**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 early 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 congregate settings remain a serious threat to the health of vulnerable populations such as people experiencing incarceration, those experiencing homelessness, and the elderly. Using the California State Prison System as a case example, we developed an individual-based model accounting for individual infectiousness through time, staff schedules, and testing schedules to simulate community transmission of SARS-CoV2 to facility staff and subsequent transmission within a 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 than testing strategies unrelated to staff schedules. Higher frequency testing may be necessary to prevent outbreaks when community prevalence is high or if characteristics of the facility make outbreaks among residents more likely. Testing staff at the beginning of consecutive workdays and limiting test turnaround time can aid outbreak prevention in congregate settings.

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## INTRODUCTION (357 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. Staff have been known to seed a number of these outbreaks 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 during 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 (12). Having a robust and responsive testing strategy remains essential to a facility’s success in stopping the spread of COVID-19. As of June 7, 2021 the Center for Disease Control and Prevention’s (CDC) 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 (13). Meanwhile, all staff should still be tested routinely due to the high risk of asymptomatic SARS-CoV-2 transmission in congregate-settings. This holds for vaccinated and unvaccinated staff as there are numerous vaccine breakthrough cases. At this time, guidance does not specify when staff should be tested during the work week to minimize the spread of COVID-19 via rapid identification and isolation of new staff cases.

Here we draw on staffing and testing schedules from carceral facilities operated by the California Department of Corrections and Rehabilitation (CDCR) to examine the relationship between staffing and testing schedules and within-facility transmission. We present an analytic framework to estimate the effect of variable testing frequencies and delays on SARS-CoV2 transmission. 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 the impact of aligning testing schedules with staffing schedules across testing frequency, background community infection rate, and within-facility transmission rate.

## METHODS (1253 words)

## Model framework and parameterization for SARS-CoV2

Building on previous work investigating the effects of non-pharmaceutical interventions (14) and testing (15) on the transmission of infectious diseases, individual contributions to SARS-CoV2 transmission through time were modeled from an infectiousness profile, , generated from key biological parameters of the virus that determine the distribution of infectiousness over time. We used the probability density function of the triangle distribution 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, as high infectiousness in the absence of symptoms is common (16–18). 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.  and ) (18). The expected number of new cases generated by an individual 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 their infectious period. The model therefore assumes that new cases are most likely to be generated around . 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 isolation following a positive test result, 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 1a). The size of the slice removed can be estimated from the probability density function of the triangle distribution and the parameters , , , and .

Figure 1b 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.

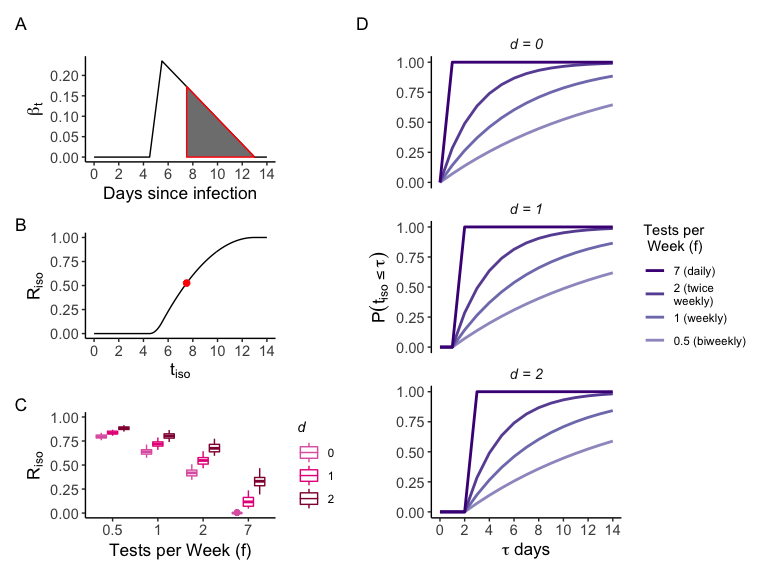
**Table 1**: Distributions and parameter values used in analytic framework and model simulations. The incubation period is defined as the time between infection and onset of infectiousness, the latent period the time between infection and symptoms, and the infectious period the total time a case is infectious.

