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Supplementary appendix

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Supplemental Appendix for Outbreaks of COVID-19 Variants in U.S. Prisons: A Mathematical Modeling Analysis of Vaccination and Re-Opening Policies

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Microsimulation Model

The transmission-dynamic stochastic microsimulation model follows individual residents and correctional staff within a prison. The model reflects the prison's residential structure and we simulate different prisons by instantiating the model with prison-specific characteristics.

Each day, for each incarcerated person and correctional staff member who is currently susceptible to infection, we compute the risk of infection using a set of transmission equations.

Transmission Equations

Equation 1 shows the transmission rate for resident i who lives in room r, building b, and yard y and who interacts with:

- Other residents, res, in the same room r (e.g., cell or dormitory [dorm])
- Other residents in the same building b
- If individual i participates in activities a, (labor l, school s, and/or other activities o), then he or she also interacts with other residents in the same yard y who participate in labor, school, and/or other activities, with participation in each activity type noted with an indicator function $1\{.\}$ in Equation 1
- Correctional staff, cs, in the same prison

$$[1]\quad rate_i = rate_r N_{eff,r}\left(\frac{I_r}{N_r}\right) + rate_b N_{eff,b}\left(\frac{I_b}{N_b}\right) + 1\{labor\} rate_a N_{l,y}\left(\frac{I_{l,y}}{N_{l,y}}\right) + 1\{school\} rate_a N_{s,y}\left(\frac{I_{s,y}}{N_{s,y}}\right) + 1\{other\ activities\} rate_a N_{o,y}\left(\frac{I_{o,y}}{N_{o,y}}\right) + \beta_{res,cs}\left(\frac{I_{cs}}{N_{cs}}\right)$$

Equation 2 shows the transmission rate for correctional staff member *j*, who interacts with:

- Residents, res, in the same prison
- Other correctional staff, cs, in the same prison

$$[2]\quad rate_j = \beta_{cs,res}\left(\frac{I_{res}}{N_{res}}\right) + \beta_{cs,cs}\left(\frac{I_{cs}}{N_{cs}}\right)$$

In both equations:

- $rate$ denotes the rate of infection per infected contact for each type of contact (room, building, or activities)
- β denotes the effective contact rate (between residents and correctional staff, correctional staff and residents, and correctional staff and other correctional staff)

- N denotes the total number of individuals
- I denotes the total number of infectious individuals
- N_{eff} denotes the number of effective contacts, in cases where it differs from the total number of individuals (room and building contacts only, details in next section)

Model Parameters

Parameters used in the microsimulation model are displayed in Table S1. Several parameters are described in more detail in subsequent subsections of this appendix.

Table S1: Prison microsimulation model parameters

Parameter	Value/Distribution	Source & Notes
Covid-19 Epidemiology		
Duration of Latent Period	Gamma distributed (mean 3·0 days, standard deviation 1·0 days)	Based on *He et al., Lauer et al., Ashcroft et al., Li et al., Wölfel et al.* (1–5); details in Appendix pages 11-12
Duration of Infectious Period	Gamma distributed (mean 3·1 days, standard deviation 2·1 days)	
Duration of Incubation Period	Gamma distributed (mean 5 days, standard deviation 2·9 days)	
Duration of Symptomatic Period	Latent Period + Infectious Period – Incubation Period	Calculated. This implies that approximately 60% of infections become symptomatic.
Daily rate of transmission per infected roommate	0·05 with dampening of effective contacts in high-occupancy rooms (details in Appendix)	Calibrated (details in Appendix pages 5-10)
Daily rate of transmission per infected non-roommate building contact	0·005	Calibrated (details in Appendix pages 5-10)
Daily rate of transmission per infected labor/activities contact	0·025	Calibrated (details in Appendix pages 5-10)
Daily effective contact rate between residents and workers	0·05	Calibrated (details in Appendix pages 5-10)
Daily effective contact rate between workers	0·15	Calibrated (details in Appendix pages 5-10)
Relative transmissibility of new Covid-19 variants	150%	Based on CDC(6)
Percent of individuals immune to wild-type infection that are immune to the variant	80%	Based on CDC(6)
Probability of hospitalization (severe infection) conditional on symptomatic infection with wild type	0·4%-27%; varies by age and comorbidities (see Appendix)	Calculated from *Verity et al.*(7) and adjusted for CDCR hospitalization rates by comorbidities. Hospitalization is defined as a case with symptoms severe enough to require inpatient treatment and does not reflect capacity or identification of symptoms.
Probability of death conditional on severe infection with wild type	3·7%-52·3%; varies by age (see Appendix)	Based on *Verity et al.*(7)
Relative risk of hospitalization (severe infection) conditional on symptomatic infection with variant of concern (relative to wild type)	1·63	*Tuite et al.*(8)
Relative risk of death conditional on severe infection with variant of concern (relative to wild type)	1·56	*Tuite et al.*(8)
Vaccine Characteristics – Wild Type		
First dose efficacy against clinical infection	85% starting 15 days after receipt of first dose	Observed effectiveness among healthcare workers in Israel(9)
Second dose efficacy against clinical infection	95% starting 10 days after receipt of second dose	Pfizer phase III vaccine trial(10)
Efficacy against transmissibility conditional on protection from clinical infection	88% for both doses	Observed effectiveness against sub-clinical infection among healthcare workers in Israel(9)
Vaccine Characteristics – Variant of Concern		
First dose efficacy against clinical infection	60% starting 15 days after receipt of first dose	Assumed
Second dose efficacy against clinical infection	80% starting 10 days after receipt of second dose	Assumed

Efficacy against transmissibility conditional on protection from clinical infection	50% for both doses	Assumed
Vaccine Coverage and Refusal		
Resident acceptance at baseline – realistic scenario	Varies by age; 36% among ages 18-29 up to 76% among ages ≥ 70	Based on CDCR data (Appendix page 22)
Resident acceptance at baseline – best-case scenario	90% across all ages	Assumed
Correctional worker coverage at baseline	40% across all ages	Based on CDCR data (Appendix page 22)
Dropout between first and second dose	0%	Based on very low dropout observed in CDCR data
Test Characteristics		
Test specificity	100%	Assumed
Test sensitivity	Varies by day of infection (see Appendix page 21)	*Kucirka et al.*(11)
Population Characteristics		
Resident joint age, sex, co-morbidity, security level, and room occupancy distribution	Varies by prison	CDCR data
Resident participation in labor and other activities	Varies by prison	CDCR data
Prison population size and structure (rooms, buildings, yards)	Varies by prison	CDCR data
Resident background mortality	Varies by age (see Appendix page 25)	CDCR data
Correctional staff population size	Ratio of 6.1 residents to 1 correctional worker	Department of Justice report(12)
Correctional staff age distribution	10% 18-29, 15% 30-39, 25% 40-49, 25% 50-59, 25% 60-69	American Community Survey data(13)
Correctional worker background mortality	Varies by age	CDC life tables(14)
Resident and correctional worker baseline immunity to wild-type infection	0%, 25%, 50%	Assumed, varies by scenario

Effective Contacts and Model Calibration

Calibrated parameters are summarized in Table S2 and described in more detail below.

Table S2: Calibrated transmission parameters

Parameter	Abbreviation	Value
Daily rate of infection per infectious room contact	$rate_r$	0.05
Daily rate of infection per infectious building contact	$rate_b$	0.005
Number of effective room contacts	$N_{eff,r}$	$\min\left\{4 + \sum_{i=0}^{(N_r-1)-4} \frac{1}{(1.1)^i},\ (N_r - 1)\right\}$
Number of effective building contacts	$N_{eff,b}$	All rooms except medium dorms: N_b Medium dorms: $\min\{100, N_b\}$
Daily rate of infection per infectious activity contact	$rate_a$	0.025
Effective contact rate between residents and correctional staff	$\beta_{res,cs}, \beta_{cs,res}$	0.05
Effective contact rate between correctional staff	$\beta_{cs,cs}$	0.15

The rate of infection per infectious room contact, $rate_r$, the rate of infection per infectious building contact, $rate_b$, and the relationships between the room or building censuses, N_r and N_b, and the effective room or building contacts, $N_{eff,r}$ and $N_{eff,b}$, were calibrated to empirical estimates of the prison within-room secondary attack rate (SAR) among residents across California state prisons, which we estimated from primary CDCR data. We categorized rooms with at least two residents into four types: double cells (2 occupants), small dorms (3-10 occupants), medium dorms (11-30 occupants), and large dorms (31 or more occupants). We simulated outbreaks in prisons with different room types and calculated the observed SAR from the model-predicted output (i.e., the number of subsequent detected secondary cases among roommates of the first case detected in a room, within 14 days of the detection of the index case, divided by the number of occupants in that room), stratified by room type. We repeated these simulations across multiple combinations of values of $rate_r$ and $rate_b$ and functional forms for $N_{eff,r}$ and $N_{eff,b}$.

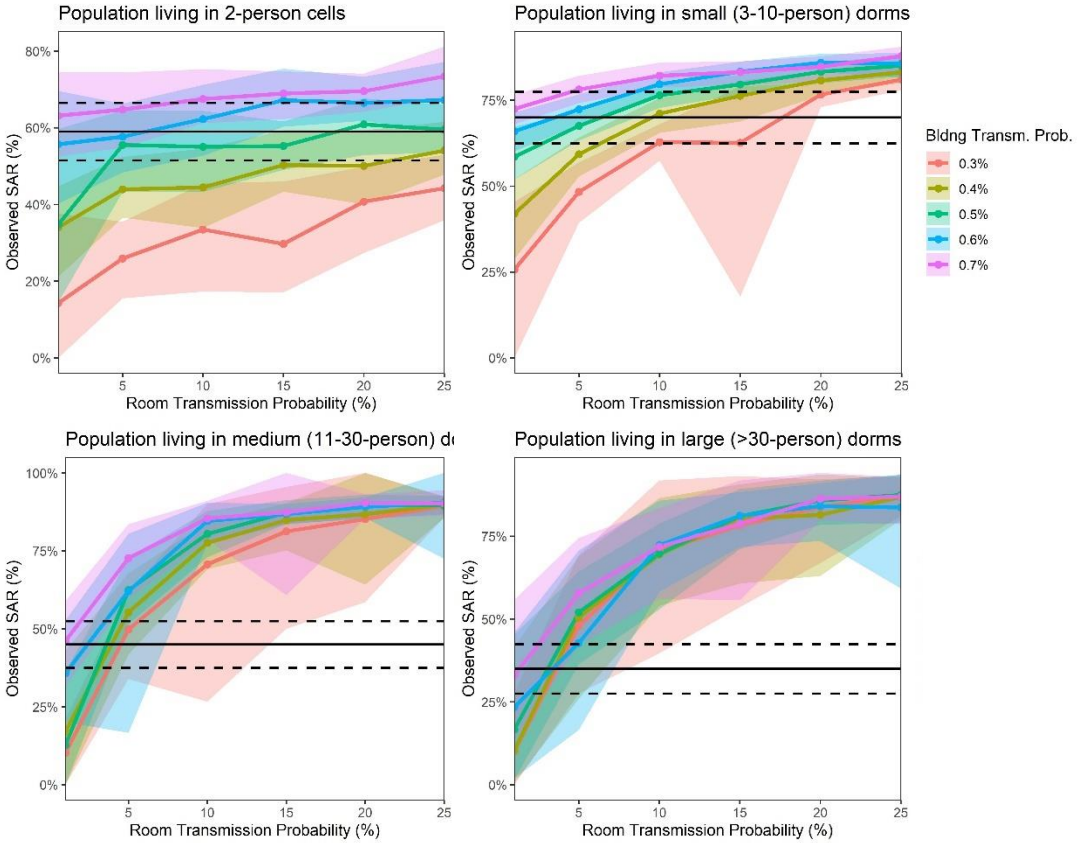
In many contexts, the number of contacts people have does not grow with constant proportionality to the total population size which is why many epidemic models use transmission terms like $\beta\frac{SI}{N}$ instead of βSI (15–17). In dormitories with tens or even hundreds of occupants, any individual may have contact with a fraction of the total occupants in any given day (in contrast to 2 person cells). Hence, we selected various functional forms for $N_{eff,r}$ to allow for effective contacts to rise more slowly than room census. Further informing this choice was that the empirical estimates of SAR do not strictly increase with room census.

The number of effective building contacts, $N_{eff,b}$, was generally selected to be equal to building census (minus room census), except that we capped $N_{eff,b}$ for medium dorms (11-30 occupants). While there are generally few large dorms per building in CDCR prisons, there are often many medium dorms in one building, yielding a large number of building contacts if uncapped. However, those living in medium (and large) dorms are likely to interact more with their roommates and less with others in the building since bathrooms, recreational rooms, and other common facilities are often specific to a dorm and not shared across dorms.

