**Testing strategies to limit COVID-19 introduction from shift-workers into a congregate setting: A modeling study**

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**Article summary line**: Aligning routine testing with work schedules among staff in carceral facilities and other congregate settings can enhance the detection of COVID-19 cases, limiting the potential for staff to trigger outbreaks in high risk settings.

**Running title**: Staff testing to prevent COVID-19 outbreaks

**Keywords:** COVID-19, outbreak prevention, testing strategies, individual-based modeling, occupational health, congregate-settings

**Abstract:** COVID-19 outbreaks in carceral facilities and other congregate settings remain a serious threat to the health of vulnerable populations such as people experiencing incarceration, those experiencing homelessness, and the elderly. We developed an individual-based model accounting for individual infectiousness over time, staff schedules, and testing schedules to simulate community transmission of SARS-CoV2 to facility staff and subsequent transmission within the facility that could cause an outbreak. Systematic testing strategies in which workers are tested on the first day of their work week were found to prevent significantly more transmission events within the facility than testing strategies that were unrelated to shift schedule. Higher frequency testing may be necessary to prevent outbreaks when community prevalence is high or the facility reproduction number, , is above 1. Testing staff at the beginning of consecutive workdays and limiting delays in test result reporting can aid outbreak prevention in congregate settings.

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## Introduction (434 words)

Since the early stages of the COVID-19 pandemic, outbreaks in congregate settings such as skilled nursing facilities (1), homeless shelters (2–5), and carceral facilities (6) have been devastating. In particular, staff have been known to seed a number of outbreaks in congregate settings across the United States (6–8). As such, routine testing of staff is essential to identify new cases and prevent case importations into resident populations. Prior analyses suggest that routine asymptomatic testing is an effective strategy to reduce transmission in homeless shelters (9), in healthcare settings (10), and prior to airline travel (11).

In correctional and detention facilities, preventing spillover from the community to facility staff and subsequently into resident populations remains a significant challenge (X). Having a robust and responsive testing strategy thus remains essential to a facility’s success in stopping the spread of COVID-19. CDC’s Interim Guidance for SARS-CoV-2 Testing in Correctional and Detention Facilities recommends that, after a known or suspected exposure to COVID-19, facility staff who are fully vaccinated should be tested for COVID-19 but need not be quarantined following a negative test if asymptomatic. Otherwise, CDC recommends that routine screening testing for staff who are not fully vaccinated be conducted at least weekly when community transmission is substantial or high. At this time, the guidance does not specify when staff should be tested during the work week to maximize testing schedules vis-à-vis rapid identification and isolation of new staff cases (12).

Even as vaccination rates increase across the United States and the world, concerns over breakthrough variants and transmission among unvaccinated populations reinforce the importance of routine screening testing, especially in congregate settings. Different testing strategies that consider the frequency and timing of testing in relation to staffing schedules and key transmission characteristics of SARS-CoV2 such as pre- and asymptomatic transmission and the duration of the latent period have not been systematically investigated.

Here we draw on staffing and testing schedules from carceral facilities operated by the California Department of Corrections and Rehabilitation (CDCR) to fill this gap. We developed an analytic framework to estimate the effect of different testing frequencies and delays in reporting results on the reproduction number, . We then develop an individual-based model which incorporates CDCR staffing and testing schedules to simulate community acquisition of SARS-CoV2 and subsequent transmission in a congregate setting. We use the model to explore via simulation the impact of aligning testing schedules with staffing schedules across testing frequencies, background community infection rates, and within-facility transmission rates.

## Staffing and testing schedules (191 words)

CDCR collects extensive operations records including information on custody staff workdays (e.g., Mon-Thurs), work shifts (e.g., morning, evening, night), and SARS-CoV2 testing schedules. We use this information to generate a realistic representation of staff working schedules in model simulations. Four typical staff workweek schedules were identified using K-means clustering. Most common was a four-day workweek in which the staff member worked four consecutive days (e.g., Monday-Thursday), though the first day of the workweek varied across staff (Figure 1). Work shifts also tended to show consistent patterns. Staff typically worked either the morning, evening, or night shift, though alternating between morning and evening shifts was also common. Tests were most often administered on Tuesdays (if the staff had Tuesday in their typical workweek) regardless of whether it was the first day of the staff’s workweek. Testing on Wednesday and Thursday was also common across work schedules. Only 10% of tests were conducted on the first day of a consecutive work period of 4 or more days. Test results were usually returned on the same day or the day after specimen collection and almost all test results were received within 2 days of specimen collection.

