TTI Explorer

12th May 2020

1 Summary

We use an individual-level transmission and contact simulation model to simulate the effectiveness and resource requirements of various test-trace-isolate (TTI) strategies for reducing the spread of SARS-CoV-2 in the UK, in the context of different scenarios with varying levels of stringency of non-pharmaceutical interventions (NPIs) over the summer period.

Model Our model builds upon the individual-level model of Kucharski et al. [2020], and stratifies individual-level transmissions by setting (household, work, school, other) from the BBC Pandemic data of 40,162 participants in the UK. It takes into account recent research on the COVID infection timeline as well as various logistical and temporal aspects of real-world implementations of TTI strategies, including: the inclusion of baseline symptom presentations in the COVID-free population, non-uniform infection profile, imperfect compliance with symptom reporting, isolating and quarantining, and non-negligible time durations needed for reporting symptoms, testing and tracing.

We consider three TTI strategies based on our simulation model: symptom-based contact tracing, test-based contact tracing, and additional testing of asymptomatic contacts. These strategies trade-off the speed of tracing contacts, the required number of tests, the required number of contacts traced, and the number of person-days spent under quarantine, and demonstrate the scale and challenge of implementing an effective TTI system for controlling the COVID epidemic.

Main Findings

- Implemented along with a larger set of NPIs, TTI can help reduce the effective reproduction number R, and can be an important tool when R is around 1.
- TTI is not by itself sufficient to reduce R significantly. This is due to leakage from the system of COVID positive cases (asymptomatic, non-compliance and low app uptake) and imperfect contact tracing (e.g. of contacts unknown to the primary case). To maximize effectiveness of the TTI system, it is crucial to maximize app uptake and compliance to reduce leakage from the system.
- The amount of time required for testing and for manual contact tracing plays a significant role in the effectiveness of TTI. For example, a reduction from 5 to 3 days total almost doubles the effectiveness of a test-based TTI strategy in our simulation.
- The resource needs of an effective TTI system scale linearly in the size of the epidemic.
- An expected high baseline of COVID-like symptoms among the general COVID negative population means that symptom-based TTI has low specificity and requires very high numbers of manual contact tracings and person-days quarantined. If a surveillance system is in place, one possibility is to combine test-based TTI with symptom-based TTI, with the choice depending on the predicted probability of

the primary case being positive (e.g. local outbreaks) and on the risk to others (e.g. in care homes or where the primary case has a large number of close contacts).

- Testing contacts has a marginal impact on R (due to identification of asymptomatic COVID positive contacts) but can significantly reduce the number of person-days of contacts quarantined. Testing too early in the incubation period, and likely variability in the length of incubation periods, might however lead to missing infected contacts.

Limitations There are several limitations to our simulation study, both in terms of simulating transmission dynamics and assumptions made regarding different TTI strategies:

- We only consider a single generation model of transmission, and do not model subsequent infections of tertiary cases, nor effects that complex social networks will have on the spread of COVID in society.
- As in Kucharski et al. [2020] we assume non-household contacts are only met once during the infectious period of the primary case. This will impact both the number of contacts needed to be traced in a TTI strategy and the timeline of infection because repeated contacts, like household contacts, are likely to be infected earlier in a primary case's infectious period.
- We suppose that once a primary case is isolated all potential future infections are prevented. This may be unrealistic, especially for household contacts.
- We assume that an individual's ability to work from home is independent of their number of daily work contacts.
- There is much that is not yet understood surrounding the dynamics of COVID transmission, including: the proportion of COVID positive cases that are asymptomatic, the infectiousness of asymptomatic cases and the infectiousness profile of a COVID positive individual.
- We do not know the likely impact of COVID NPIs on the prevalence of COVID-like symptoms in the general population over the next year. This has implications for the resource requirements of symptom-based TTI strategies.
- We do not account for the varying prevalence of COVID across different regions, demographics and sectors, as well as the varying risk factors of COVID for different individuals. A surveillance system can be important, both in the identification and management of local outbreaks, and in the incorporation of a spatio-temporal predictive model for $\mathbb{P}(\text{COVID positive} \,|\, \text{symptoms and covariates})$ to help improve the efficiency of a resource-constrained TTI system.
- It is difficult to gauge public compliance towards a given TTI strategy. There are various socio-economic factors that may need to be considered here, such as if contacts advised to isolate will be compensated for wages while they are quarantined. A recent study by Bodas and Peleg [0] suggested that public compliance towards self-isolation in Israel would drop from 94% to 57% if compensation was removed.

We perform sensitivity analyses where appropriate in Section D.

2 Methods

Our simulation model consists of three stages: generation of the characteristics of primary cases, generation of the contacts of the primary cases, and the application of test-trace-isolate strategies to the primary cases and their contacts. We specialise the setting of our model to what might be expected during summer months (June-August) in the UK.

Generation of primary cases We include a baseline of 100k symptomatic but COVID-free primary cases. This is around the estimated pre-pandemic number of individuals presenting symptoms of fever or cough on any given day over the summer period according to Bug Watch (Smith et al. [2019]). While

current COVID NPIs have been shown to reduce the presentation of other respiratory illnesses **?**, 100k is a reasonable worst case scenario. We assume 20k new COVID infections each day. This is around the upper bound estimated by for May 10. As there is no consensus for proportion of asymptomatic COVID cases, we followed Kucharski et al. [2020] and set this at 40%, with probability of infection due to social contact reduced by 50% relative to symptomatic cases. For the infection timeline of each COVID positive primary case, we assume a latent period of 3 days, mean 2 days of pre-symptomatic infectious period before reporting symptoms, and a non-uniform infection profile over 10 days peaking on the day before the expected day of symptom presentation He et al. [2020].

Generation of contacts We followed the model of Kucharski et al. [2020] for our contact generation. In summary, we use the BBC Pandemic dataset (Klepac et al. [2018]), which contains data on the social contacts of 40,162 UK participants, to simulate the number of daily close contacts of the primary case. The total number of daily contacts for the primary case is broken down into the following categories: household, work/school and other. To simulate secondary cases, we assume that each contact of the primary case has a probability of being infected over the course of the infectious period, independent of the remaining contacts. We assume new work/other contacts for each day of the simulation, whereas household contacts are assumed to have repeated contact with the primary case on each day of simulation. Additionally, due to the close nature of contacts made at home, household contacts suffer a higher risk of transmission than work/other contacts in our model. Since we assume a non-uniform infection profile, contacts made early during the infectious period also suffer a higher risk of transmission in line with the findings of He et al. [2020].

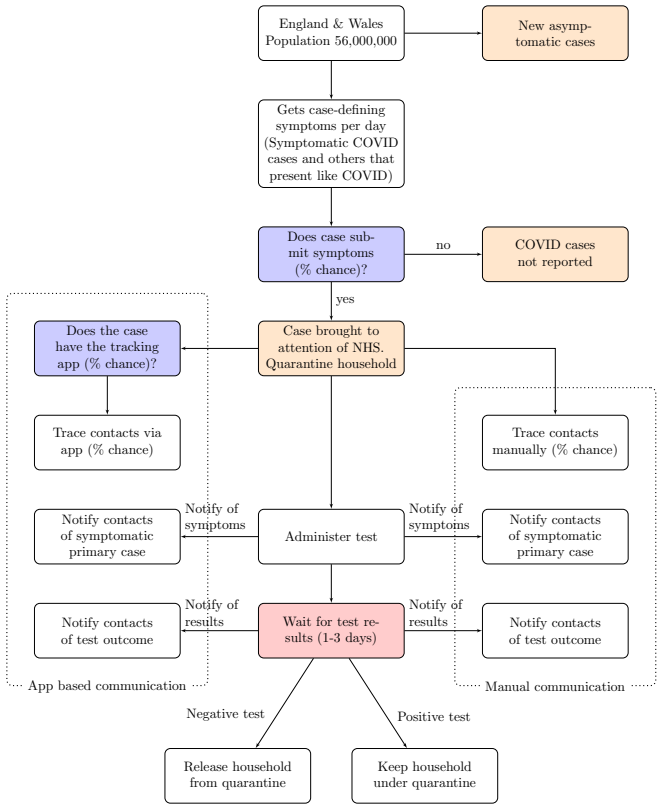
TTI Strategies The three core TTI strategies that we will analyse are summarised as follows:

- Symptom-based TTI: Start contact tracing and isolate contacts as soon as a primary case reports COVID-like symptoms.
- Test-based TTI: Start contact tracing and isolate contacts once a primary case is confirmed by a test to be COVID positive.
- Test-based TTI with contact testing: Start contact tracing and isolate contacts once primary case is confirmed by a test to be COVID positive. Test all close contacts of a confirmed COVID positive primary case.

