

# Engagement and adherence trade-offs for SARS-CoV-2 contact tracing.

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## Abstract

Contact tracing is an important tool for allowing countries to ease lock-down policies introduced to combat SARS-CoV-2. For contact tracing to be effective, those with symptoms must self-report themselves while their contacts must self-isolate when asked. However, policies such as legal enforcement of self-isolation can create trade-offs by dissuading individuals from self-reporting. We use an existing branching process model to examine which aspects of contact tracing adherence should be prioritised. We consider an inverse relationship between self-isolation adherence and self-reporting engagement, assuming that increasingly strict self-isolation policies will result in fewer individuals self-reporting to the programme. We find that policies that increase the average duration of self-isolation, or that increase the probability that people self-isolate at all, at the expense of reduced self-reporting

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rate, will not decrease the risk of a large outbreak and may increase the risk, depending on the strength of the trade-off. These results suggest that policies to increase self-isolation adherence should be implemented carefully. Policies that increase self-isolation adherence at the cost of self-reporting rates should be avoided.

*Keywords:* COVID-19, contact tracing, branching processes, SARS-CoV-2, adherence, engagement, case isolation, quarantine

## 1. Background

Since the first cases of SARS-CoV-2 in China in late 2019<sup>1</sup> the virus has spread globally, resulting in over 600,000 confirmed deaths by August 2020<sup>2</sup>. Lockdown in the UK began in March 2020<sup>3</sup> and reduced  $R_0$  below 1 while also triggering unprecedented reductions in economic activity<sup>4</sup>. As lockdown restrictions are relaxed, both in the UK and in other countries, other methods for keeping  $R_0$  below one are needed. Large-scale contact tracing is one of the potential methods for keeping virus spread under control<sup>5,6,7</sup>.

During the current SARS-CoV-2 outbreak, contact tracing has been used to great effect in a number of countries including Vietnam and South Korea<sup>8,9</sup>. Two broad classes of contact tracing include manual tracing and digital tracing using a smartphone app<sup>10</sup>. Manual contract tracing is the only system currently running in the UK though it is expected that a contact tracing app will be launched soon. In manual contact tracing, trained public health staff ask a case for the names and contact details of people they have recently been in close proximity with, as well as asking for information on which public areas the infected person has visited. The tracers will then identify as many contacts as possible and ask them to self-isolate for a period. Adherence to the contact tracing system is an important determinant of its efficacy<sup>11,6,10</sup>.

Adherence applies to a number of different aspects of contact tracing<sup>12</sup>. Untraced individuals with symptoms must report themselves to the contact tracing system. They then must give identifying information about the people they have been in close proximity with. Then, both the index case, and the traced contacts, must self-isolate for a period<sup>13,14</sup>. If the contact tracing system uses home swab tests, the swabs must be taken carefully<sup>15,16</sup>. Adherence to each of these steps will be imperfect.

Although there are many unobserved variables involved, we can start to

29 examine some of these adherence rates using public statistics from the UK  
30 tracing system<sup>17</sup>. For example, of the 6,923 people who were referred to  
31 the contact tracing system between the 11th and 17th of June, 70% were  
32 reached. However, these 6,923 cases certainly do not represent 100% of the  
33 new cases in the country that week. Of the 6,923, 74% gave details of at  
34 least one contact though it is not possible to tell how many of the remaining  
35 26% actually had no contacts. 82% of close contacts were reached and asked  
36 to self-isolate.

37 However, these adherence rates are not fixed parameters and can be influ-  
38 enced by policy. For example, economic support for those missing work<sup>14,18</sup>,  
39 daily phonecalls to monitor adherence<sup>19</sup> or legal ramifications for break-  
40 ing self-isolation, such as those implemented in Singapore and Taiwan<sup>19</sup>,  
41 might be expected to increase self-isolation rates<sup>18</sup>. In particular, this work  
42 was originally undertaken in response to a question from policy makers ask-  
43 ing whether legally mandating self-isolation for close-contacts would reduce  
44 transmission rates. Furthermore there are likely to be trade-offs and de-  
45 pendencies between parameters. In particular, contact tracing relies on self  
46 reporting of symptoms in order to initially identify a chain of transmission  
47 but introducing penalties for non-compliance to self-isolation might be ex-  
48 pected to decrease the proportion of people that report themselves to the  
49 system in the first instance. In general there are few direct, individual bene-  
50 fits to self reporting oneself to a contact tracing system; instead the benefits  
51 are communal and the drivers for self reporting are likely to be altruism or  
52 social norms<sup>20,21</sup>. However, there are direct costs both to the individual that  
53 self reports and to their close contacts. Self-isolation is mentally difficult<sup>22</sup>  
54 and will come with economic costs for many<sup>20,23,24,14,25</sup>. Legally enforcing  
55 self-isolation exacerbates these costs.

56 The exact form that these trade-offs would take are difficult to know.  
57 Adherence to self-isolation requirements might largely be binary with people  
58 complying for the full 14 days (as requested in the UK) or not adhering  
59 at all. In this case, legal enforcement would be expected to increase the  
60 proportion of people that self-isolate. Alternatively, it is possible that self-  
61 isolation adherence is more continuous with people adhering for a few days  
62 instead of the full 14 days. Similarly, legal enforcement might be expected  
63 to increase the duration of isolation. Finally, if swab tests are being self-  
64 administered, people might be less careful or less willing to endure discomfort  
65 if the consequences of a positive test are more severe (though this might  
66 change as saliva tests are produced<sup>26,27</sup>). While it is difficult to know the

functional effects of different levels of compliance, it is even more difficult to quantify the strengths of the trade-offs. Legal enforcement might have a weak effect on improving self-isolation adherence<sup>22</sup> but a strong deterrent effect on self-reporting. Alternatively, perhaps legal mandation has a strong effect on self-isolation adherence without being a strong deterrent to self-reporting rates. Furthermore, the shapes of these trade-offs are likely to differ in different countries and social groups based on culture, trust in the government and other factors. Careful quantitative and qualitative studies will need to be conducted to quantify these effects.

Here we use a previously published branching process model<sup>11,6</sup> to examine the effects of these trade-offs on the risk of a large outbreak of SARS-CoV-2. We examine trade-offs between self-isolation duration and self-isolation probability with self-reporting rates, contact information reporting probabilities and sensitivity of home swab tests. It is important to note however that we do not consider the societal costs<sup>28</sup> of legal enforcement of self-isolation; we aim to quantify the benefits of these policies without considering the costs noting that the costs are not easy to directly compare to the benefits.

## 2. Methods

In this paper we extend a previous model of SARS-CoV-2 transmission<sup>11</sup>. An overview of the model is given in Figure S1 while parameter values and references are given in Table 1. At the individual-level, the number of potential secondary contacts are modelled by a negative binomial distribution while the exposure times of these new infections are modelled as a gamma distribution. Self-isolating individuals are assumed to be unable to transmit the disease (assuming isolation within households) and therefore potential secondary cases are avoided if the gamma-distributed exposure time occurs during self-isolation of the primary case. The timing of self-isolation depends on whether the case was traced as a potential contact or not and a number of factors affecting adherence as described in detail below. The model proceeds as a branching process with each simulation being seeded with twenty untraced, infected individuals.

