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Supplementary appendix

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Supplementary information

for

Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts

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Contents

1. Effect of the reproduction number on probability of achieving control

In Figure S1 the middle column of plots represents the scenario shown in Figure 3a, where there is 15% of transmission before symptom onset, a short delay from symptom onset to isolation, no asymptomatic cases, and 20 initial cases. Figure S1 then shows how changing the reproduction number changes the probability of achieved control for each scenario of number of initial cases, length of delay to isolation, percent of transmission before symptoms and fraction subclinical (asymptomatic) on each row.

Across all scenarios, higher reproduction numbers are associated with lower probability of control. When 30% of transmission occurs before symptom onset (3rd row, right-hand column), increasing the reproduction number to 3.5 causes a drastic decrease in the probability of control. Subclinical infection also has a marked effect on the probability to control, especially for R_0 of 2.5 or greater.

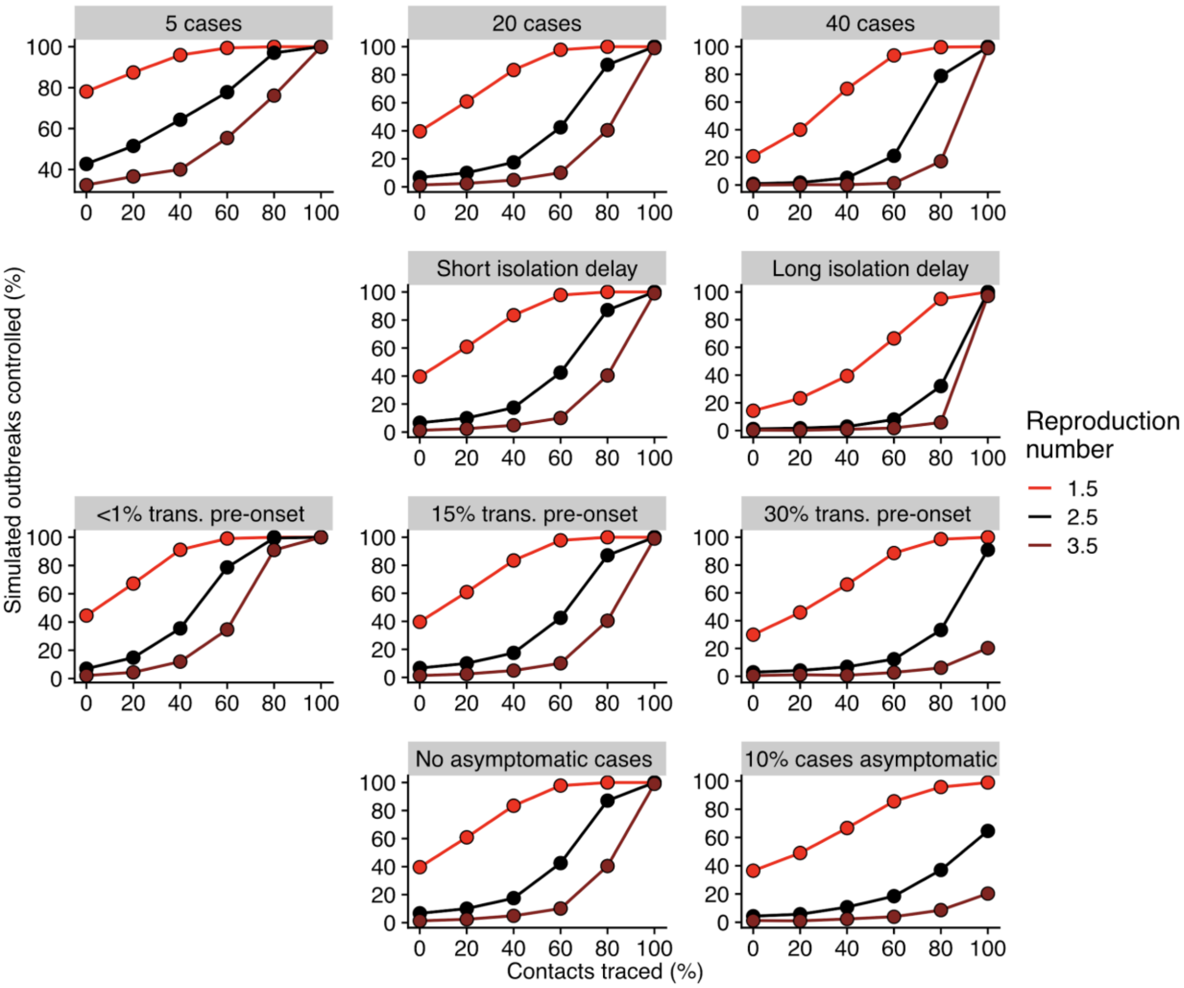

Fig S1. The black line in the central column shows the baseline assumption of the main paper: The baseline scenario is R_0 of 2.5, 20 initial cases, a short delay to isolation, 15% of transmission before symptom onset, and 0% subclinical infection. Each row then shows a further scenario of the model for each value of R_0 tested.

2. The effect of the number of initial cases on the probability of achieving control

The more initial cases at the beginning of the branching process, the harder the outbreak is to control. In Figure S2, where there are 5 initial cases (light blue line), the probability of control is much higher than when there are 20 and 40 cases (black and dark blue line respectively). A large factor when there are 5 initial cases is that there are many scenarios where the outbreak dies out due to stochastic variation in the number of new infected cases [20]. Because the dispersion parameter in the negative binomial is 0.16, this causes more draws where the number of new cases is 0 and more larger non-zero draws. This behaviour has been observed before from branching process models using overdispersion to represent super-spreading events [20]. In Supplementary section 7 we test the effect of overdispersion on the probability of achieving control.

