causes people to be infected. Some of the initially infected are vaccinated, and some are not (reflective of the starting vaccination level).

7. The process `runif(.N) <= .get_vaccination_level(...)` is run over the entire population.
8. Only the AstraZeneca and Pfizer vaccines are explored in this simulation because of both data availability against the Delta strain and Australia's short-term future vaccine supply. A study by the European Centre for Disease Prevention and Control (July 2021) strongly suggest that future supply of Moderna will have similarly effectiveness against infection. However, these parameters should evolve as necessary.

Finishing the initial population construction gives a dataset with `n_population` rows and a number of variables indicating age, vaccination status and type, and days since first dose. Some of this population are infected, and (potentially) spread the virus to others in the next iteration.

1.2 Iteration `i=1`: first round of subsequent infections

The first iteration is on 'day' `iteration * serial_interval` (e.g. `1 * 5` if the serial interval is 5 days), and starts with the `aus` dataset created in iteration zero described above.

1.2.1 Vaccinate more people

The first step is updating people's vaccines:

- People with a first dose get their time progressed (`days_since_first_dose := days_since_first_dose + serial_interval`).
- People with a first dose whose days are above their second-dose waiting period are converted to 'fully vaccinated'.
- The number of newly first-dose vaccinated people is then calculated with a logistic curve with a growth parameter of `vaccination_growth_steepness`.[9]
- Each newly vaccinated person is given a type of vaccine and the characteristics that come with it – either a mix of AZ and Pf, or just Pf (`only_pfizer_after_opening = TRUE`).

9. `vaccination_growth_steepness` defines how quickly additional people are vaccinated after opening, defaulting to 0.01. This is the growth parameter (`c`) in the logistic curve `M/(1+((M-n0)/n0)*exp(-c*t))`, where `n0` is the starting vaccination level defined by \c{vaccination_levels}.

1.2.2 Infect more people

The number of previous 'newly infected' (in the last iteration) people along with the `R` parameter are used to work out the number of people that *would be infected without vaccines*. The number of previously newly infected is split by vaccinated and unvaccinated because vaccinated infectious people are less likely to *transmit* the virus (described in the `vac_transmission_rate` parameter). The number of 'maybe infected' (i.e. the number of infected if it weren't for vaccine protection) is generated with:

```
n_maybe_infected = R * (n_infected_and_vaccinated *
vac_transmission_rate) + (n_infected_and_unvaccinated)
```

A number `n_maybe_infected` of the `aus` population are then 'exposed' to these infections. Whether they become infected depends on:

- if a contact has already been infected, they are not infected; otherwise
- if a contact has one or two dose vaccine, they are infected if the random number drawn for them is more than their vaccine protection;[10] otherwise
- if a contact is not already infected or vaccinated, they become infected.

Those who are newly infected in the process above are labelled as `newly_infected = TRUE`.

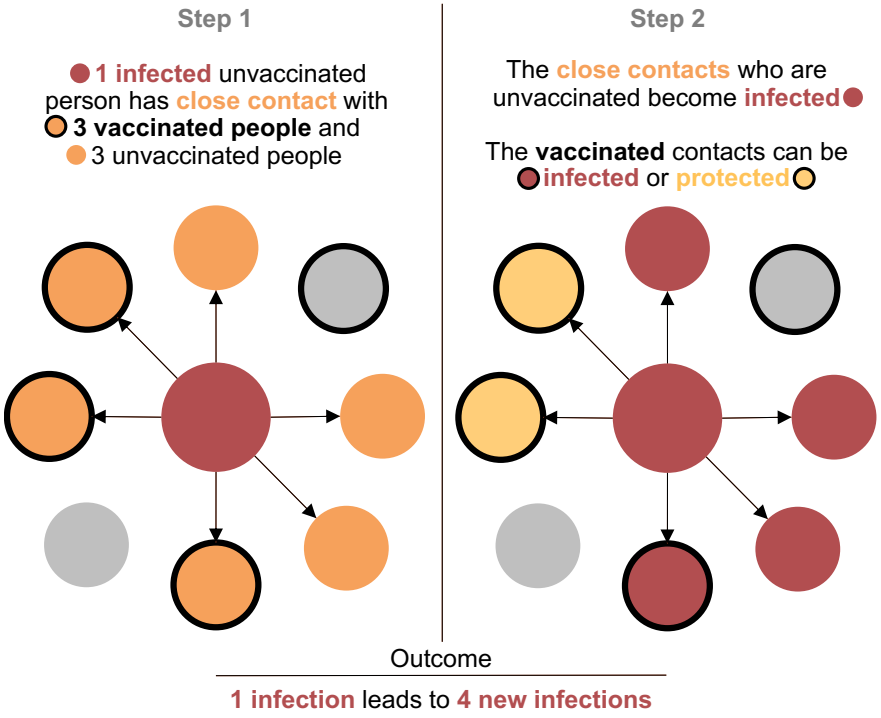
This process is described in the schematics in Figures 1.1, 1.2, 1.3, and 1.4.

10. For example, if a person has two doses of the Pfizer vaccine, they have 0.85 protection. This process would randomly generate a number between 0 and 1, and if it was **less than** than 0.85, the person would be protect If the number was greater than their protection level, the person would become infected.

Figure 1.1: Infection steps: unvaccinated index case

Scenario: A variant with an R of 6. Vaccine offers 88% protection against infection and, if infected, a 50% reduction in transmissibility. 50% of the population are vaccinated.

An unvaccinated person has become infected.



In this example scenario, the input R is 6 and half the population are vaccinated. Vaccine offers 60 per cent protection against infection and, if infected, a 50 per cent reduction in transmissibility. One unvaccinated

Figure 1.2: Infection steps: vaccinated index case

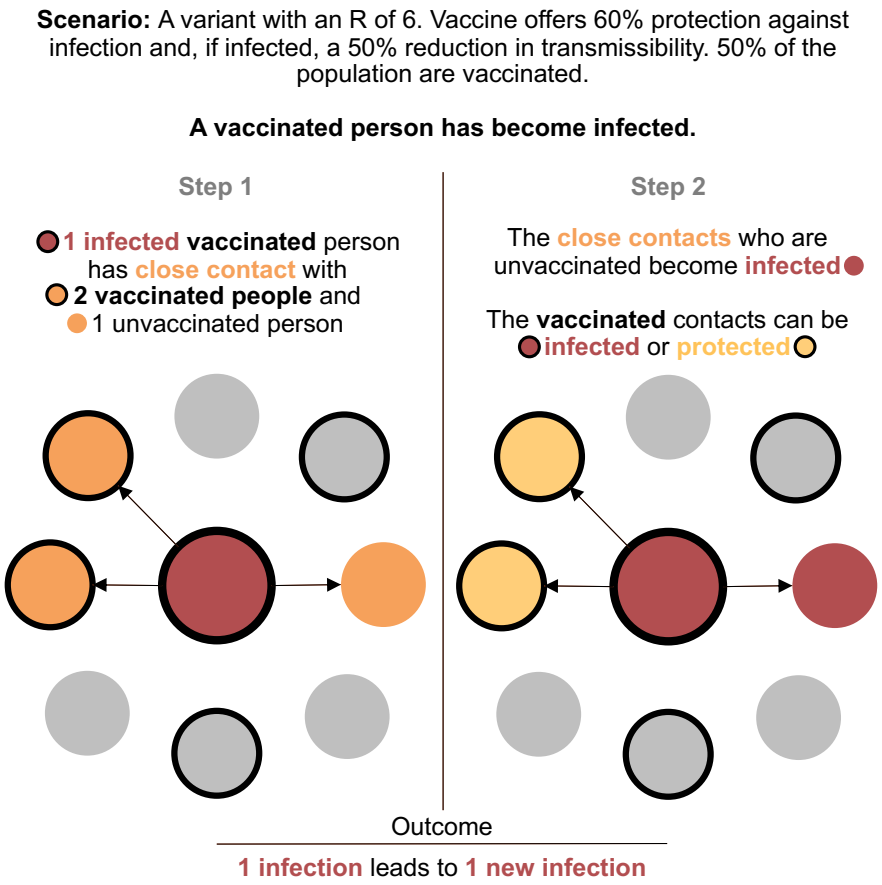
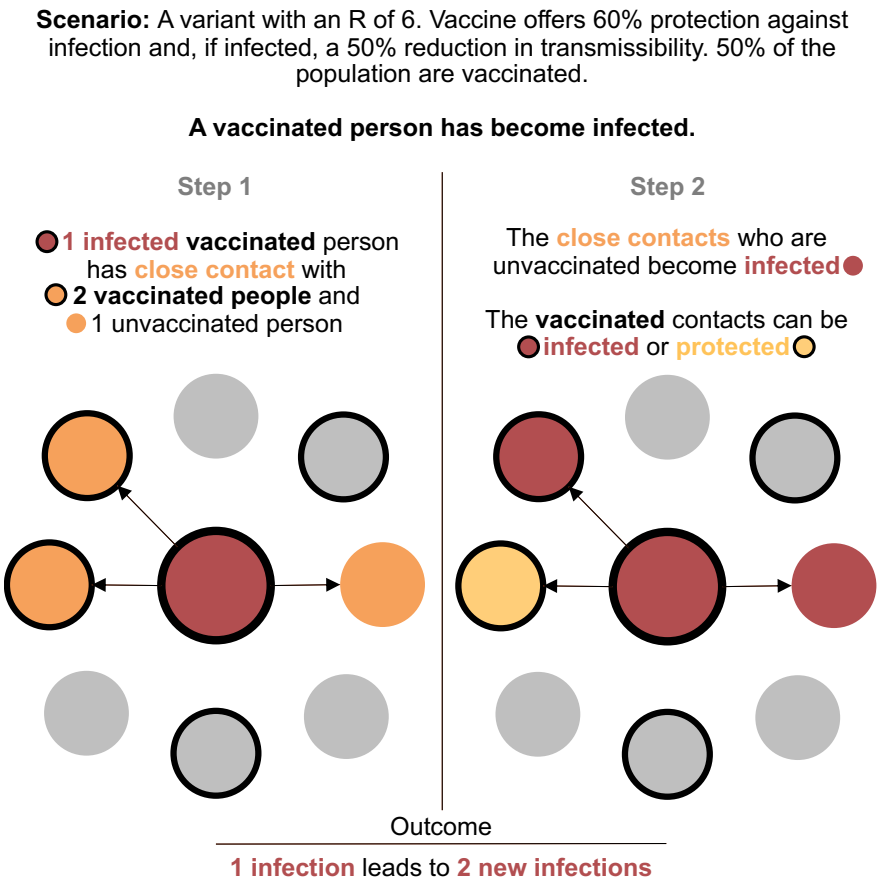


Figure 1.3: Infection steps: vaccinated index case, alternative outcomes



person is infected. They come into close contact[11] with six people, three of whom are vaccinated. The unvaccinated contacts become infected. Each of the vaccinated contacts has a 60 per cent chance of avoiding infection.[12]

1.2.3 Externally introduced cases

Added to the `newly_infected` group above are the daily (scaled by iterations) are Covid cases from external arrivals, determined by `n_daily_introductions`. During each iteration, a random sample of `n_daily_introductions * serial_interval` vaccinated people are infected.