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Distribution** | **Source** |
| **Incubation Period ()** | *Lognormal*(1.63, 0.5) | (19) |
| **Latent Period ()** | *Uniform*(0, 2) | (18,20) |
| **Infectious Period ()** | *Uniform*(7, 10) | (18,20) |

We define the test frequency, , as the average number of tests per week. Assuming testing is done randomly through time and is independent of symptoms or known contacts, the probability of being infectious and going days without being tested and isolated can be estimated as , where, for example if testing is conducted weekly. The probability that isolation has occurred by day can then be estimated as if 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: . Figure 2d shows that such delays have a detrimental effect on the probability of achieving prompt isolation, particularly by making isolation prior to the delay () impossible.

Testing frequency and delay can also be incorporated into estimation of , with the reduction in due to isolation estimated from infectiousness on day weighted by the probability of being isolated on day . Discretizing, this gives:

Figure 2c shows distributions of derived from 100 random draws sampling from uncertainty in the SARS-CoV2 latent, incubation, 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 similar when testing every day () with a two-day turnaround time for test results () vs testing twice per week () with immediate test results () (fig 1c, median 0.42 and 0.33, respectively).



**Figure 1. 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 among most frequent testing scenarios.

## Individual-based model simulations

### Model setup

We next describe the development and simulation of an individual based model to incorporate staff schedules and expand the modeling framework above to a facility-level setting. In a modeled facility, staff are assigned a work schedule that determines time frames when they are in the facility interacting with 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 for 180 days 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 test 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 are restricted from working for 10 days ( for 10 days) and are not required to undergo systematic testing for 90 days following a positive result ( for 90 days).

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 according to the community prevalence when they are not working () or from fellow staff while working () where the force of infection is . The expected number of infections in the facility generated by staff is estimated from each simulation as: .

### Staffing and testing strategies

CDCR collects operations records for custody staff including information on 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 by sampling from standard work schedules identified among CDCR custody staff using K-means clustering.

Two experimental testing strategies were considered in model simulations. Under a random testing strategy, testing for each worker occurs at random during their work shifts depending on the frequency (i.e. with , workers would be tested during two of their 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 their work week; for , systematic testing always occurs on the first and third days; and for , testing occurs on each of the first four work days in a week.

We assume all tests conducted when return a positive result. 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, analyses, and visualizations were compiled in R software version 4.0.4 (24) with aid from the tidyverse (25), triangle (26), and patchwork (27) packages. Code is made available freely online at <https://github.com/cmhoove14/CDCR-Staff-Testing>.

## RESULTS (640 words)

## CDCR staff working and testing schedules

CDCR collects extensive operations records including information on custody 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

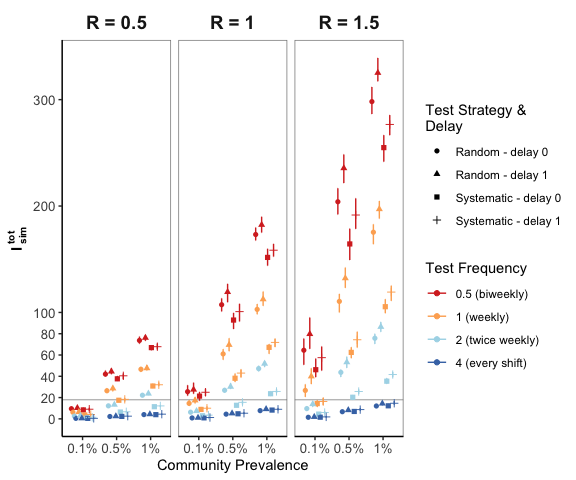
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**Figure 2. California Department of Corrections and Rehabilitation custody staff and testing schedules**. Four typical weekly work schedules (y-axis) were identified among CDCR custody staff. These include a Monday to Thursday workweek (N=5969 staff), a Tuesday to Saturday workweek (N=9243 staff), a Thursday to Sunday workweek (N=6180 staff), and a Saturday to Tuesday 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.

## Simulation Results

Systematic testing strategies were found to consistently outperform random testing strategies in terms of preventing infections within simulated facilities. Figure 3 shows a comparison of the number of infections generated () when implementing random vs systematic testing strategies across testing frequencies, community prevalences, and within-facility with either no delay or a one day delay between test administration and result disclosure. In the highest transmission scenario (), testing randomly once per week resulted in a median 175.4 (IQR 164.13 - 182.85) expected infections, whereas testing systematically on the first day of the work week resulted in 105.4 (IQR 99.27 - 112.45; Fig 3, right panel in pink). However, systematic weekly testing with a one-day delay leads to 119.14 (IQR 110.88 - 125.18).