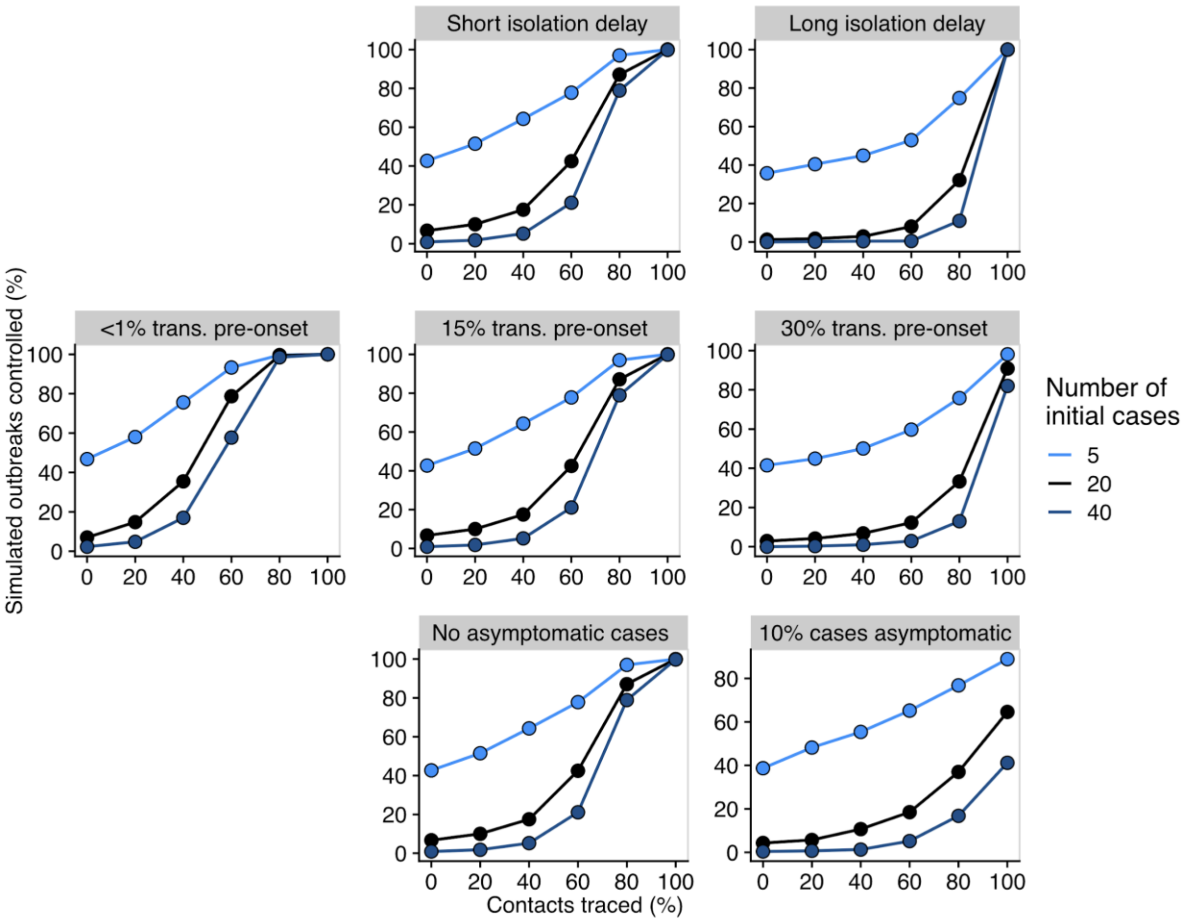

Fig S2. The black line in the central column shows the baseline assumption of the main paper: The baseline scenario is R_0 of 2.5, 20 initial cases, a short delay to isolation, 15% of transmission before symptom onset, and 0% subclinical infection. Each row then shows a further scenario of the model for each value of the number of initial cases.

3. Effect of delay between onset and isolation on probability of achieving control

Decreasing the delay between symptom onset and isolation increases the probability of controlling a simulated outbreak across all scenarios. Quicker isolation prevents new infections from happening and reduces the effective reproduction number. However, as can be seen in Figure S3 (2nd row, right-hand column), the presence of asymptomatic cases (that will never be isolated) decreases the impact that prompt isolation has on control probability.