### 2.1. Secondary case distribution

The heterogeneity in the number of potential secondary cases caused by an individual is modelled as a negative binomial distribution. For symptomatic cases we use a mean value of 1.3 secondary cases while asymptomatic

Parameter	Values	Refs
Self-isolation probability	30%–90%	32
Self-reporting probability	30%–90%	
Test sensitivity	35%–65%	33,34,35
Minimum isolation duration	1–14 days	
Maximum isolation duration	7, 14 days	
Contact tracing coverage (%)	40%–80%	
Number of initial cases	20	
Symptomatic $R_S$ under physical distancing	1.3	
Asymptomatic $R_S$ under physical distancing	0.65	
Dispersion of $R_S$ , $k$	0.16	31,11
Proportion asymptomatic	50%	36,37
Delay: onset to isolation	1 day	
Incubation period (Lognormal)	mean log: 1.43, sd log: 0.66	38
Infection time (Gamma)	shape: 2.12, rate: 0.69 day <sup>-1</sup>	38
Infection time shift	-3 days	38
Time to trace contacts (days)	1 day	
Delay: isolate to test result	1 days	

Table 1: Model parameters values/ranges. Parameters taken from the literature are fixed and for other parameters a range of values are explored.

cases are given a 50% lower infection rate. This relates to a scenario where strong social distancing and good hygiene is still being observed. Earlier work<sup>6,7</sup> and preliminary analyses indicated that contact tracing is unable keep the risk of an outbreak low without being paired with social distancing so this is the scenario we focus on. Estimates for the dispersion parameter,  $k$ , for SARS-COV-2 range from  $k = 0.1$  (0.05–0.2) for pre-lockdown UK<sup>29</sup> to  $k = 0.25$  (0.13–0.88) for Tianjin, China during lockdown measures<sup>30</sup>. Given this range we have kept the parameter as used in<sup>11,31</sup> setting  $k = 0.16$ . This value of  $k$  yield a strongly skewed distribution with most individuals causing zero potential secondary cases.

## 2.2. Infection profile

Individuals are labelled as symptomatic or asymptomatic with a probability of 50%<sup>36,37</sup>. The onset time of symptoms is modelled as a lognormal

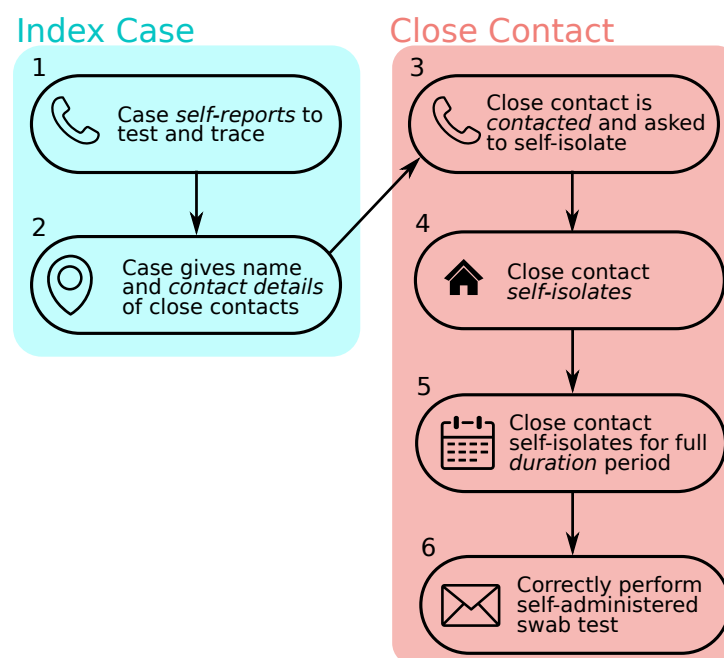


Figure 1: Overview of adherence in test and trace. An untraced individual must self-report and give the name and details of close contacts. The contact tracing team must then manage to contact the close contacts. The close contacts must self-isolate when asked and remain in self-isolation for the full isolation period (14 days in the UK). In some systems, the isolated individual is given a self-administered swab test which must be administered correctly. There is imperfect adherence or performance at each of these stages. In this paper we focus on trade-offs between self-report rate (stage 1) and self-isolation adherence (stages 4 and 5). We combine stages 2 and 3 into one parameter, which we call control effectiveness.

115 distribution with mean 1.43 days and sd of 0.66<sup>39</sup>. All individuals, whether  
 116 symptomatic or asymptomatic are given a symptom onset time as the expo-  
 117 sure time of secondary cases is calculated relative to this time. The exposure  
 118 time for each new potential case is drawn from a gamma distribution with  
 119 shape parameter of 17.77 and a rate of 1.39 day<sup>-1</sup>. This distribution is cen-  
 120 tred three days before the onset of transmission<sup>38</sup>. The sampled exposure  
 121 time is compared to the infector's exposure time and resampled if it occurs  
 122 before the infector was infected. If the exposure time of a potential secondary  
 123 case occurs during the primary case's self-isolation, the infection event does  
 124 not occur and the Ppotential secondary case does not become a case. These

125 distributions are shown in Figure S2.

### 126 2.3. Contact tracing

127 The first stage in the contact tracing system is an untraced, symptomatic  
128 individual self-reporting themselves. The control effectiveness, i.e. the pro-  
129 portion of an individual's epidemiological contacts that are recalled, divulged  
130 and successfully contacted by the contact tracing team, is varied between  
131 40%–80%. If contact tracing is successful, the traced individual is asked to  
132 self-isolate. We assume it takes one day to contact a contact. If a traced con-  
133 tact subsequently shows symptoms or returns a positive test the next round  
134 of contact tracing is initiated. That is, the contacts of the traced contact are  
135 then traced.

### 136 2.4. Testing

137 As a baseline we assume that tests have a sensitivity of 65% and that  
138 it takes one day for results to be returned. This reflects the sensitivity of  
139 tests observed in the community<sup>34,33</sup>. Given a positive test result contact  
140 tracing for the tested individual is initiated. A negative test allows the tested  
141 individual to be immediately released from quarantine. Any contacts of a  
142 negative-testing case that were successfully identified prior to receiving the  
143 test result are still isolated and tested. In a branching process model only  
144 infected individuals are modelled. Therefore we do not track the number of  
145 uninfected people that are unnecessarily asked to quarantine. Test specificity  
146 affects the number of uninfected people asked to quarantine but does not  
147 directly affect the spread of the disease and therefore we do not define a test  
148 specificity. In this study we are concerned with quantifying the benefits of  
149 contact tracing and do not attempt to weigh the epidemiological benefits  
150 against the sociological costs.

### 151 2.5. Adherence trade-offs

152 We consider three main trade-offs. As we do not have good data to  
153 define the shapes of these trade-offs we run simulations for all combinations  
154 of parameters.

155 First, we assume that without policies to encourage self-isolation most  
156 people attempt some self-isolation but the lack of adherence is with respect  
157 to the duration of self-isolation that decreases. We keep the probability  
158 of self-isolation constant at 70%. We assume that each person that does  
159 self-isolate isolates for an amount of time taken from a uniform distribution



between a minimum and maximum value. For the maximum values we use either the full 14 days currently recommended in the UK or a shorter seven day maximum isolation. We vary the minimum duration of self-isolation from 1 day to being equal to the maximum duration.