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 (e.g. compare circles to squares and of the same color inf figure 3) though in the highest transmission scenarios, greater than twice-weekly testing may be needed. 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.

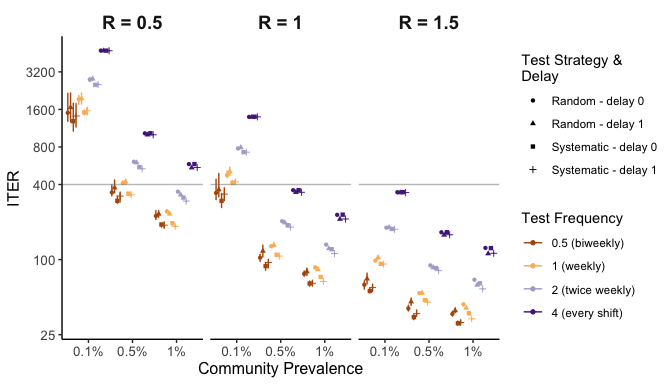


**Figure 3. Number of expected infections generated in a facility from model simulations comparing random and systematic testing strategies across transmission scenarios, test frequencies, and test delays**. Systematic testing strategies (n, Ê) prevent more infections than random strategies (l, p) across all transmission scenarios and test frequencies. More infections are expected in transmission scenarios with higher within facility and higher community prevalence. Preventing test delays (squares compared to crosses and triangles compared to circles) and increasing test frequency (red=lowest frequency, blue=highest frequency) also reduces the number of infections. 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) under a systematic testing strategy needed to maintain the upper quartile of expected infections in the facility below a threshold of 1 every ten days across transmission scenarios conveyed by the within-facility basic reproduction number (), community prevalence (CP), and test delay.

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  |  |  |  |
|  | 0 | 1 | 1 |
|  | 2 | 2 | 4 |
|  | 2 | 4 | 4 |
|  |  |  |  |
|  | 0 | 1 | 2 |
|  | 2 | 2 | 4 |
|  | 2 | 4 | 4 |

An alternative threshold approach to aid decision-making, particularly in resource-constrained settings, is the ITER, interpreted as the number of tests needed to prevent on infection. Figure 4 shows estimates of the ITER across transmission scenarios, test strategies, and test frequencies. In the highest transmission scenario (, community prevalence), testing systematically on the first day of every other work week with no delay (, fig 4 squares) leads to 30.84 (IQR 29.6 - 32.38), while increasing test frequency to weekly () results in 37.11 (IQR 36.61 - 37.61), to twice weekly (): 64.54 (IQR 64.22 - 65), and to every shift (): 123.62 (IQR 122.72 - 124.31). These values approximately correspond to test positivity rates of 3.24%, 2.69%, 1.55%, and 0.81% due to the interpretation of the ITER as the number of tests per positive result. It is also clear from figure 4 that testing frequency has the most influence on the within the same transmission scenario, with minimal differences between test strategies and delays. 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.



**Figure 4. Incremental test effectiveness ratio (ITER) from simulations across transmission scenarios and testing frequencies and strategies**. 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 (906 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 the 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 (15). 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). Lower thresholds than one expected infection event 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 into resident populations from April 2020-March 2021 across 35 facilities resulted in outbreaks of greater than 10 resident cases (28), 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 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 infections in 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 (29). However, sometimes 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.

The exclusion of these additional interventions 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. Furthermore, we assume that the probability density function of the triangle distribution is an accurate representation of SARS-CoV2 viral dynamics and therefore infectiousness through time. Though this function captures the general viral dynamics profile seen previously (15,18), other distributions or functions may also be applicable. 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 sparked by staff infections are a hazard. Other applicable settings may include the introduction of hospital acquired infections from newly admitted patients or from hospital staff (30), introduction of other respiratory pathogens such as influenza or pertussis into congregate settings (31), or tuberculosis transmission between communities and populations experiencing incarceration (32). 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 (14). 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, we have shown 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. We conclude that systematic testing of staff working with high-risk populations in congregate settings should continue until community transmission or within-facility transmission potential are sufficiently reduced to prevent outbreaks.

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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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