Simulations

Chris Hoover et al

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Individual-based simulation framework

- All staff are assigned a work schedule that determines time frames when they are working. $\mathbf{I}(w_{it})$ is an indicator function for whether staff member i is working at the facility on day t.

- In addition to their work schedule, all staff are assigned a testing schedule, encoded by function $\mathbf{T}(w_{it})$.

- All staff are subject to two sources of infection: community and workplace, represented by force of infection parameters λ_c and λ_w, respectively. In addition, we introduce a partitioning parameter, α, representing the relative probability of acquiring infection in the workplace versus in the community, therefore $\lambda_w = \lambda_c\alpha$ and $\Lambda_{it} = \lambda_c\alpha\mathbf{I}(w_{it}) + \lambda_c(1 - \mathbf{I}(w_{it}))$. New cases at each time step are then generated by subjecting all susceptible staff to a Bernoulli trial where $p = \Lambda_{it}$

- Whenever a new staff infection is generated, parameters for the individual are drawn to determine the latent period (t_{latent}), the incubation period ($t_{incubation}$), and the total infectious period ($t_{infectious}$) to generate an infectiousness profile (β_{it}). Assuming constant $\mathcal{R}$ across all individuals, the expected number of workplace cases produced on day t by individual i is $r_{it} = \mathcal{R}\beta_{it}\mathbf{I}(w_{it})$

- Main outcome is expected number of cases transmitted by staff over the simulation timeframe: $\mathbf{E}[cases] = \sum_{t=1}^{t_{sim}}\sum_{i=1}^{n}\mathbf{I}(w_{it})r_{it}$

- Isolated staff are not retested, but recovered staff are tested as normal

Individual based model simulations

Goal 1: Determine impact of different testing interventions on expected number of imported cases

Basically interested in three variables: pcr vs antigen testing (which basically comes down to turnaround time if we assume antigen tests are equal to pcr in their ability to detect active infection), random vs systematic day of testing, and frequency of testing. We propose the following scenarios encompassing combinations of these variables to explore:

- **S1)** No testing

- **S2)** Random PCR testing once per work week with test report on second day following test

- **S3)** Random antigen testing once per work week with immediate test report

- **S4)** PCR testing on first day of work week with test report on second day following test

- **S5)** Antigen testing on first day of work week with immediate test report

- **S6)** Random PCR testing twice per work week with test report on second day following test
- **S7)** Random antigen testing twice per work week with immediate test report
- **S8)** PCR testing on first and third day of work week with test report on second day following test
- **S9)** Antigen testing on first and third day of work week with immediate test report
- **S10)** PCR testing on all days of work week with test report on second day following test
- **S11)** Antigen testing on all days of work week with immediate test report

No workplace transmission ($\alpha = 0$) scenarios

Table 1: Expected cases imported into facility across different testing scenarios indicated by test frequency, f, test delay, d, and systematic vs random testing day.

scenario	delay	testday	testfreq	Expected Cases	Tests Conducted	Avoided/1000 Tests
S1	0	None	0	149 (144 - 162)	0 (0 - 0)	NaN
S2	2	rand	1	95 (92 - 107)	17917 (17913 - 17934)	3.02
S4	2	1	1	72 (69 - 80)	17934 (17930 - 17947)	4.30
S6	2	rand	2	67 (64 - 75)	35654 (35642 - 35698)	2.31
S3	0	rand	1	63 (61 - 74)	17906 (17901 - 17922)	4.79
S8	2	13	2	51 (48 - 56)	35606 (35589 - 35651)	2.75
S10	2	1234	4	37 (36 - 42)	71086 (71051 - 71156)	1.57
S5	0	1	1	36 (34 - 45)	17936 (17929 - 17949)	6.28
S7	0	rand	2	28 (26 - 34)	35546 (35531 - 35597)	3.39
S9	0	13	2	9 (9 - 12)	35611 (35591 - 35654)	3.92
S11	0	1234	4	0 (0 - 0)	70854 (70814 - 70960)	2.10

This makes it clear that decreasing the delay between test and isolation is more important than increasing frequency. In addition, systematic testing is superior to random testing when infections are only acquired from the community, with systematic testing always resulting in fewer expected cases than random testing. Some systematic testing scenarios even perform similarly to random testing scenarios with higher frequency (e.g. compare S5 to S7). Systematic testing on the first day of the work week with instant turnaround (e.g. antigen testing) also results in the most cases avoided per test conducted.