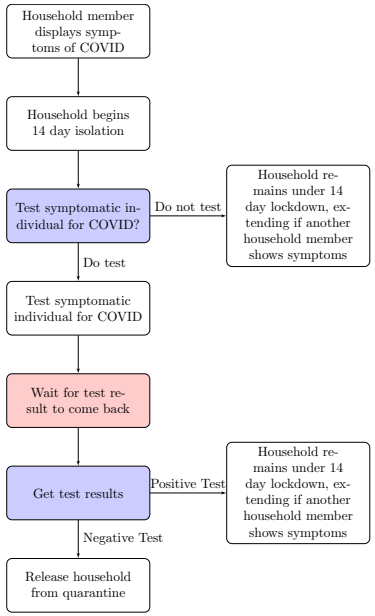
For each strategy, the primary case and members of their household are asked to isolate when the primary case first presents symptoms, following current UK government guidelines. Traced contacts are asked to quarantine while the primary case is being tested, and then continue to quarantine for 14 days if the test was positive or they test negative themselves. If traced contacts show symptoms they are entered into the TTI system as primary cases.

We model both NHSx app-based and manual contact tracing, assuming that 35% of the population will download and regularly use the app. This is estimated assuming that around 60% of the population downloads the app (this is the current proportion of the Isle of Wight population who has downloaded NHSx app during its trial), and 60% of those downloads are regularly using it (this is on the lower side of estimates of usage of the Zoe app). We assume a compliance level of 80% for both symptom reporting as well as requests to quarantine or isolate. The success of TTI can be quite sensitive to the compliance level, which can in turn be affected by appropriate public messaging, incentives and coordination with employers. We assume that the time taken to obtain a test result is 2 days, and that it takes 1 day following this for contacts to be manually traced (app tracing is assumed instantaneous). This is optimistic relative to the TTI process in the early containment phase (PHE, personal communications), which required 3 and 2 days respectively, but we believe it is achievable and has a significant impact on the effectiveness of TTI.

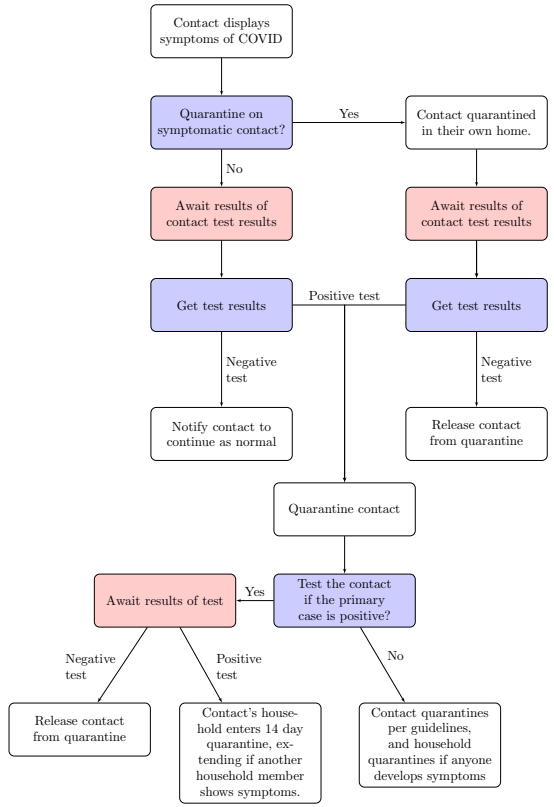
Diagrams of these strategies can be found in Figure 1



(a) Diagram of a case passing through the TTI system



(b) Decision tree for a household contact of an individual in the TTI system



(c) Decision tree for a non-household contact of an individual in the TTI system

Figure 1: Diagrams detailing the flow of new cases, their household contacts, and non-household contacts through the various TTI system.

3 Results

We first compare our proposed TTI strategies against the current (as of 12th May 2020) UK guideline of isolating primary cases and household contacts when the primary case becomes symptomatic, but no contact tracing. We display our results in Figure 2, comparing for effective R, number of contacts manually traced, number of tests needed and number of person-days that contacts spent in quarantine. We combine the TTI strategies with five possible NPI scenarios, which we label S5 to S1. S5 the most severe, modelling the lockdown measures that were relaxed on 10th May 2020, and S1 is the least severe, akin to no additional NPIs. More information on the exact configurations of our NPI scenarios can be found in Section B.1.

As we can see in Figure 2, the proposed TTI measures lead to a reduction in the R for every NPI scenario. We include 95% confidence intervals over our 120k primary cases. However, it is also clear that TTI on its own is not sufficient to reduce R below 1 without other NPIs: indeed the effective R values for all proposed TTI strategies are significantly above 1.5 in S1, when no NPIs are adopted. Note that it is only in the context of S4, which models strict NPIs such as school closures and severe restrictions on daily non-household contacts, that the incorporation of TTI brings R below 1.

In terms of resource requirements, it is clear that symptom-based TTI requires more manual traces and person-days in quarantine compared to test-based TTI, with the same number of tests needed. Note that there is only a small difference between the R values under different TTI strategies. Therefore, one possible conclusion from Figure 2 is that when posed with resource constraints and a large number of symptomatic primary cases, it may be preferable to adopt test-based TTI over symptom-based TTI, but only in combination with other strict NPIs in order to prevent uncontrolled transmission.

When considering test-based TTI with and without contact testing, a trade-off emerges between the extra tests needed and the gained ability to safely release from quarantine the uninfected contacts of COVID-positive cases. Testing is ineffective in detecting infection during the latent period, so repeat testing is advisable to avoid infected contacts being released prematurely.

Having demonstrated that TTI should be adopted in unison with other NPIs, we now analyse three specific areas in which policy can help to improve the effectiveness of TTI: the time delay in testing and tracing, the uptake of the app, and the level of public compliance.

We first evaluate the impact on R of the time delay in testing and manual tracing for the test-based TTI strategy. The results are shown in Table 1. The testing delay is the time between the primary case reporting symptoms and the results of a test being returned, while the manual tracing delay is the time between a primary case being confirmed COVID positive and the identification and quarantining of their contacts. The results indicate that, in order for the test-based TTI strategy to be effective, both of these delays should be reduced. This is particularly important in the context of less stringent NPIs such as S1-S2, in which social contacts are more numerous and containment relies heavily on test and trace. However, we find non-negligible reductions in the effective R across all NPIs considered when the delays are reduced. Indeed, for S4, reducing the test/trace delays from *e.g.* 2/3 to 1/1 brings the effective R below one. Note that our default settings, 2 days delay in test results and 1 day delay in manual tracing, for these delays in Figure 2 are set at an optimistic but potentially achievable level for the UK, and are shorter than those obtained during the early containment phase, which is 3/2 days respectively (PHE, personal communication).

Figure 3 shows the effect on R of changes in app uptake and public compliance. On the left, we see that there is a slight downward trend in mean effective R as app uptake is increased, keeping all other parameters constant. One reason for this is that our default setting for manual tracing delay is at just 1 day, compared to no delay for app traces. If viewed in the context of a longer manual trace delay, this chart would further emphasise the critical role of the app in reducing R.

We note that under the current system, an increase in app usage does not cause a reduction in the number of manual traces required. The primary case will not know which of their contacts have been traced through the app, nor will the government, therefore it is still necessary to trace manually as many contacts as possible.