1.2.4 Hospitalisation and ICU

An infected person may require hospitalisation. Of these, a subset may require ICU care. For Covid-19, these likelihoods vary significantly with age.

Unvaccinated hospitalisation and ICU admission rates are derived from data collected during Covid outbreaks in Australia to May, 2021, shown in Table 1.1.

On a number of measures, results demonstrate significant improvements in outcome compared with earlier (first wave) data. These outcomes are assumed to continue through 2022 and beyond.

Length of stay

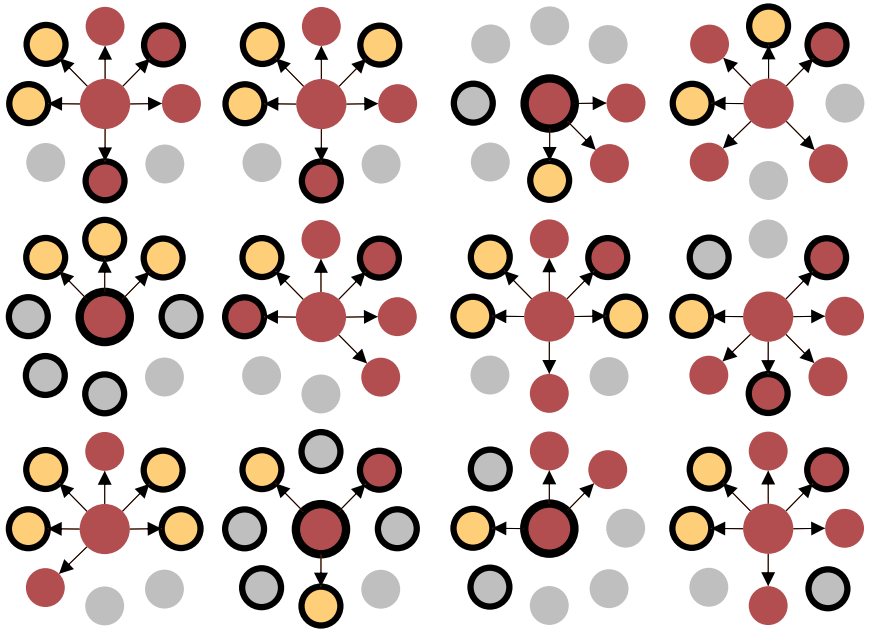
The model uses length-of-stay distributions based on SPRINT-SARI data which are shown in Table 1.2.

11. 'Close contact' is shorthand here for 'people that would have been infected if it were not for vaccine protection'.
12. In the model, each vaccinated person has a vaccine type – AstraZeneca or Pfizer – with infection, hospitalisation and death protection characteristics. See Section 1.4.

Figure 1.4: Second iteration

Scenario: A variant with an R of 6. Vaccine offers 60% protection against infection and, if infected, a 50% reduction in transmissibility. 50% of the population are vaccinated.

12 people are infected.



Outcome

12 infections lead to **35 new infections,** R_{eff} = 2.9

Ventilation days represents the average duration of mechanical (invasive) ventilation; the process of supporting a sedated, intubated patient with a ventilator. Invasive ventilation is resource-intensive in that these patients require 1:1 nursing supervision and will generally have a longer ICU stay. The use of less invasive breathing support (in the form of high flow oxygen and non-invasive ventilation) increased during the second wave, in part contributing to shortening lengths of ICU stay.

These elements determine the lengths of stay and resource requirements of hospitalised patients. Hospital length of stay will include ICU time (patients are rarely discharged home directly from ICU and rather will usually recover on the ward). Median (and IQR) are appropriate given wide variance in length of ICU stay (some admissions will be prolonged – greater than two weeks).

An agent of the model who requires hospitalisation and/or ICU (determined by vaccination status and the pre-vaccination age rates shown in Table 1.1) will have a length of stay drawn from the distributions in Table 1.2. Half of ICU patients will require mechanical ventilation, which adds between 4 and 17 days to their ICU stay.

ICU capacity

Australian ICU capacity is described in Litton et al (2020). There are 191 ICUs in Australia, with baseline activity capacity of 2,378 beds. Surveyed capacity of 175 ICUs suggest maximal surge would add an additional 4,258 beds, meaning total surge capacity of about 6,600 beds.

However, limitations of total ventilator capacity – about 5,000 – and both nursing and medical workforce shortfalls mean that this 'surge' capacity would require substantial reallocation of resources. Additional

Table 1.1: Number of COVID cases, hospitalisations, and people admitted to ICU by age in Australia to May 2021

Age	Cases	Hospitalisations		ICU admissions		Death	
	n	n	%	n	%	n	%
0-9	1,486	42	2.9	3	0.2	0	0.00
10-19	2,390	32	1.4	4	0.2	0	0.00
20-29	5,990	173	3.0	20	0.3	1	0.02
30-39	4,719	211	4.7	35	0.7	2	0.05
40-49	3,409	264	8.1	50	1.5	1	0.03
50-59	3,011	374	12.8	107	3.6	15	0.53
60-69	2,008	432	22.1	115	5.7	34	1.82
70-79	1,344	511	38.9	104	7.7	148	11.7
80-89	1,230	652	53.6	33	2.7	374	31.0
90+	783	356	46.2	2	0.2	315	40.5

Notes: Data only included from four states and territories with the most reliable data across both hospital and ICU fields: ACT, NSW, Tasmania and Victoria.

Source: National Notifiable Diseases Surveillance System (2021).

Table 1.2: Length of stay distributions

	25th percentile	Median	75th percentile
Hospital length of stay, days	8.6	14.2	21.1
ICU length of stay, days	2.4	5.9	11.1
Ventilation, days	4.0	8.0	17.0

Source: SPRINT-SARI Australia Project. See https://www.anzics.com.au/current-active-endorsed-research/sprint-sari/.

facilities would be required, as was carefully planned out the outbreak of the pandemic in Australia.[13]

1.2.5 Deaths

Whether each person in the newly infected group (eventually) dies is then determined using an age-wise infection fatality ratio shown in Section 1.4.1.[14]

The `covid_age_death_prob` function also includes a 20 per cent reduction in the death rate to reflect improvements in treatment for COVID patients since early-mid 2020,[15] and implement a fatality rate cap of 40 per cent0.[16]

1.2.6 Summary

When an iteration of vaccinations, infections and deaths is finished, the following results are summarised and stored (see Section 1.5.)

- `iteration`
- `new_maybe_infected_i`
- `new_cases_i`
- `new_local_cases_i`
- `new_os_cases_i`
- `new_cases_vaccinated2_i`
- `new_dead_i`
- `new_dead_vaccinated2_i`
- `new_vaccinated_i`
- `total_vaccinated1_i`
- `total_vaccinated2_i`
- `total_pf_i`
- `total_az_i`

The summary table is then appended to previous iterations of results, and the `aus` dataset moves onto the next iteration.

1.3 Iterations `i = 2, i = 3, ..., i = n_iterations`

The process described in Section 1.2 is then repeated in the second iteration (see Figure 1.4).

As time (iterations) goes on, there are two major influencers of the: the (new) proportion of the population who are vaccinated, and the proportion who become immune through infection or death.

Once Australia beings to gradually beings to reopens its external borders, it is assumed that external arrivals add to the numbers of residents infected with COVID (the `newly_infected`).

1.4 Default model parameters

The default parameters for the `simulate_covid` function are described below.

1.4.1 Virus characteristics

`R = 5`
The average number of additional people an infected person will

13. See Towell et al (2020) for example.
14. See Levin et al (2020).
15. On discussion with the authors of Levin et al (ibid).
16. See Table 1.1.

infect in an unvaccinated society. It incorporates both the R0 of the variant and behaviours and policies may reduce alter transmission. A single numeric with default 5 to represent the Delta variant in a low-restriction society.[17]

`serial_interval = 5`
The average number of days between a person becoming infected and infecting others. A single numeric with default of 5, appropriate for wild type/Delta variant.[18] A shorter `serial_interval` will speed up the virus spread over time.

`death_rate = ''loglinear''`
The likelihood that an infected unvaccinated person dies by age. Can be a character element `''loglinear''`, the default, which uses the log-linear relationship between age and mortality described in Levin et al (2020):

$$\frac{10^{(-3.27+0.0524\times age)}}{100}$$

This likelihood of death given infection is capped at 40 per cent, equivalent to the risk of a 90+ year old during outbreaks in Australia throughout 2020.[19]

`treatment_death_reduction = 0.2`
The reduction in mortality from treatments. A single numeric with default 0.2 that proportionally reduces `death_rate` values. e.g. with `treatment_death_reduction = 0.2`, a person with a 10 per cent pre-treatment risk of dying from Covid would have an 8 per cent risk with treatment.[20]

17. See Kucharski et al (2021).
18. See Pung et al (2021).
19. National Notifiable Diseases Surveillance System (2021). See Table 1.1.
20. Note that this treatment is applied to all infections, regardless of hospital or ICU capacity or demand. The number of deaths resulting from Covid in scenarios in which ICU capacity is exceeded is therefore underestimated.

`kids_R_reduction` The proportion reduction in transmission of children under the age of 18. A numeric defaulting to `0.2`.

Vaccine characteristics

`vaccination_levels = c(0, 0, 0, 0.5, 0.6, 0.9, 0.9, 0.9, 0.9, 0.9)`
Starting vaccination levels. Either a single numeric for a uniformly distributed population wide vaccination rate, or vector of length 10 representing the vaccination levels for age groups `0-10`, `11-20`, `21-30`, `...`, `91+`.

`vaccination_growth_factor = 0.008`
Defines how quickly additional people are vaccinated after opening. This is the growth parameter (`c`) in the logistic curve `M/(1+((M-n0)/n0)*exp(-c*t))`, where `n0` is the starting vaccination level defined by `vaccination_levels`.

`p_max_vaccinated = 0.9`
Maximum proportion of the population able to be vaccinated. This is the maximum level parameter (`M`) in the logistic curve (as above), where `n0` is the starting vaccination level defined by `vaccination_levels`.

`only_pfizer_after_opening = TRUE`
When the simulation starts, newly vaccinated people only get `TRUE` the Pfizer vaccine (the default), or `FALSE` a mix of Pfizer and AstraZeneca.

`over60_az_share = 0.8`
The proportion of vaccinated people over 60 years old who have the AstraZeneca vaccine. Single numeric defaulting to 0.80. Used for vaccine distribution before the simulation starts and, when `only_pfizer_after_opening = FALSE`, for new vaccines during the simulation.

`under60_az_share = 0.2`
The proportion of vaccinated people 60-years-old and younger who have the AstraZeneca vaccine. Single numeric defaulting to 0.20. Used for vaccine distribution before the simulation starts and, when `only_pfizer_after_opening = FALSE`, for new vaccines during the simulation.