Second, we examine the trade-off between self-report probability and self-isolation probability. We expect that policies that increase self-isolation probability will reduce self-report probability. We use values of self-isolation from 10% – 70% in increments of 20% and examine all combinations with self-report probabilities from 10% – 70% also in increments of 20%. The upper bound for self-isolation here is certainly above the rate of self-isolation currently being achieved in the UK. However, it is below the target rate for other national contact tracing programmes<sup>32</sup>. Furthermore, the very strict restrictions applied to travellers entering countries such as Singapore could also be considered an upper bound on feasible policies. Many of the policies used in these areas, such as enforced isolation in government run hotels, GPS ankle bracelets, and daily video calls, would be considered draconian if applied to the population at large but could be reasonably expected to produce self-isolation rates of 90%. In contrast to the first trade-off, we assume that everyone that does self-isolate does so for the full maximum value of either 7 or 14 days.

Finally, we assume that policies that increase self-isolation probability will decrease test sensitivity. This scenario applies to the case of home administered tests. With strong incentives to test negative, people will be less likely to perform swabs correctly. We therefore examine a range of test sensitivities from a baseline of 65% down to 35% in increments of 10%.

## 2.6. Simulation process

Results presented are the combined output of 15,000 simulations for each parameter combination, or scenario, considered. We define a simulation as leading to a large outbreak if it has more than 2,000 cumulative cases or if there are still infected cases after 300 days. The threshold of 2,000 cases was chosen by running simulations with a maximum of 5,000 cases and noting that of the simulated epidemics that went extinct, 99% of extinction events occurred before reaching 2,000 cases. Nearly all simulations either went extinct or reached 2,000 cases with very few simulations lasting longer than 300 days. These simulations were then used to calculate the probability of a large outbreak given a certain set of conditions. 95% Clopper-Pearson exact confidence intervals were also calculated. The model was written in R



197 and the code and testing suite<sup>40</sup> is publicly available on GitHub ([https://github.com/timcdlucas/ringbp/tree/adherence\\_tradeoff\\_runs](https://github.com/timcdlucas/ringbp/tree/adherence_tradeoff_runs)).  
198

### 199 3. Results

#### 200 3.1. Trade-off between self-isolation duration against self-report probability

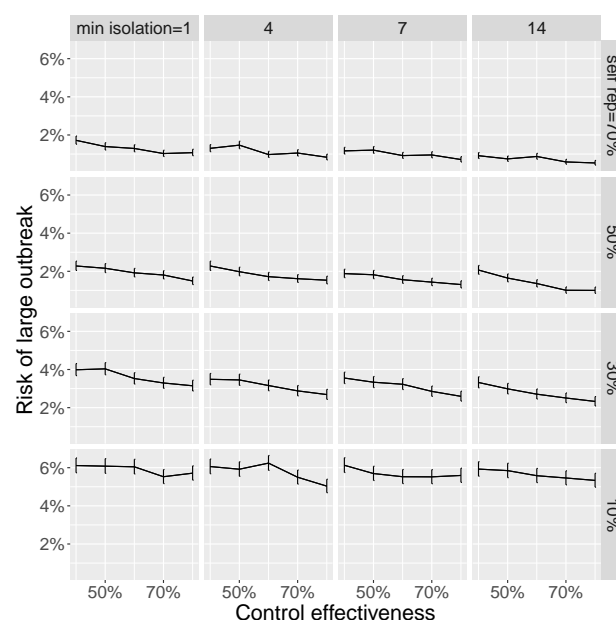


Figure 2: Trade-off between self isolation time (columns) and self report rate (rows) with error bars denoting 95% confidence intervals. Individuals self isolate for a randomly selected duration between min isolation and 14 days. Untraced, symptomatic individuals self-report with a probability that varies across the rows. The proportion of close contacts that are divulged and asked to self-isolate varies across the x-axis of each subplot. The y-axis shows the risk of a large outbreak (greater than 2,000 cases) over 15,000 simulations. The probability that an individual self-isolates at all is fixed at 70%. If we assume we are currently near the top left we expect that introducing legal ramifications for breaking self isolation to move us down and right. This generally increases risk.

201 We find that increasing the duration of self-isolation increases the risk of  
202 a large outbreak in the presence of reductions in self-reporting rates. The  
203 probability of a large outbreak for all combinations of self-isolation duration  
204 and self-report rates are shown in Figure 2. If we assume that we are currently  
205 in the top left panel (high self report rates but isolation taken uniformly

between 1 and 14 days), policies that move us down and right generally increase the risk of a large outbreak. For example, if we consider a control effectiveness of 60%, with a self-isolation duration of between 1 and 14 days and a self-report rate of 70% the risk of a large outbreak is 1%. If we increase the self-isolation duration to always be 14 days but reduce the self-report rate to 10%, the probability of a large outbreak increases from 1% to 6%. If the trade-off is very weak, such that increasing self-isolation duration to always be 14 days only decreases self-report rates to 50%, we see no change in the probability of an outbreak.

If we assume a more pessimistic starting scenario of a self-isolation duration of between 1 and 14 days and self-reporting rates of 10% and given a control effectiveness of 60% we have a 6% risk of a large outbreak. We find that increasing self-report rates gives a larger reduction in risk. Increasing self-report rates from 10% to 70% reduces risk from 6% to 1%. In contrast, increasing the duration of isolation to always being 14 days does not change the risk of a large outbreak. We find that reducing the maximum isolation duration from 14 days to 7 days consistently increases the risk of a large outbreak (Figure S3–S5).

### 3.2. Trade-off between self-isolation probability against self-report probability

We find that increasing self-isolation probability while decreasing self report probability does not strongly alter the probability of a large outbreak. The probability of a large outbreak for all combinations of self-isolation rates and self-report rates are shown in Figure 3. If we assume that we are currently in the top left panel (high self report rates but low self-isolation rates), policies that increase self-isolation rates but decrease self-report rates would move us down and right. However, whether this decreases the risk of an outbreak depends on the strength of the trade-off. For example, if we consider a control effectiveness of 60%, with a self-isolation rate of 10% and a self-report rate of 70% the risk of a large outbreak is 6%. If we increase the self-isolation rate to 70% and equivalently reduce the self-report rate to 10%, the probability of a large outbreak is still 6%. If the trade-off is weak, such that increasing self-isolation from 10% to 70% only incurs a reduction in self-report rate to 50%, the reduction in risk of a large outbreak is substantial, reducing from 6% to 1.5%. However, if the trade-off is strong, such that increasing self-isolation from 10% to 30% causes a reduction in self reporting rate from 70% to 10%, the risk of an outbreak instead marginally increases from 6% to 7%.