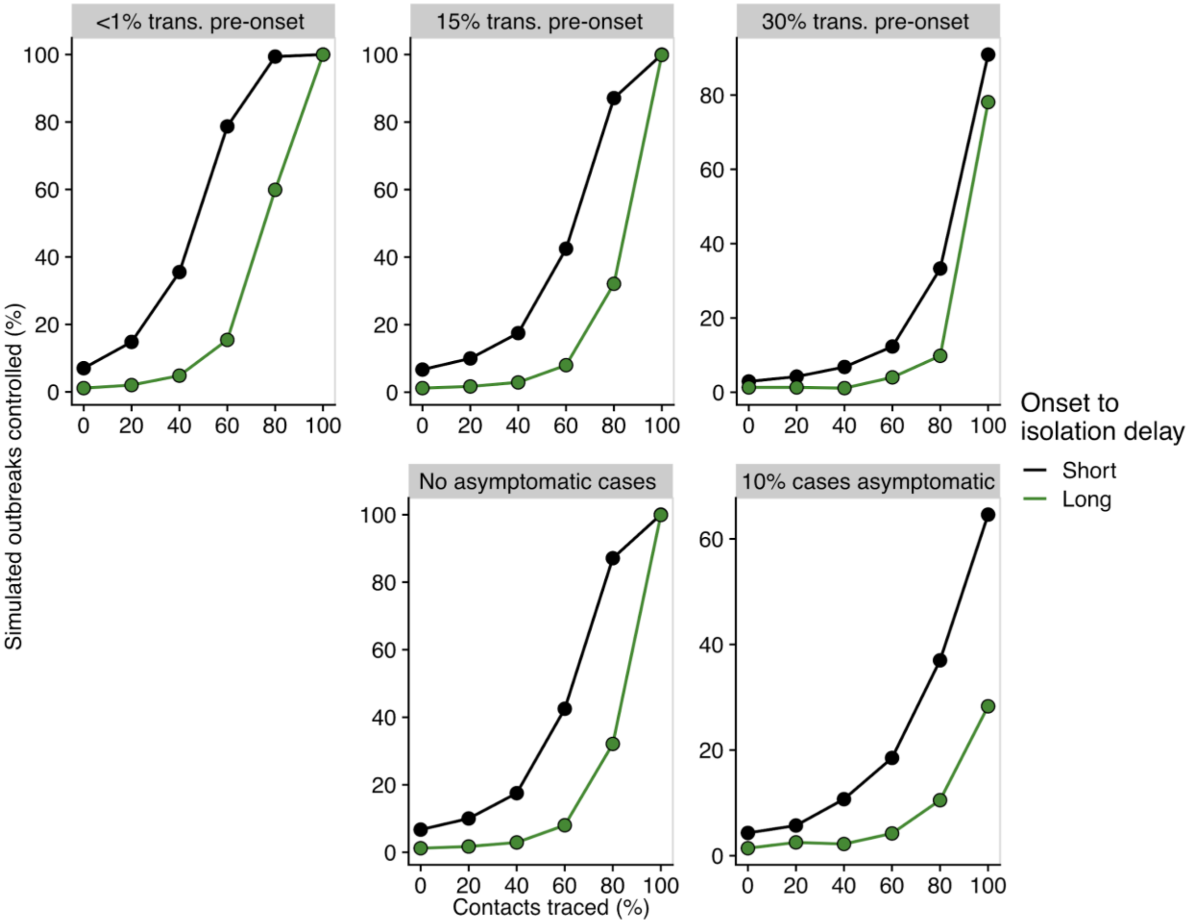

Fig S3. The black line in the central column shows the baseline assumption of the main paper: The baseline scenario is R_0 of 2.5, 20 initial cases, a short delay to isolation, 15% of transmission before symptom onset, and 0% subclinical infection. Each row then shows a further scenario of the model for the short and long delay.

4. Effect of proportion of transmission before symptoms on probability of achieving control

The higher the proportion of transmission that occurs before symptom onset, the lower the proportion of model runs that are controlled. This is primarily because tracing contacts and isolating them at symptom onset cannot prevent transmission that happens before symptoms. The interaction between asymptomatic cases and transmission before symptom onset can make an outbreak very hard to control, in Figure S4 below the basic reproduction number is 2.5 and there is a short delay from onset to isolation. However, even if 100% of contacts are traced there is still only approximately 30% probability that a simulated outbreak is controlled if 10% of cases are asymptomatic and 30% of transmission happens before symptom onset.

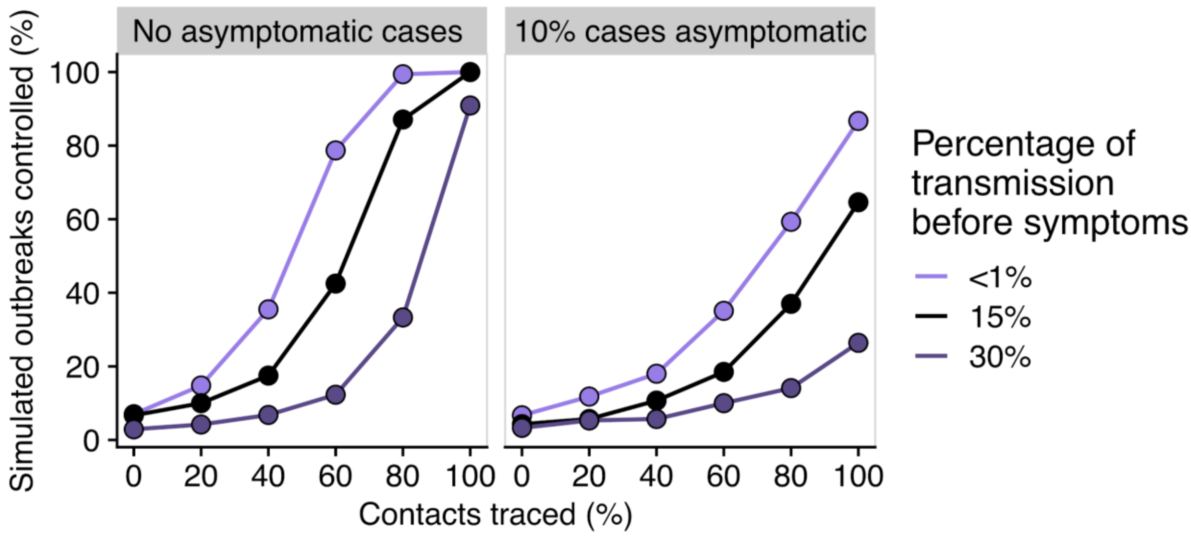

Fig S4. The black line in the central column shows the baseline assumption of the main paper: The baseline scenario is R_0 of 2.5, 20 initial cases, a short delay to isolation, 15% of transmission before symptom onset, and 0% subclinical infection. The figure then shows the effect of subclinical (asymptomatic) infection on the probability of achieving control.