Background pattern

Description automatically generated

**Figure 1. California Department of Corrections and Rehabilitation custody staff and testing schedules**. Four typical weekly work schedules (y-axis) were identified among CDCR custody staff. These include a Monday to Thursday workweek (N=5969 staff), a Thursday to Sunday workweek (N=6180 staff), a Tuesday to Saturday workweek (N=9243 staff), and a Monday to Tuesday/Saturday to Sunday workweek (N=6936 staff). The red shading shows the mean proportion of staff workdays that consist of a particular day of the week (x-axis; i.e. darker shades of red indicate that staff with the specified schedule very commonly work on that day). The size of the black circles represents the mean proportion of the total number of tests administered to each group that were given on the specified day.

## Model framework and parameterization for SARS-CoV2 (667 words)

Building on previous work investigating the effects of non-pharmaceutical interventions (13) and testing (14) on the transmission of infectious diseases, individual contributions to SARS-CoV2 transmission through time are modeled from an infectiousness profile, , generated from key biological parameters of the virus that determine the distribution of infectiousness over time. A triangle distribution is used to model , with infectiousness beginning after the latent period, ending after the duration of the infectious period, and peaking at some point in between (, , , and a<c<b ; Fig 2a).

The viral dynamics of SARS-CoV2 make control efforts challenging, high infectiousness in the absence of symptoms is common (15–17). In terms of the infectiousness profile for SARS-CoV2, this means that peak infectiousness tends to coincide with the onset of symptoms (for cases that are symptomatic), but occurs after completion of the latent period (i.e. >) (17). The expected number of new cases generated at time is thus , where is the effective reproduction number interpreted as the expected number of cases generated by a new case over the duration of the infectious period. The model therefore assumes that new cases are most likely to be generated around the time of peak infectiousness, . Table 1 lists the distributions of , , and used here.

In the presence of interventions that isolate infectious individuals prior to , e.g. through contact tracing, self-isolation following the onset of symptoms, or testing, the effect of isolation on can be directly estimated from the time to isolation as , where is the time at which isolation occurs. Reducing via improved contact tracing or more frequent testing can thus be represented as removing a larger slice from the overall infectiousness triangle by reducing (Fig 2a). The size of the slice removed is dependent on the shape of the overall triangle distribution, which is primarily determined by and , and the location of in relation to . For instance, if , then the proportional reduction in can be estimated as .

Figure 2b shows the relationship between and is sigmoidal, implying earlier isolation is incrementally more effective and the benefits of isolation level off later in the infectious period. Other interventions that reduce across all levels of infectiousness such as wearing a mask or reducing the contact rate between infectious and susceptible individuals can also be accommodated simply by multiplying by a constant.

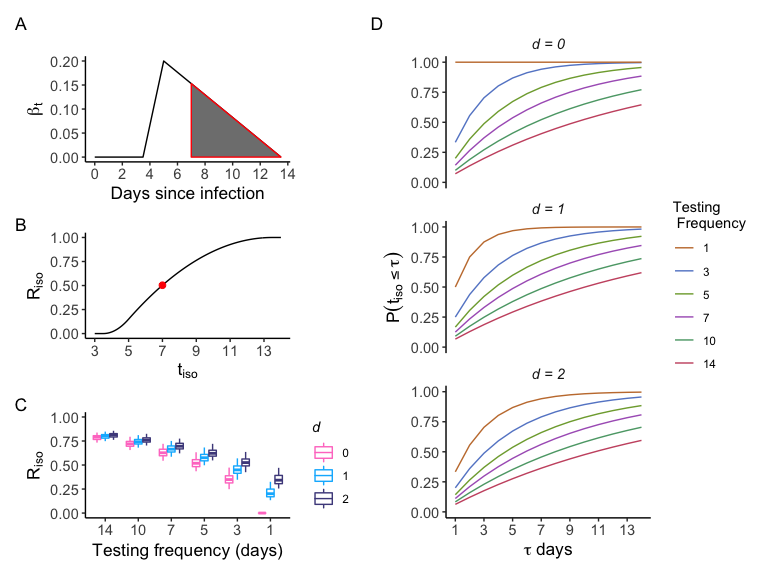
**Table 1**: Distributions and parameter values used in analytic framework and model simulations