`vac_transmission_reduction = 0.5`
The reduction in the likelihood of transmission from an infected vaccinated person relative to an infected unvaccinated person. A single numeric with default 0.5, representing a 50 per cent reduction in transmission from vaccinated infection people.[21]

In addition, built-in variables control the levels of protection against infection and hospitalisation for both the AstraZeneca and Pfizer vaccines, shown in Table 1.3. Both vaccines are assume to offer a 99 per cent reduction in risk of death against the Delta variant.[22]

Simulation characteristics

`n_population = 26e6`
Population size for each simulation. A single numeric defaulting to 26,000,000 (about the size of the Australian population).

`n_start_infected = 10`
The number of people infected at the beginning of the simulation. Defaults to `100` people infected at day `0`.

`n_daily_introductions = 1`
The number of new infections introduced each day of the simulation.

`n_iterations = 60`
Number of iterations the simulation runs for. A single integer

21. From Harris et al (2021). See Table 1.3.
22. Although this assumption will be updated as more data are collected overseas.

Table 1.3: Both the AstraZeneca and Pfizer vaccines are effective

	Vaccine dose	
	One dose	Two doses
Protection against symptomatic infection		
Reduction in likelihood of developing a symptomatic infection from the Delta variant: Lopez Bernal et al (2021, Table 2).		
AstraZeneca	30% (24-35%)	67% (61-72%)
Pfizer	36% (23-46%)	88% (85-90%)
Reduction in transmissibility		
Reduction in secondary attack rate given infection: Harris et al (2021, Table 1).		
AstraZeneca	48% (38-57%)	–
Pfizer	46% (38-53%)	–
Protection against hospitalisation		
Reduction in likelihood of hospitalisation: European Centre for Disease Prevention and Control (2021, Table 1).		
AstraZeneca	77% (71-82%)	94% (90-99%)
Pfizer	76% (72-79%)	96% (90-99%)

Notes: 95% confidence intervals shown in parentheses. Lopez Bernal et al (2021) adjusts for 'period (calendar week), travel history, race or ethnic group, sex, age, index of multiple deprivation, clinically extremely vulnerable group, region, history of positive test, health or social care worker, and care home residence'. The Harris et al (2021) study was conducted on infections in the UK in January and February 2021, and therefore is assumed to capture the reduction in transmissibility from the Alpha variant which was the dominant variant at the time. The study was only only able to capture the effect of one dose of either AstraZeneca or Pfizer. European Centre for Disease Prevention and Control (2021, Table 2) shows the protection against 'any hospitalisation' seven days after first or second dose. European Centre for Disease Prevention and Control (ibid, Table 3) also shows the limited evidence available for vaccine protection against death, which is between 98 and 99 per cent for pooled analysis of multiple vaccine types.

defaulting to 60. Means that the simulation runs for `serial_interval * n_iterations` days.

`run_simulations = 100`
The number of times the simulation is run. A single integer defaulting to 100.

1.5 Output

The simulation returns a dataset containing one row per scenario, simulation and iteration. For each row, columns provide information on:

`scenario`: The scenario name.

`runid`: The simulation run number.

`iteration`: The iteration of the scenario simulation run.

`day`: Days since beginning of simulation, where `day = iteration * serial_interval`.

`new_maybe_infected_i`: the number of new possible Covid cases in iteration `i` (interpreted as contacts that would become cases without vaccines).

`new_cases_i`: the number of new Covid cases in iteration `i`.

`new_dead_i`: the number of new Covid dead in iteration `i`.

`new_vaccinated_i`: the number of new people fully vaccinated in iteration `i`.

`total_cases_i`: the cumulative number of Covid cases after iteration `i`.

`total_dead_i`: the cumulative number of Covid dead after iteration `i`.

`total_vaccinations_i`: the cumulative number of Covid vaccinations after iteration `i`.

`rt_i`: The average number of new infections in this iteration cased by a case in the previous iteration. Derived with `rt_i = new_local_cases_i / lag(new_cases_i)`.

`in_population`: Input population in the simulation, equal to the `n_population`.

`in_R`: Input `R` value.

`in_vaccination_levels`: Input `vaccination_levels`.

2 Modelled scenarios

12 key scenarios are presented and discussed in Duckett et al (2021). These scenarios vary in their `R` and `vaccination_levels`.[23] In each of the Figures to follow, the values for these parameters along with `n_daily_introductions` and the post-opening growth rate for vaccinations, are displayed in the chart title, with the distribution of vaccine coverage by age shown in the first panel. The values for other parameters are the defaults provided in Section 1.4.

Scenarios presented in the report:

- Figure 2.1 on the next page: R = 4, 50% vaccination rates, 1 new external case per day
- Figure 2.2 on page 15: R = 5, 50% vaccination rates, 1 new external case per day
- Figure 2.3 on page 15: R = 6, 50% vaccination rates, 1 new external case per day
- Figure 2.4 on page 16: R = 4, 70% vaccination rates, 1 new external case per day
- Figure 2.5 on page 16: R = 5, 70% vaccination rates, 1 new external case per day
- Figure 2.6 on page 17: R = 6, 70% vaccination rates, 1 new external case per day
- Figure 2.7 on page 17: R = 4, 75% vaccination rates, 1 new external case per day
- Figure 2.8 on page 18: R = 5, 75% vaccination rates, 1 new external case per day
- Figure 2.9 on page 18: R = 6, 75% vaccination rates, 1 new external case per day
- Figure 2.10 on page 19: R = 4, 80% vaccination rates, 1 new external case per day
- Figure 2.11 on page 19: R = 5, 80% vaccination rates, 1 new external case per day
- Figure 2.12 on page 20: R = 6, 80% vaccination rates, 1 new external case per day

There are also 12 additional scenarios explored:

- Figure 2.13 on page 20: R = 4, 80% vaccination rates, 100 new external cases per day
- Figure 2.14 on page 21: R = 5, 80% vaccination rates, 100 new external cases per day
- Figure 2.15 on page 21: R = 6, 80% vaccination rates, 100 new external cases per day
- Figure 2.16 on page 22: R = 6, 75% vaccination rates without vaccinating under-12s, 1 new external case per day
- Figure 2.17 on page 22: R = 5, 80% vaccination rates without vaccinating under-12s and without further growth, 1 new external case per day
- Figure 2.18 on page 23: R = 6, 75% vaccination rates without vaccinating under-12s, 100 new external cases per day
- Figure 2.19 on page 23: R = 6, 80% vaccination rates without vaccinating under-12s, 100 new external cases per day

23. See Section 1.4.

- Figure 2.20 on page 24: R = 5, 80% vaccination rates without further growth, 1 new external case per day
- Figure 2.21 on page 24: R = 6, 85% vaccination rates with no further growth, 1 new external case per day
- Figure 2.22 on page 25: R = 7, 85% vaccination rates, 1 new external case per day
- Figure 2.23 on page 25: R = 8, 85% vaccination rates, 1 new external case per day
- Figure 2.24 on page 26: R = 10, 85% vaccination rates, 1 new external case per day