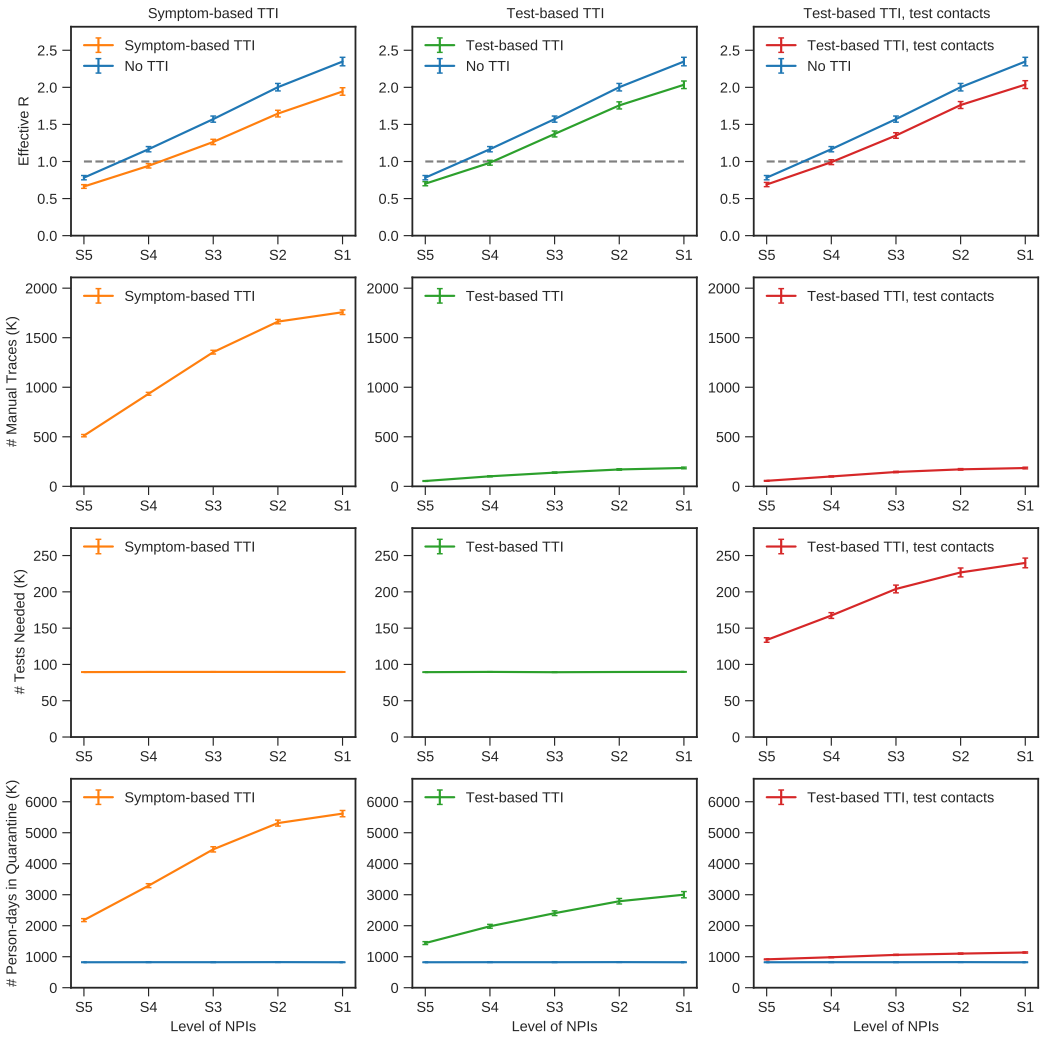


Figure 2: Impact on effective reproduction number R and resource requirements of various TTI strategies, across five sets of NPIs with different stringency's.

Days delay (Test/Trace)	S5	S4	S3	S2	S1
No TTI	0.78 ± 0.03	1.14 ± 0.04	1.59 ± 0.04	2.01 ± 0.05	2.34 ± 0.06
3/3	0.74 ± 0.03	1.07 ± 0.03	1.49 ± 0.04	1.88 ± 0.05	2.19 ± 0.05
3/2	0.72 ± 0.03	1.05 ± 0.03	1.46 ± 0.04	1.84 ± 0.05	2.14 ± 0.05
2/3	0.72 ± 0.03	1.04 ± 0.03	1.45 ± 0.04	1.83 ± 0.05	2.14 ± 0.05
3/1	0.71 ± 0.03	1.02 ± 0.03	1.42 ± 0.04	1.79 ± 0.04	2.09 ± 0.05
2/2	0.70 ± 0.03	1.01 ± 0.03	1.41 ± 0.04	1.78 ± 0.04	2.08 ± 0.05
1/3	0.70 ± 0.03	1.01 ± 0.03	1.41 ± 0.04	1.78 ± 0.04	2.08 ± 0.05
2/1	0.69 ± 0.03	0.98 ± 0.03	1.37 ± 0.04	1.73 ± 0.04	2.02 ± 0.05
1/2	0.69 ± 0.03	0.98 ± 0.03	1.36 ± 0.04	1.72 ± 0.04	2.02 ± 0.05
1/1	0.67 ± 0.03	0.96 ± 0.03	1.33 ± 0.04	1.68 ± 0.04	1.98 ± 0.05

Table 1: The impact on Effective R of reducing delays for testing and manual tracing in the TTI system, for the test-based TTI strategy.

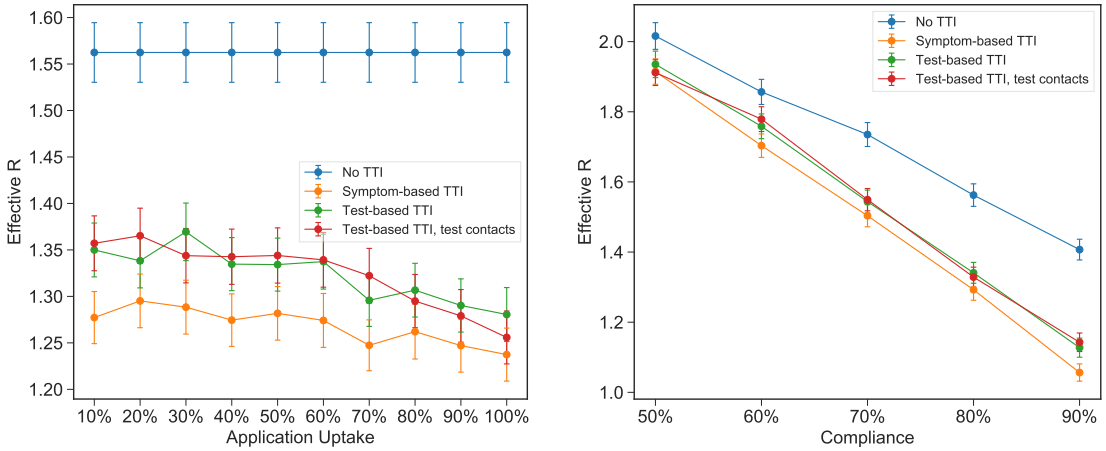


Figure 3: For the S3 lockdown scenario, we investigate the effect of varying 2 key parameters for TTI effectiveness. **Left**: Tracing application uptake rate. **Right**: Overall policy compliance rate. Results for other lockdown scenarios can be found in appendix C

On the other hand, the app will help trace those contacts that are unable to be manually traced, e.g. those unknown to the primary case.

Finally, the right hand plot of Figure 3 highlights the benefit of increasing public compliance towards TTI measures. There is a clear reduction in R across all TTI strategies as compliance is increased in the S3 scenario. Note that our results suggest an increase in the compliance parameter from 80% to 90% would result in a 0.2 reduction in R.

A Case and Social Contact Generation

We use a single stage transmission model consisting of a simulated primary case with simulated social contacts. We assume the primary case is infectious for 10 days, with our simulation starting when the primary case becomes infectious and ending 10 days thereafter.

For each primary case, we simulate whether they are asymptomatic COVID positive, symptomatic COVID negative, or symptomatic COVID positive. We also simulate their age and whether they will report COVID-like symptoms (should they have them) during the simulation. If the primary case does report symptoms, we further simulated the day on which they report them. Social contacts made during the infectious period are generated conditional on the age of the case and are categorised as home, work/school and other. The number of daily contacts made in each of these categories is sampled according to the BBC Pandemic dataset (Klepac et al. [2018]) and then fixed for the duration of the simulation. The home contacts are assumed to repeat their contact with the primary case each day, while each of the work and other contacts encounter the primary case only once during the simulation.

If the primary case is COVID positive, then each of their contacts suffers a risk of infection for each encounter with the primary case (which is drawn independently for each encounter). The risk of infection for a home contact over the simulation period is larger than that of a contacts in the work and other categories. Consistent with recent research He et al. [2020], we model the risk of infection due to an encounter with the primary case as varying over the infectious period, see Figure 4 and Section A.3.