Sensitivity analyses

Self-isolation

Incorporate self-isolation at symptom onset with $p_{symp} = 0.6$, meaning 60% of cases will have symptoms coinciding with peak infectiousness and will self-isolate.

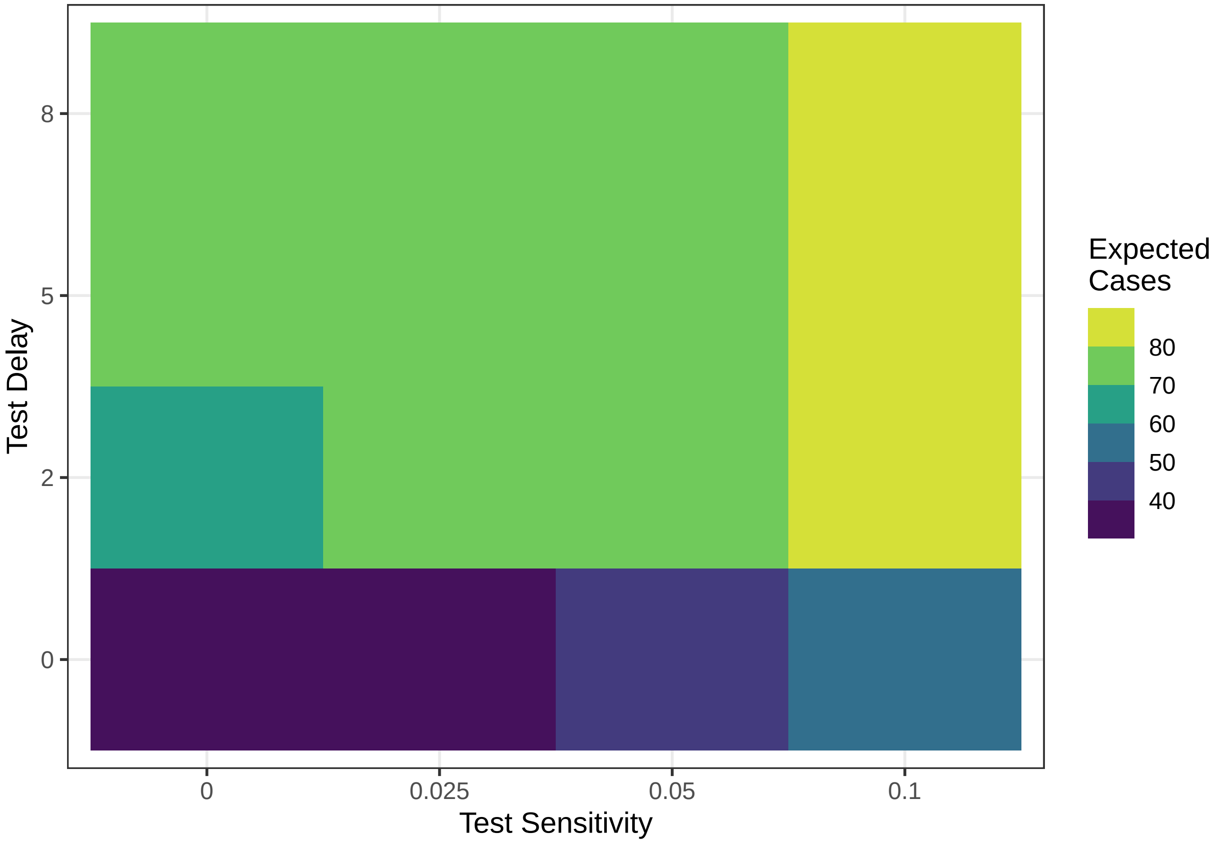
Could also just include this as a scenario on it's own in the table above?