Figure 2.1: Outcomes: R = 4, 50% vaccination rates, 1 new external case per day

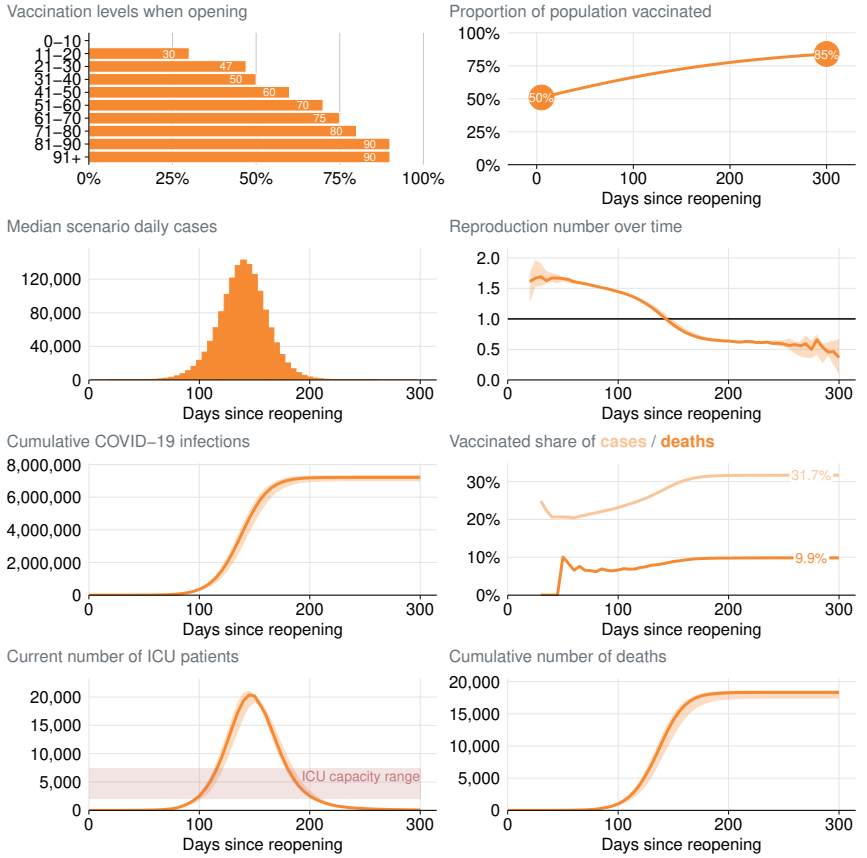


Figure 2.2: Outcomes: R = 5, 50% vaccination rates, 1 new external case per day

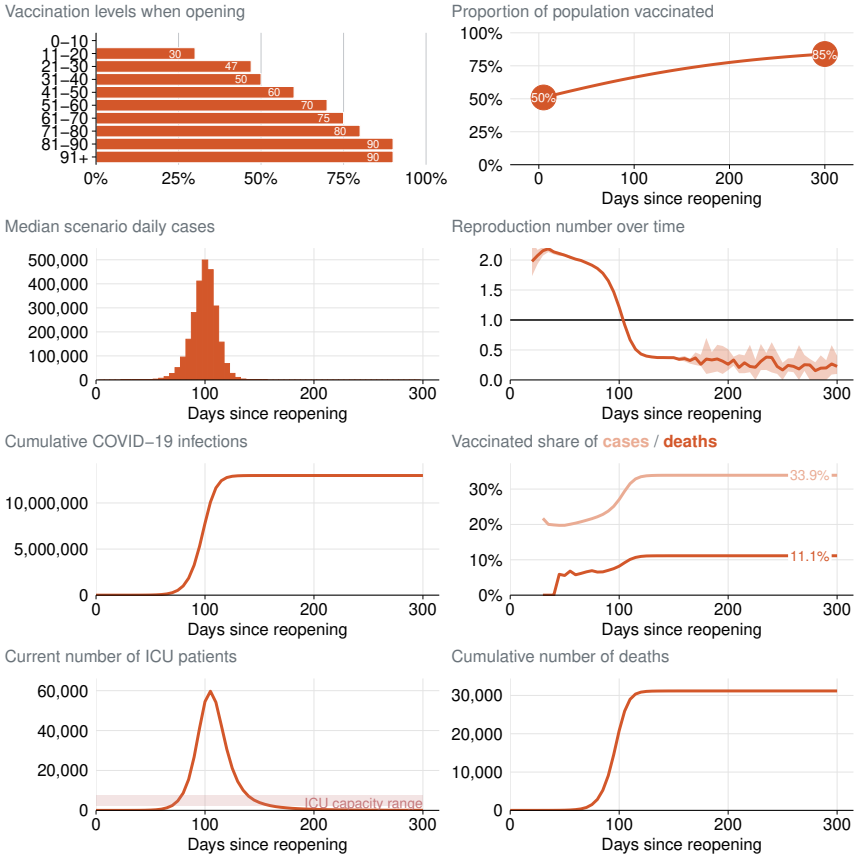


Figure 2.3: Outcomes: R = 6, 50% vaccination rates, 1 new external case per day

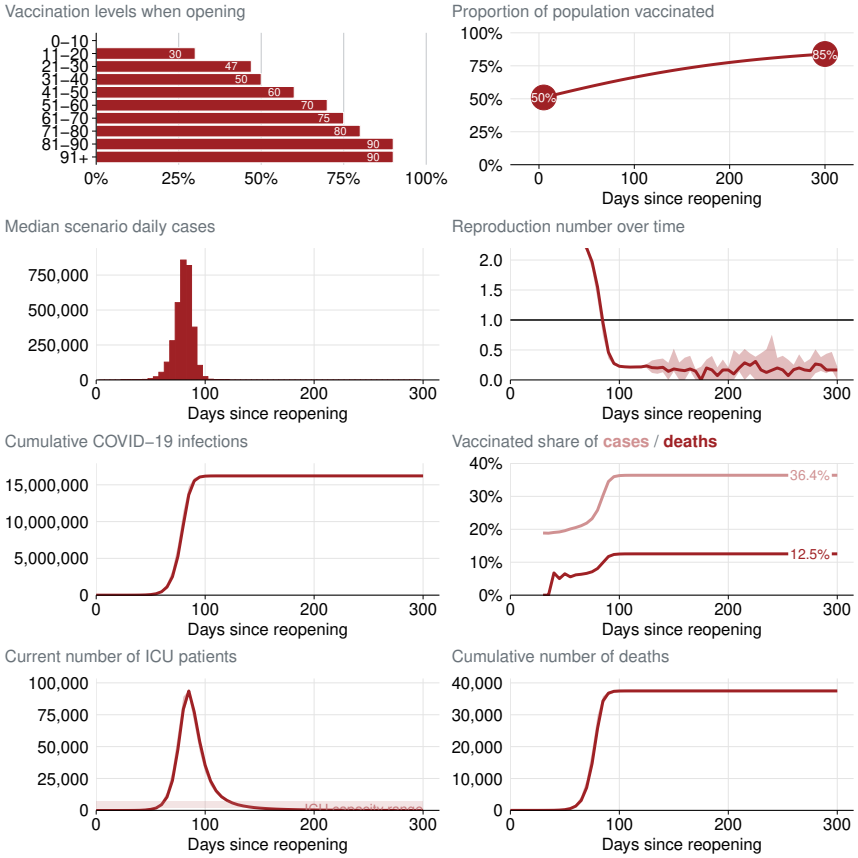


Figure 2.4: Outcomes: R = 4, 70% vaccination rates, 1 new external case per day

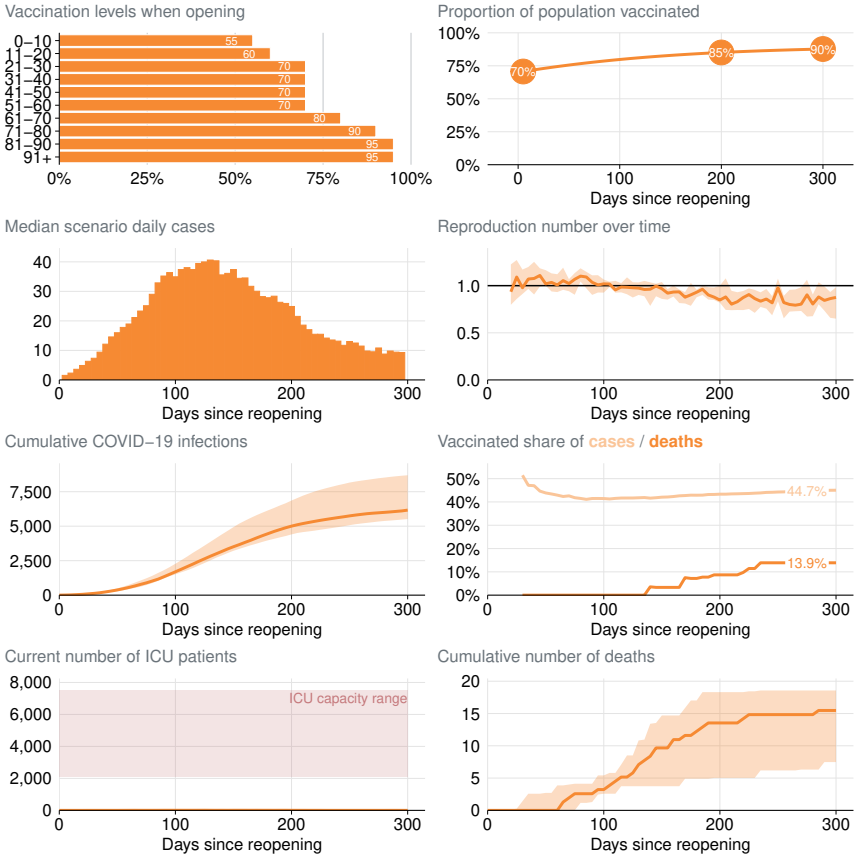


Figure 2.5: Outcomes: R = 5, 70% vaccination rates, 1 new external case per day

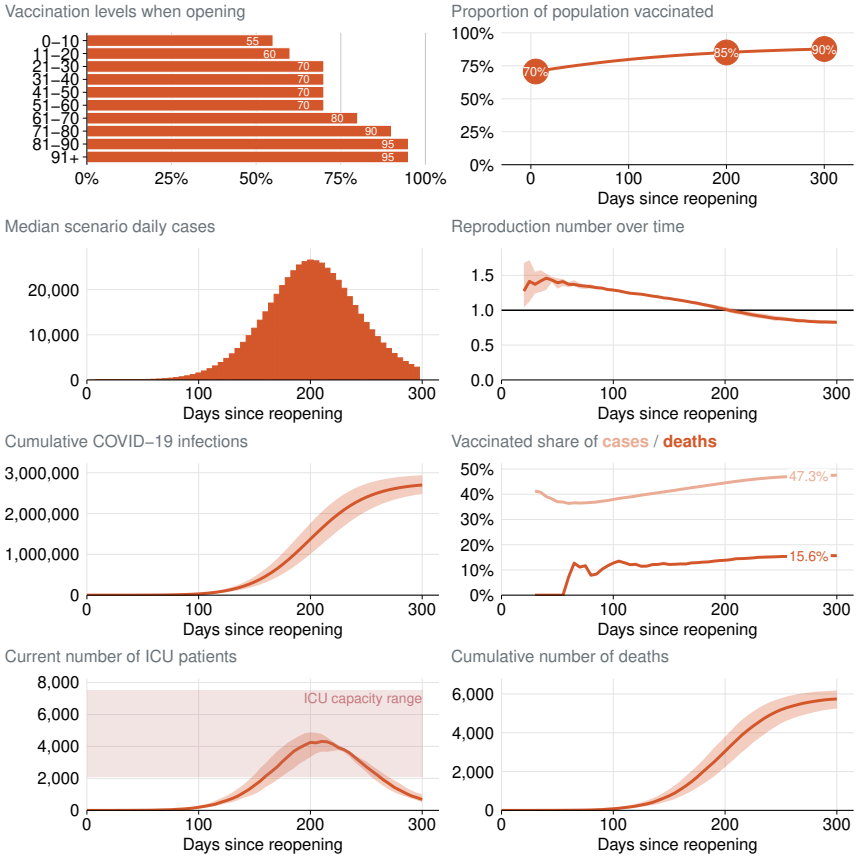


Figure 2.6: Outcomes: R = 6, 70% vaccination rates, 1 new external case per day