5. Effect of initial case number on controlled outbreak size

Of the outbreaks that were controlled, larger numbers of initial cases leads to higher numbers of weekly cases. This logically follows, since more index cases will lead to more secondary cases. Number of weekly cases has ramifications for the amount of logistical effort required to control the outbreak, since it means that the number of cases initially infected will require more effective contact tracing to control the outbreak (in terms of percentage of contacts successfully traced) and that more contacts will need to be traced each week.

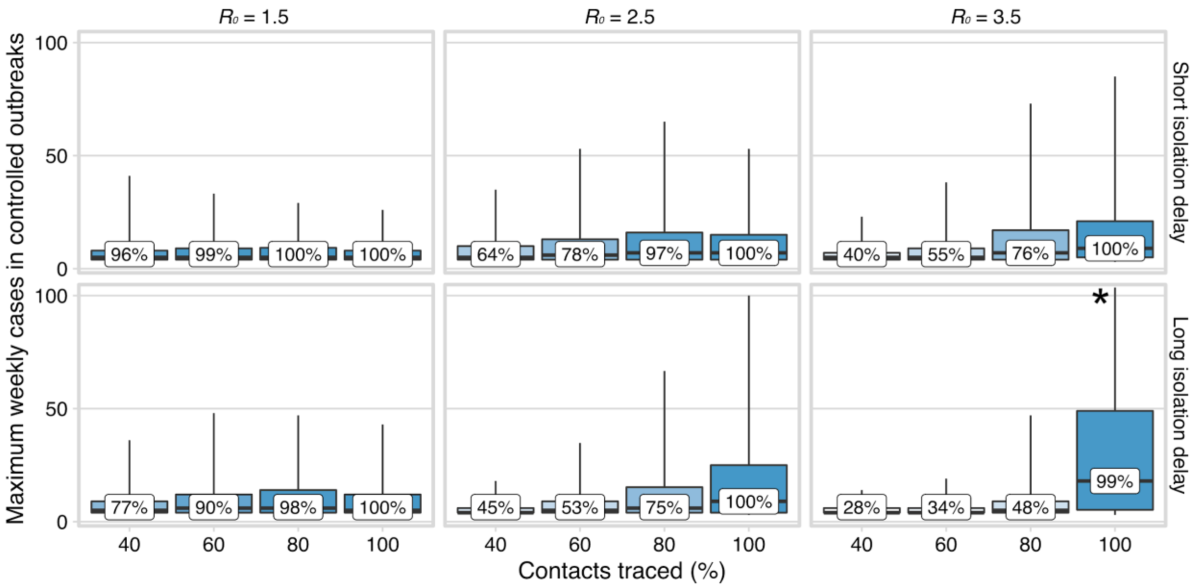

Figure S5A: A copy of Figure 5 for an initial case number of 5 cases instead of 40 cases.* indicates that the 95% interval extends out of the plotting region.

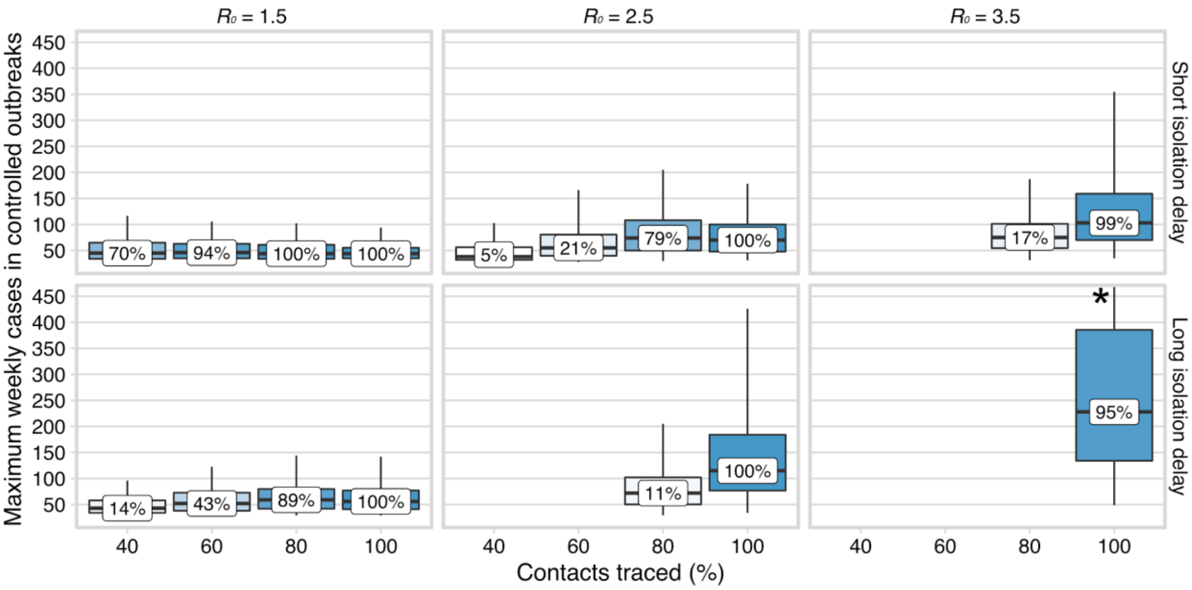

Figure S5B: A copy of Figure 5 for an initial case number of 40 cases instead of 20 cases.* indicates that the 95% interval extends out of the plotting region.