We compared the model-predicted SAR to corresponding empirical estimates of SAR, and selected parameters which yielded model output that fell within the 95% confidence bounds of the empirical estimates across room types (Figure S1). Based on these simulations, we selected a daily transmission rate per infected room contact of 0.05 (which roughly corresponds to a transmission probability of 5%) and a daily transmission rate per infected building contact of 0.005 (which roughly corresponds to a transmission probability of 0.5%). We capped effective building contacts for medium dorms at 100 contacts and established the following functional form for effective room contacts (Table S2, equation 3, Figure S2):

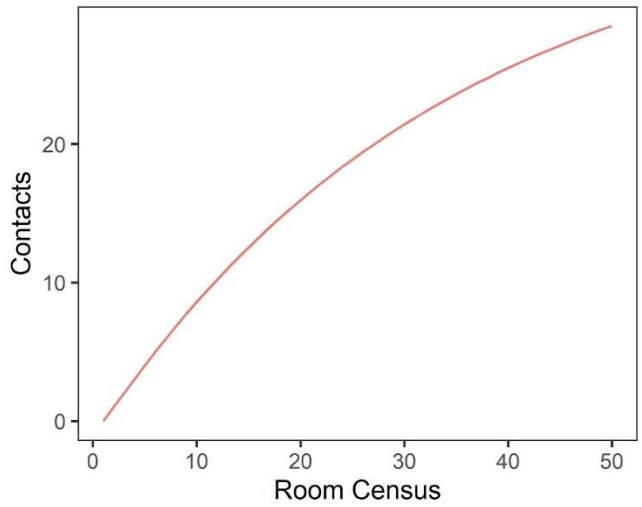
[3] $$N_{eff,r_i} = \min\left\{4 + \sum_{i=0}^{(N_{r_i}-1)-4} \frac{1}{(1.1)^i},\ (N_{r_i} - 1)\right\}$$

Figure S1: Fit of modeled secondary attack rate to empirical estimates, with contact dampening



Empirical estimates are shown in black (solid lines), with confidence intervals shown via dashed lines. The 0.5th and 99.5th percentiles on modeled output are shown via colored shading, while the means are shown via colored lines.

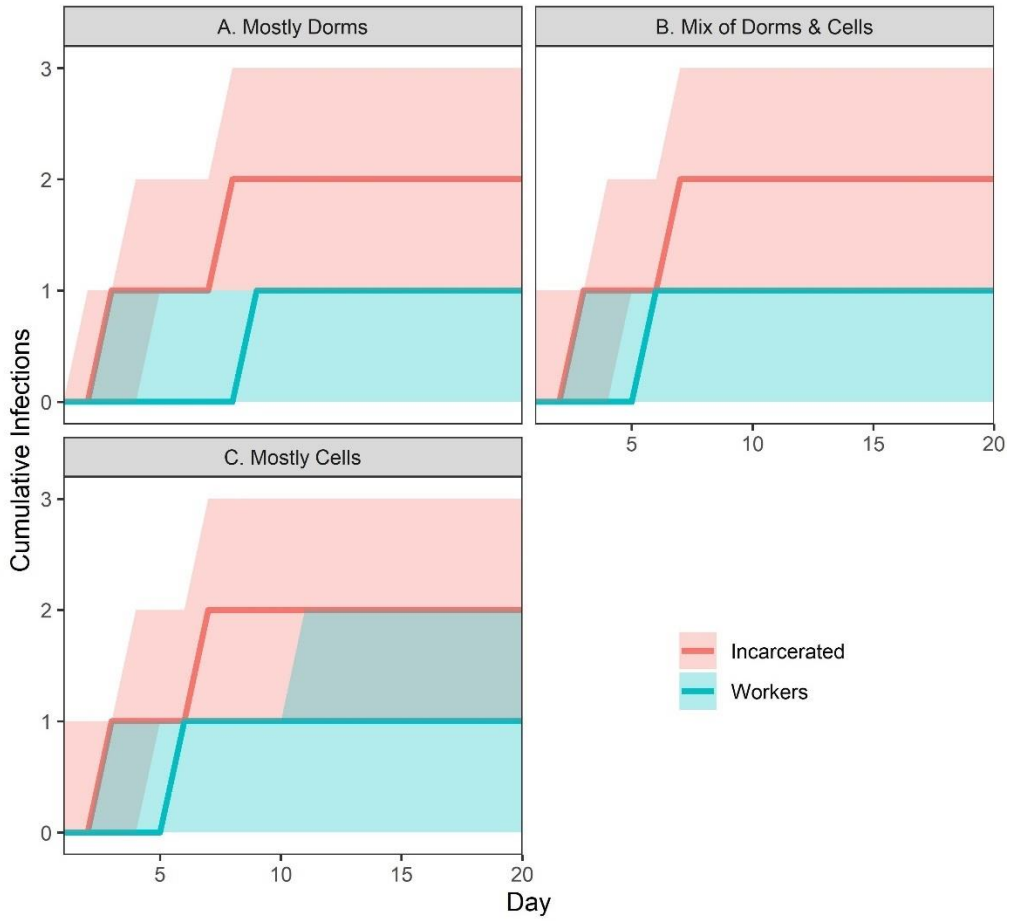
Figure S2: Calibrated relationship between room census and effective room contacts



The remaining transmission-related parameters ($rate_a$, $\beta_{res,cs}$, $\beta_{cs,res}$, and $\beta_{cs,cs}$) were selected after these initial four parameters ($rate_r, rate_b, N_{eff,r}$, and $N_{eff,b}$) were calibrated, since they were found to have relatively little influence on the within-room SAR. Transmission from activity-specific contacts and between residents and correctional staff are important in the model because they cause outbreaks that start in one building to spread to additional buildings and yards. This follows from considering a scenario in which an outbreak has already taken off in one part of the prison. In such a case, it can spread elsewhere in the prison even if the activity transmission rate and effective contact rates are minimal because it only requires one activity contact or staff member to be infected/infectious and then transmit to someone else from another part of the prison for the outbreak to then spread through building and room contacts in that other area. We selected the effective contact rates between staff and between staff and residents so that the average infected staff person would infect one other staff member and 1-2 residents (Figure S3; $\beta_{res,cs}, = \beta_{cs,res} = 0.05$ and $\beta_{cs,cs} = 0.15$)), implying a basic reproductive number on the high end of estimates from free living populations (4,18). We selected the rate of transmission per infected labor/school/other activity contact, $rate_a = 0.025$, which is half of the room transmission rate, to reflect the fact that activity contacts are likely of shorter duration and proximity than in-room contacts, especially with non-pharmaceutical interventions such as masking and attempts to physically distance are in place at activities.

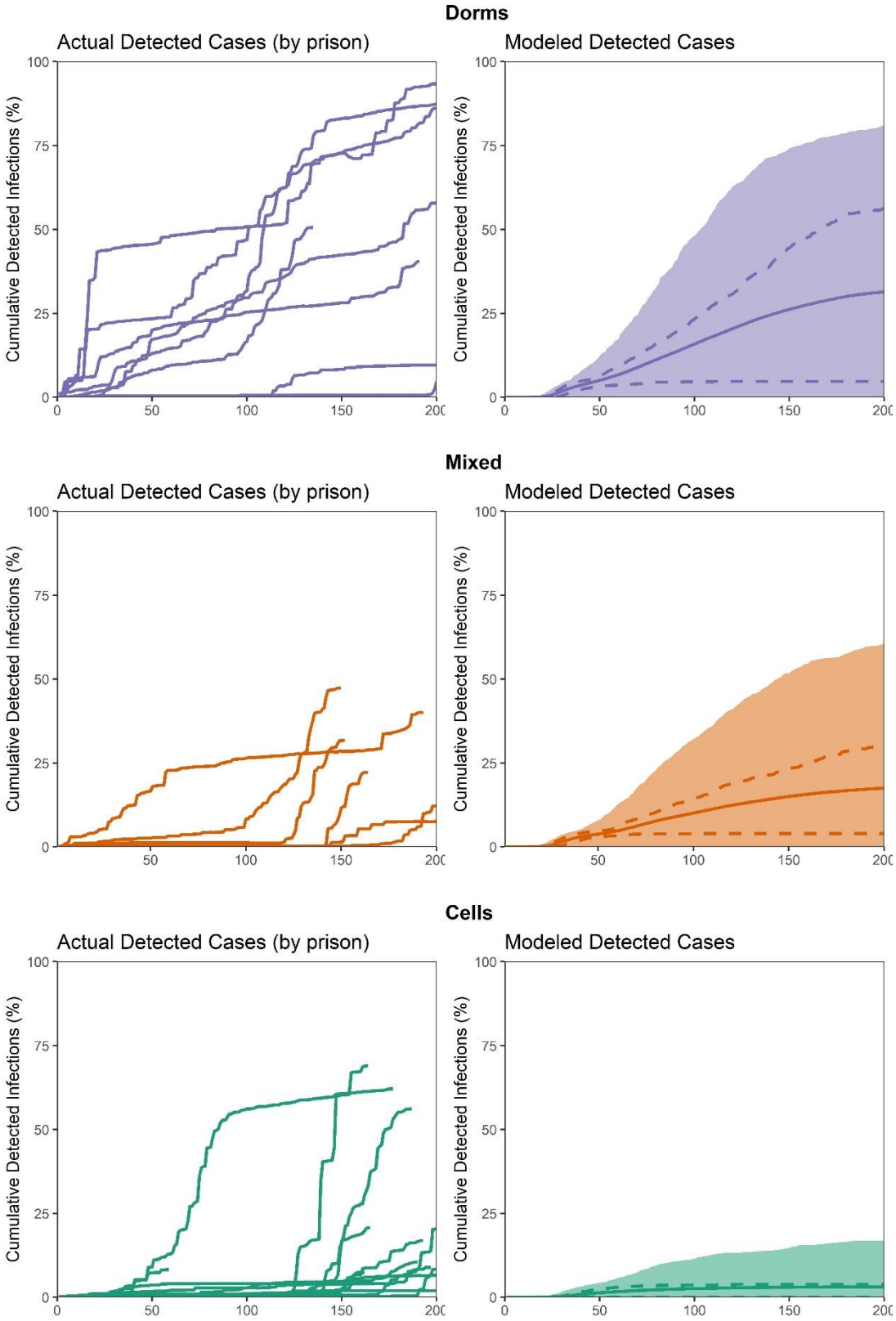
After selecting these transmission rates, we conducted validity checks by modeling cumulative detected infections across the five prison types with no vaccination, no resumption of in-person activities, and continued NPI usage, with a single importation of a wild type infection (Figure S4). We found that the distribution of modeled output across 500 simulations was generally consistent with actual detected infections trajectories from the CDCR prisons (Figure S4). In some cases, the model appears to slightly underestimate detected infections. This was expected given that many prisons likely experienced multiple infection importations, while the model conservatively assumed only a single imported infection on day 1, and because we model testing and surveillance protocols consistent with CDCR policy as of early 2021, but testing volumes were lower and more variable across prisons in mid-2020, when many large outbreaks occurred. One of the greatest discrepancies between the data and modeled output is observed for one of the women's prisons. There are two quite different women's prisons in CDCR, and the prison with the larger outbreak is one that consists of mostly dorms (while the modeled prison consists of mostly cells). We would expect the data from the women's prison with dorms to look more like a mixture of the modeled output for the women's prisons (with cells) and the prisons with mostly dorms.