A.1 Primary Case Generation

In this section, we provide a more detailed description of the primary case generation procedure. A `case` is generated as described below. See this in conjunction with the parameter choices given in Table 2.

1. Sample whether age of `case` is under 18 according to probability `p_under18`.
2. Sample the `presentation` of `case`: symptomatic COVID negative, asymptomatic COVID positive or symptomatic COVID positive.
3. If `case` is symptomatic: sample whether they will report symptoms according to the probability `compliance_level`, otherwise, `case` is considered unreported.
4. If `case` reports symptoms: sample the `day_of_reporting` during the 10 day infectious period.
5. If `case` reports symptoms: sample whether reporting is done through app with probability `app_coverage`, otherwise, reporting is done manually.

Parameter	Setting	Notes
`p_under18`	0.21	Probability that the case is under 18 years of age. This affects contact sampling from BBC Pandemic dataset (Klepac et al. [2018]).
`presentation`	$\sim$ Categorical $\left(\frac{100}{120}, 0.4 \times \frac{20}{120}, 0.6 \times \frac{20}{120}\right)$	Distribution over whether primary case is symptomatic COVID negative, asymptomatic COVID positive or symptomatic COVID positive respectively.
`compliance_level`	80%	Proportion of individuals who will adhere to the government guidelines, report symptoms when they occur, and adhere to a quarantine on being traced as a contact.
`app_coverage`	0.35	Probability that a primary case has the app and uses it.
`day_of_reporting`	$\sim$ Categorical(0, 0.25, 0.25, 0.2, 0.1, 0.05, 0.05, 0.05, 0.05, 0.00)	Distribution over days that primary case reports COVID-like symptoms and isolates, given that case is symptomatic and decides to report symptoms. Contacts are assumed to be prevented starting from day of reporting and isolation.

Table 2: Modelling choices for case generation

A.2 Simulating Social Contact

Once a `case` has been generated following the procedure in Section A.1, we simulate their contacts and resulting COVID transmissions, if any. For each simulated contact, we record the *day of first encounter* with primary case during the infectious period, *whether COVID transmission occurred* and, if so, the *day of transmission*. The simulation of contacts and resulting secondary cases is described below. This is in conjunction with parameter choices given in Table 3. Note the procedure below applies if `case` is over 18. If `case` is under 18, the procedure is identical, but with `n_work` replaced by `n_school`.

1. Sample a participant from the BBC Pandemic dataset, yielding the numbers `n_home`, `n_work` and `n_other` of daily home, work and other contacts the participant had respectively. We assume `case` has repeated contact with all `n_home` contacts on all 10 days. For work and other contacts, we assume `case` has contact with `n_work` and `n_other` new contacts on all 10 days.
2. If `case` is symptomatic COVID positive, for each contact, sample whether the contact resulted in transmission:
   (a) For home: with probability `sar_home`, contact results in transmission. If the contact is infected, the day of infection is sampled from the `infection_profile` for home contacts.
   (b) For work/other: with probability p, contact results in transmission, defining
   $$p = 10 \times s \times k$$
   where s is `sar_work` or `sar_other` depending on the contact type and k is the value of the `infection_profile` (for work/other contacts) for the day of encounter between `case` and the contact. p is chosen here to maintain both the correct average number of and `infection_profile` for secondary non-household cases.
3. If `case` is asymptomatic COVID positive, perform step 2, with all secondary attack rates scaled by `asymptomatic_factor`.
4. If `case` is symptomatic COVID negative, all contacts are uninfected.

Parameter	Setting	Notes
`asymptomatic_factor`	0.5	Factor by which to reduce probability of transmission when the primary case is asymptomatic following Kucharski et al. [2020].
`sar_`	`home`: 0.3, `work`: 0.045, `other`: 0.045	Secondary attack rate. Marginal probability a contact (in respective category) is infected by primary case over the duration of the infectious period.
`infection_profile`	Derived from He et al. [2020]. See Figure 4 and Section A.3.	Proportional to the probability that contact is infected given day of encounter. Draw independently for each day of contact.

Table 3: Modelling choices for case generation

A.3 Modelling secondary infection risk over time

To capture the temporal aspects of TTI policies it is crucial to model the secondary infection risk over the infectious period, which is how the distribution of the initial infection of secondary contacts varies over the length of time that a primary case is infectious. In order to do this, we need to understand the timeline of infection for the primary case. When a case is infected it is widely supposed for COVID that there is an initial latent period of around 3 days, when the case is neither infectious nor symptomatic He et al. [2020]. For our purposes, the latent period of the primary case is not important, although we will be interested in the latent period of the positive secondary contacts, in order to count the fraction of the secondary contact's infectious period that they are not traced by our TTI policies. As a result, we only start modelling primary cases once they become infectious, like in Kucharski et al. [2020].

At this point, in order to capture the secondary infection risk over time we need to model the infectiousness profile, which is the distribution of relative infectiousness of the primary case over the course of his/her infectious period. The infectiousness profile often assumes $t = 0$ to be the time when the infector develops symptoms. However, we will set $t = 0$ to be the start of the infectious period, because that is the point from which our model starts simulating cases and contacts.

One way to approximate the infectiousness profile would be to collect viral shedding data of the primary case over the course of the infectious period. For our purposes, the infectiousness profile is useful as it is exactly the distribution of when positive secondary contacts are infected for contacts who are only met once during the infectious period, and if there is a constant number of such new contacts each day. In our model this is the case for work and other contacts, and hence the infectiousness profile is exactly the secondary infection risk distribution for our non-household contacts.

The recent findings of He et al. [2020], inferred that the infectiousness profile should be skewed towards early transmission, with 44% (95% confidence interval, 25%-69%) presymptomatic transmission. Indeed, He et al. [2020] fit a Gamma distribution to the inferred infectiousness profile using data of 77 known transmission pairs, with shape parameter 2.11 and rate parameter 0.69.

One has to be careful of the distinction between relative infectiousness of primary cases, measured in terms of viral shedding, and the relative likelihood of when a repeated secondary contact, such as a household contact who goes on to be infected, was initially infected with COVID. For example, Uniform infectiousness over the infectious period will correspond to a Geometric distribution for the initial infection of a secondary contact who the primary case meets everyday. Because most of the pairs of data that He et al. [2020] fit were repeated contacts, this means that the Gamma distribution they fit has undue bias towards early and/or presymptomatic infection. In order to account for this bias, we will use shape parameter 2.8 and rate parameter 0.69 to model our infectiousness profile. That is to say, the mean time of infection for secondary non-household contacts will be delayed by one day relative to the fitted Gamma distribution in He et al. [2020]. Our model uses a discretised version of this fitted Gamma distribution for the infectiousness profile

of our primary cases over the infectious period. We present a sensitivity analysis for our assumptions in Section D.

For household contacts, because our model assumes that home contacts are met everyday, as opposed to work/other daily contacts who are different contacts each day, this implies that the distribution of when a home secondary contact was infected is skewed more towards early transmission, as can be seen in Figure 4. This distribution can be sampled by flipping a coin each day of the infectious period independently with probability heads equal to the infection profile on that day. The process stops either when we get first heads (and the transmission happens) or when we get to the end of the infectious period.

We choose to discretise over an infectious period of ten days compared to only a five day period in Kucharski et al. [2020]. This is in line with the assumption that the presymptomatic period lasts for approximately 2-3 days on average and that infectivity is much lower after the first week of symptom onset, as shown in Wölfel et al. [2020]. We assume that the infectiousness profile is identical across primary cases, including asymptomatic cases, following the discretised Gamma distribution.

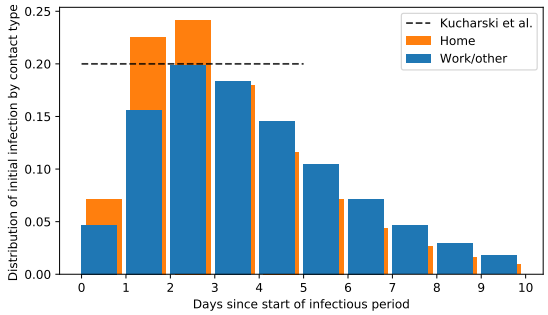


Figure 4: Our assumed distribution (blue/orange) of initial exposure to COVID for positive secondary cases. We compare to Kucharski et al. [2020] (black dotted line).