Table 2: Expected cases imported into facility with self-isolation upon symptom onset and $p_{symp} = 0.6$ across different testing scenarios indicated by test frequency, f, test delay, d, and systematic vs random testing day.

scenario	delay	testday	testfreq	Expected Cases	Tests Conducted	Avoided/1000 Tests
S1	0	None	0	67 (65 - 81)	0 (0 - 0)	Inf
S2	2	rand	1	47 (44 - 56)	15952 (15816 - 16210)	6.37
S4	2	1	1	37 (35 - 43)	15880 (15755 - 16288)	7.03
S6	2	rand	2	36 (33 - 40)	31704 (31440 - 32287)	3.57
S3	0	rand	1	32 (31 - 39)	15884 (15759 - 16262)	7.35
S8	2	13	2	27 (26 - 33)	31726 (31476 - 32359)	3.83
S10	2	1234	4	22 (21 - 26)	63184 (62772 - 64389)	2.01
S5	0	1	1	21 (20 - 26)	15906 (15769 - 16145)	8.03
S7	0	rand	2	15 (14 - 19)	31582 (31393 - 32096)	4.24
S9	0	13	2	6 (6 - 9)	31596 (31338 - 32113)	4.51
S11	0	1234	4	0 (0 - 0)	63150 (62654 - 64371)	2.36

PCR test turnaround time and antigen test sensitivity

```
## `summarise()` has grouped output by 'delay'. You can override using the `.groups` argument.
```



Clear that test sensitivity is secondary to test delay in terms of reducing case importations. This makes sense from the infectiousness profile perspective as well if we think of test sensitivity as delaying the time until a case is identified. Since infectiousness rises quickly in the beginning, there's a short window in which low sensitivity tests will not detect a case, and this window is shorter than even a minor turnaround time between test and result that may be expected with a pcr test.

$\alpha \neq 0$ **scenarios**

Table 3: Expected cases imported into facility with equivalent community and workplace transmission across different testing scenarios indicated by test frequency, f, test delay, d, and systematic vs random testing day.

scenario	delay	testday	testfreq	Expected Cases	Tests Conducted	Avoided/1000 Tests
S1	0	None	0	174 (168 - 188)	0 (0 - 0)	-Inf
S2	2	rand	1	114 (110 - 127)	17904 (17898 - 17921)	1.95
S4	2	1	1	82 (80 - 92)	17916 (17911 - 17931)	3.72
S6	2	rand	2	79 (76 - 87)	35595 (35584 - 35638)	1.97
S3	0	rand	1	76 (73 - 86)	17892 (17884 - 17907)	4.07
S8	2	13	2	59 (58 - 64)	35536 (35518 - 35574)	2.53
S10	2	1234	4	44 (43 - 49)	70923 (70895 - 71020)	1.48
S5	0	1	1	42 (39 - 49)	17919 (17911 - 17933)	5.98
S7	0	rand	2	33 (31 - 38)	35478 (35459 - 35517)	3.26
S9	0	13	2	11 (10 - 14)	35528 (35510 - 35571)	3.88
S11	0	1234	4	0 (0 - 0)	70664 (70630 - 70772)	2.11

Results hold when adding in workplace transmission: systematic testing on the first day results in most cases avoided per test conducted.

Thoughts/Reflections/Next steps

I think the systematic (vs random) testing results are interesting enough to form a message/paper around. I think framing the results around optimal testing strategies for leaky/inconsistent/overlapping cohorts might help make them a bit more generalizable. The one additional analysis I would consider is using the CDCR staff work and test schedules directly to see a) how close they are to the optimal strategy identified here (testing on first day of work schedule), b) how inconsistencies in the work schedule like overtime shifts affect expected number of cases, and/or c) try and estimate some sort of counterfactual cases avoided had testing occurred optimally vs how it was actually implemented