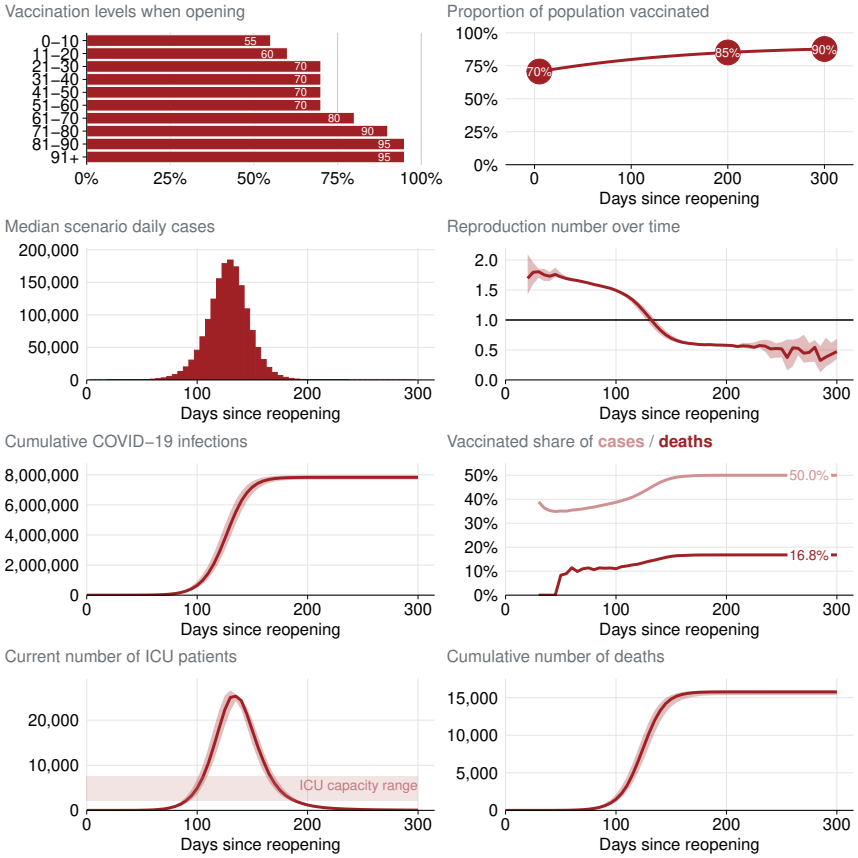


Figure 2.7: Outcomes: R = 4, 75% vaccination rates, 1 new external case per day

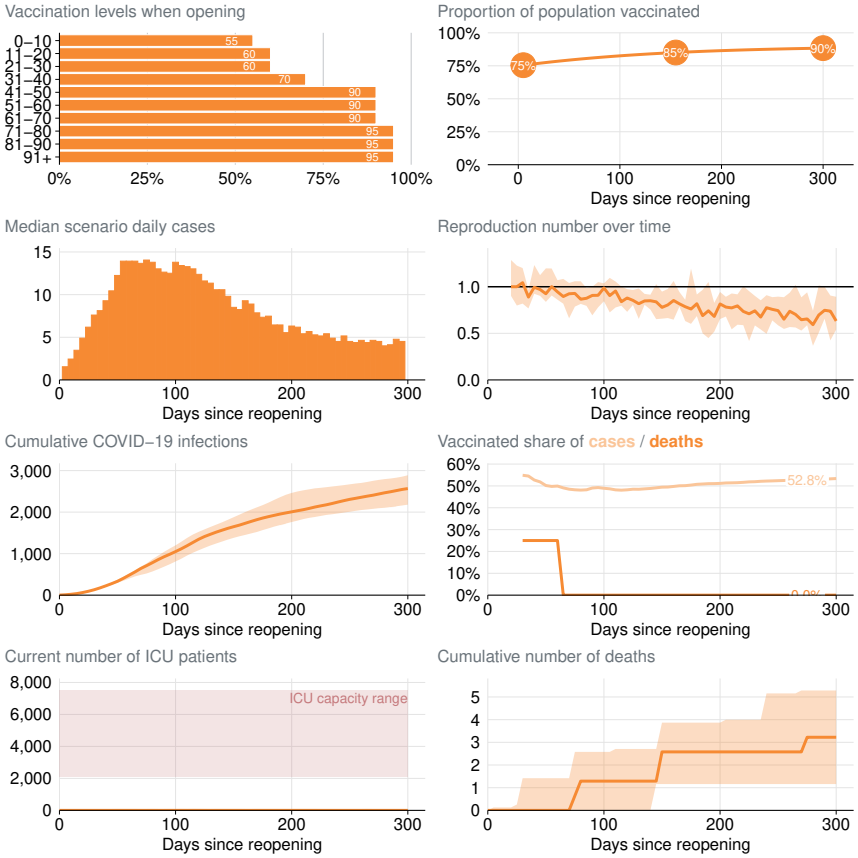


Figure 2.8: Outcomes: R = 5, 75% vaccination rates, 1 new external case per day

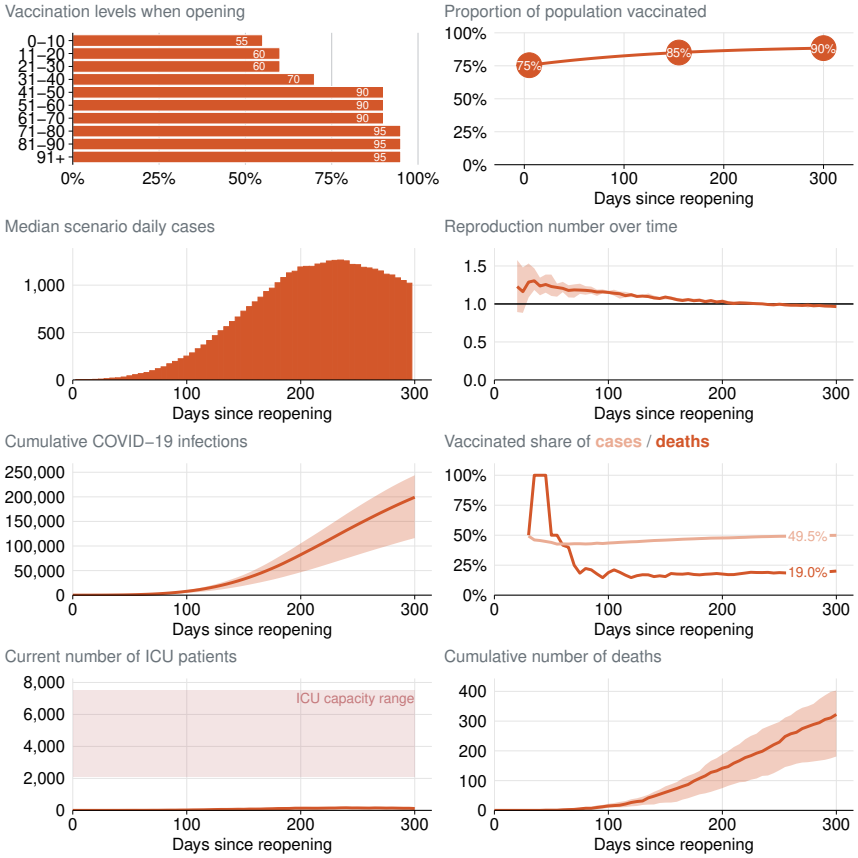


Figure 2.9: Outcomes: R = 6, 75% vaccination rates, 1 new external case per day

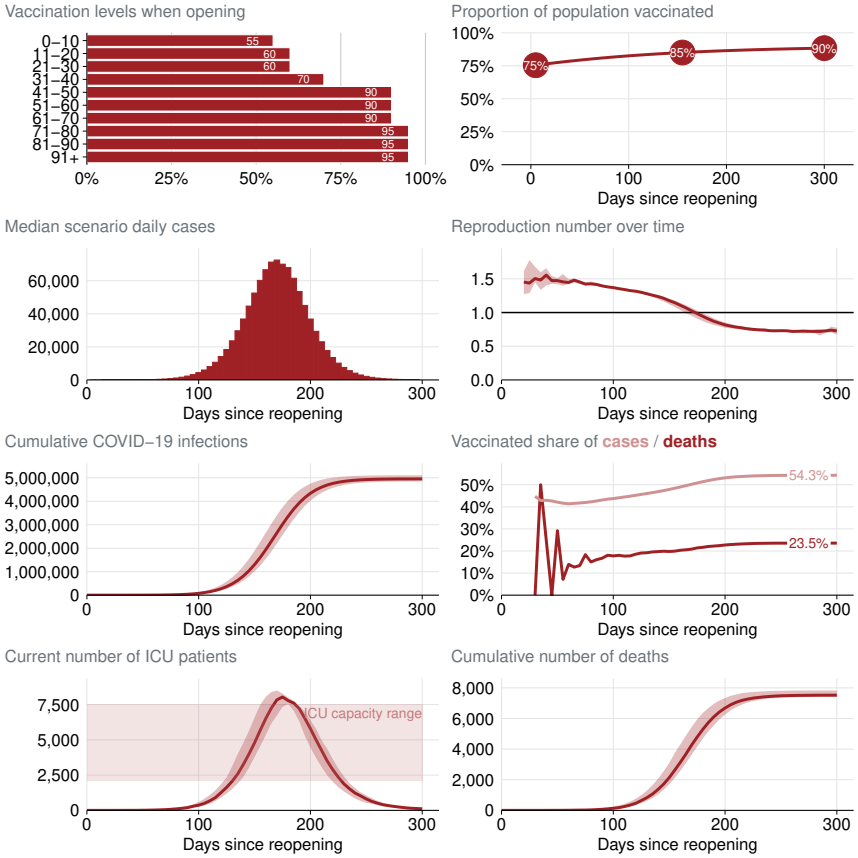


Figure 2.10: Outcomes: R = 4, 80% vaccination rates, 1 new external case per day

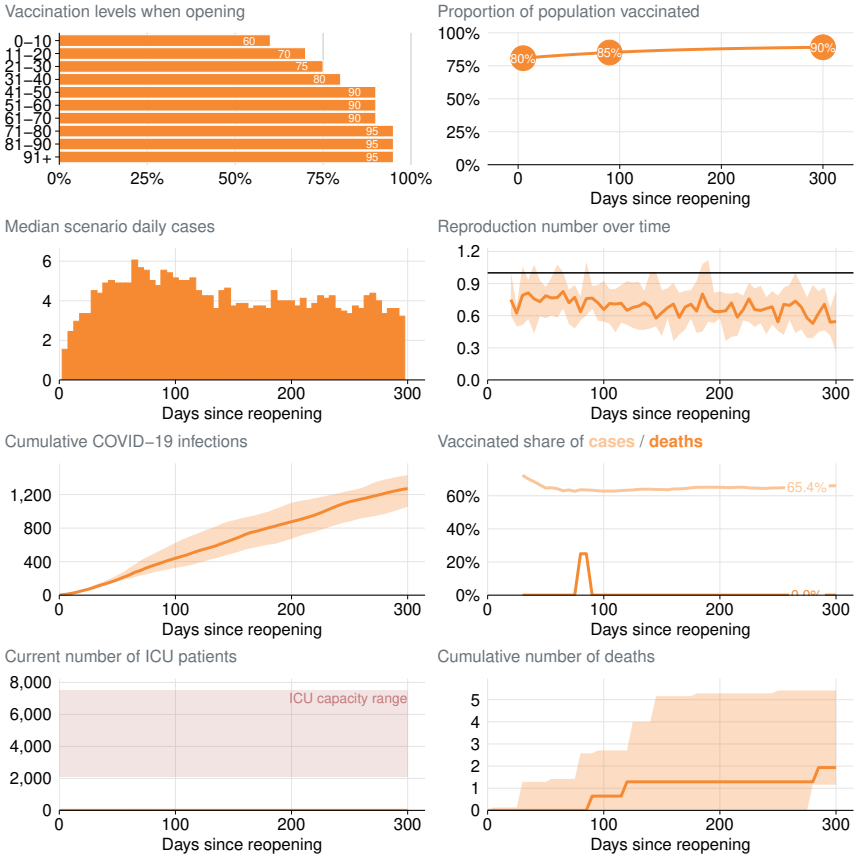


Figure 2.11: Outcomes: R = 5, 80% vaccination rates, 1 new external case per day