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Distribution** | **Source** |
| **Incubation Period ()** | *Lognormal*(1.63, 0.5) | (17) |
| **Latent Period ()** | + *Uniform*(-2, 0) | (16,18) |
| **Infectious Period ()** | (-) + *Uniform*(6.5, 9.5) | (16,18) |
| **Community Prevalence** | [0.1%, 0.5%, 1%] |  |
|  | [0.5, 1.0, 1.5] |  |

Assuming testing is independent of symptoms, known contacts, and other reasons for explicitly seeking testing, the probability of going days without being tested from the testing frequency, , can be estimated as and the probability that as , assuming isolation occurs immediately after testing. Given substantial turnaround times between testing and isolation, particularly when relying on PCR-based tests, the delay between testing and isolation, , can also be incorporated as: , where is simply the average number of days between tests. Figure 2d shows that such delays have a detrimental effect that is greater than additive on the probability of achieving prompt isolation. For example, with a daily testing frequency and no delay, . However, increasing the delay to 1 or 2 days leads to 0.875 and 0.704, respectively.

Testing frequency and delay can also be incorporated into estimation of , essentially as the infectiousness on day weighted by the probability of remaining un-isolated on day :

Figure 2c shows distributions of derived from 100 random draws sampling from uncertainty in the SARS-CoV2 latent, peak, and total infectious periods, across test frequencies ranging from daily () to biweekly () and test delays from 0 to 2 days. These results again reiterate the importance of reducing test delays, as is approximately the same when testing every day () with a two-day turnaround time for test results () as testing every three days () with immediate test results () (fig 2c, median 0.35 and 0.34, respectively).

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**Figure 2. Model framework and analytic results**. A) Example infectiousness profile for , , , , with shaded area demonstrating infectiousness slice removed if , leading to . B) as a function of with same parameters as in A and point indicating scenario depicted in A. C) Boxplots showing distributions of as a function of testing frequency, , and test delay, , incorporating uncertainty in , , and by drawing parameter sets for each, with baseline . Boxplots indicate median, interquartile range, and full range of values of . D) Relationship between testing frequency, , test delay, , and probability isolation occurs by day , i.e. , demonstrating that delays in testing substantially reduce the probability of prompt isolation, particularly in more frequent testing scenarios.

## Individual-based model simulations (643 words)

### Model setup

To incorporate staff schedules and expand the modeling framework above to a facility-level setting, we next describe the development of individual based microsimulations. In a modeled facility, staff are assigned a work schedule that determines time frames when they are in the facility and interacting with facility residents and other staff working at the same time. We denote as an indicator function for whether staff member is working at the facility on day . In addition to their work schedule, all staff are assigned a testing schedule, encoded by function , with different testing schedules discussed further below. The model is simulated at an 8-hour time step, with each time step corresponding to a work shift as described below.

Staff move through susceptible (S), exposed (E), infected (I), and recovered (R) states, with the infected state corresponding to time when . Parameters for newly exposed staff are drawn to determine , , and , from which an infectiousness profile, is generated. Tested staff produce a positive result if and , at which time they enter a quarantined (Q) state immediately if , or first enter a tested (T) state before Q if there is a delay between test administration and the test result. Staff in state Q have for 10 days and have for 90 days following a positive result.