B TTI Strategies

In this section we describe how we model different TTI strategies.

Three types of case pass through the TTI funnel:

- Symptomatic COVID cases.
- Asymptomatic COVID cases.
- Cases presenting with COVID-like symptoms, but COVID negative.

From the perspective of TTI, asymptomatic COVID cases are invisible and contribute to an unavoidable baseline R that only other NPIs, like physical distancing measures, can help reduce. On the other hand, cases that present symptoms similar to COVID, but are not COVID positive, can only contribute to an increase in the cost of TTI and have no impact on R.

We consider three options for contact tracing, with decisions made around when to isolate the contacts of an individual, and whether to test contacts of positive cases, or just quarantine them. These can be summarised as:

1. Isolate household contacts immediately, and isolate non-household contacts upon positive COVID test.
2. Isolate household contacts immediately, and isolate non-household contacts upon positive COVID test. Test these contacts for COVID.

3. Isolate all contacts on a primary case presenting with symptoms.

We consider Strategy 1 as the baseline TTI strategy. Strategy 2 trades off using extra tests to get contacts who are not infected out of quarantine quicker. Strategy 3 isolates contacts faster, to allow them less chances to cause new infections, but will cause the quarantining of many additional people from cases presenting like COVID that are not in fact COVID.

Figure 1 demonstrates various paths that each new primary case and contact can take within our model.

We suppose that symptomatic cases have two routes via which they can enter the TTI system: by submitting symptoms manually to the NHS or by using the NHSx app. The proportion of the population with the app is governed by the `app_coverage` parameter, and is sampled independently for each case and contact. If a case is sampled as having the app, they are assumed to use it to report symptoms and allow the use of app tracking. We assume that some cases do not submit symptoms, due to either not taking them serious enough, or not complying with the guidelines. In our model this is governed by the `policy_adherence` parameter. This compliance also applies to contacts traced, sampled independently for each case and contact.

If the symptomatic primary case enters the TTI system they are assumed to follow the government guidelines and isolate at home alongside the rest of their household. We make this assumption as to have been tested, a case would have to have already voluntary reported symptoms. In the case where no contact tracing is being performed, we assume that no tests are performed on symptomatic individual who reports symptoms (or would have report symptoms), but they do still isolate at home, as is the current situation.

There is a delay in getting test results back, and this delay is governed by the `test_delay` parameter in our model. Given that there is a significant delay between testing an individual and getting a result, a choice is presented here: do we perform contact tracing before, or after the test results? Both of these options are explored.

Upon initiating contact tracing, a case's contacts are traced manually, and also via the app if the case has the app. App based tracing succeeds with a probability governed by the `app_coverage` parameter, sampled independently for each contact. Manual tracing succeeds if a person is able to identify a contact and provide details of them. Using data from Klepac et al. [2018] we calculate the likelihood a person has met a contact before at work, at school and elsewhere (denoted as `other` category). These are encoded in the `work_met_before_proportion`, `school_met_before_proportion` and `other_met_before_proportion`. These probabilities are sampled independently for each contact to see if manual contact tracing is effective. We also assume a fixed time delay in contacting a person's contact from the point at which we decided to quarantine them. These delays are encoded in the `manual_trace_delay` and `app_trace_delay`. Once a person is traced, they adhere to the quarantine with probability defined by the `policy_adherence` parameter.

For non-household contacts, once they are traced by the TTI system (either before or after the test results), they are advised to isolate themselves at home for 14 days. If they have isolated on notification of symptoms of a primary case, and if that person is tested and comes back negative, the contacts are released from quarantine. If they have quarantined after notification of a positive test of the primary case, they remain in the quarantine the full 14 days. We consider also an additional scenario where the contacts of an individual are tested on a positive test of a primary case. In order to avoid further simulation, we suppose that a fraction of positive secondary contacts will go on to become COVID positive in line with our assumptions in section A.2. In this case, if a contact tests negative they may be released from quarantine early.

It is very possible in many scenarios that we do not manage to notify a contact that they are infections before they become infectious. We count these infectious contacts partially, as described in appendix A.

A full table of the parameters used in the TTI strategies can be found in Table 4. We choose realistic defaults for these in line with current situation in the UK, and perform sensitivity analysis over them later to see either the effect of expending effort to improve these parameters, or to account for errors in our assumptions.

B.1 Non Pharmaceutical Interventions (NPIs)

Following the results of Kucharski et al. [2020], it seems likely that TTI strategies on their own will be insufficient to reduce R below 1. As a result, we also model a combination of TTI with other NPIs. In our initial results section, we report our conclusions for five NPI severities, ranked from strongest to weakest:

1. S5 - Current Lockdown (as of 9th May 2020)
2. S4 - Slightly relaxed work and social restrictions
3. S3 - Moderately relaxed work and social restrictions
4. S2 - Strongly relaxed work and social restrictions
5. S1 - No social restrictions, but quarantining of symptomatic households remains in place

Each of these scenarios modify a further set of parameters that influence the effectiveness of a TTI strategy. These are listed in Table 5. These parameters affect two factors: the reduction in number of contacts a given person has due to social distancing measure, and how likely it is to trace a particular contact during the stages of lockdown.

The `work_from_home_proportion` and `school_from_home_proportion` govern the fraction of adults and children not going to their normal place of work/school. For each case we sample uniformly from $[0, 1]$ interval, and if the sampled value is lower than these thresholds, we remove all of the work/school contacts for that individual.

The `max_other_contacts` parameter governs the effects of general social distancing. If a person has more other contacts per day than the value of this parameter, we remove the excess.

For each of these five social distancing scenarios, we also run our three TTI strategies, giving twelve different possible strategies in total that we can simulate and present results for.

B.2 Metrics to evaluate TTI strategies

One key goal of this study is to compare the effectiveness and cost of various TTI strategies.

In terms of effectiveness, the main metric we use is the reduction number R that our strategies result in. In terms of cost, we report results for the number of: manual traces, tests required, and person-days spent in quarantine.

B.3 Parameters

Attribute	Current setting	Notes
app_coverage	35%	The proportion of the population who take up using the NHSx tracing app
test_delay	2 days	Delay between test and result, assumed 0 days in Kucharski et al. [2020]
manual_trace_delay	1 day	Delay between a test result and notifying contacts manually, assumed 0 days in Kucharski et al. [2020]
app_trace_delay	0 days	Delay between a test result and notifying contacts via app, assumed 0 days in Kucharski et al. [2020]
policy_adherence	80%	Proportion of individuals who will adhere to the government guidelines, report symptoms when they occur, and adhere to a quarantine on being traced as a contact.
quarantine_length	14 days	Length of quarantine

Table 4: Parameters for different strategies

Attribute	L5	L4	L3	L2	L1	Notes
work_from_home_proportion	65%	55%	45%	25%	0%	The proportion of the population not going into their regular workplace
school_from_home_proportion	100%	100%	50%	0%	0%	The proportion of school-aged children not going into schools
max_other_contacts	1	4	10	20	-	A hard limit placed on the number of non-home, non-work contacts a person has per day.
work_met_before_proportion	79%	79%	79%	79%	79%	The average proportion of work contacts a person has met before, allowing them to manually trace a contact. Taken from Klepac et al. [2018].
school_met_before_proportion	90%	90%	90%	90%	90%	The average proportion of school contacts a person has met before, allowing them to manually trace a contact. Taken from Klepac et al. [2018].
other_met_before_proportion	100%	100%	90%	75%	52%	The average proportion of other contacts a person has met before, allowing them to manually trace a contact. Taken proportion from Klepac et al. [2018], adjusted for lockdown.

Table 5: Parameters for different lockdown severities

C Key parameters for the effectiveness of TTI strategies

This appendix contains additional plots investigating the effect of various parameters on the efficacy of TTI strategies, expanding the plots in the main text to cover all lockdown scenarios.

In particular, in Figure 5 we consider variation in application uptake and compliance within the population. In the left hand column, we examine the effect of increasing app uptake on the effective R of TTI strategies, we see that the app is most significant as the lockdown severity is decreased. In the right hand column we observe that compliance with requests to isolate and to contact tracing is a highly significant factor in the effectiveness of TTI strategies.