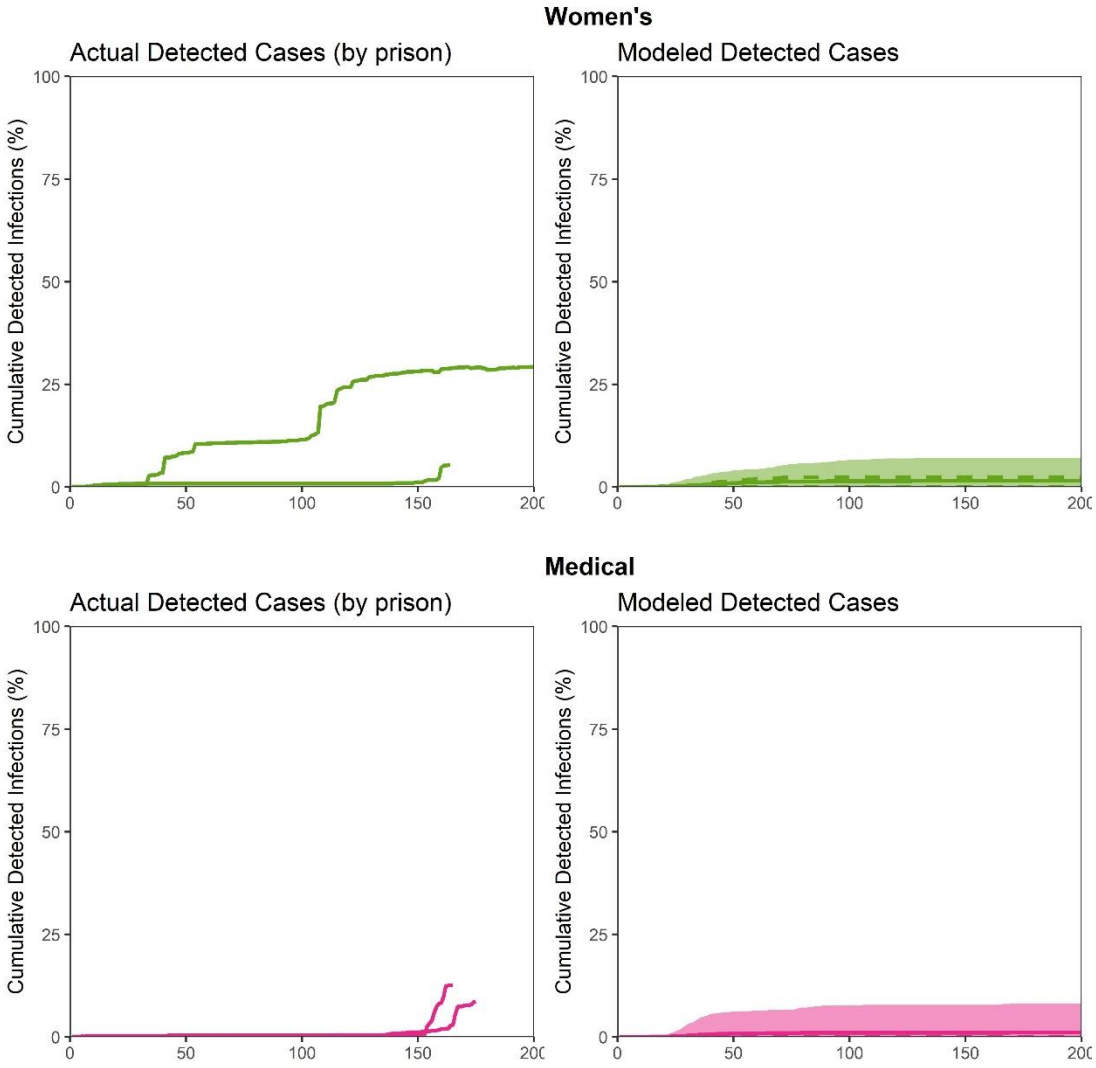
Figure S3: Calibrated secondary infections from one index staff infection



The figure shows the results of seeding one staff member infected with wild-type COVID-19 in a prison with no vaccination and no baseline immunity to infection. We simulated for 20 days, with all transmission between residents disabled to focus on staff-related transmission. Medians with interquartile ranges are shown.

Figure S4: Model validation – comparison of modeled detected case trajectories against empirical epidemic curves from CDCR prisons.





Left panels show cumulative infections over time from CDCR prisons. Infections are shown for 200 days from the first day an infection was detected (day 1), which varies by prison. Each line in the left panels represents a single prison. Data cover all of 2020. Some prisons had outbreaks later in 2020 and thus data were not available for the full 200 days. Two prisons are excluded from this analysis because their outbreaks are known to have been caused by multiple importations at once (via transfers from other prisons that had been undergoing large outbreaks). Prisons with 0 detected infections (these were mostly prisons with cells) are also excluded.

Right panels show only those modeled infections that were detected (i.e., via testing and surveillance). Solid lines indicate averages across 500 simulations, dashed lines indicate the 25th and 75th percentiles, and shading indicates the 2.5th and 97.5th percentiles. Simulations were run without vaccination, without resumption of in-person activities, with NPIs, with 0% immunity at baseline, and with a single resident infection seeded on day 1.

Modeling the residential arrangement of prisons

Our model replicates a prison's residential arrangement, including the number of rooms by occupancy, within buildings, and in turn within yards. This allows the analysis to simulate the spread of infections across a prison. Supplemental videos demonstrating the simulated spread of COVID-19 infections in two prisons (the prison with mostly dorms and the high-security prison with mostly cells) are available at https://www.sc-cosmo.org/prisons-microsimulation-paper-june-2021/.

Latent, incubation, infectious, and symptomatic periods

Our model incorporates: a latent period (time from infection to becoming infectious); an incubation period (time from infection to symptom onset); and an infectious period (time from becoming infectious to becoming recovered). For each individual who becomes infected, we draw the duration of his/her latent period, incubation period, and infectious period from gamma distributions parameterized to be consistent with previous literature. If an individual's sampled duration of the incubation period is longer than the sum of their sampled latent and infectious periods, then the infection is asymptomatic. Otherwise, some individuals develop symptoms prior to becoming infectious and the rest become infectious prior to becoming symptomatic depending on whether the latent period is longer than the incubation period or vice versa, respectively.

We estimated the parameters of these three duration distributions by synthesizing evidence from several published studies (1–5,19). We fit gamma distributions to the means and distributions of various durations and intervals reported in these studies (including probability density functions, cumulative distribution functions, and quantiles).

For the incubation period, we estimated gamma distribution shape and rate parameters of (2.97, 0.59), which yield a mean duration of incubation of 5 days with 95% of durations between 1.0 and 12.0 days. These estimates closely match the mean (5.2 days) and upper bound (12.5 days) estimated in *Li et al.* (4) and used in *He et al.* (1,19), as well as the mean (5.1 days) and upper bound (11.5 days) reported in *Lauer et al.* (2).

The durations of the latent and infectious periods are more difficult to estimate empirically and require additional assumptions. Infections are not typically observed from the date of infection and the date on which an individual starts and stops being infectious is also typically unknown. The latter can be proxied by viral test data, but there is a lack of evidence translating viral test results into conclusions regarding levels of infectiousness. We used data from *He et al.* and other sources (5,20) on the infectivity profile (infectiousness over time relative to the date of symptom onset) along with our incubation period parameters to estimate the parameters for the latent and infectious period distributions.

The estimated shape and rate parameters of the fitted gamma distribution for the latent period are (9.00, 3.00). These parameters yield a mean duration of latency of 3 days, with 95% of latency durations between 1.5 and 4.9 days. These estimates result in 33% of transmission occurring prior to symptom onset for infections that develop symptoms, and 50% of all transmission (including pre-symptomatic and asymptomatic) occurring among infectors that are not at the time symptomatic. Although comparability is limited due to the study sample (which likely overrepresents symptomatic infections), this estimate is consistent with *He et al.* which reports that 30-57% of infections occurred prior to symptom onset.

The estimated shape and rate parameters of the fitted gamma distribution for the infectious period were (2.18, 0.70), yielding a mean duration of infectiousness of 3.12 days, with 95% of infectious durations between 0.6 and 7.0 days. With the estimated durations of these three periods, we can describe the infectivity profile over time (infectiousness relative to date of symptom onset) and compare it to the literature: *He et al.* report that "infectiousness declines quickly within 7 days" (of symptom onset) and *Wölfel et al*. report no positive cultures after 8 days of symptom onset (5). In our model, 95% of infectors who eventually develop symptoms transmit between 4 days before developing symptoms and 7 days after.

The estimation of infectiousness over time is complicated by significant unknowns with respect to the relationship between RT-PCR viral load threshold cycle (Ct) values and transmissibility. Still, one benchmark is whether the samples can be cultured. For example, *Jaafar et al.* report that less than 3% of positive test samples with Ct values ≥ 35 could be cultured (20). Applying this threshold to the *He et al.* data, the average infection had a Ct value ≥ 35 by around 4-5 days after symptom onset (see Figure 2 in *He et al.*). In our model, the average symptomatic infector is infectious for 3.8 days after symptom onset - a slightly shorter duration than *He et al.* We expect this difference given that we include very mild symptomatic cases (that are likely to be less infectious), while *He et al.* (and many other studies) are hospital-based and thus biased toward somewhat more severe (and potentially more infectious) cases. Note that the average duration of infectiousness after symptom onset (3.8 days, for infectors with symptoms) exceeds the average infectious duration (3.1 days) for all infectors in our model. This is because infectious durations are on average longer for those who develop symptoms, given that only those whose infectious periods last beyond the incubation period develop symptoms in our model.

Together, these distributions yield a mean symptomatic serial interval of 5.4 days, with 95% of infector-infectee pairs having serial intervals between -0.2 and 12.1 days. These results closely match the serial interval distribution and mean of 5.8 days reported in *He et al.* (1,19) (see also the top panel of *He et al.'s* corrected Figure 1C).

We also validated these model parameters against additional published literature that became available after we had initially fit the distributions. The US CDC has published assumptions for modeling and additional sources supporting these assumptions (21). For example, they report an average incubation period of approximately 6 days based on *McAloon et al.* and *Ma et al.* (2,22). *McAloon et al.*, a meta-analysis of published studies, estimates an incubation period of 5.8 (95% CI 5.0 to 6.7) days. They also noted "that uncertainty increases towards the tail of the distribution: the pooled parameter estimates (95% CIs) resulted in a median incubation period of 5.1 (95% CI 4.5 to 5.8) days, whereas the 95th percentile was 11.7 (95% CI 9.7 to 14.2) days." *Ma et al.* point out heterogeneity in incubation durations in their Multimedia Appendix 5, with approximately a day shorter duration for individuals exposed for 2+ days compared to those exposed for only 1 day and for individuals who are household versus non-household contacts. In general, these findings suggest a shorter incubation time for prison settings in which individuals are housed closely together for substantial periods of time and hence should generally have more intense exposures to viral particles. The CDC also assumes a serial interval of approximately 6 days, based on both *He et al.* and *Saurabh et al.* (1,19,23). All of these estimates comport well with the distributions that we use.

Testing, Quarantine, and Isolation

Based on CDCR policy, we model four main types of case detection among residents:

1. Background surveillance testing: CDCR developed a COVID-19 risk score to grade each resident's probability of severe health outcomes following COVID-19 infection. Scores correspond to the presence of demographic and clinical characteristics identified in the scientific literature as risk factors for severe COVID-19-related illness (e.g., age >65 years, immunocompromised) (Table S3) (24). Residents are flagged as high-risk if their COVID-19 risk score is at least 4. Some prisons house older and more medically vulnerable individuals than others. If a prison houses fewer than 60 high-risk residents, we model testing for all high-risk residents every 2 weeks. Otherwise, a random selection of 15 high-risk residents in each yard is tested every 2 weeks.

2. Reactive testing: When a case is detected (e.g., via surveillance testing), contacts of the infected resident are also tested. These contacts include everyone in the same room as the detected individual as well as 20% of residents in the same building (but different rooms). If reactive testing identifies additional cases, this could trigger outbreak-level testing (see below).

3. Outbreak-level testing: A single case will only trigger reactive testing. However, if 2 or more cases are detected in the prison within a 14-day window, outbreak-level testing is triggered for all yards in which cases were detected. If all detected cases were in the same building, 80% of the residents of that building are tested. If cases were detected in multiple buildings in the same yard, 80% of the residents of that yard are tested.

4. Testing of hospitalized patients: All infections that are severe enough to require hospitalization are detected and subsequently tested. Regardless of test result (i.e. even if the result is a false negative), these severely infected individuals are isolated and hospitalized.

All detected cases are isolated for 14 days. All residents of a building with a detected case are put into quarantine, during which they continue to interact with others in the same building and with staff but they no longer interact with any residents outside of their building (e.g., via activities). Quarantine lasts for 14 days after the last day on which a case was detected. For buildings undergoing large outbreaks, quarantine could therefore last far longer than 14 days. We include a 4-day lag between the day a test sample is taken and the day a detected case is isolated, and their building quarantined.

Detection of staff infections is modeled in a simplified way. Correctional staff infections can only be detected via symptom screening, not via surveillance testing. Every staff member is screened daily. Symptomatic infected staff (regardless of infectious status) have a 50% chance of being detected for each day they are symptomatic. Thus, the probability of detection increases with duration of symptoms. Asymptomatic infected staff have a 0% chance of being detected. Detected staff isolate for 14 days from the day of detection.

Table S3: COVID-19 risk score criteria

Condition	Definition	Weighted Score
Age 65+	Chronologic age of 65 years or above	4
Advanced liver disease	Has advanced liver disease (cirrhosis/end stage liver disease)	2
Asthma	Persistent asthma (moderate or severe) as defined by the California Correctional Health Care Services (CCHCS) asthma condition specifications	1
Cancer	High risk cancer as defined by the CCHCS cancer condition specifications (excludes most diagnoses of skin cancer and "personal history of" cancers")	2
Chronic Lung Disease (other)	Has cystic fibrosis, pneumoconiosis, or pulmonary fibrosis	1
Chronic Obstructive Pulmonary Disease (COPD)	Has Chronic Obstructive Pulmonary Disease	2
Cardiovascular Disease (CVD)	Has any of the following:" cerebrovascular disease, congestive heart failure, congenital heart disease, ischemic heart disease, peripheral vascular disease, thromboembolic disease, and valvular disease	1
Cardiovascular Disease (CVD; high risk)	Is high risk for any of the following:" cerebrovascular disease, congestive heart failure, congenital heart disease, ischemic heart disease, peripheral vascular disease, thromboembolic disease, and valvular disease	1
Diabetes	Has diabetes	1
Diabetes (high risk)	Meets the criteria for high risk diabetes as defined by the CCHS diabetes condition specifications	1
HIV	Has HIV	1
HIV (poorly controlled)	Has HIV with a CD4 count < 200	1
Immunocompromised	Has any of the following: aplastic anemia, histiocytosis, immunosuppressed, organ transplant, other transplant	2
Morbid Obesity	Body Mass Index of 40 or above	1
Other Chronic Conditions	Has any of the following with a high-risk rating: hypertension, coccidiomycosis, connective tissue disorder, dementia/Parkinson's disease, endocrine disorder, multiple sclerosis, myasthenia gravis, neurologic disorder, vasculitis	1
On Dialysis	On hemodialysis	2
Pregnant	Actively pregnant	1

Source: Chin et al. (24)

Prisons

In the main text, we present analyses for five prisons: a minimum-to-medium security men's prison in which most residents are housed in dormitories ("dorms"), a maximum-security men's prison in which most residents are housed in cells ("cells"), a medium-security men's prison that includes a mix of residents living in a mix of celled housing and dormitories ("mixed"), a medical prison that houses male residents requiring special medical care who tend to be older and sicker than residents in the main prisons ("medical"), and a women's prison that combines female residents across security levels in yards of varying security levels ("women's", this prison has mostly cells and also has a smaller population). Details on the residential arrangement and populations of these prisons are shown in Table 1 and Appendix Figures S5-S9.