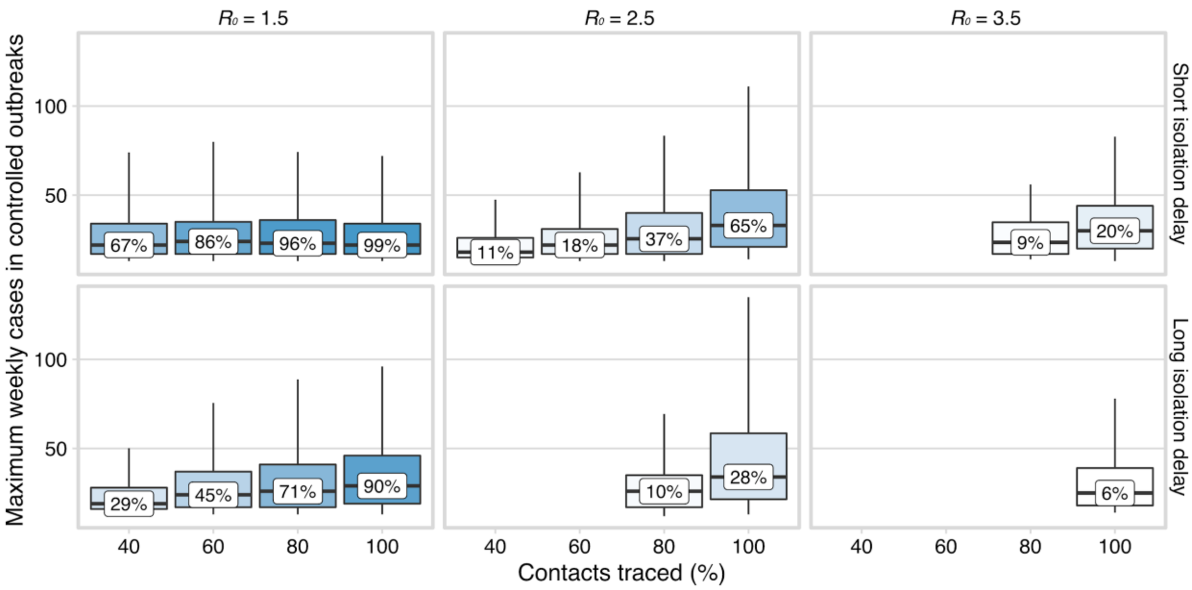

Figure S5C: A copy of Figure 5 for 10% percent asymptomatic cases. * indicates that the 95% interval extends out of the plotting region.

6. Proportion of transmission before symptom onset

The serial interval distribution is conserved for the tested values of the proportion of transmission that occurs before symptom onset (Figure S6).

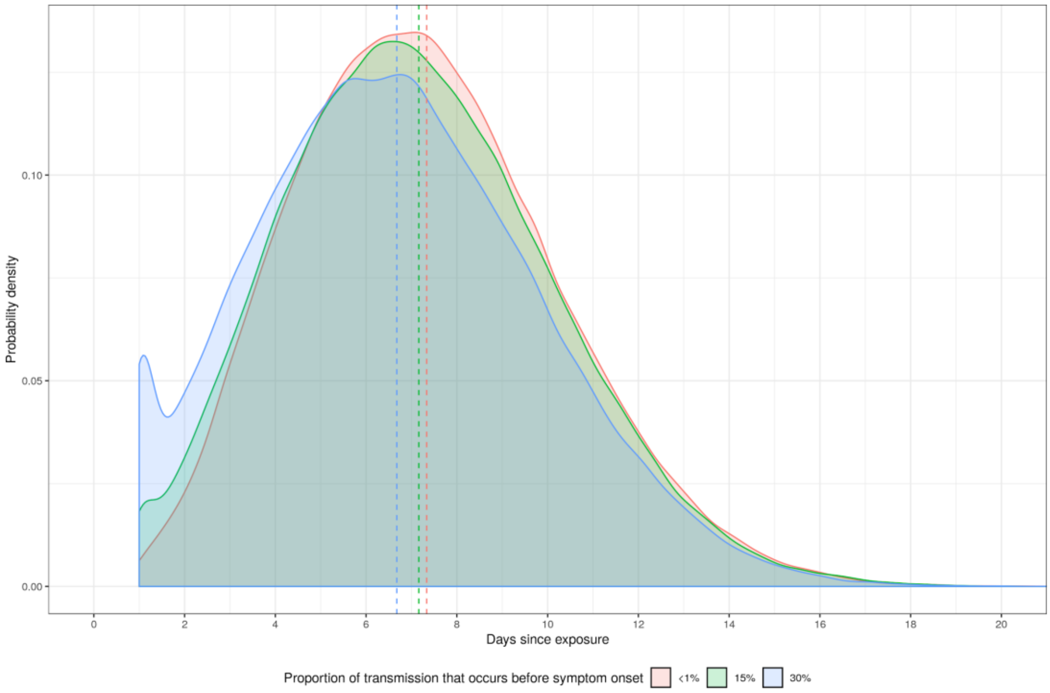

Figure S6: The unconditional serial intervals that correspond to the three values of proportion of transmission that occurs before symptom onset (Table 1). The lower values are truncated at 1 so when 30% of transmission occurs before symptoms there is a small amount of bunching since serial interval values are biased towards lower values.

7. Sensitivity to heterogeneity in secondary case distribution (k, the overdispersion parameter)

We tested the sensitivity of our findings to the overdispersion parameter of the negative binomial distribution. In the main text, the value used is that found for SARS (0.16) and implies a high level of heterogeneity in the number of secondary cases generated by each infected case. We also tested a value of 2, similar to that observed for influenza[25] (Figure S7a).

The probability of achieving control of outbreaks was lower when there was less heterogeneity in the number of secondary cases (Figure S7b). This occurred for all values of the reproduction number tested, by the percentage of transmission before symptoms. For an R_0 of 3.5, and 30% of transmission before symptoms, control was never observed, even at 100% tracing of contacts. The maximum number of cases was generally higher when heterogeneity was lower, despite the R_0 value remaining fixed.