Assuming constant across all individuals, the expected number of cases produced in the facility on day by individual is . Staff may acquire infection from the community or workplace, therefore we denote two separate forces of infection, and . Infection for each individual is simulated at each time step by subjecting each staff member to a bernoulli trial with . The expected number of infections in the facility generated by staff is estimated from each simulation as: .

### Staffing and testing strategies

Generation of work schedules in simulations was informed by observed CDCR schedules by sampling one of the consecutive 4-day sequences of work days shown in figure 1 and a regular shift (morning, evening, night) for each worker. A fifth shift was then added to each worker’s weekly schedule by randomly sampling from all other potential shifts. Two testing strategies were considered. Under a random-time testing strategy, testing for each worker occurs at random during their five shifts depending on the frequency (i.e. with , workers would be tested during two of their five shifts, chosen at random each week). Under a systematic testing strategy, each worker is always tested on the same day(s) of their shift each week. For , systematic testing always occurs on the first day of the regular 4-day work schedule; for , systematic testing always occurs on the first and third days; and for , testing occurs on each of the regular 4-day work days.

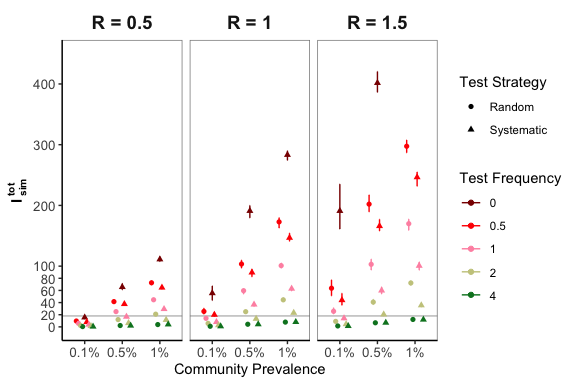
We assume rapid tests in which the test result is known immediately after the test is conducted () are used and further assume that all tests conducted when return a positive result. This is in line with field assessments showing that rapid tests such as the Abbott BinaxNOW have high sensitivity among infectious individuals, even as they are not reliable among individuals with lower viral loads that are unlikely to be infectious (19–21). The total number of tests conducted in each simulation is recorded as: . Combined with the expected number of cases in the simulation, we estimate the incremental test effectiveness ratio (ITER) as: , where is the number of infections in a reference scenario with no testing. The ITER can be interpreted as the number of tests needed to prevent one infection in the simulation scenario being evaluated.

All simulations and analyses were conducted in R software version 4.0.4 (23) with aid from the tidyverse (24), triangle (25), and patchwork (26) packages. Code is made available freely online at <https://github.com/cmhoove14/CDCR-Staff-Testing>.

## Simulation Results (360 words)

Systematic shift testing strategies were found to consistently outperform random shift testing strategies in terms of preventing infections within simulated facilities. Figure 3 shows a comparison of the number of infections generated () when implementing a random vs systematic testing strategy across testing frequencies, community prevalences, and within-facility . In the highest transmission scenario (), testing randomly once per week resulted in a median 169.92 (IQR 159.07 - 177.43), whereas testing systematically on the first day of the work week resulted in 100.6 (IQR 93.41 - 106.93; Fig 3, right panel in pink).

The horizontal gray line in figure 3 demonstrates a potential threshold number of infections to avoid exceeding at . This threshold corresponds to an average of 1 transmission event within the simulated facility every ten days. Implementing a systematic–rather than random–testing strategy can be sufficient to prevent from exceeding such a threshold without changing the frequency in many transmission scenarios. Table 2 additionally shows the testing frequency in tests per week under a systematic testing strategy necessary to ensure that the upper quartile of expected transmission events is maintained below this threshold.