The figures below show percentages of residents by various characteristics. The security level is based on CDCR's security level system, where 1 is the lowest security level, and 4 is the highest security level. Room sizes are characterized by the number of occupants and include single cells (1 occupant), double cells (2 occupants), small to medium dorms (3-30 occupants), large dorms (31+ occupants). Comorbidities include advanced liver disease, asthma, cancer, COPD, chronic lung disease, cardiovascular disease, diabetes, HIV, immunocompromised, kidney disease (e.g., on dialysis). The activities panel shows the percent of residents that participated in any of the three types of activities out of their rooms (but still in the prison) in the past week with at least 1 other resident. On this panel, "Before Closures" indicates January 2020 (before closures due to COVID-19), and "With Closures" indicates November 2021 (with closures to due COVID-19 implemented). "Labor" includes both jobs that support the upkeep of the prison (resident workers at medical prisons, laundry, kitchen duty, etc.) and industries. "School" includes any educational activities. These are all set to 0% in the "post" period because CDCR has had residents participate in educational activities in their rooms to minimize transmission. "Other" includes several additional activities, including medical appointments, group therapy, and worship.

Figure S5: Low-to-medium security prison with mostly dorms

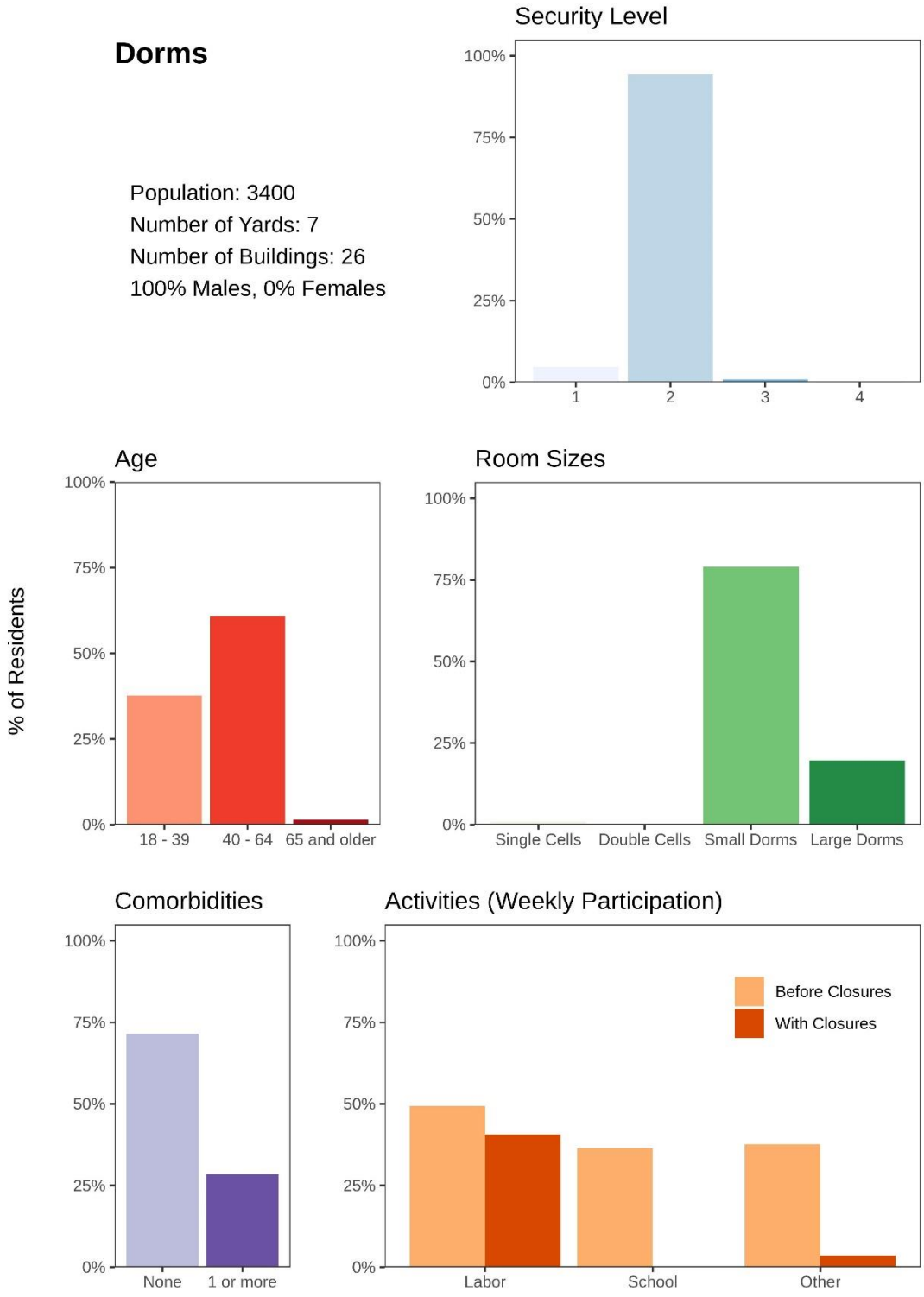


Figure S6: Medium/mixed security prison with a mix of cells and dorms

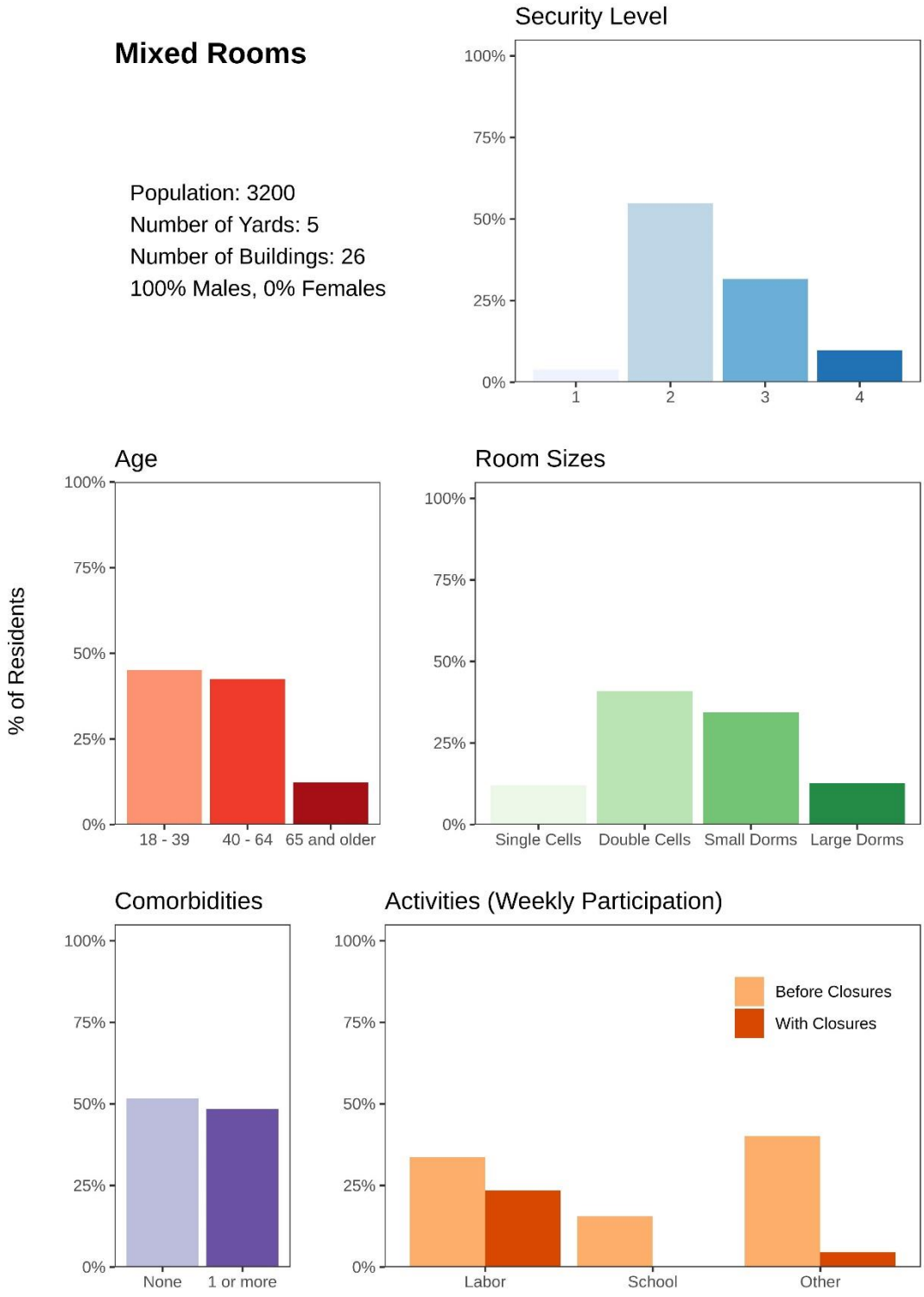


Figure S7: Higher security prison with mostly cells

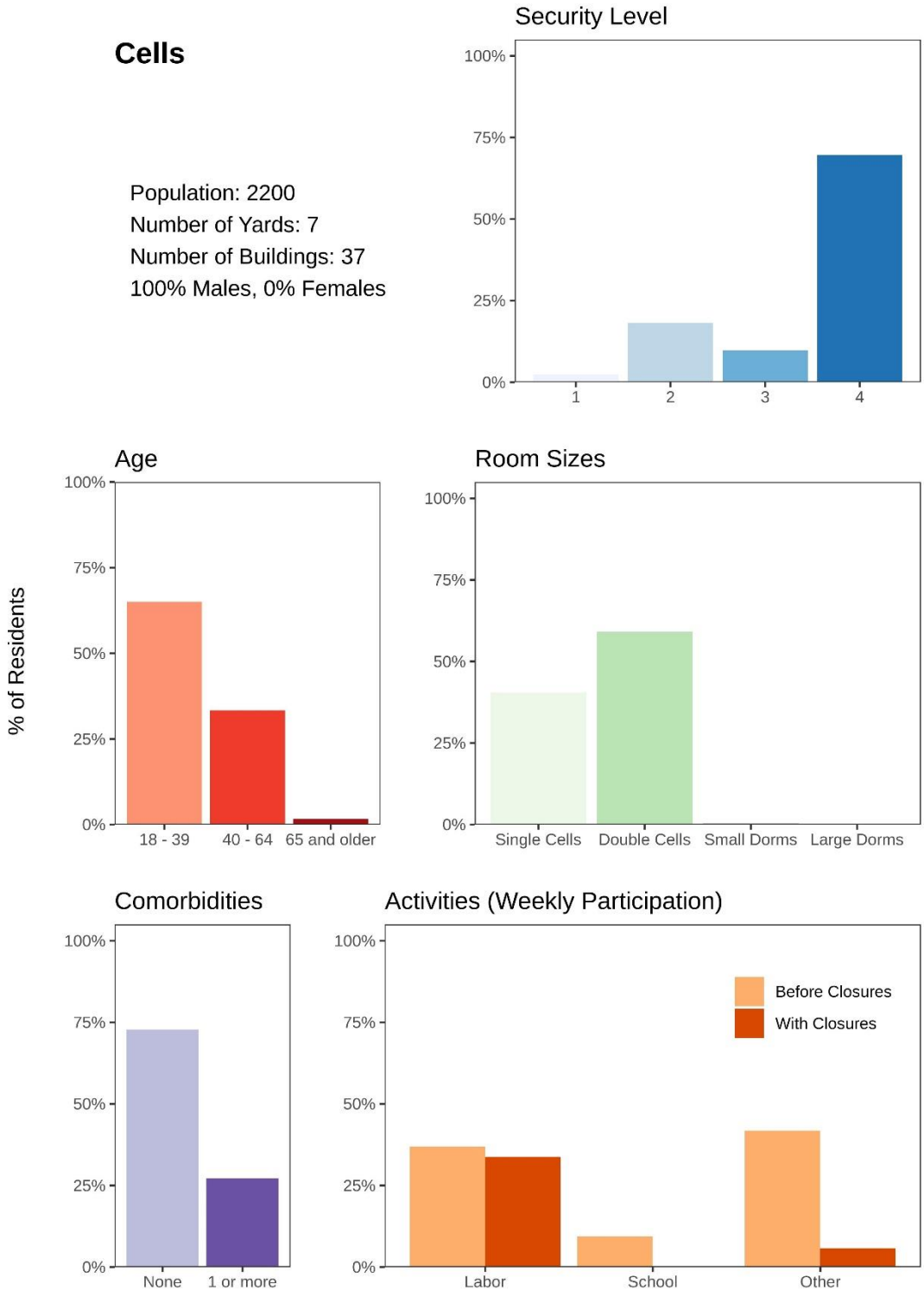


Figure S8: Women's prison with mixed security levels and mixed housing

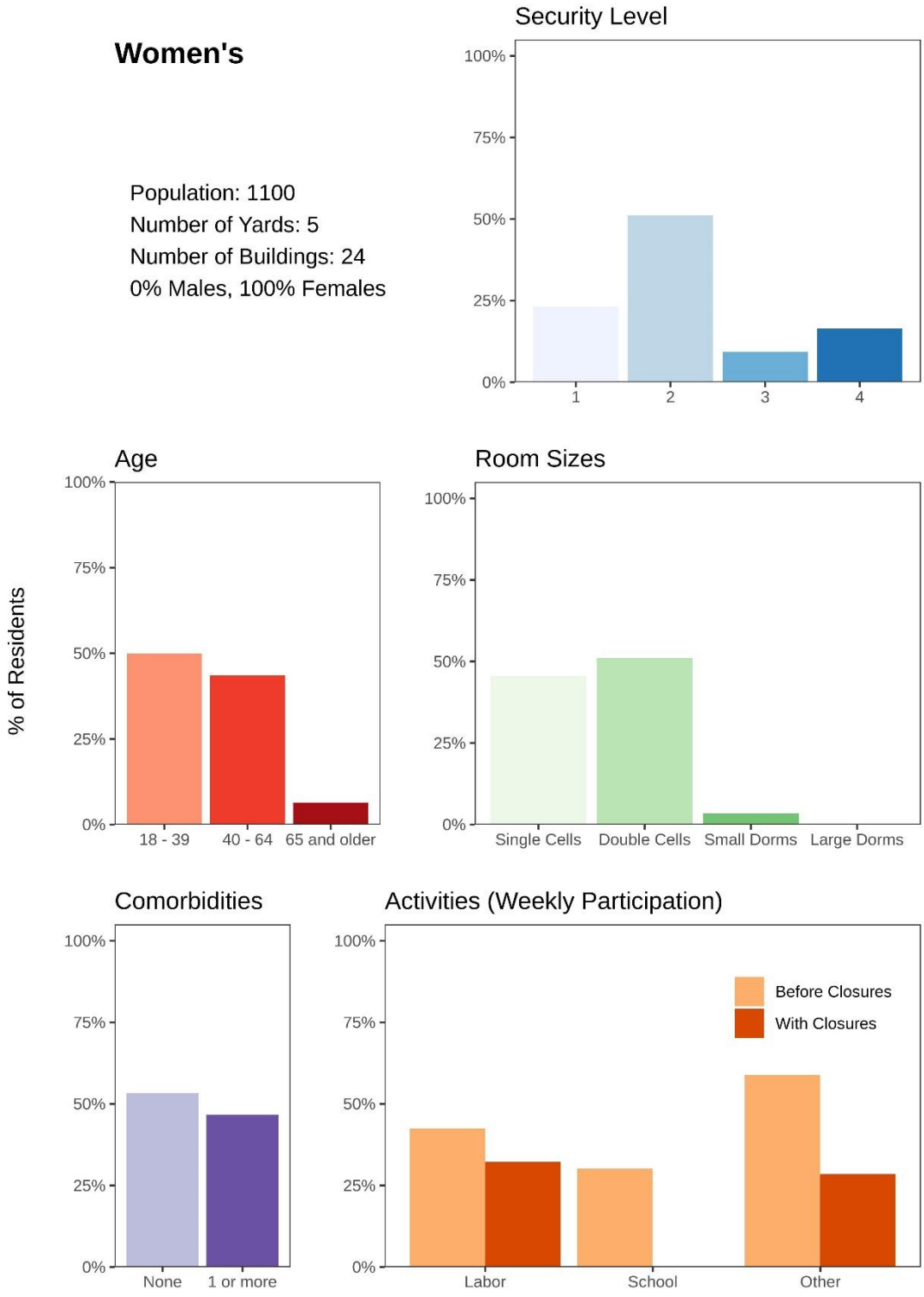
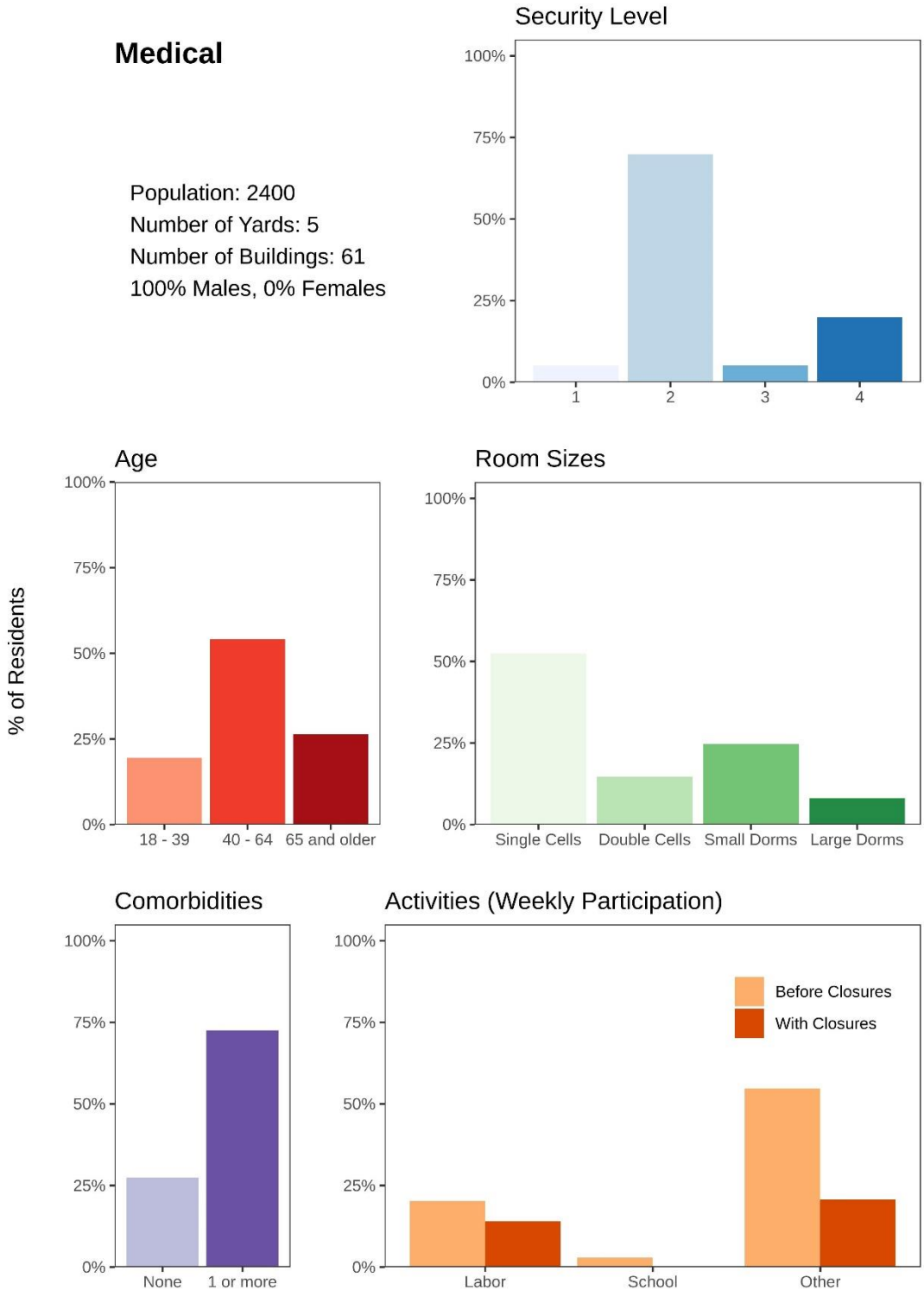


Figure S9: Medical prison with older and more medically vulnerable residents



Additional Model Parameter Details