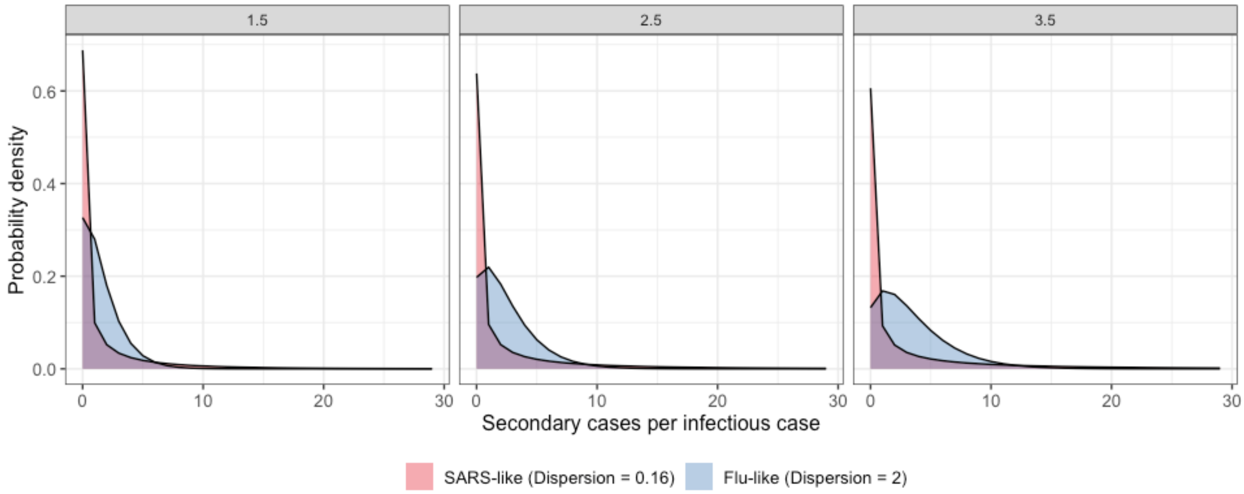

Figure S7a: How the dispersion parameter used in the negative binomial distribution affects the distribution of the average number of secondary cases. In each panel, the average value (R_0) is 1.5, 2.5 or 3.5.

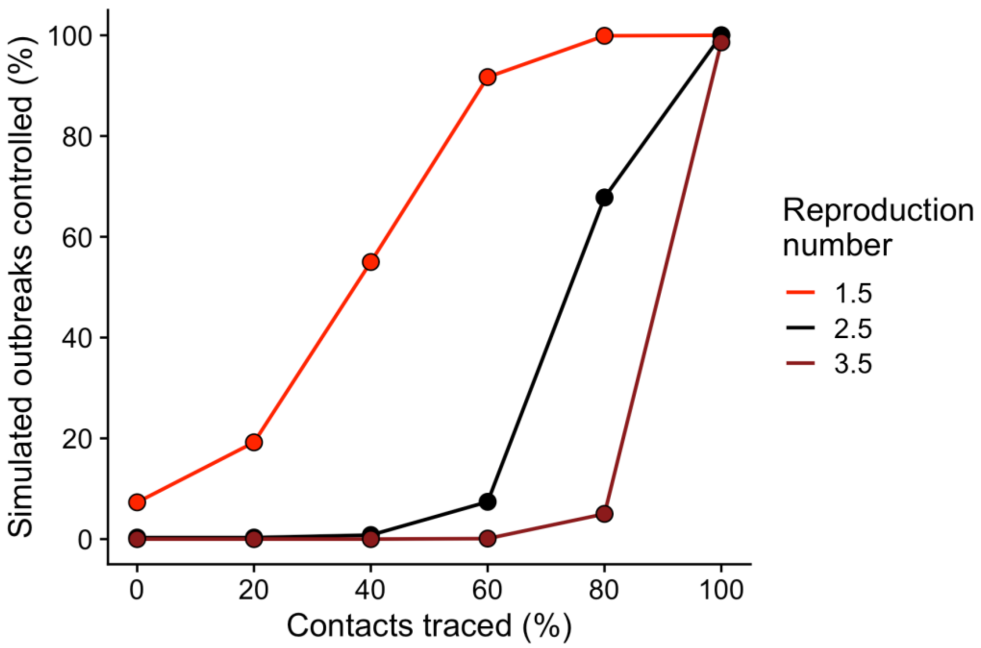

Figure S7b: An initial case number of 20 cases and a new run of simulations with identical parameters as the main analysis (Figure 3a) except with a dispersion parameter for R_0 of 2, which is similar to that observed for influenza[25].