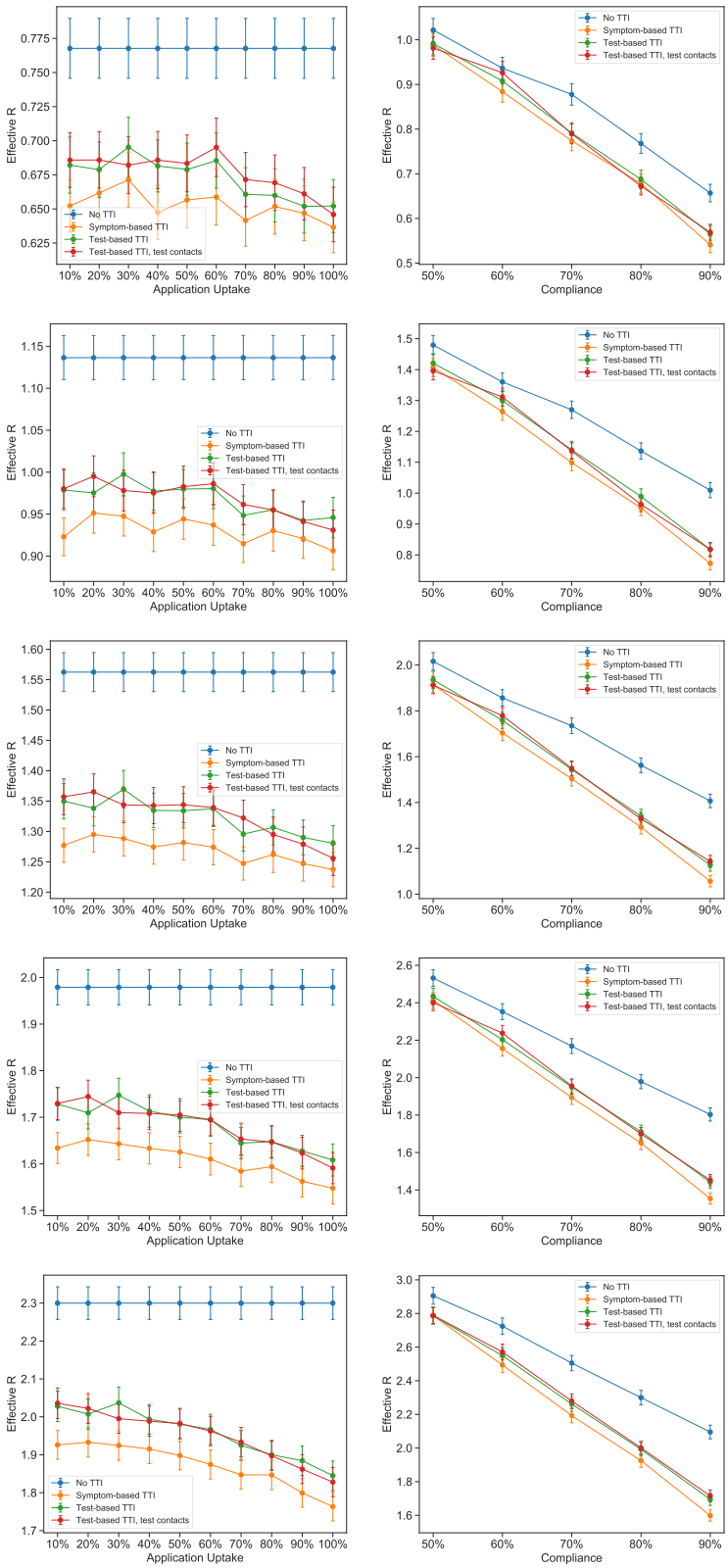


Figure 5: **Left**: Effect of varying the app uptake on effective R. **Right**: Effect of varying the policy adherence on effective R. **Top to Bottom**: S5 down to S1.

D Sensitivity analysis

This appendix investigates the sensitivity of our model to a number of assumptions we have made about the number of COVID cases in the UK, and the typical timeline of a COVID infection.

Figure 6 shows the variation in the number of tests needed for TTI strategies under changes in the number of COVID positive cases and the number of COVID negative cases with COVID like symptoms. Our results are consistent across these case for all severity levels S5-S1. Across the cases, the increase in tests needed for the TTI strategies is due to an increased number of symptomatic individuals.

Figure 7 considers variation in the effective R of TTI strategies under changes in the timeline of a COVID infection. Again we observe that, within measurement error, our results are consistent across the cases. In the left hand column, the effective R of TTI strategies is reduced if the primary case is most infectious later in the lifetime of their infection; here, the primary case causes fewer secondary infections before isolation. In the middle column we see a similar phenomena in reverse: the effective R increases with the time taken for a primary to report symptoms and isolate. In the right hand column we see that the effective R is relatively insensitive to the length of the latent period. Increased latent period allows TTI more time to track contacts of a primary case before they become infectious (if infected).[1]

[1] Recall that the simulation begins at the *end* of the latent period of the primary case.

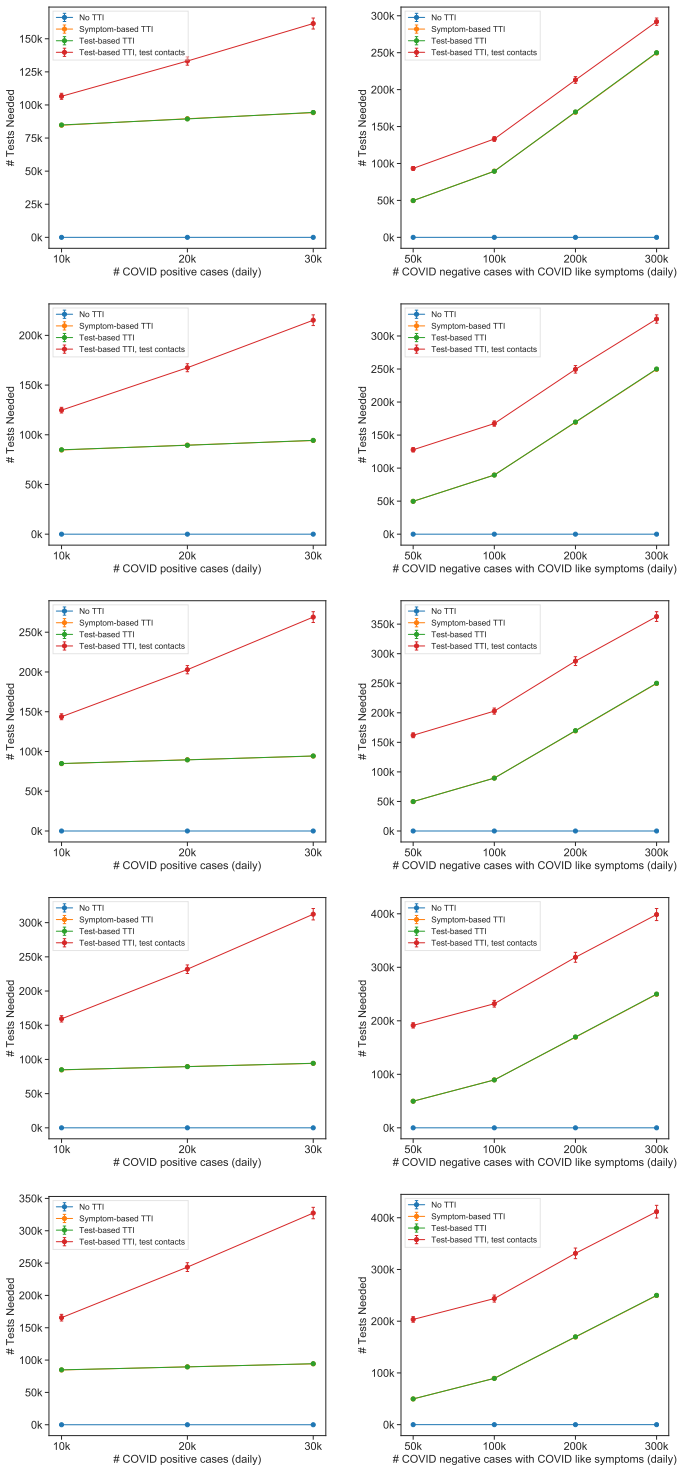


Figure 6: **Left**: Effect of varying number of new COVID cases per day on the number of tests needed. **Right**: Effect of varying the number of COVID negative cases with COVID-like symptoms on the number of tests needed. **Top to Bottom**: S5 down to S1.