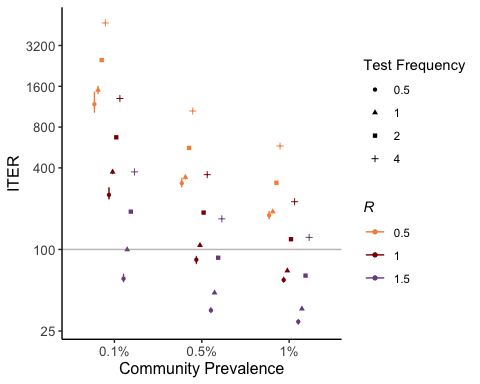


**Figure 3. Number of expected infections in a facility from model simulations comparing random- and systematic- shift testing strategies across transmission scenarios and test frequencies**. Systematic shift testing strategies ([triangles]) prevent more infections than random shift strategies ([circles]) across all transmission scenarios and test frequencies. The horizontal gray line serves as a reference to assess the testing frequency needed to maintain (corresponding to one transmission event every ten days) across different transmission scenarios. Error bars represent the interquartile range of derived from 100 simulations per scenario.

**Table 2**: Test frequency (tests per week) needed under a systematic shift testing strategy to maintain upper quartile of expected transmission events below a threshold of 1 every ten days across transmission scenarios conveyed by the within-facility basic reproduction number () and community prevalence.

|  |  |  |  |
| --- | --- | --- | --- |
| Community Prevalence |  |  |  |
| 0.1% | 0 tests per worker per week | 1 | 1 |
| 0.5% | 2 | 2 | 4 |
| 1% | 2 | 4 | 4 |

Figure 4 shows estimates of the number of tests needed to prevent one infection (ITER, as described above) across transmission scenarios only for systematic testing strategies since they were found to substantially outperform random strategies. In the highest transmission scenario (, community prevalence), testing on the first day of every other work week (, fig 4 circles) leads to 29.31 (IQR 28.08 - 30.35), while increasing test frequency to weekly, , results in 36.49 (IQR 36.02 - 36.9), to : 64.12 (IQR 63.67 - 64.49), and to : 122.73 (IQR 121.86 - 123.49). These values approximately correspond to test positivity rates of 3.41%, 2.74%, 1.56%, and 0.81% due to the interpretation of the ITER as the number of tests administered per positive result. Figure 4 also provides an example reference line at , corresponding to an approximate test positivity, to demonstrate how testing frequency may be determined from the transmission scenario and target ITER, which may be influenced by the number of tests available.

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**Figure 4. Incremental test effectiveness ratio (ITER) from simulations implementing systematic testing across transmission scenarios and testing frequencies**. The ITER remains relatively low in higher transmission scenarios even at high () testing frequencies, potentially favoring such high-frequency testing strategies when within-facility transmission () and/or community prevalence are high. The y-axis is log-transformed and the horizontal line at is provided to aid visual comparison across scenarios. Error bars represent the interquartile range of expected infections derived from 100 simulations per scenario.

## Discussion (946 words)

Here we have built on previous modeling and simulation analyses to demonstrate that systematic testing strategies with fast turnaround that align testing schedules with working schedules prevent more transmission events than non-systematic testing strategies or those with a delay between testing and disclosure of a test result. A major benefit of such strategies is that they do not require higher testing frequency, nor large additional logistical investments. As such, we believe that there is substantial value in implementing systematic rapid testing at the beginning of each staff member’s work week for staff working in high-risk COVID-19 facilities such as carceral facilities, skilled nursing facilities, and homeless shelters.

For SARS-CoV-2, pre- and asymptomatic transmission make viral testing a key component of prevention strategies. Preventing delays between testing and the test result is also found to be an essential component to any testing strategy. Confirmatory PCR testing may also be necessary in scenarios where less sensitive rapid tests with quicker turnaround time are used as an initial screen. Additionally, increasing the frequency of testing may be necessary in settings with high community prevalence or the opportunity for rapid spread within a facility (e.g. rapid variant transmission, low vaccination rates, inadequate mitigation practices). Testing all four days of a regular work week was necessary to prevent more than one transmission event per ten days within a facility over the 6-month simulation period considered here when community prevalence was 1.5% and . In the lowest transmission setting with 0.5% community prevalence and , the same threshold was met without any systematic testing. For intermediate transmissions scenarios or lower transmission event thresholds, testing frequencies ranging from biweekly to weekly to twice per week may be required in order to slow down transmission. Lower thresholds than one introduction per ten days may also be necessary to prevent outbreaks in carceral facilities and other congregate settings. A prior analysis of publicly available CDCR case data estimated 46% of 118 introductions from April 2020-March 2021 across 35 facilities resulted in outbreaks of greater than 10 resident cases (27), though this estimate includes data from early in the pandemic when there were more fully susceptible individuals, fewer protocols to reduce transmission, and limited testing resources.