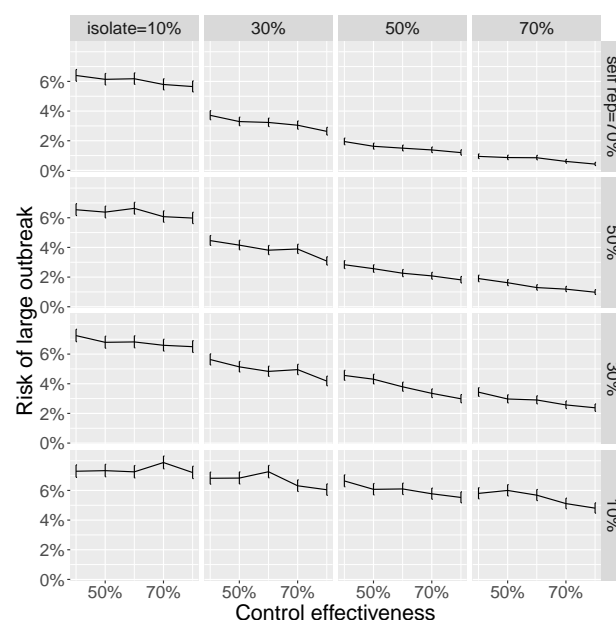


Figure 3: Trade-off between self-isolation probability (columns) and self-report probability (rows) with error bars denoting 95% confidence intervals. The y-axis shows the risk of a large outbreak (greater than 2,000 cases) over 15,000 simulations. If we assume we are currently near the top left we expect that introducing legal ramifications for breaking self isolation to move us down and right. Whether this decreases risk depends on the strength of the trade-off. If the trade-off is weak, such that as we move from the top left to isolation probability of 70% and self report probability of 50%, risk is reduced. In contrast, if increasing isolation probability from 10% to 30% incurs a drop in self reporting from 70% to 10%, risk does not change.

243 We could instead assume a more pessimistic starting scenario of self-  
244 isolation rates of 10% and self-reporting rates of 10%. Given a control ef-  
245 fectiveness of 60% we have a 7% risk of a large outbreak. However, from  
246 this scenario we can consider whether it is better to increase self-isolation  
247 or to increase self-reporting. Increasing self isolation probability to 70% re-  
248 duces risk to 6% and increasing self-report probability to 70% also reduces  
249 risk to 6%. Increasing both to 30% reduces risk to 5%. Overall, these two  
250 parameters are relatively evenly balanced.

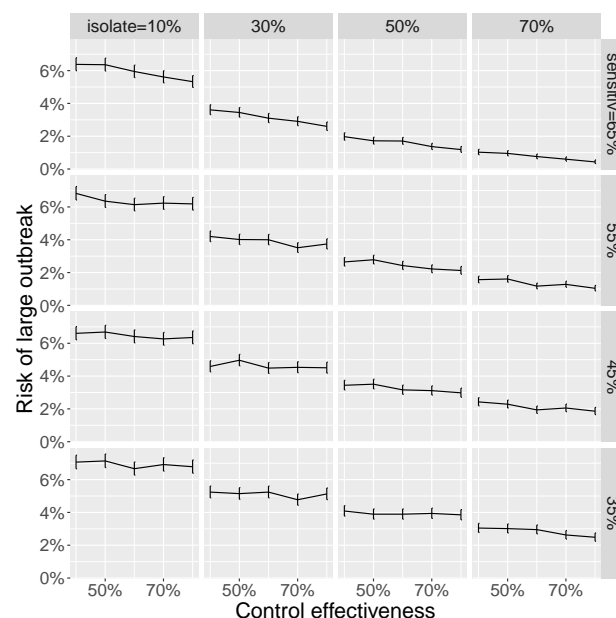


Figure 4: Trade-off between self isolation probability (columns) and test sensitivity (rows) with error bars denoting 95% confidence intervals. Untraced, symptomatic individuals self-report with a probability that varies across the rows. The proportion of close contacts that are divulged and asked to self-isolate varies across the x-axis of each subplot. If we assume we are currently near the top left, introducing legal ramifications for breaking self isolation might move us down and right. This generally decreases risk unless the trade off is very strong such that a small increase in isolation probability incurs a large decrease in test sensitivity.

### 3.3. Trade-off between self-isolation duration against test sensitivity

To model a decrease in careful administration of home swab tests, we vary the test sensitivity and isolation adherence. We find that increasing self-isolation rates decreases the risk of a large outbreak even if this occurs in combination with reductions in test sensitivity. The probability of a large outbreak for all combinations of self-isolation rate and test sensitivity are shown in Figure 4. If we assume that we are currently in the top left panel (relatively high test sensitivity but low self-isolation rates), policies that increase self-isolation rates but decrease test sensitivity would move us down and right and this in general yields reduced risks of a large outbreak. For example, if we consider a control effectiveness of 60%, with a self-isolation rate of 10% and a test sensitivity of 65% the risk of a large outbreak is 6%. If

263 we increase the self-isolation rate to 70% while reducing the test sensitivity  
264 to 35%, the probability of a large outbreak reduces from 6% to 3%.

## 265 4. Discussion

266 Overall we have found that policies that increase self-isolation rates at  
 267 the expense of self-report rates are unlikely to improve the effectiveness of  
 268 contact tracing systems. If the primary trade-off is between the duration  
 269 of self-isolation and the probability of self-reporting, we find that policies  
 270 that increase self-isolation and reduce self-report rates will cause either an  
 271 increase or no change in the probability of a large outbreak depending on the  
 272 strength of the trade-off. When the primary trade-off was instead between the  
 273 probability of self-isolation and the rate of self report policies that increase  
 274 self-isolation rates and reduce self-report rates can increase or marginally  
 275 decrease the probability of a large outbreak depending on the strength of  
 276 the trade-off. Overall this implies that policies such as fines, and police  
 277 enforcement of self-isolation will have either little benefit or a negative effect.  
 278 Broadly, policies that improve self-report rates, even at the expense of self-  
 279 isolation rates should be used. This might include publicity that encourages  
 280 people to self-report by reminding them that there are no legal consequences  
 281 to them or their contacts for doing so.

282 Policies that improve self-report rates or self-isolation rates without an  
 283 associated trade-off will also improve contact tracing efficacy. For example,  
 284 economic support and employment protection for individuals that self-isolate  
 285 would be expected to improve self-isolation rates<sup>14,18,25</sup> without decreasing  
 286 self-report rates. Similarly, efforts to communicate the reasons why people  
 287 should self-report and self-isolate may improve both of these rates simulta-  
 288 neously<sup>18,25</sup>.

289 One of the core assumptions to this work is that legal consequences for  
 290 breaking self-isolation would improve self-isolation rates. However, the evi-  
 291 dence for this is not strong and there is evidence that feelings of shame do not  
 292 promote adherence<sup>21,25</sup>. In contrast there is good evidence that other factors  
 293 such as income and boredom<sup>41</sup> do affect self-isolation rates. How effectively  
 294 legal consequences for breaking self-isolation can increase self-isolation rates  
 295 is a complex question that will depend on cultural norms, perceived enfor-  
 296 cability, and the strength of economic and psychological consequences for  
 297 self-isolation. An important consequence of this is that self-isolation rates  
 298 and the effectiveness of policies aimed to improve these rates will be strongly  
 299 correlated such that individuals that are most likely to infect each other are  
 300 also likely to have similar self-isolation rates. This is not included in our  
 301 model but has the potential to strongly reduce contact tracing efficacy in

302 certain groups and locations.

303 With regards to test sensitivity, our results are relevant only to self-  
 304 administered swab-tests. Swab-tests may be replaced with reliable paper-  
 305 based tests. Given that we found that optimising self-isolation rates over  
 306 test-sensitivity minimises risk, other considerations such as test timing and  
 307 access are probably more important. Furthermore, currently in the UK,  
 308 traced contacts are not allowed out of quarantine after a negative test so the  
 309 system is more robust to low test sensitivity than in our simulations.