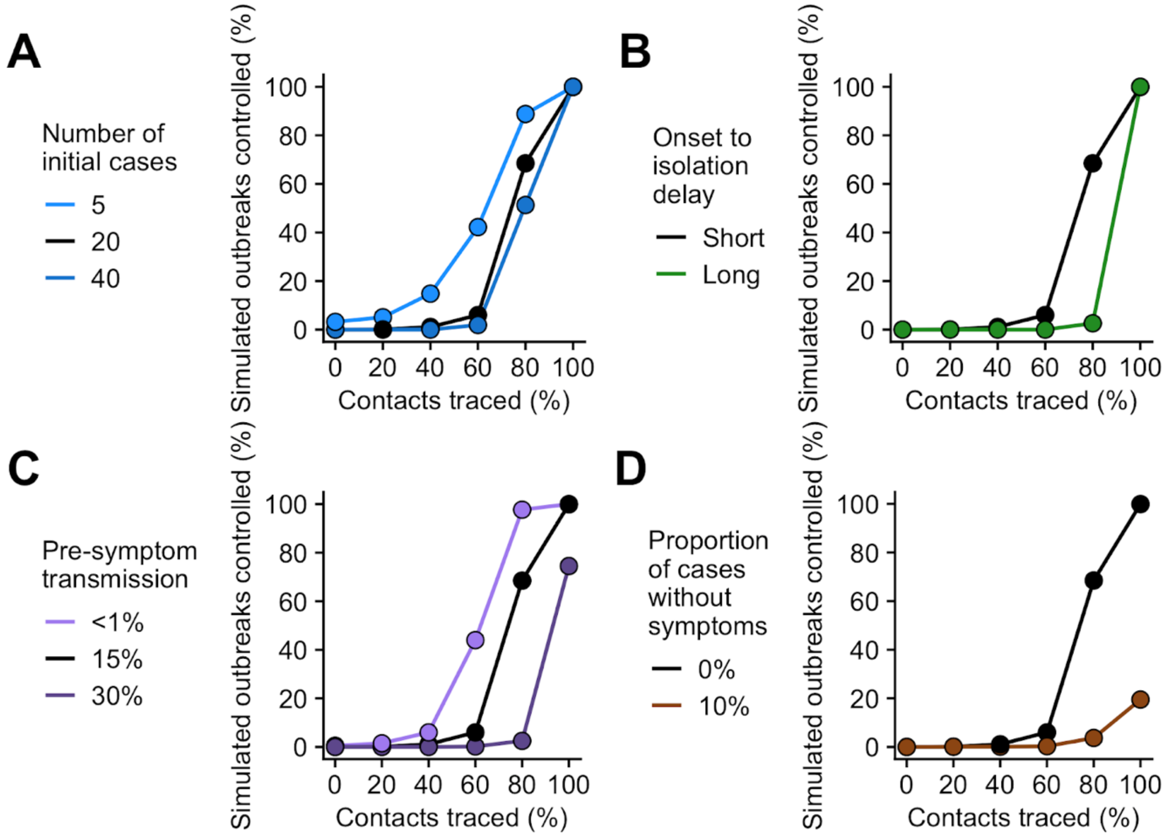

Figure S7c: A version of Figure 4 for an initial case of 20 and the same parameters as the main analysis but with a dispersion parameter for R_0 of 2.

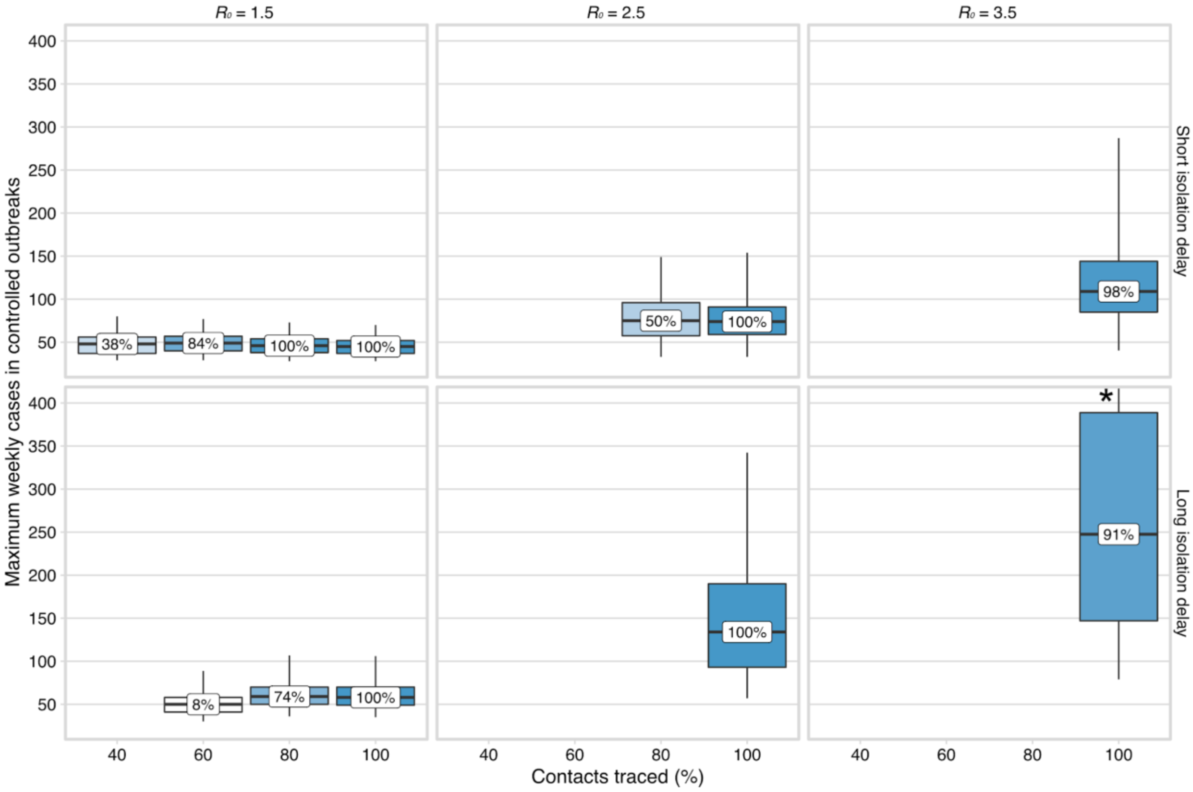

Figure S7d: A version of Figure 5 with the same parameters as the main analysis but with a dispersion parameter for R_0 of 2.* indicates that the 95% interval extends out of the plotting region.

8. Detailed visualisation of the model

The main text figure shows a simplified version of the model without asymptomatic transmission. Figure S8 shows all possible pathways.