We also present the incremental test effectiveness ratio (ITER) as a per-test measure of effectiveness for systematic testing across a range of frequencies and transmission scenarios. In resource-constrained environments in which tests are difficult to acquire or limited funds are available to purchase tests, the ITER and its relationship to test positivity may be used to guide decisions on test frequency.

Even though systematic testing strategies can reduce within-facility transmission, they are not capable of preventing all transmission events. Systematic testing represents one tool of many that should be implemented to prevent SAS-CoV2 introductions into congregate facilities. Universal masking, medical isolation and quarantine, avoiding crowds, proper ventilation, and facility-wide vaccination all play an important role in mitigating COVID-19 transmission in correctional facilities and other congregate settings. However, low vaccine acceptance rates among both residents and staff in correctional settings coupled with a rapidly spreading COVID-19 variant puts this population at continued risk of localized outbreaks. Therefore, it is increasingly important that facilities implement routine, systematic testing of staff for early identification of COVID-19 cases (including breakthroughs) and prevent outbreaks from occurring not only within a facility, but also spilling over into other facilities and nearby communities.

These additional mitigation measures were not included in the models described here, which is a potential limitation. However, we expect them to lead to simple proportional reductions in the simulated number of transmission events in a facility. We therefore expect consistent relative findings between testing strategies and frequencies across different transmission scenarios. An additional limitation is that we do not distinguish between staff-to-staff and staff-to-resident transmission events within a simulated facility, but rather record the total number of transmission events. Estimation of staff-staff and staff-resident contact rates or reproduction numbers would enable more precise accounting and simulation of importation events and subsequent transmission within a facility. Finally, we assume that the community force of infection among staff is constant through time and across individuals. In reality, community prevalence can increase rapidly, necessitating a corresponding increase in test frequency. Furthermore, some staff may be more or less likely to acquire infection in the community or in the facility based on compliance with social distancing and masking policies, their household structure, and other behavioral factors.

The modeling and simulation framework presented here is applicable beyond COVID-19 in congregate settings in which outbreaks introduced by staff are a concern. This may include the introduction of hospital acquired infections from newly admitted patients or from hospital staff (28), introduction of other respiratory pathogens such as influenza or pertussis into congregate settings (29), or tuberculosis transmission between communities and populations experiencing incarceration (30). Accurate parameterization of key natural history traits of the pathogen in question such as the latent, incubation, and infectious periods is essential to estimate the impact of nonpharmaceutical interventions such as asymptomatic screening (12). Pathogens that cause symptoms prior to infectiousness (), for instance, may be more effectively controlled at lower cost via symptom screening and subsequent isolation.

In conclusion, the models described here show that aligning the timing of testing with regular working schedules for staff in congregate settings can substantially improve the efficacy of asymptomatic screening. Two metrics, the number of expected within-facility transmission events and the ITER, derived from simulated facilities are presented to inform decisions on the frequency of systematic testing needed in different transmission scenarios to limit transmission under key thresholds. Thus, we conclude that in congregate-settings that are high risk of SARS-CoV-2 transmission, staff should continue to be tested routinely.

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## Disclaimer

The findings and conclusions in this report are those of the author(s) and do not necessarily represent the official position of the U.S. Department of Health and Human Services, the Centers for Disease Control and Prevention, or the authors' affiliated institutions.

## Biographical sketch

Dr. Hoover is a postdoctoral scholar at the Francis I. Proctor foundation at the University of California, San Francisco. He is interested in using quantitative methods to inform intervention strategies to reduce the global burden of infectious diseases.

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