310 Here we have focused solely on the probability of a large outbreak as a  
 311 consequence of policy change. However, there are other costs and benefits to  
 312 changing values of self-report rates and self-isolation rates. High self-report  
 313 rates not only improves contact tracing efficacy directly, it also creates a more  
 314 effective system for measuring the incidence of SARS-CoV-2 in the commu-  
 315 nity. This gives better early warning for when an outbreak is beginning in  
 316 an area or group and allows for health care resources to be deployed more  
 317 efficiently. In contrast, self-isolation comes with many economic and social  
 318 costs both for the individual and the community. Avoiding strict penalties  
 319 for breaking self-isolation allows those most affected by these costs to self-  
 320 isolate less and may increase buy-in to the system as a whole. Furthermore,  
 321 enforcement of self-isolation policies are an infringement on a basic liberty.  
 322 While we have not tried to compare these costs to the epidemiological bene-  
 323 fits, they must always be taken into account when implementing policy.



## 324 5. CRediT contribution statement

325 Conceptualisation: All authors  
 326 Formal Analysis: ELD, TCDL  
 327 Funding acquisition: TDH  
 328 Investigation: ELD, TCDL, AB, LP, DA, TC, LY  
 329 Methodology: ELD, TCDL  
 330 Software: ELD, TCDL  
 331 Visualization: ELD, TCDL, LY  
 332 Writing – original draft: ELD, TCDL  
 333 Writing – review & editing: All authors

## 334 6. Declaration of competing interest

335 The authors declare that they have no known competing financial inter-  
 336 ests or personal relationships that could have appeared to influence the work  
 337 reported in this paper.

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## References

- [1] South China Morning Post, Coronavirus: China's first confirmed Covid-19 case traced back to November 17 [Accessed 2nd June; URL: <https://www.scmp.com/news/china/society/article/3074991/coronavirus-chinas-first-confirmed-covid-19-case-traced-back>], 2020.
- [2] M. Roser, H. Ritchie, E. Ortiz-Ospina, J. Hasell, Coronavirus Pandemic (COVID-19), <https://ourworldindata.org/covid-deaths>, 2020. Accessed: 2020-08-10.
- [3] Coronavirus: Strict new curbs on life in UK announced by PM , <https://www.bbc.co.uk/news/uk-52012432>, 2020. Accessed: 2020-06-27.
- [4] GDP monthly estimate, UK: April 2020, <https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpmonthlyestimateuk/april2020>, 2020. Accessed: 2020-06-27.
- [5] A. Aleta, D. Martín-Corral, A. P. y Piontti, M. Ajelli, M. Litvinova, M. Chinazzi, N. E. Dean, M. E. Halloran, I. M. Longini Jr, S. Merler, et al., Modelling the impact of testing, contact tracing and household quarantine on second waves of covid-19, *Nature Human Behaviour* (2020) 1–8.
- [6] E. L. Davis, T. C. Lucas, A. Borlase, T. M. Pollington, S. Abbott, D. Ayabina, T. Crellen, J. Hellewell, L. Pi, G. F. Medley, et al., An imperfect tool: Covid-19's test & trace's success relies on minimising the impact of false negatives and continuation of physical distancing., *medRxiv* (2020).
- [7] M. E. Kretzschmar, G. Rozhnova, M. C. Bootsma, M. van Boven, J. H. van de Wijgert, M. J. Bonten, Impact of delays on effectiveness of contact tracing strategies for covid-19: a modelling study, *The Lancet Public Health* (2020).
- [8] S. M. Le, Containing the coronavirus (COVID-19): Lessons from Vietnam, <https://blogs.worldbank.org/health/>

- 388 containing-coronavirus-covid-19-lessons-vietnam, 2020. Ac-  
389 cessed: 2020-06-03.
- 390 [9] S. Park, G. J. Choi, H. Ko, Information technology-based tracing strat-  
391 egy in response to covid-19 in south korea—privacy controversies, *Jama*  
392 (2020).
- 393 [10] L. Ferretti, C. Wymant, M. Kendall, L. Zhao, A. Nurtay, L. Abeler-  
394 Dörner, M. Parker, D. Bonsall, C. Fraser, Quantifying SARS-CoV-  
395 2 transmission suggests epidemic control with digital contact tracing,  
396 *Science* 368 (2020).
- 397 [11] J. Hellewell, S. Abbott, A. Gimma, N. I. Bosse, C. I. Jarvis, T. W.  
398 Russell, J. D. Munday, A. J. Kucharski, W. J. Edmunds, F. Sun, et al.,  
399 Feasibility of controlling COVID-19 outbreaks by isolation of cases and  
400 contacts, *The Lancet Global Health* (2020).
- 401 [12] S. BeidasRinad, M. ButtenheimAlison, S. KilaruAustin, A. AschDavid,  
402 G. VolppKevin, G. LawmanHannah, C. CannuscioCarolyn, et al., Opti-  
403 mizing and implementing contact tracing through behavioral economics,  
404 *NEJM Catalyst Innovations in Care Delivery* (2020).
- 405 [13] L. E. Smith, R. Amlôt, H. Lambert, I. Oliver, C. Robin, L. Yardley,  
406 G. J. Rubin, Factors associated with adherence to self-isolation and  
407 lockdown measures in the uk; a cross-sectional survey, *medRxiv* (2020).
- 408 [14] M. Bodas, K. Peleg, Self-isolation compliance in the covid-19 era influ-  
409 enced by compensation: Findings from a recent survey in israel: Public  
410 attitudes toward the covid-19 outbreak and self-isolation: a cross sec-  
411 tional study of the adult population of israel, *Health Affairs* 39 (2020)  
412 936–941.
- 413 [15] C. P. Seaman, L. T. T. Tran, B. J. Cowling, S. G. Sullivan, Self-collected  
414 compared with professional-collected swabbing in the diagnosis of in-  
415 fluenza in symptomatic individuals: A meta-analysis and assessment of  
416 validity, *Journal Of clinical virology* 118 (2019) 28–35.
- 417 [16] N. Dhiman, R. M. Miller, J. L. Finley, M. D. Sztajnkrzyer, D. M. Nestler,  
418 A. J. Boggust, S. M. Jenkins, T. F. Smith, J. W. Wilson, F. R. Cock-  
419 erill III, et al., Effectiveness of patient-collected swabs for influenza  
420 testing, in: *Mayo Clinic Proceedings*, volume 87, Elsevier, pp. 548–554.