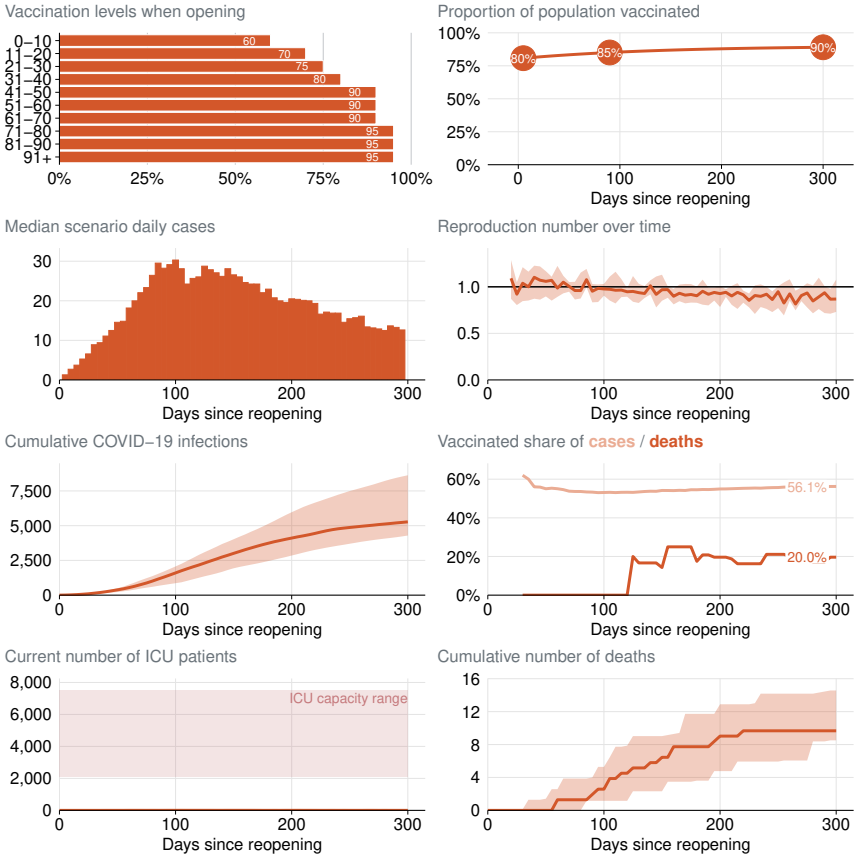


Figure 2.12: Outcomes: R = 6, 80% vaccination rates, 1 new external case per day

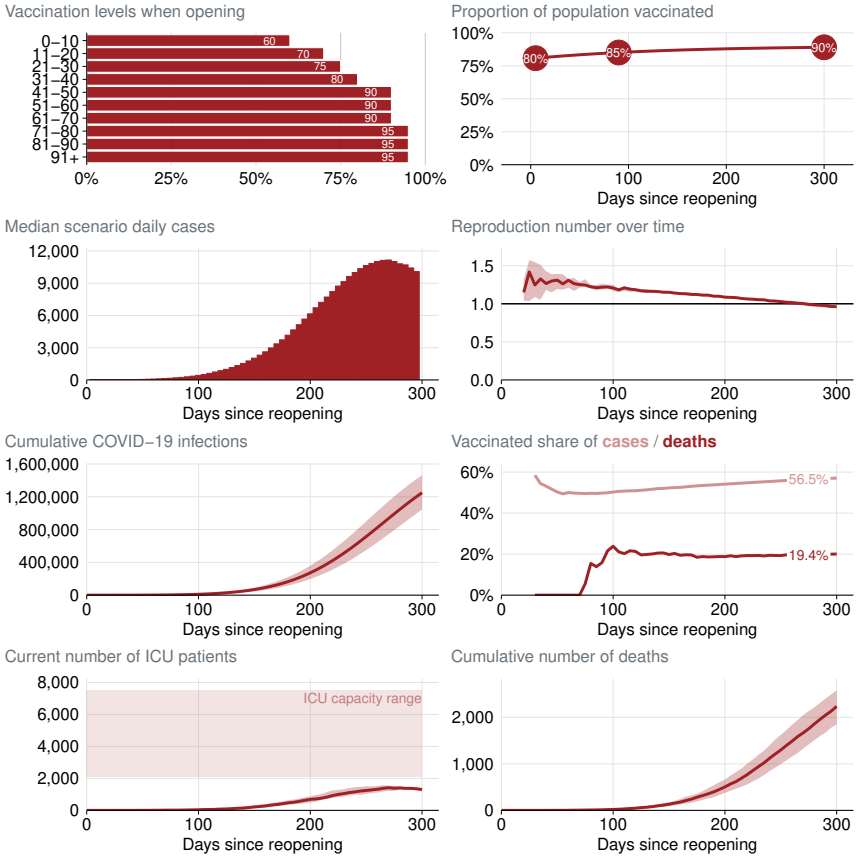


Figure 2.13: Outcomes: R = 4, 80% vaccination rates, 100 new external cases per day

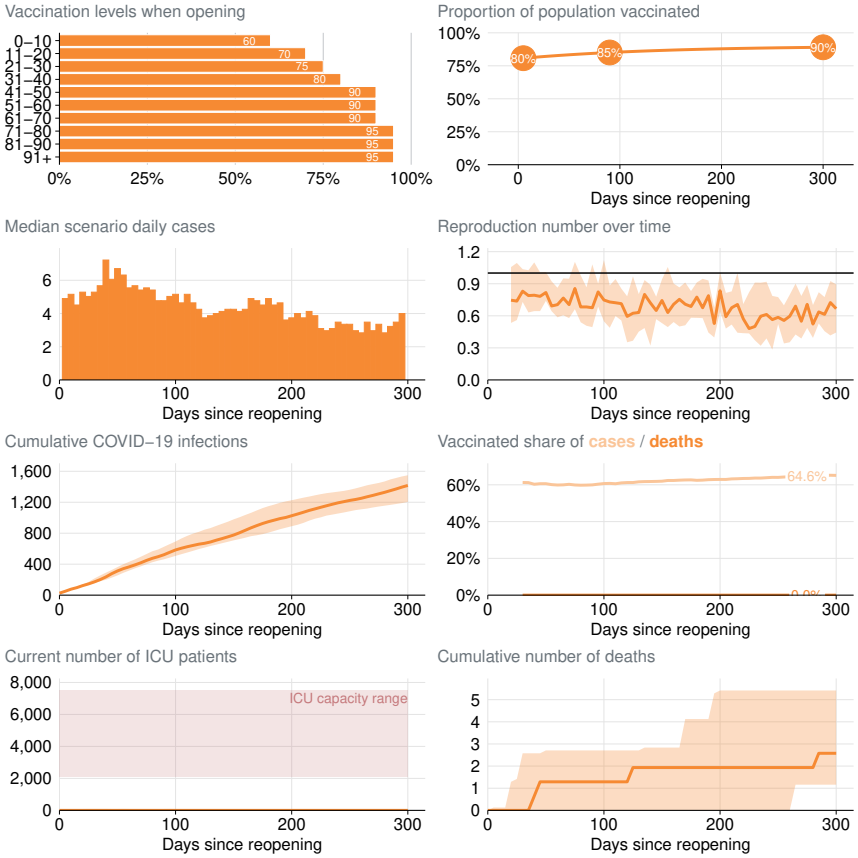


Figure 2.14: Outcomes: R = 5, 80% vaccination rates, 100 new external case per day

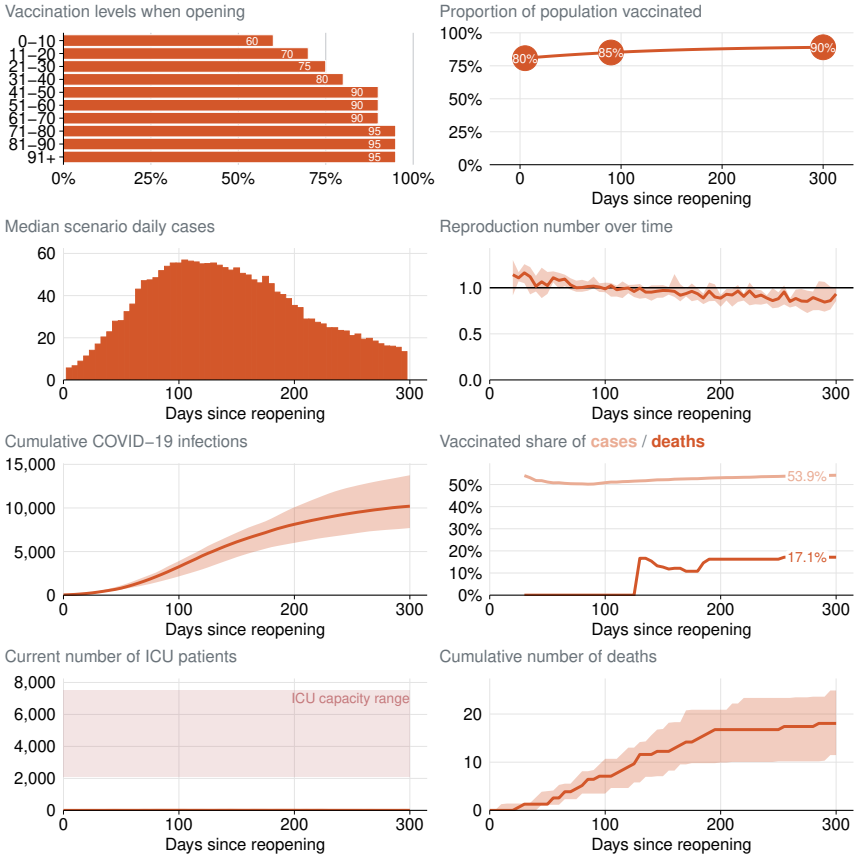


Figure 2.15: Outcomes: R = 6, 80% vaccination rates, 1 new external case per day

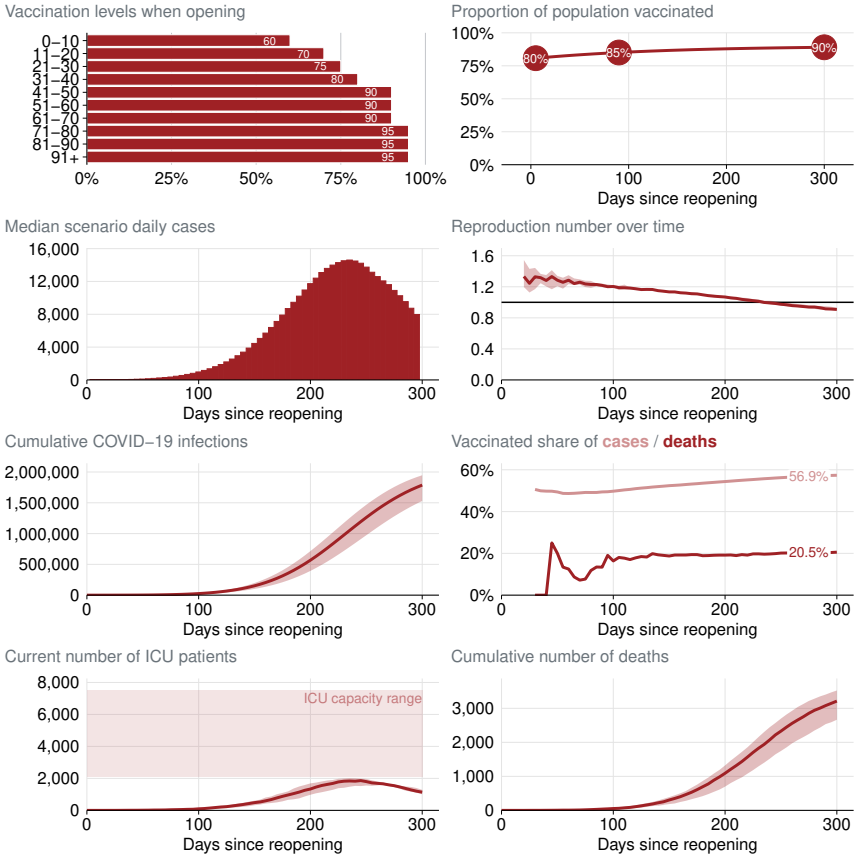


Figure 2.16: Outcomes: R = 6, 75% vaccination rates without vaccinating under-12s, 100 new external case per day