This section describes several model parameters in more detail, including test sensitivity, hospitalization rates, and mortality rates.

Test Sensitivity

Test sensitivity by day of infection, based on (11), is described in Table S4.

Table S4: Probability of testing negative by day of infection (false negative rate)

Day	Median [range]
1	100% [100-100%]
2	100% [95.5-100%]
3	97.6% [56.9-99.9%]
4	70.4% [29.1-94.0%]
5	38.3% [18.3-63.6%]
6	24.5% [14.1-39.4%]
7	19.8% [12.5-30.3%]
8	18.8% [12.1-28.4%]
9	19.7% [12.9-29.3%]
10	21.8% [14.6-31.8%]
11	24.7% [16.9-35.3%]
12	28.2% [19.7-39.4%]
13	32.3% [23.0-43.8%]
14	36.5% [26.5-48.4%]
15	40.9% [30.2-52.7%]
16	45.2% [34.0-57.0%]
17	49.3% [37.9-61.0%]
18	53.2% [41.4-64.6%]
19	56.7% [45.1-67.8%]
20	59.9% [48.5-70.8%]
21	62.8% [51.5-73.3%]

Resident vaccine acceptance levels

We model two vaccine coverage scenarios (Table S5). Realistic vaccine acceptance is based on empirical acceptance rates observed among residents of CDCR prisons (25). We calculated the probability of acceptance by age, and then adjusted all the age-based probabilities down by 15 percentage points. This adjustment was made because CDCR initially prioritized highest risk populations and acceptance rates tended to decrease over time as offers were expanded to higher fractions of their total population.

Table S5: Resident vaccine acceptance by scenario

Resident Age (years)	Realistic Vaccine Acceptance	Best-Case Vaccine Acceptance
18-29	36%	90%
30-39	46%	90%
40-49	57%	90%
50-59	66%	90%
60-69	71%	90%
70-79	76%	90%
≥ 80	76%	90%

Staff vaccine acceptance levels

We model 40% vaccination among correctional staff, based on analysis of staff vaccination levels among CDCR staff (Figure S10).

Figure S10: Staff vaccine acceptance

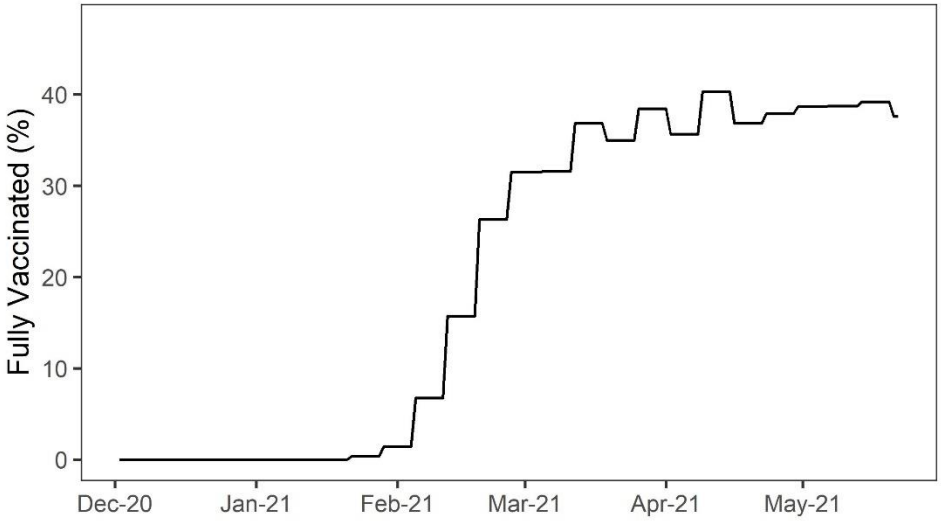


Figure shows the average weekly percentage of CDCR prison staff who are fully vaccinated (2 doses of mRNA vaccine or 1 dose of Janssen vaccine). Coverage fluctuates slightly over time because of variation in which staff members work during any given week.