- 421 [17] Weekly NHS Test and Trace bulletin, England: 11 to 17  
422 June 2020, [https://www.gov.uk/government/publications/  
423 nhs-test-and-trace-statistics-england-11-june-to-17-june-2020/  
424 weekly-nhs-test-and-trace-bulletin-england-11-to-17-june-2020#  
425 fn:1](https://www.gov.uk/government/publications/nhs-test-and-trace-statistics-england-11-june-to-17-june-2020/weekly-nhs-test-and-trace-bulletin-england-11-to-17-june-2020#fn:1), 2020. Accessed: 2020-06-27.
- 426 [18] S. Michie, R. West, M. B. Rogers, C. Bonell, G. J. Rubin, R. Amlôt,  
427 Reducing sars-cov-2 transmission in the uk: A behavioural science ap-  
428 proach to identifying options for increasing adherence to social distanc-  
429 ing and shielding vulnerable people, *British Journal of Health Psychol-*  
430 *ogy* (2020).
- 431 [19] S.-C. Chung, S. Marlow, N. Tobias, I. Alogna, A. Alogna, S.-L. You, A  
432 rapid systematic review and case study on test, contact tracing, testing,  
433 and isolation policies for covid-19 prevention and control, *medRxiv*  
434 (2020).
- 435 [20] N. M. Baum, P. D. Jacobson, S. D. Goold, “listen to the people”:  
436 public deliberation about social distancing measures in a pandemic, *The*  
437 *American Journal of Bioethics* 9 (2009) 4–14.
- 438 [21] G. A. Travaglino, C. Moon, Explaining compliance with social distanc-  
439 ing norms during the covid-19 pandemic: The roles of cultural orienta-  
440 tions, trust and self-conscious emotions in the us, italy, and south korea  
441 (2020).
- 442 [22] C. DiGiovanni, J. Conley, D. Chiu, J. Zaborski, Factors influencing  
443 compliance with quarantine in toronto during the 2003 sars outbreak,  
444 *Biosecurity and bioterrorism: biodefense strategy, practice, and science*  
445 2 (2004) 265–272.
- 446 [23] K. D. Blake, R. J. Blendon, K. Viswanath, Employment and compli-  
447 ance with pandemic influenza mitigation recommendations, *Emerging*  
448 *infectious diseases* 16 (2010) 212.
- 449 [24] J. A. Horney, Z. Moore, M. Davis, P. D. MacDonald, Intent to receive  
450 pandemic influenza a (h1n1) vaccine, compliance with social distancing  
451 and sources of information in nc, 2009, *PLoS One* 5 (2010) e11226.
- 452 [25] R. F. Baggaley, A. Ben, L. Chappell, E. Davis, C. Dye, R. Eggo,  
453 L. Fearon, M. Fyles, K. Hampson, A. Menon-Johansson, J. Meyrick,

- 454 D. Mollison, J. Nicholls, M. Pareek, L. Pellis, G. S. Tomba, C. Trotter,  
455 K. Turner, C. Webb, L. Yardley, T. D. Hollingsworth, J. Gog, Recom-  
456 mendations for augmenting contact tracing in the UK: Learning from  
457 other diseases, Isaac Newton Institute for Mathematical Sciences (2020).  
458 Accessed: 2020-08-18.
- 459 [26] A. L. Wyllie, J. Fournier, A. Casanovas-Massana, M. Campbell,  
460 M. Tokuyama, P. Vijayakumar, B. Geng, M. C. Muenker, A. J. Moore,  
461 C. B. Vogels, et al., Saliva is more sensitive for sars-cov-2 detection in  
462 covid-19 patients than nasopharyngeal swabs, Medrxiv (2020).
- 463 [27] C. B. Vogels, D. Brackney, J. Wang, C. C. Kalinich, I. Ott, E. Kudo,  
464 P. Lu, A. Venkataraman, M. Tokuyama, A. J. Moore, et al., Salivadirect:  
465 Simple and sensitive molecular diagnostic test for sars-cov-2 surveillance,  
466 medRxiv (2020).
- 467 [28] U. Schuklenk, K. M. Gartland, Confronting an influenza pandemic: eth-  
468 ical and scientific issues, 2006.
- 469 [29] A. Endo, S. Abbott, A. J. Kucharski, S. Funk, et al., Estimating the  
470 overdispersion in COVID-19 transmission using outbreak sizes outside  
471 China, Wellcome Open Research 5 (2020) 67.
- 472 [30] Y. Zhang, Y. Li, L. Wang, M. Li, X. Zhou, Evaluating transmission  
473 heterogeneity and super-spreading event of COVID-19 in a metropolis  
474 of China, International Journal of Environmental Research and Public  
475 Health (2020) 3705.
- 476 [31] J. O. Lloyd-Smith, S. J. Schreiber, P. E. Kopp, W. M. Getz, Super-  
477 spreading and the effect of individual variation on disease emergence,  
478 Nature 438 (2005) 355–359.
- 479 [32] A. Verrall, Rapid audit of contact tracing for covid-19 in new zealand,  
480 Ministry of Health 310 (2020).
- 481 [33] L. M. Kucirka, S. A. Lauer, O. Laeyendecker, D. Boon, J. Lessler, Vari-  
482 ation in false-negative rate of reverse transcriptase polymerase chain  
483 reaction-based SARS-CoV-2 tests by time since exposure, Annals of  
484 Internal Medicine (2020).

- 485 [34] C. Menni, A. M. Valdes, M. B. Freidin, C. H. Sudre, L. H. Nguyen, D. A.  
486 Drew, S. Ganesh, T. Varsavsky, M. J. Cardoso, J. S. E.-S. Moustafa,  
487 et al., Real-time tracking of self-reported symptoms to predict potential  
488 COVID-19, *Nature Medicine* (2020) 1–4.
- 489 [35] P. van Kasteren, B. van der Veer, S. van den Brink, L. Wijsman,  
490 J. de Jonge, A. van den Brandt, R. Molenkamp, C. Reusken, A. Meijer,  
491 Comparison of seven commercial RT-PCR diagnostic kits for COVID-  
492 19, *Journal of Clinical Virology* 128 (2020).
- 493 [36] K. Mizumoto, K. Kagaya, A. Zarebski, G. Chowell, Estimating the  
494 asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases  
495 on board the Diamond Princess cruise ship, Yokohama, Japan, 2020,  
496 *Eurosurveillance* 25 (2020) 2000180.
- 497 [37] E. Lavezzo, E. Franchin, C. Ciavarella, G. Cuomo-Dannenburg, L. Bar-  
498 zon, C. Del Vecchio, L. Rossi, R. Manganelli, A. Loregian, N. Navarin,  
499 et al., Suppression of COVID-19 outbreak in the municipality of Vo,  
500 Italy, *medRxiv* (2020).
- 501 [38] X. He, E. H. Lau, P. Wu, X. Deng, J. Wang, X. Hao, Y. C. Lau, J. Y.  
502 Wong, Y. Guan, X. Tan, et al., Temporal dynamics in viral shedding  
503 and transmissibility of COVID-19, *Nature Medicine* (2020) 1–4.
- 504 [39] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, R. Ren, K. S.  
505 Leung, E. H. Lau, J. Y. Wong, et al., Early transmission dynamics in  
506 Wuhan, China, of novel coronavirus–infected pneumonia, *New England*  
507 *Journal of Medicine* (2020).
- 508 [40] T. C. D. Lucas, T. M. Polling, E. L. Davis, T. D. Hollingsworth, Re-  
509 sponsible modelling: Unit testing for infectious disease epidemiology,  
510 *medRxiv* (2020).
- 511 [41] W. Wolff, C. S. Martarelli, J. Schöler, M. Bieleke, High boredom prone-  
512 ness and low trait self-control impair adherence to social distancing  
513 guidelines during the covid-19 pandemic, *International Journal of En-  
514 vironmental Research and Public Health* 17 (2020) 5420.