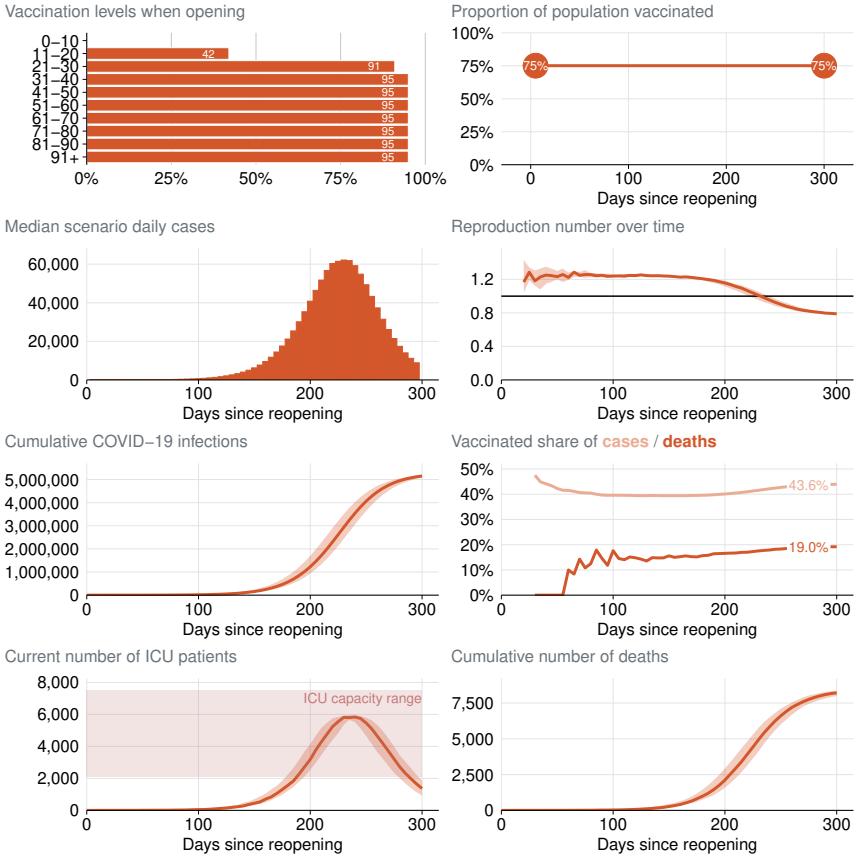


Figure 2.17: Outcomes: R = 5, 80% vaccination rates without vaccinating under-12s and without further growth, 1 new external case per day

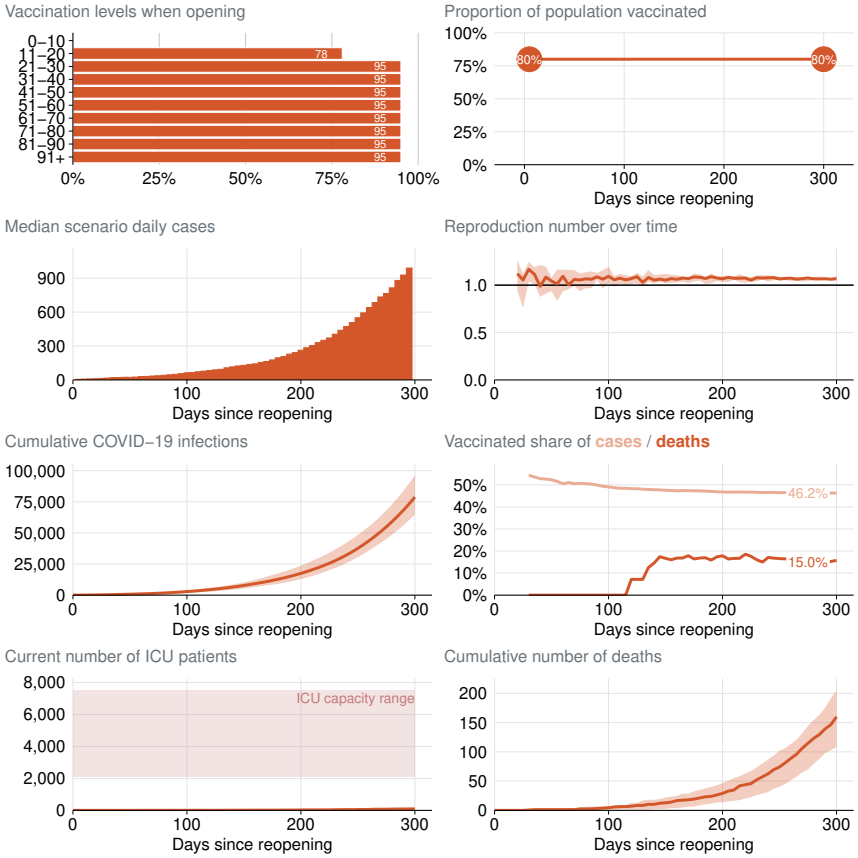


Figure 2.18: Outcomes: R = 6, 75% vaccination rates without vaccinating under-12s, 100 new external case per day

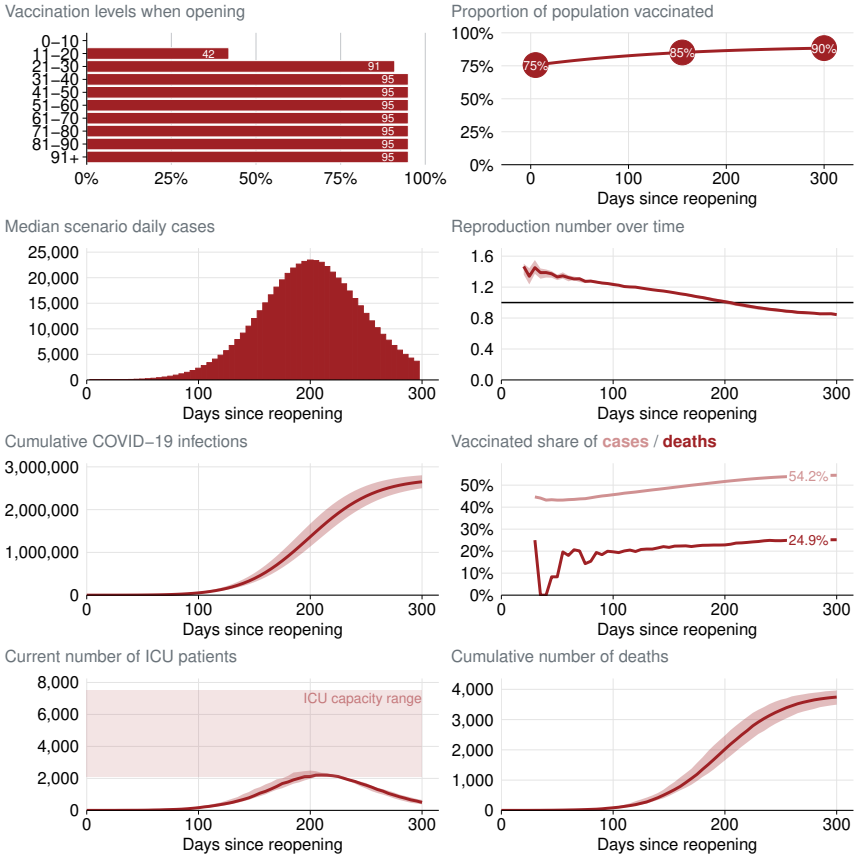


Figure 2.19: Outcomes: R = 6, 80% vaccination rates without vaccinating under-12s, 100 new external case per day

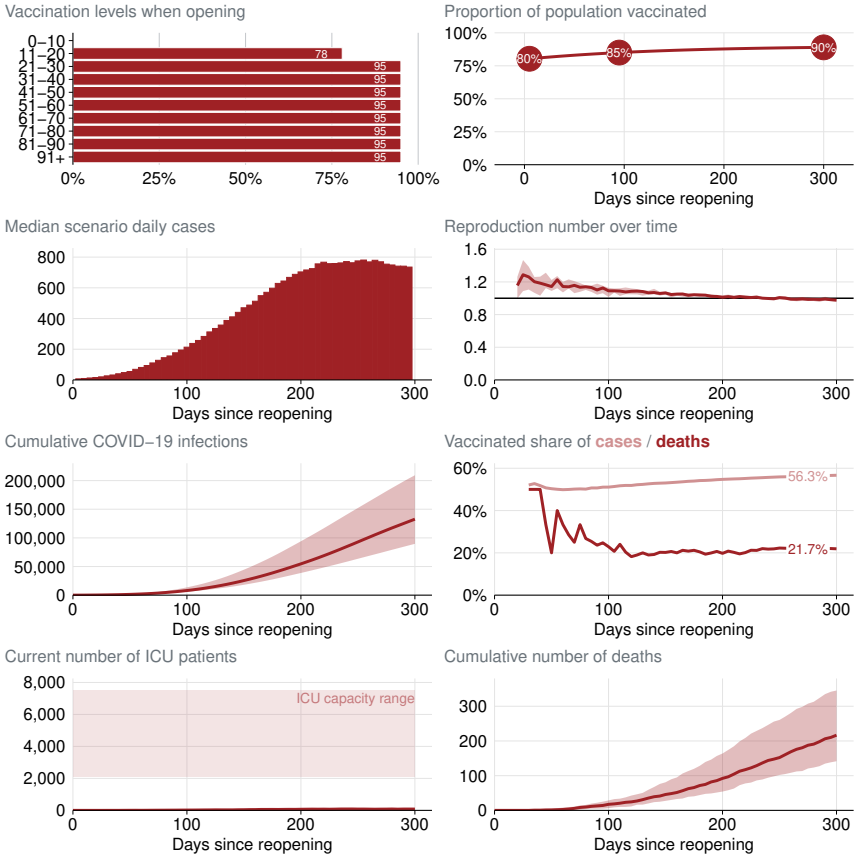


Figure 2.20: Outcomes: R = 5, 80% vaccination rates without further growth, 1 new external case per day