Resident COVID-19 hospitalization and mortality rates

For residents, the probability of requiring hospitalization (conditional on having symptomatic COVID-19 infection) and the probability of dying from COVID-19 (conditional on requiring hospitalization) were based on residents' age and comorbidities. We obtained hospitalization and mortality rates by age from published sources (7,26). We also calculated empirical hospitalization and mortality rates by age and COVID-19 risk score from CDCR data (Figure S11). As mentioned above, the COVID-19 risk score is a metric developed by CDCR to measure the presence of demographic and clinical characteristics identified in the scientific literature as risk factors for severe COVID-19-related illness (Table S3). To adjust the published estimates to reflect prison-specific hospitalization and mortality rates and allow risks of severe outcomes to depend not just on age but also comorbidities, we applied COVID-19 risk score-based multipliers to the published age-based hospitalization and mortality rates. This yielded hospitalization and mortality rates by both age and COVID-19 risk score that were consistent with empirical estimates from CDCR data. This also allows hospitalization and mortality rates to reflect any underdiagnosis of chronic conditions. The resulting COVID-19 hospitalization and mortality rates are shown in Table S6. Note that hospitalization is modeled as any case severe enough to require hospitalization and is not meant to reflect case detection or hospital capacity.

Figure S11: COVID-19 hospitalization and mortality among CDCR residents by age and COVID-19 risk score

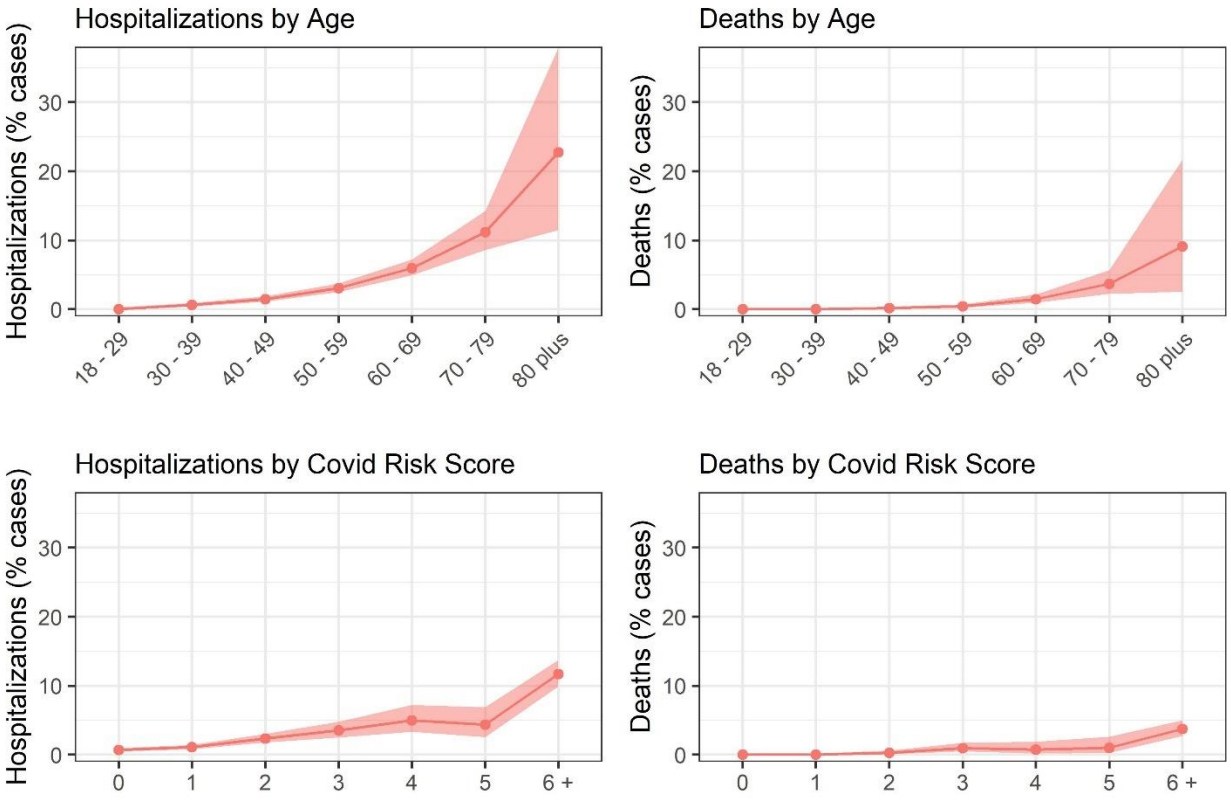


Table S6: Resident COVID-19 hospitalization and mortality rates

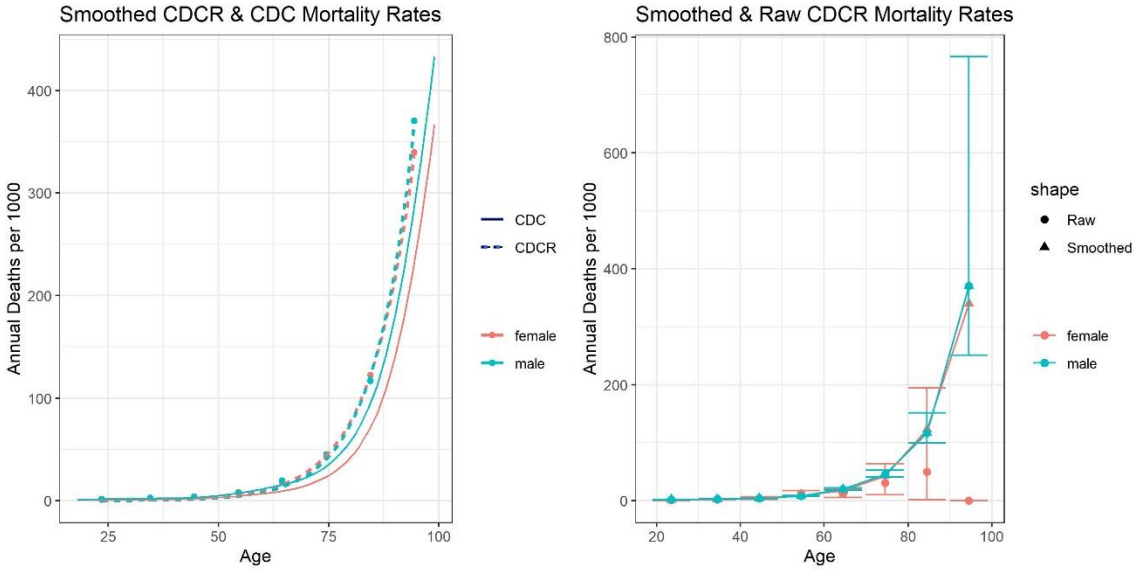
Resident Age (years)	Resident COVID-19 Risk Score	Probability of requiring hospitalization, conditional on symptomatic infection	Probability of death, conditional on requiring hospitalization
18-29	0-2	0.4%	3.7%
	3-7	0.8%	
	≥ 8	1.1%	
30-39	0-2	1.0%	3.8%
	3-7	2.0%	
	≥ 8	2.9%	
40-49	0-2	1.7%	5.0%
	3-7	3.4%	
	≥ 8	5.1%	
50-59	0-2	3.3%	9.3%
	3-7	6.5%	
	≥ 8	9.8%	
60-69	0-2	5.5%	19.7%
	3-7	11.0%	
	≥ 8	16.4%	
70-79	0-2	8.1%	31.3%
	3-7	16.2%	
	≥ 8	24.2%	
≥ 80	0-2	9.0%	52.3%
	3-7	18.0%	
	≥ 8	27.0%	

Table shows hospitalization and death probabilities with wild type infection. We model a 1.63 relative increase in the risk of hospitalization and a 1.56 relative increase in the risk of death with variant infection (8).

Resident background mortality rates

We estimated background mortality among residents by age and sex based on empirical mortality data from CDCR covering residents of California prisons from November 1, 2016, through October 31, 2019. For males, we used unadjusted rates by age calculated from the CDCR data. For females, who make up less than 5% of the resident population of prisons in California, estimates were noisier because there were relatively fewer deaths. We therefore used background mortality rates from CDC life tables (14) (for females, by age), but adjusted these mortality rates using smoothed hazard rate ratios that reflect higher mortality among incarcerated women compared to the general population. The resulting mortality rates used in the model are shown in Figure S12.

Figure S12: Unadjusted and adjusted CDCR background mortality rates and CDC background mortality rates



Left panel shows adjusted background mortality rates used in the model (dashed lines) compared to CDC background mortality rates by age and sex. Right panel shows adjusted background mortality rates used in the model (triangles) compared to the raw unadjusted mortality rates (circles).

Correctional staff population age distribution and COVID-19 mortality rates

The age and sex distributions of correctional staff were based on census data for correctional workers from the American Community Survey (13). We assumed that there are 6.1 residents per 1 correctional staff, based on data from the Department of Justice which determined the size of the correctional staff for each prison we modeled (12). Background mortality rates were consistent with age-sex-specific background mortality for the US population, obtained from CDC life tables (14).

The probability of dying from COVID-19 (conditional on having symptomatic COVID-19 infection) was based on staff members' age only and was obtained from public sources (7,26) (Table S7). Hospitalization for staff was not modeled.

Table S7: Correctional staff parameters

Staff Age (years)	Percentage of staff population (total, by age)	Percentage of age group that are males	Annual background mortality rate	Probability of death, conditional on symptomatic wild type COVID-19 infection
18-29	10%	76.6%	0.0012	0.03%
30-39	15%	79.7%	0.0019	0.08%
40-49	25%	77.9%	0.0030	0.17%
50-59	25%	79.3%	0.0070	0.64%
60-69	25%	80.8%	0.0145	2.37%

We model a 1.56 relative increase in the risk of death with variant infection (8).

EQUATOR network reporting guidelines

Because EQUATOR has not published guidelines for mathematical modeling studies, we instead report the relevant features of a non-economic model-based policy analysis using the CHEERS checklist (Table S8) (27).

Table S8: CHEERS Checklist

Section/Item	Recommendation	Location
Title and Abstract		
1. Title	Identify the study as an economic evaluation or use more specific terms such as "cost-effectiveness analysis", and describe the interventions compared.	Title – note that we identify the study as a mathematical modeling study in the title (as it is not an economic evaluation or cost-effectiveness analysis)
2. Abstract	Provide a structured summary of objectives, perspective, setting, methods (including study design and inputs), results (including base case and uncertainty analyses), and conclusions.	Abstract
Introduction		
3. Background and Objectives	Provide an explicit statement of the broader context for the study.	Research in Context (Evidence before this study)
	Present the study question and its relevance for health policy or practice decisions.	Introduction (last paragraph)
Methods		
4. Target Population and Subgroups	Describe characteristics of the base case population and subgroups analyzed, including why they were chosen.	Methods ("model" subsection, "data" subsection), Table 1, Appendix pages 15-20
5. Setting and Location	State relevant aspects of the system(s) in which the decision(s) need(s) to be made	Methods ("model" subsection, "data" subsection), Table 1, Appendix pages 15-20
6. Study Perspective	Describe the perspective of the study and relate this to the costs being evaluated.	Not applicable to a non-economic evaluation modeling study
7. Comparators	Describe the interventions or strategies being compared and state why they were chosen.	Methods ("resumption of activities and NPIs" subsection, "vaccination" subsection)
8. Time Horizon	State the time horizon(s) over which costs and consequences are being evaluated and say why appropriate.	Methods ("outcomes" subsection)
9. Discount Rate	Report the choice of discount rate(s) used for costs and outcomes and say why appropriate.	Not applicable to a non-economic evaluation modeling study
10. Choice of Health Outcomes	Describe what outcomes were used as the measure(s) of benefit in the evaluation and their relevance for the type of analysis performed.	Methods ("outcomes" subsection)
11. Measurement of Effectiveness	Describe fully the design features of the single effectiveness study and why the single study was a sufficient source of clinical effectiveness data.	Table S1, Methods ("vaccination" subsection, "resumption of activities and NPIs" subsection)
12. Measurement and Valuation of Preference Based Outcomes	If applicable, describe the population and methods used to elicit preferences for outcomes.	Not applicable to a non-economic evaluation modeling study
13. Estimating Resources and Costs	Describe approaches used to estimate resource use associated with the alternative interventions. Describe primary or secondary research methods for valuing each resource item in terms of its unit cost. Describe any adjustments made to approximate to opportunity costs.	Not applicable to a non-economic evaluation modeling study
14. Currency, Price Data, and Conversion	Report the dates of the estimated resource quantities and unit costs. Describe methods for adjusting estimated unit costs to the year of reported costs if necessary. Describe methods for converting costs into a common currency base and the exchange rate.	Not applicable to a non-economic evaluation modeling study
15. Choice of Model	Describe and give reasons for the specific type of decision analytical model used. Providing a figure to show model structure is strongly recommended.	Figure 1, Methods ("model" subsection)