## 515 8. Supplementary material



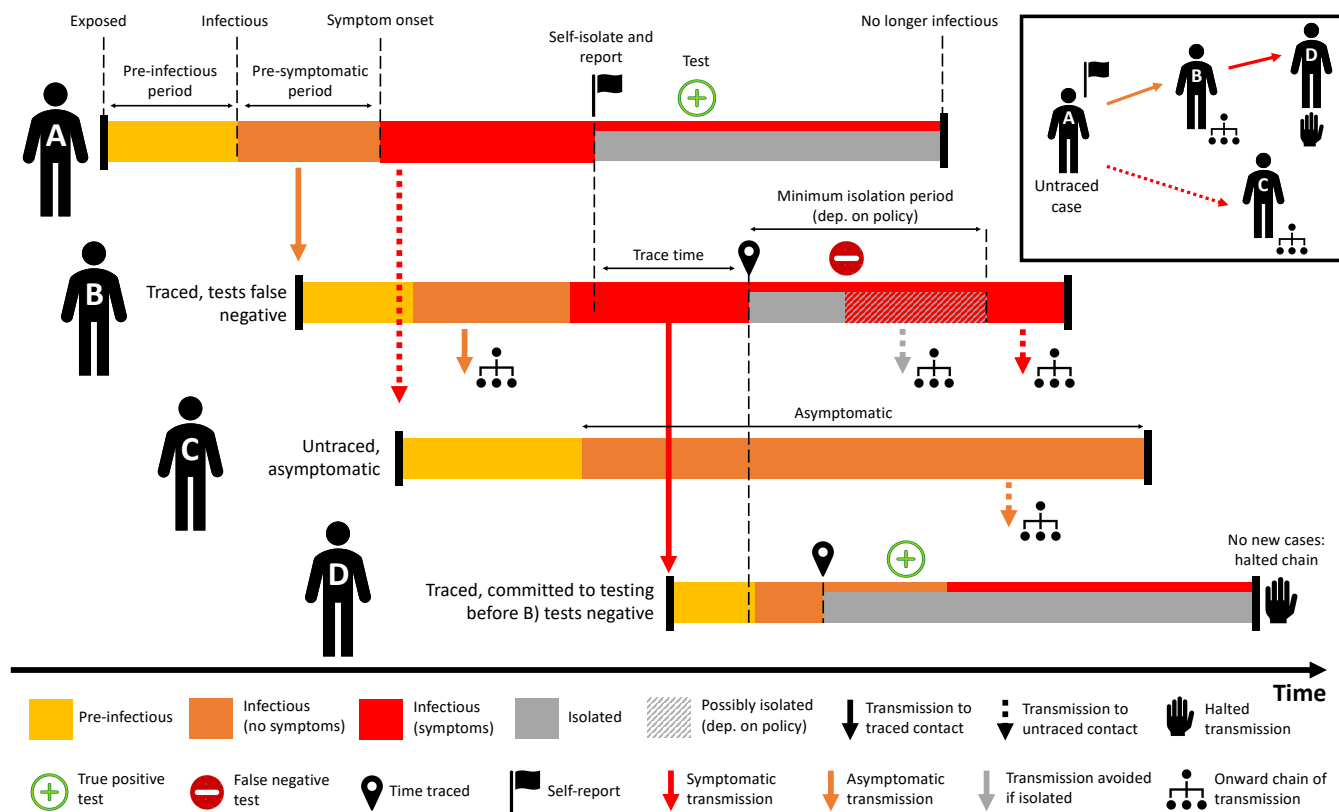


Figure S1: Overview of the contact tracing process implemented in our model. **Person A** isolates and self-reports to the contact tracing programme with some delay after symptom onset, by which time they have infected Persons B and C. When Person A self-reports contact tracing is initiated. They are then tested with positive result and remain isolated for their infectious period. **Person B** was infected by A prior to their symptom onset and is detected by tracing after some delay, after infecting Person D. After isolating they are tested, with a false negative result. This leads to B either a) stopping isolation immediately or b) finishing a minimum 7 day isolation period. Both may allow new onward transmission. **Person C** was infected by A but not traced as a contact. Person C does not develop symptoms but is infectious, leading to missed transmission. **Person D** was traced and tested before the false negative test was returned for Person B. The test for D returns positive, meaning that D remains isolated, halting this chain of transmission.

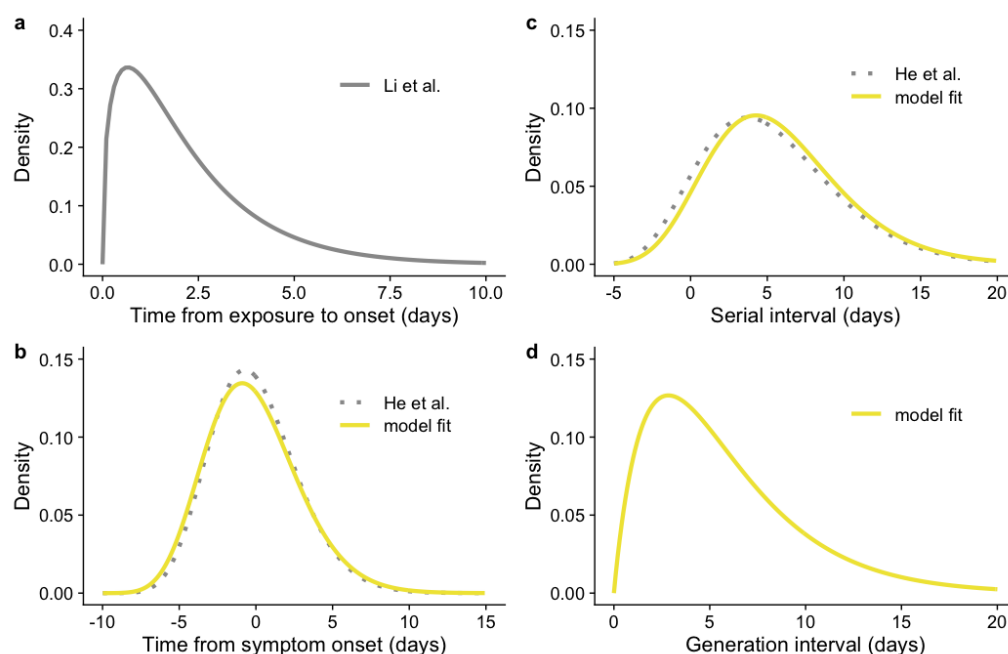


Figure S2: Distributions for a) incubation period (exposure time to symptom onset) from Li et al.<sup>39</sup>; b) transmission profile relative to symptom onset, fitted to data and compared to He et al.<sup>38</sup>; c) serial interval, fitted and compared to He et al.<sup>38</sup>; and d) generation interval, combined distribution from a) and b) with re-sampling to prevent negative serial intervals, as described in the main text.