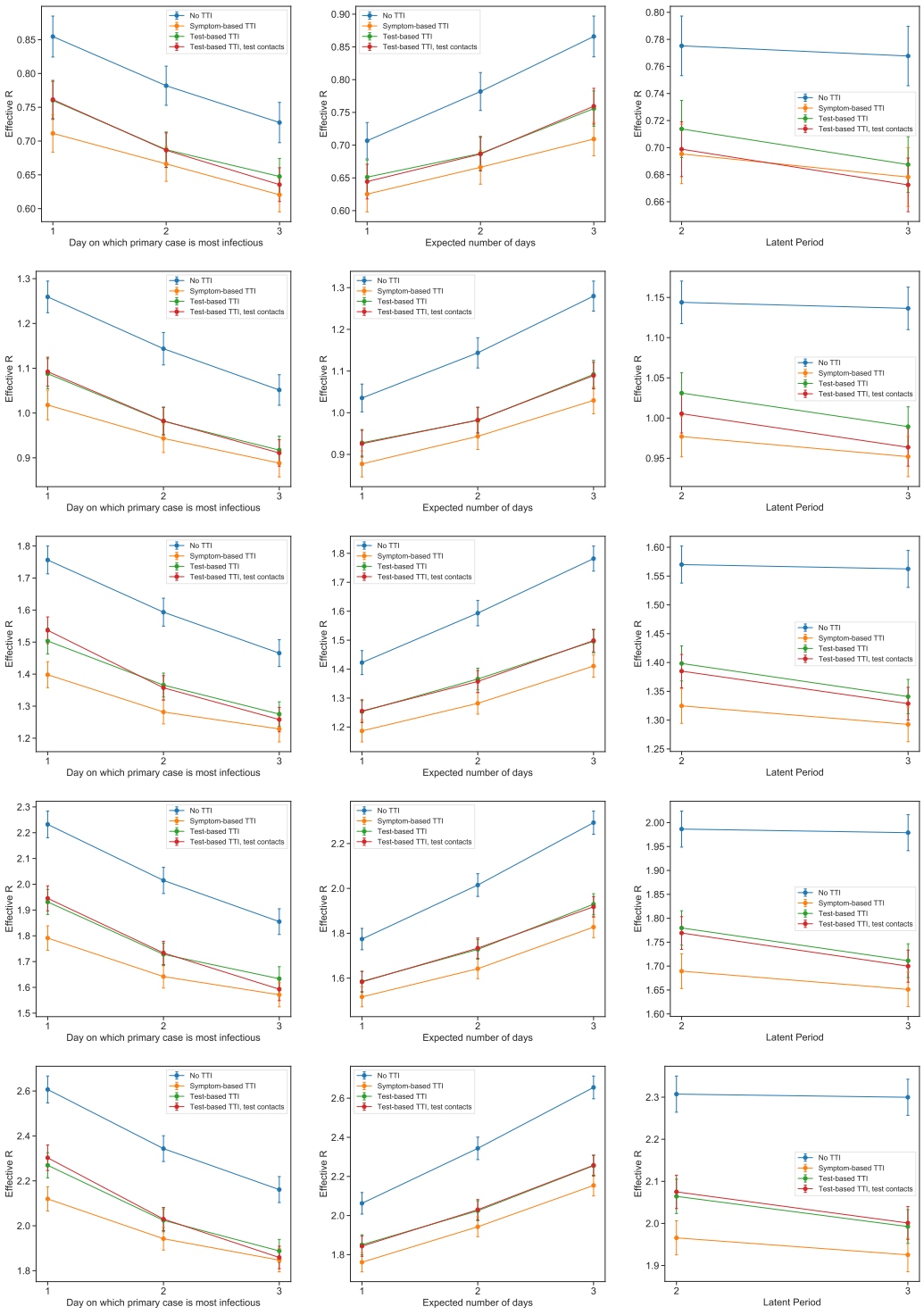


Figure 7: **Left**: Effect of varying most infectious day of the infectious period for COVID cases on R. **Middle**: Effect of varying expected day of symptom reporting (measured from after the end of the incubation period) on R. **Right**: Effect of varying the latent period on R. **Top to Bottom**: S5 down to S1.