16. Assumption	Describe all structural or other assumptions underpinning the decision-analytical model.	Methods ("model" subsection, "COVID-19 epidemiology" subsection, "COVID-19 variants and immunity" subsection), Table S1, Appendix pages 1-14, Appendix pages 21-26
17. Analytical Methods	Describe all analytical methods supporting the evaluation. This could include methods for dealing with skewed, missing, or censored data; extrapolation methods; methods for pooling data; approaches to validate or make adjustments (such as half cycle corrections) to a model; and methods for handling population heterogeneity and uncertainty.	Model ("technical details" subsection), Appendix pages 5-12, Appendix pages 22-26
Results		
18. Study Parameters	Report the values, ranges, references, and, if used, probability distributions for all parameters. Report reasons or sources for distributions used to represent uncertainty where appropriate. Providing a table to show the input values is strongly recommended.	Table S1
19. Incremental Costs and Outcomes	For each intervention, report mean values for the main categories of estimated costs and outcomes of interest, as well as mean differences between the comparator groups. If applicable, report incremental cost-effectiveness ratios.	Figures 2-4 (outcomes only because this is a non-economic evaluation modeling study), Results (paragraphs 1-12)
20. Characterizing Uncertainty	Describe the effects on the results of uncertainty for all input parameters, and uncertainty related to the structure of the model and assumptions.	Results (paragraphs 10-13), Appendix figures S13-S34
21. Characterizing Heterogeneity	If applicable, report differences in costs, outcomes, or cost-effectiveness that can be explained by variations between subgroups of patients with different baseline characteristics or other observed variability in effects that are not reducible by more information.	All results (heterogeneity in prison types and populations), Figure S35 (stochastic variation)
Discussion		
22. Study Findings, Limitations, Generalizability, and Current Knowledge	Summarise key study findings and describe how they support the conclusions reached. Discuss limitations and the generalisability of the findings and how the findings fit with current knowledge.	-Summary of study findings: Discussion (paragraphs 1-4) -Limitations and generalizability: Discussion (paragraphs 5-7) -Current knowledge: Discussion (paragraph 2, paragraph 8)
Other		
23. Source of Funding	Describe how the study was funded and the role of the funder in the identification, design, conduct, and reporting of the analysis. Describe other non-monetary sources of support.	Methods ("role of the funding source" subsection), Acknowledgements
24. Conflicts of Interest	Describe any potential for conflict of interest of study contributors in accordance with journal policy. In the absence of a journal policy, we recommend authors comply with International Committee of Medical Journal Editors recommendations.	Declaration of Interests. All authors have submitted ICMJE forms to the journal.

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Supplementary Results

Figure S13: Cumulative resident cases requiring hospitalization per 1000 infections over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection

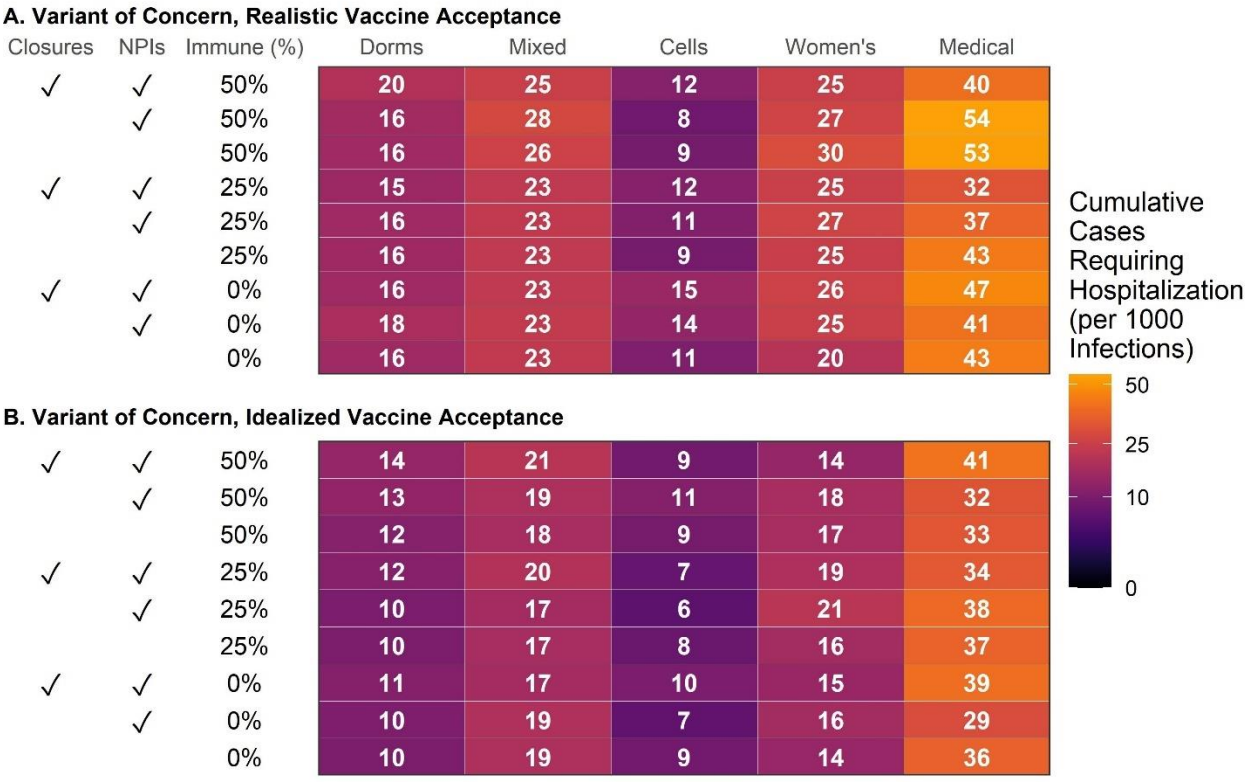


Figure shows average cumulative severe cases (requiring hospitalization) among infected residents (not all residents) across 500 model simulations over 200 days for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S14: Upper bound on cumulative resident cases requiring hospitalization over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single variant infection

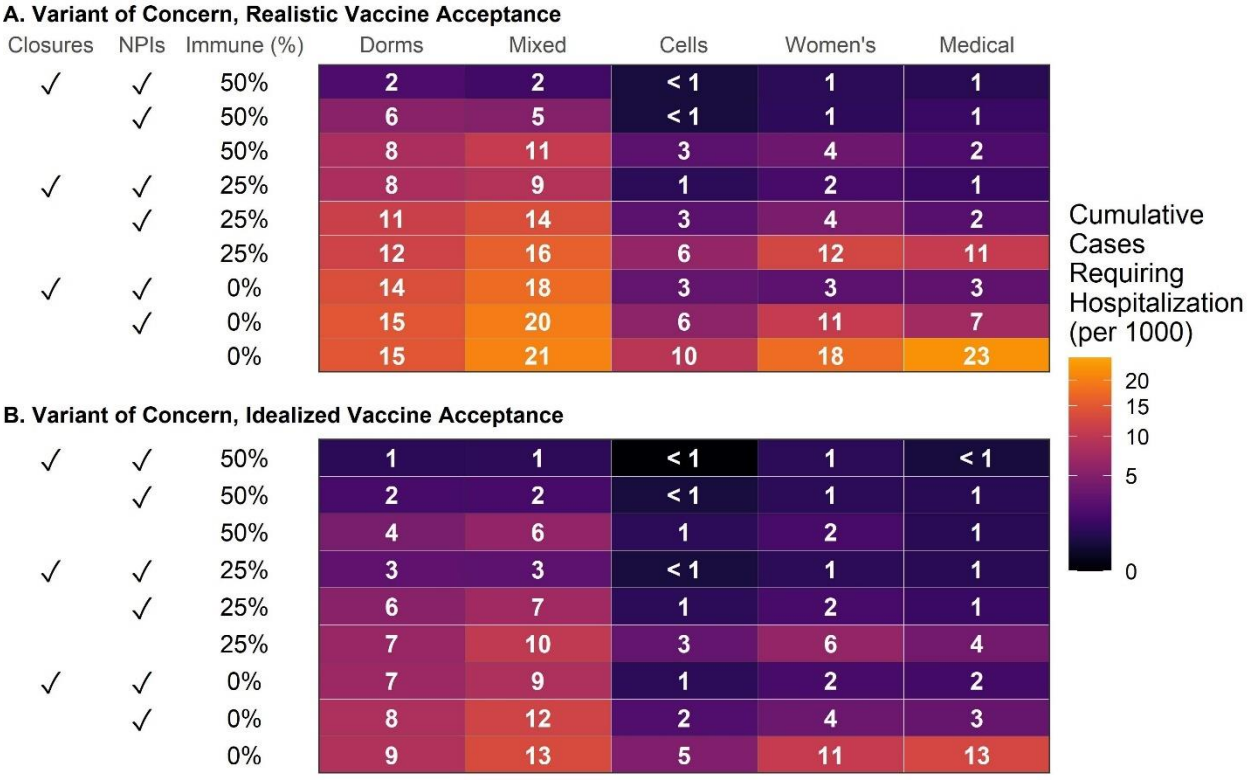


Figure shows the 95th percentile of cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days for each scenario shown. "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S15: Median reduction in resident infections over 200 days from vaccination compared to no vaccination, by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection

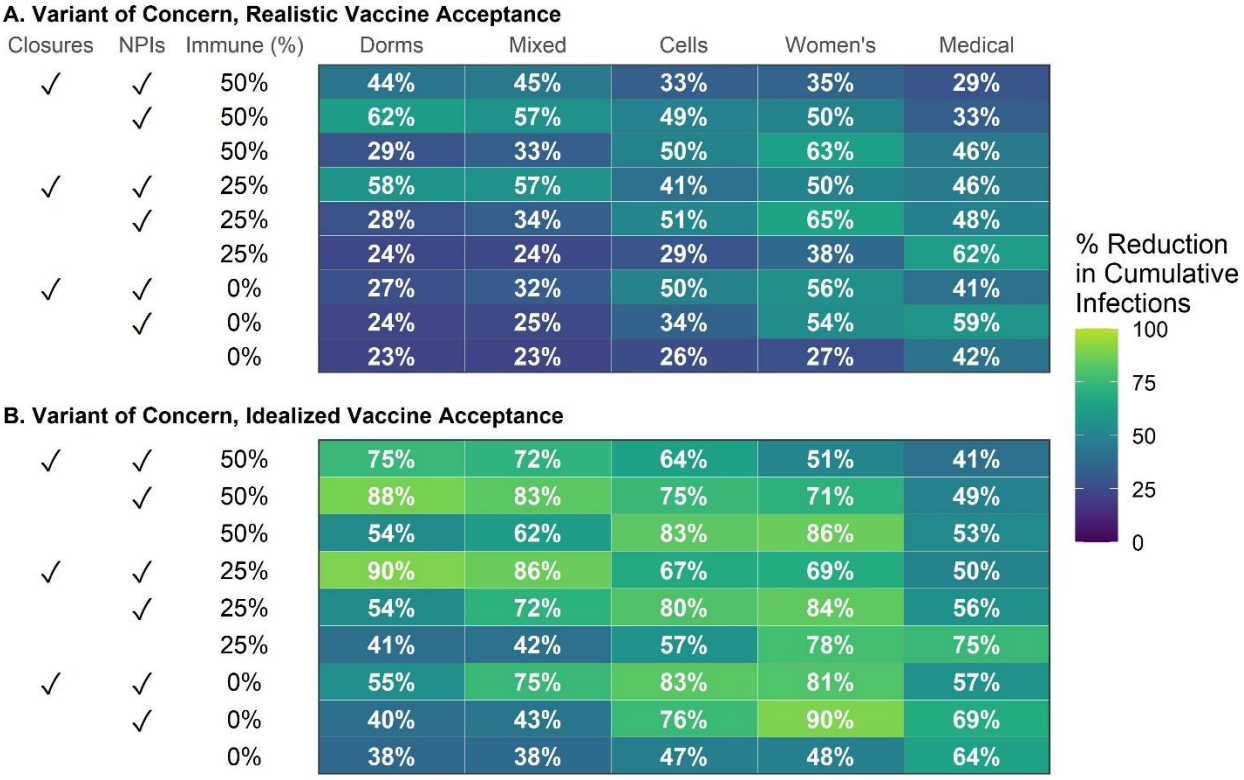


Figure shows the median reduction from vaccination (compared to no vaccination) in cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S16: Median reduction in resident cases requiring hospitalization over 200 days from vaccination compared to no vaccination, by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection