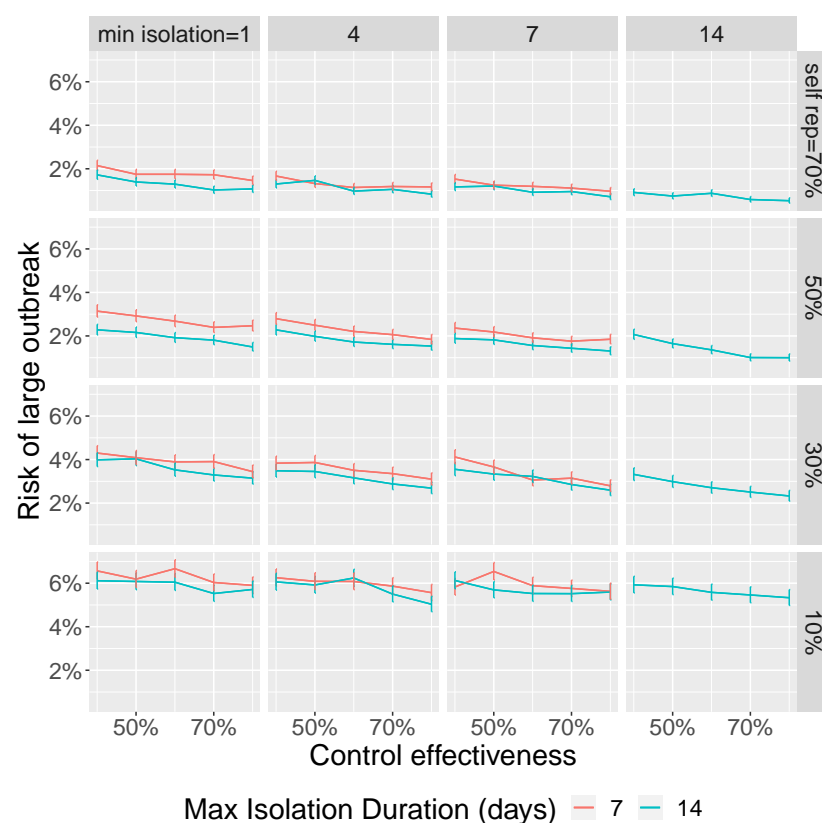


Figure S3: Trade-off between self isolation time (columns) and self report rate (rows) with error bars denoting 95% confidence intervals. Individuals self isolate for a randomly selected duration between min isolation 4 and 14 days. Untraced, symptomatic individuals self-report with a probability that varies across the rows. The proportion of close contacts that are divulged and asked to self-isolate varies across the x-axis of each subplot. Self isolation probability is fixed at 70%. If we assume we are currently near the top left we expect that introducing legal ramifications for breaking self isolation to move us down and right. This generally increases risk.

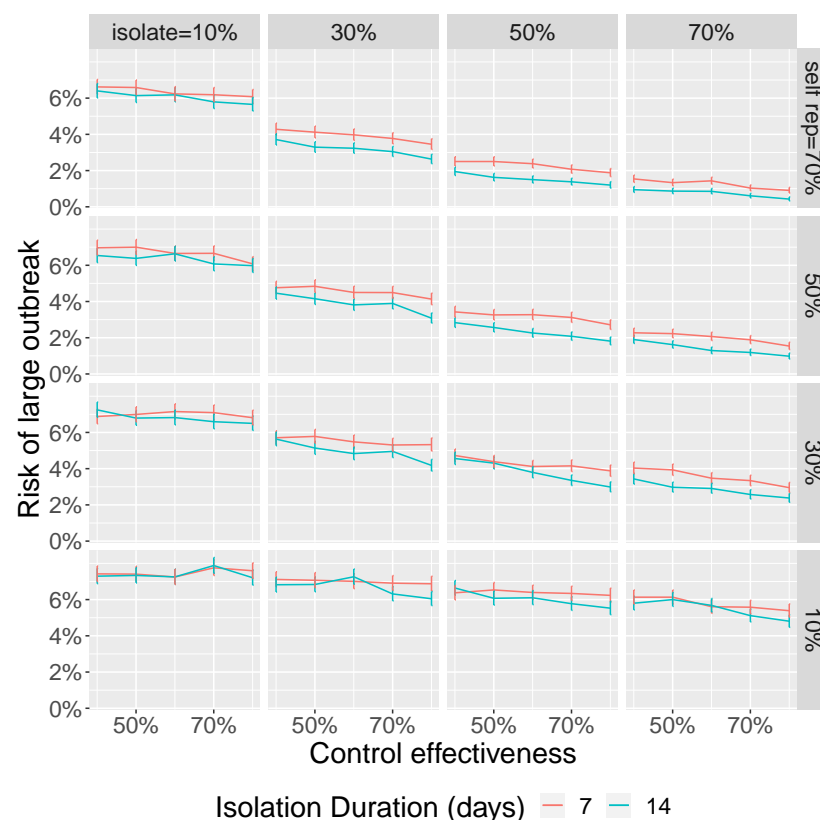


Figure S4: Trade-off between self isolation probability (columns) and self report (rows) with error bars denoting 95% confidence intervals. If we assume we are currently near the top left we expect that introducing legal ramifications for breaking self isolation to move us down and right. Whether this decreases risk depends on the strength of the trade-off.

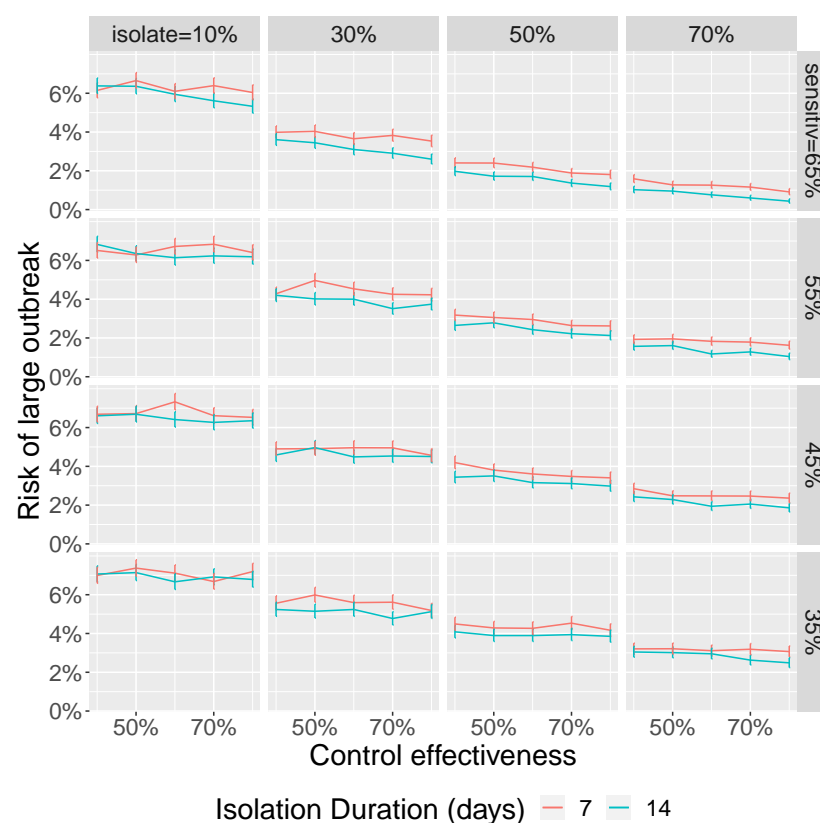


Figure S5: Trade-off between self isolation time (columns) and self report rate (rows) with error bars denoting 95% confidence intervals. Individuals self isolate for a randomly selected duration between min isolation4 and 14 days. Untraced, symptomatic individuals self-report with a probability that varies across the rows. The proportion of close contacts that are divulged and asked to self-isolate varies across the x-axis of each subplot. Self isolation probability is fixed at 70%. If we assume we are currently near the top left we expect that introducing legal ramifications for breaking self isolation to move us down and right. This generally increases risk.