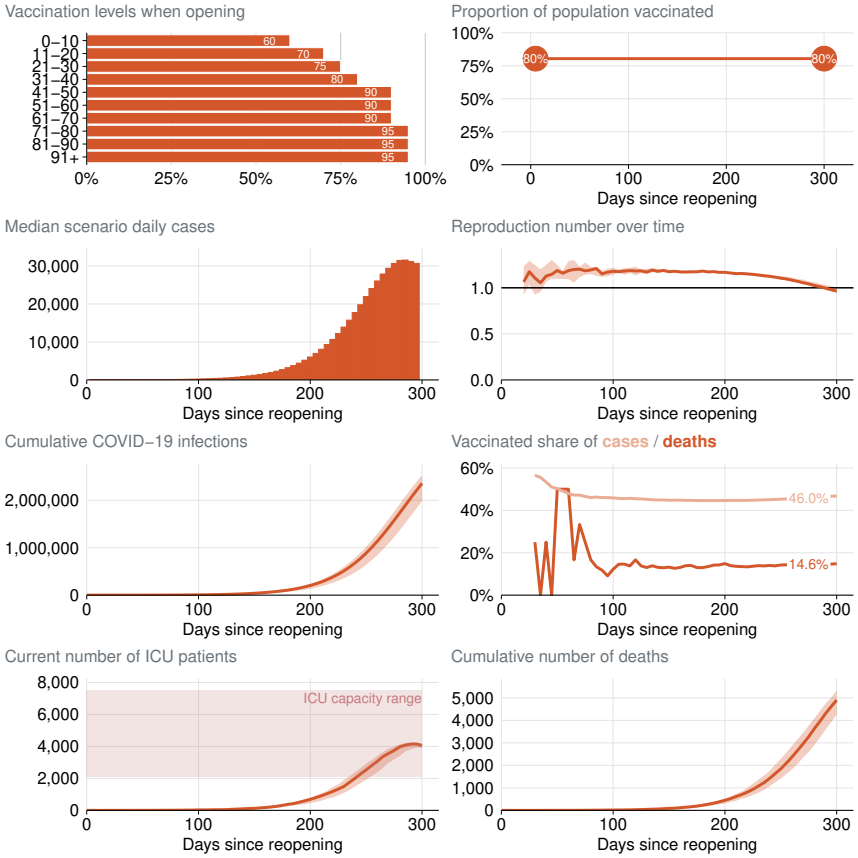


Figure 2.21: Outcomes: R = 6, 85% vaccination rates with no further growth, 1 new external case per day

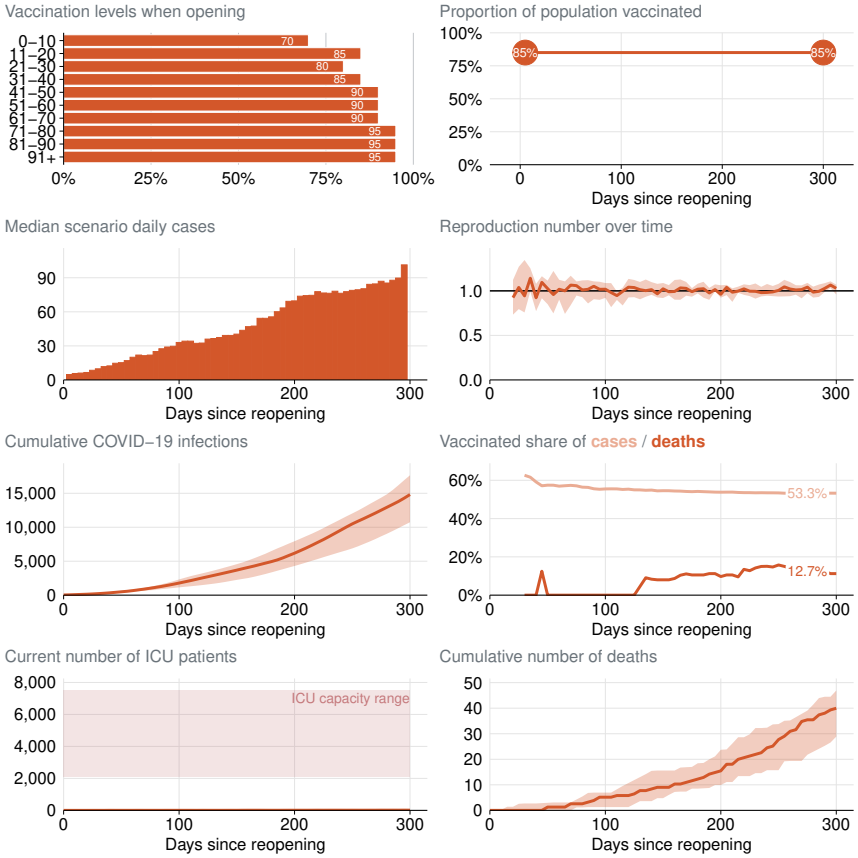


Figure 2.22: Outcomes: R = 7, 85% vaccination rates, 1 new external case per day

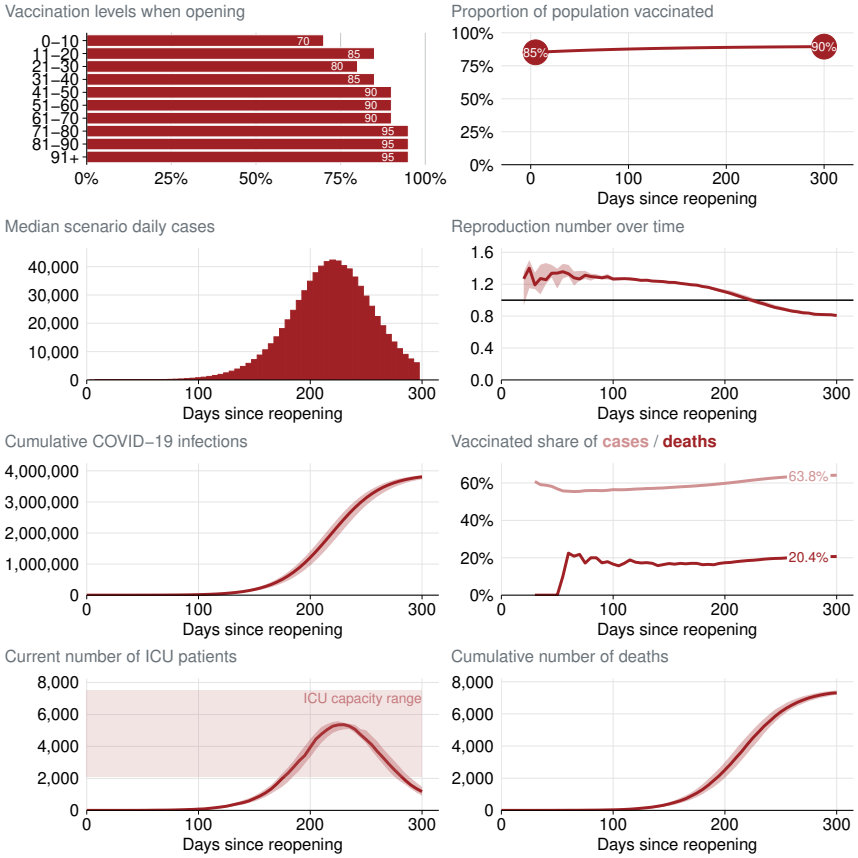


Figure 2.23: Outcomes: R = 8, 85% vaccination rates, 1 new external case per day

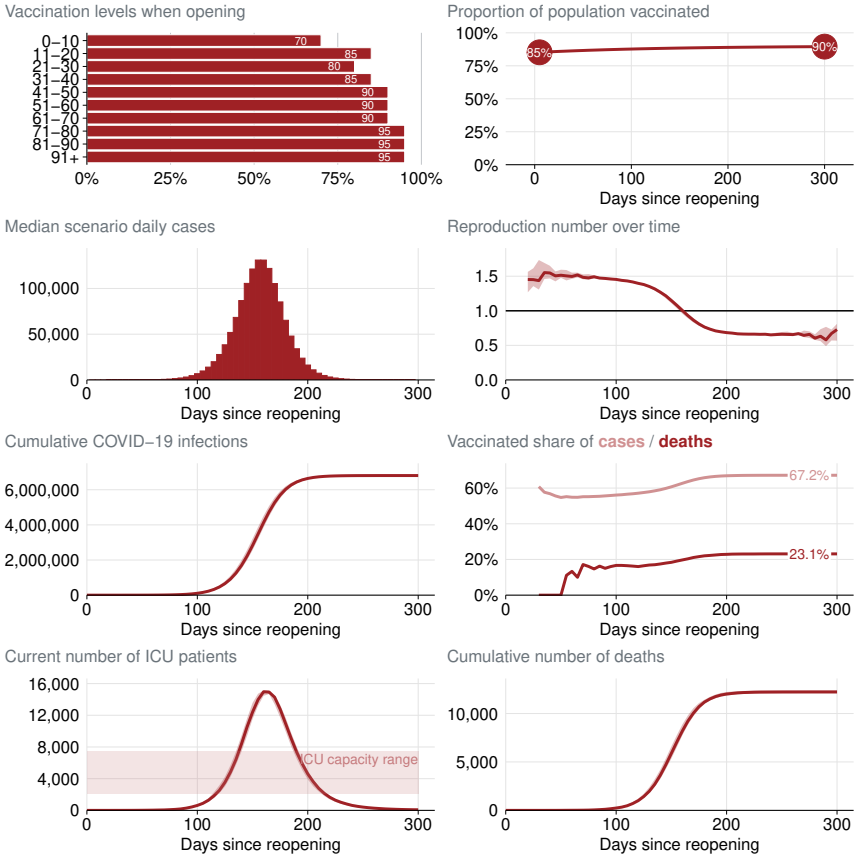
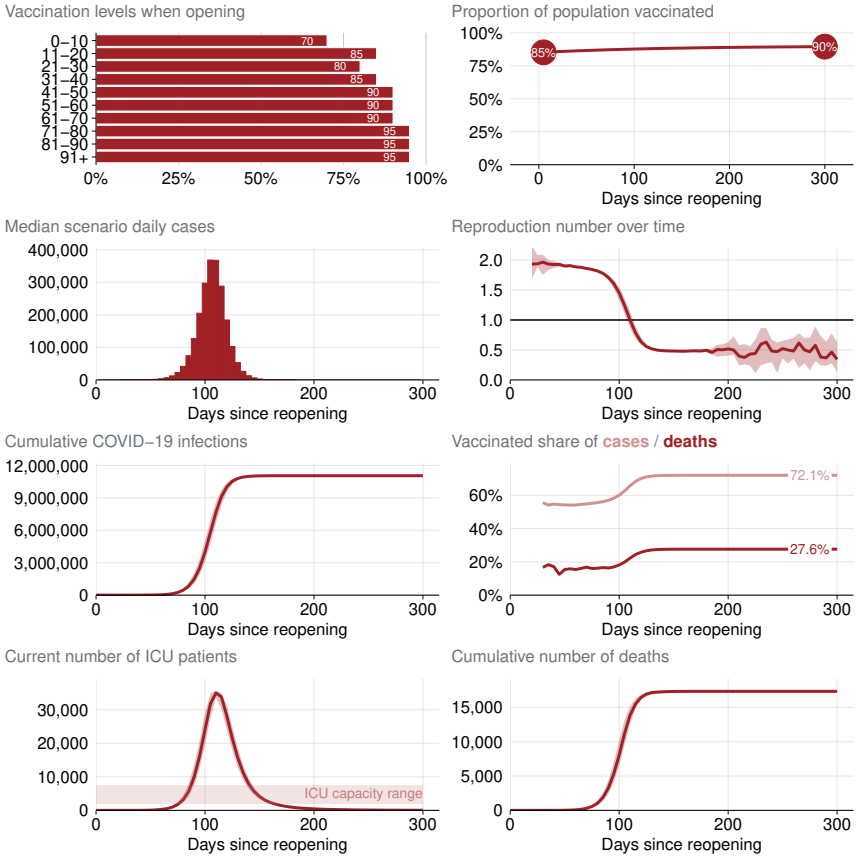


Figure 2.24: Outcomes: R = 10, 85% vaccination rates, 1 new external case per day



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