E Diagrams of TTI strategy

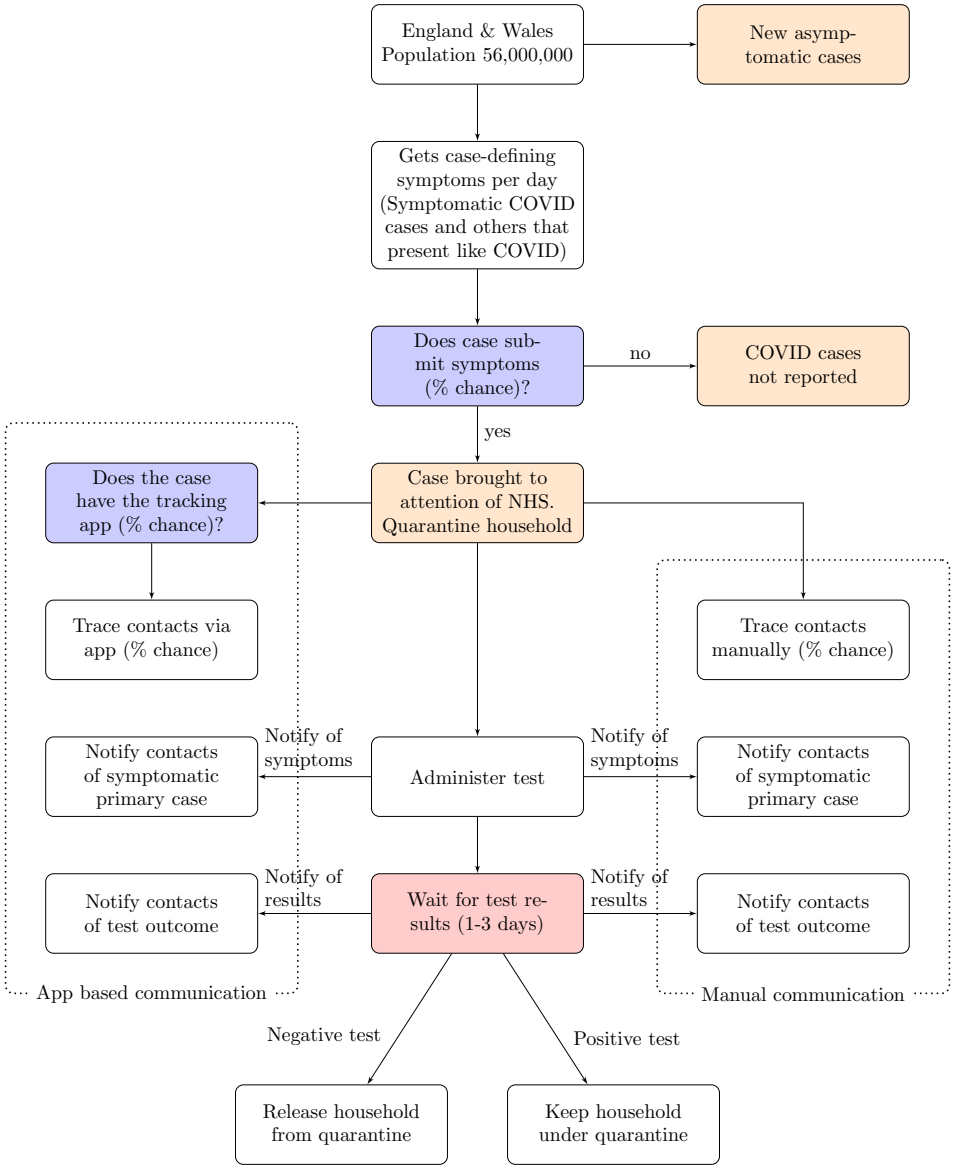


Figure 8: Diagram of an individual passing through the TTI system

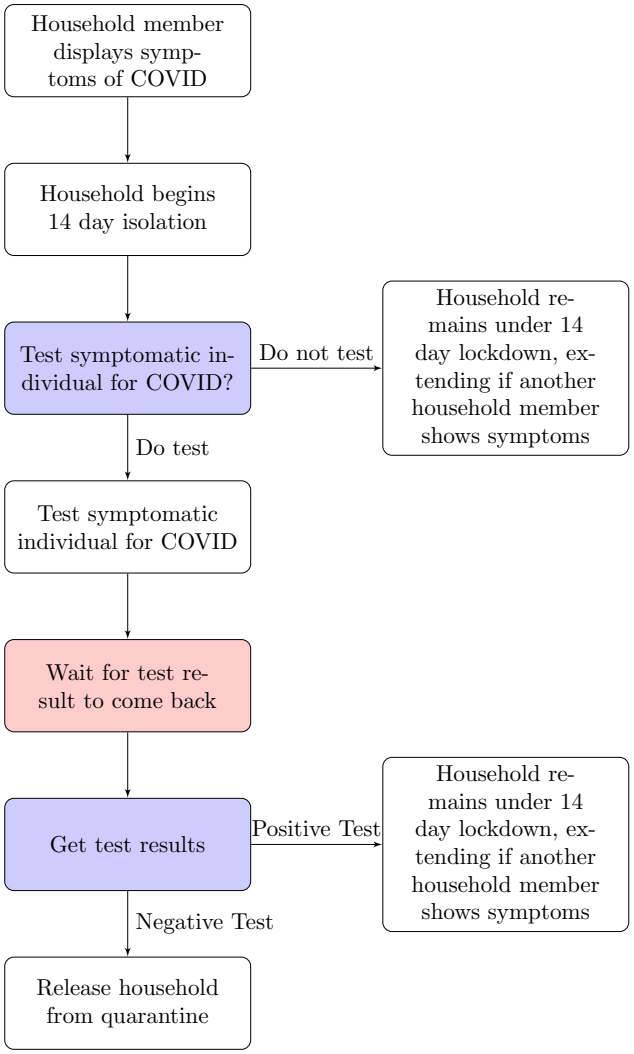


Figure 9: Decision tree for a household member of an individual in the TTI system

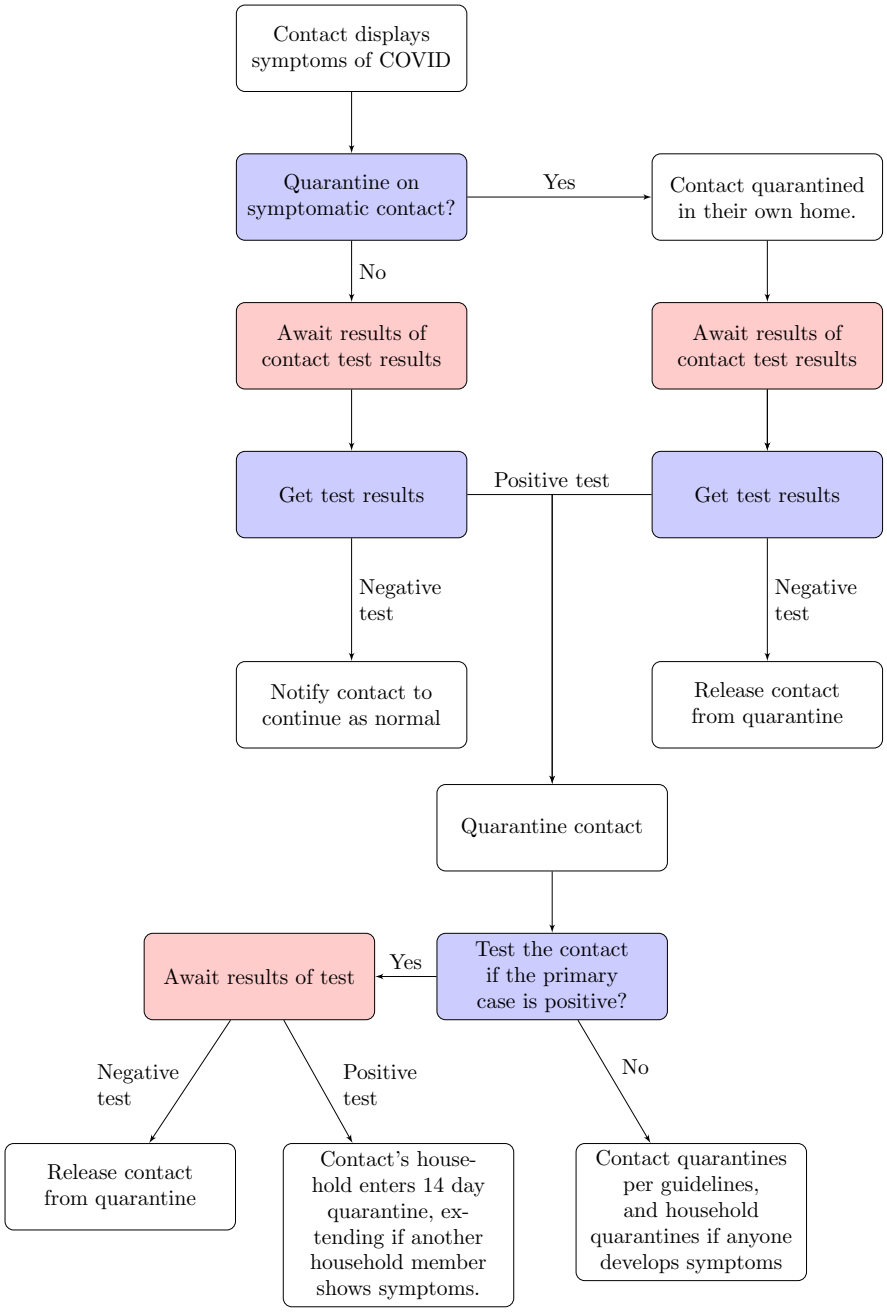


Figure 10: Decision tree for a non-household member of an individual in the TTI system

References

Adam J Kucharski, Petra Klepac, Andrew Conlan, Stephen M Kissler, Maria Tang, Hannah Fry, Julia Gog, John Edmunds, and . Effectiveness of isolation, testing, contact tracing and physical distancing on reducing transmission of SARS-CoV-2 in different settings. *medRxiv*, 2020. doi: 10.1101/2020.04.23.20077024. URL https://www.medrxiv.org/content/early/2020/04/29/2020.04.23.20077024.

Moran Bodas and Kobi Peleg. Self-isolation compliance in the COVID-19 era influenced by compensation: Findings from a recent survey in Israel. *Health Affairs*, 0(0):10.1377/hlthaff.2020.00382, 0. doi: 10.1377/hlthaff.2020.00382. URL https://doi.org/10.1377/hlthaff.2020.00382. PMID: 32271627.

Catherine M Smith, Anne Conolly, Christopher Fuller, Suzanne Hill, Fabiana Lorencatto, Franziska Marcheselli, Susan Michie, Jennifer S Mindell, Matthew J Ridd, Laura J Shallcross, Georgios Tsakos, Andrew Hayward, and Ellen B Fragaszy. Symptom reporting, healthcare-seeking behaviour and antibiotic use for common infections: protocol for bug watch, a prospective community cohort study. *BMJ Open*, 9(5), 2019. ISSN 2044-6055. doi: 10.1136/bmjopen-2018-028676. URL https://bmjopen.bmj.com/content/9/5/e028676.

Xi He, Eric H. Y. Lau, Peng Wu, Xilong Deng, Jian Wang, Xinxin Hao, Yiu Chung Lau, Jessica Y. Wong, Yujuan Guan, Xinghua Tan, Xiaoneng Mo, Yanqing Chen, Baolin Liao, Weilie Chen, Fengyu Hu, Qing Zhang, Mingqiu Zhong, Yanrong Wu, Lingzhai Zhao, Fuchun Zhang, Benjamin J. Cowling, Fang Li, and Gabriel M. Leung. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nature Medicine*, Apr 2020. ISSN 1546-170X. doi: 10.1038/s41591-020-0869-5. URL https://doi.org/10.1038/s41591-020-0869-5.

Petra Klepac, Stephen Kissler, and Julia Gog. Contagion! The BBC Four Pandemic - The model behind the documentary. *Epidemics*, 24:49–59, March 2018. URL http://researchonline.lshtm.ac.uk/id/eprint/4647173/.

Roman Wölfel, Victor M Corman, Wolfgang Guggemos, Michael Seilmaier, Sabine Zange, Marcel A Müller, Daniela Niemeyer, Terry C Jones, Patrick Vollmar, Camilla Rothe, et al. Virological assessment of hospitalized patients with COVID-2019. *Nature*, pages 1–10, 2020.