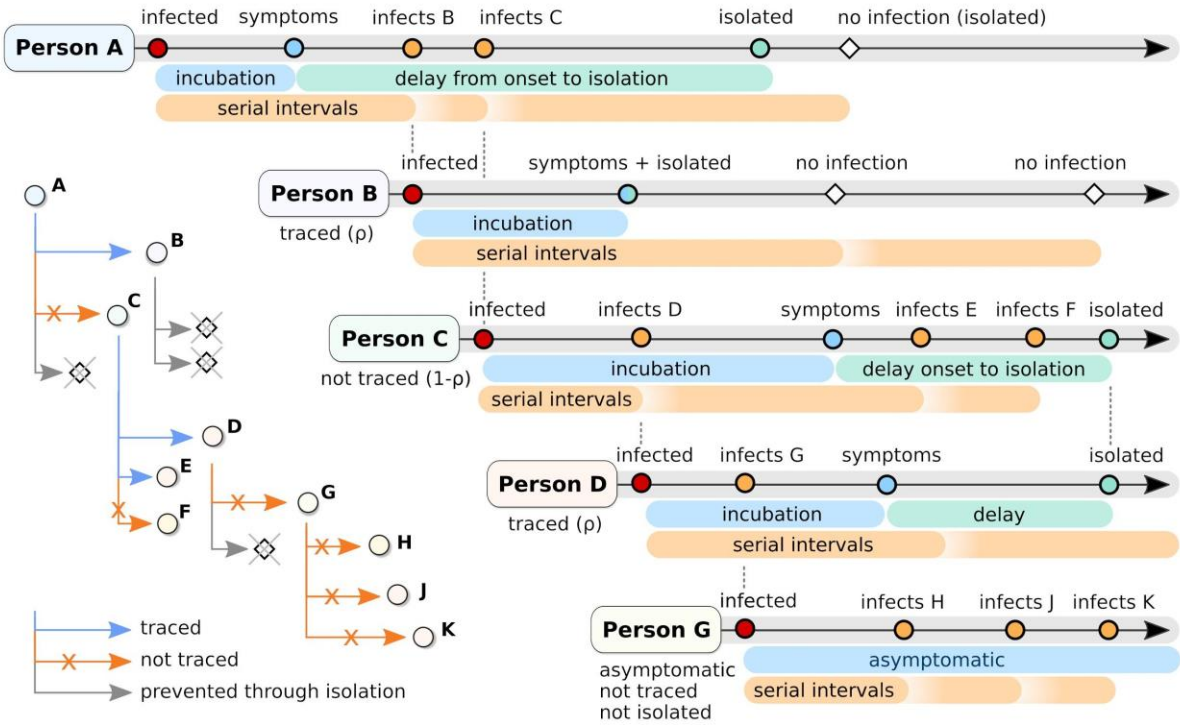

Figure S8: Persons A-F are infected as explained in the main text. Person D is a special case of a person that is traced even though their infector, person C was missed by contact tracing. Person D can be isolated through two possible routes: either they get isolated independently from person C after symptom onset + a delay. Or they are isolated through contact tracing immediately when their infector person C gets isolated, reflecting the possibility that person C names them as a contact. Person G is the special case of a person who is asymptomatic. In the model they are never isolated and are missed by contact tracing. In addition, all people they infect will also be missed by contact tracing. Person H, J, and K can however be isolated when or if they themselves show symptoms. On the left, the entire pathway of transmissions is shown.

9. Outbreak trajectories for baseline parameters

Outbreaks generated by the simulation are shown (Figure S9). Smaller outbreaks occurred for lower transmission.

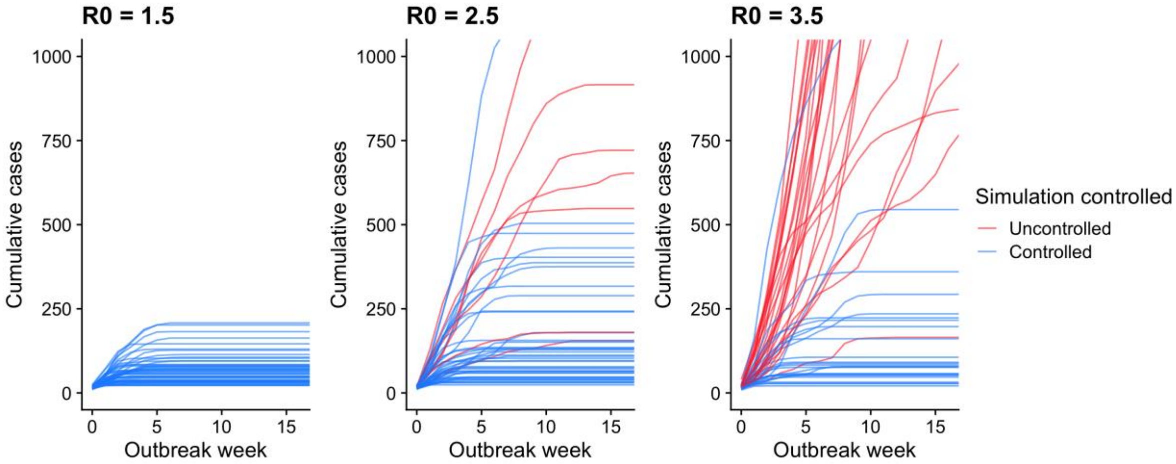

Figure S9. Figure shows 50 randomly sampled epidemic trajectories for R_0 values 1.5, 2.5 and 3.5. The other characteristics are as in the baseline scenario. Colours show if the outbreak was controlled or not controlled in the simulation. For R_0 equal to 1.5, 2.5 and 3.5, 100%, 87%, and 40% of simulated outbreaks were controlled respectively.