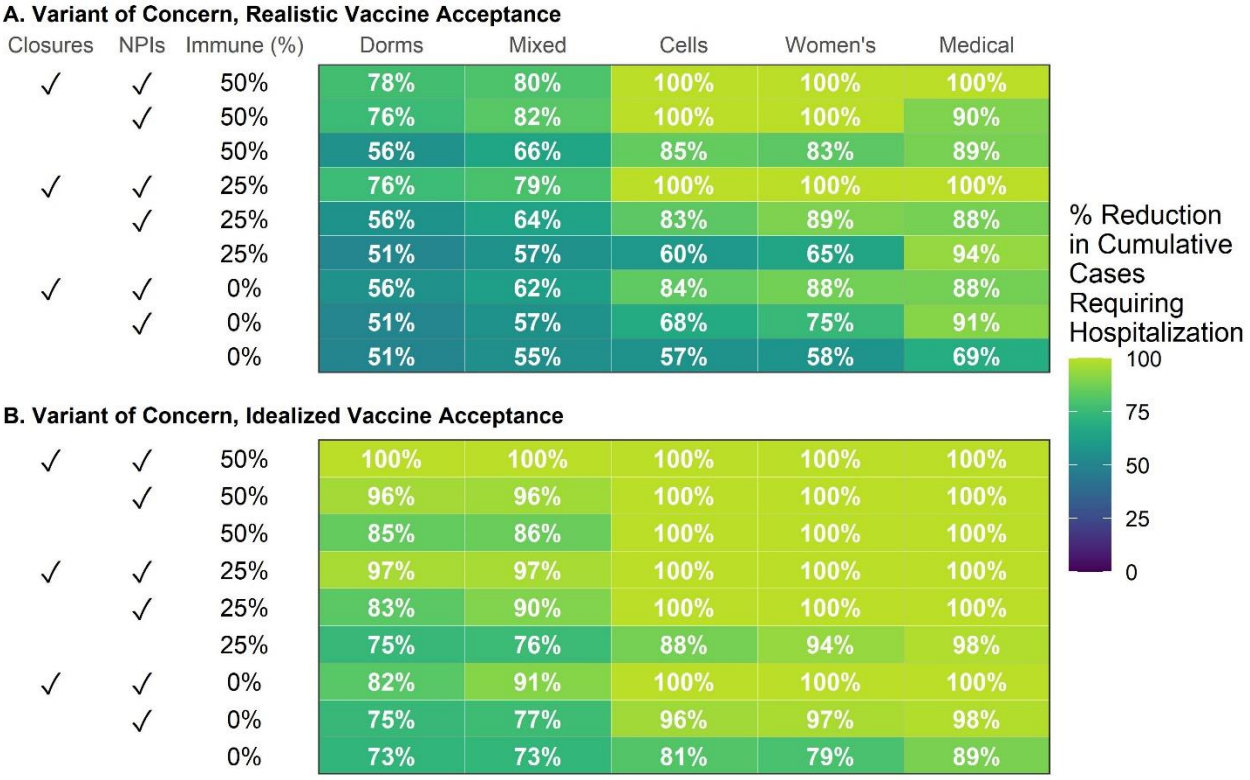


Figure shows the median reduction from vaccination (compared to no vaccination) in cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days for each scenario shown. "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S17: Cumulative resident infections over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single wild type infection

Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S18: Cumulative resident cases requiring hospitalization over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single wild type infection

Figure shows average cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S19: Cumulative resident infections over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on continual importation of variant infections

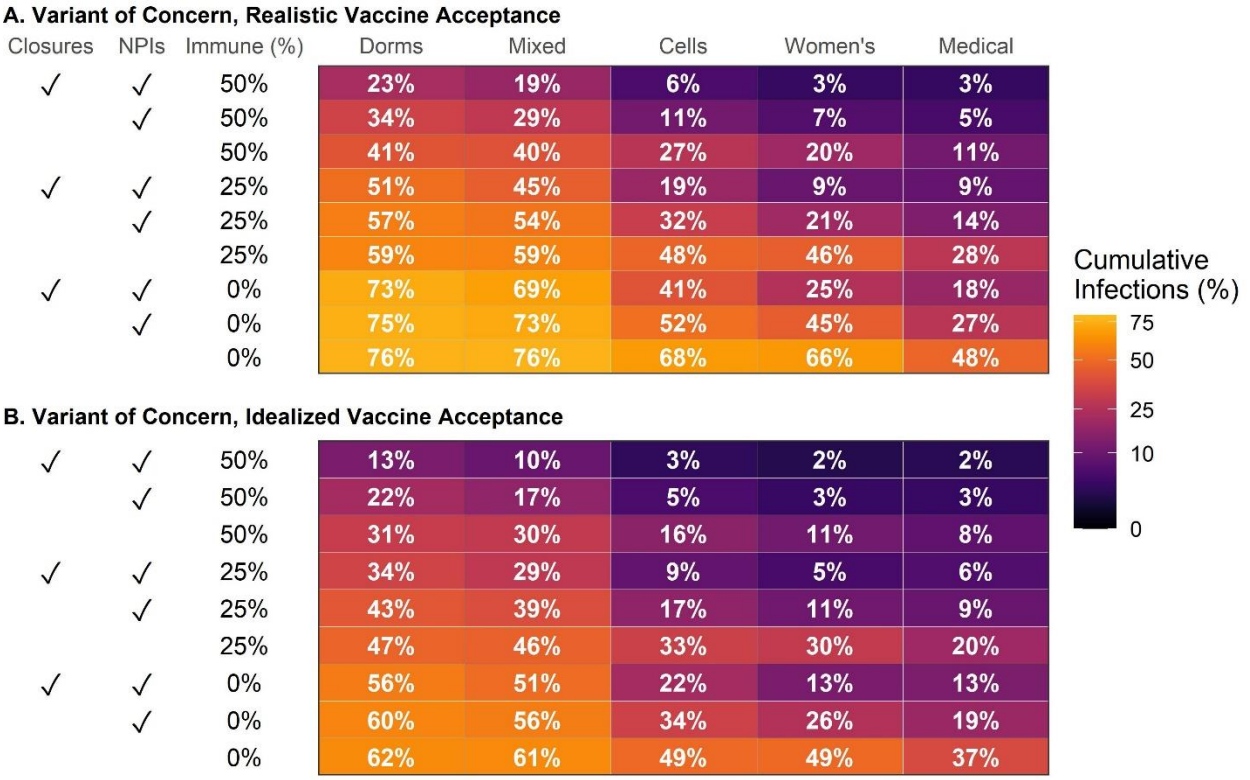


Figure shows average cumulative infections among residents across 500 model simulations over 200 days with 0.1% daily incidence among susceptible staff members for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S20: Cumulative resident cases requiring hospitalization over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on continual importation of variant infections

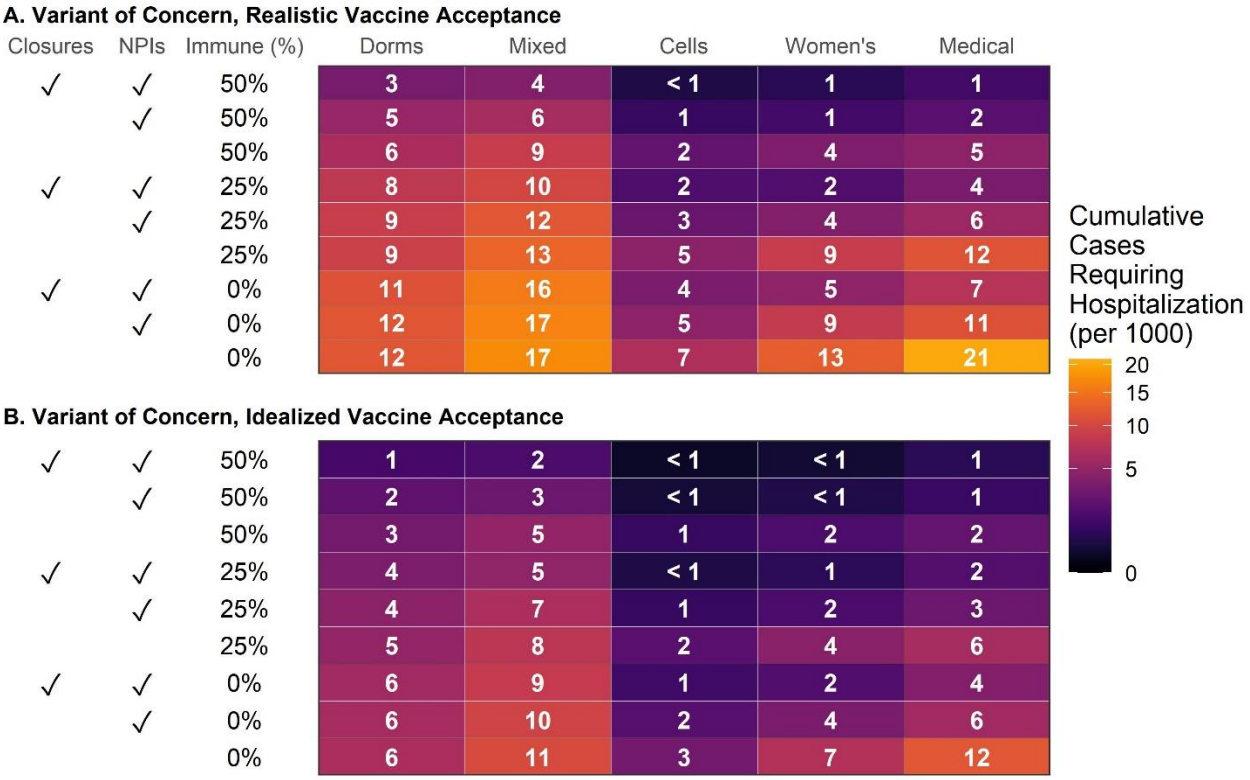


Figure shows average cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days with 0.1% daily incidence among susceptible staff members for each scenario shown. "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S21: Cumulative resident infections over time with realistic vaccine coverage by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single variant infection

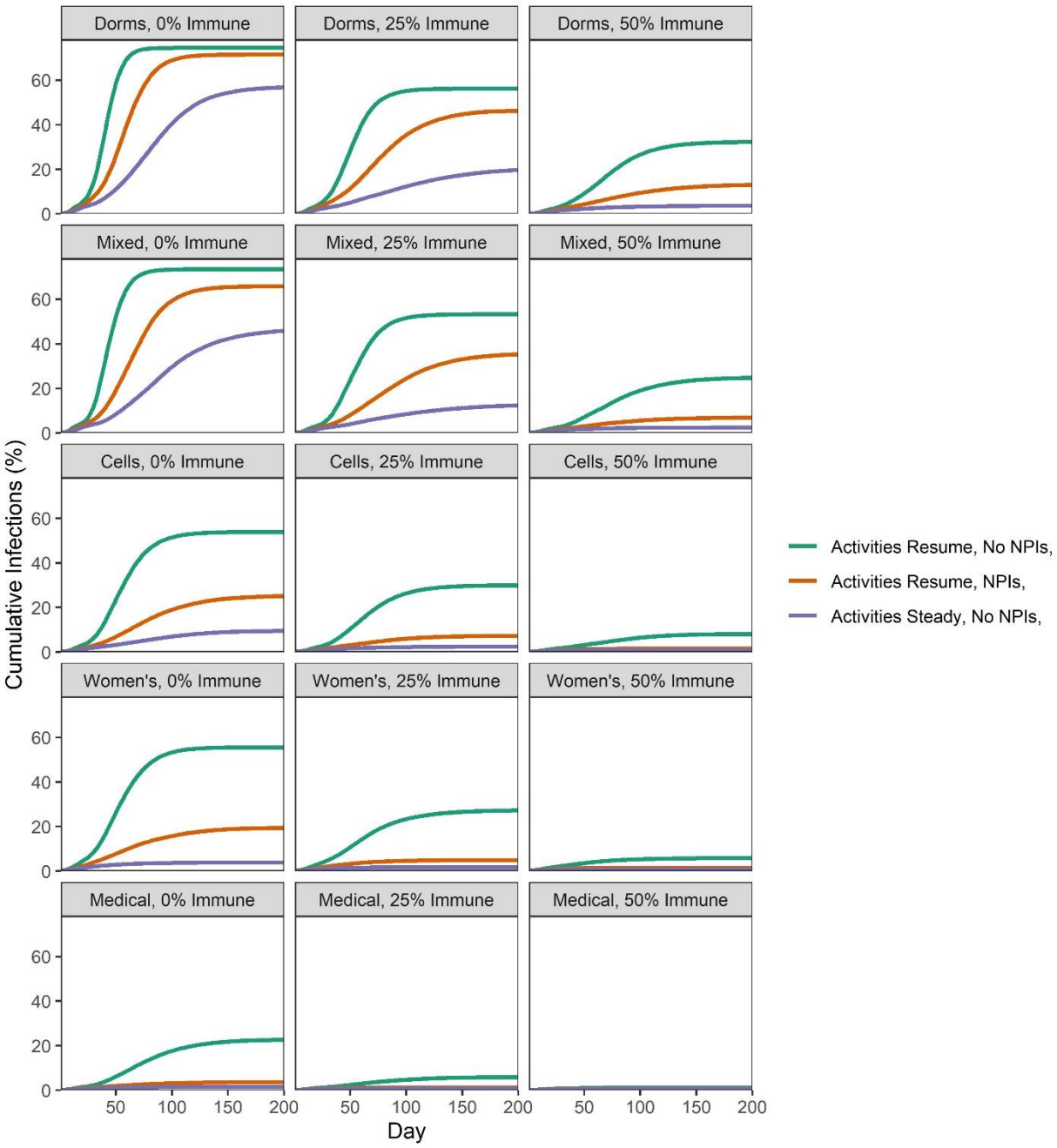


Figure shows average cumulative infections among residents across 500 model simulations over time for each scenario shown. In the realistic vaccine coverage scenario, coverage varies by age (see Table S5).

Figure S22: Cumulative resident infections over time with best-case vaccine coverage by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single variant infection

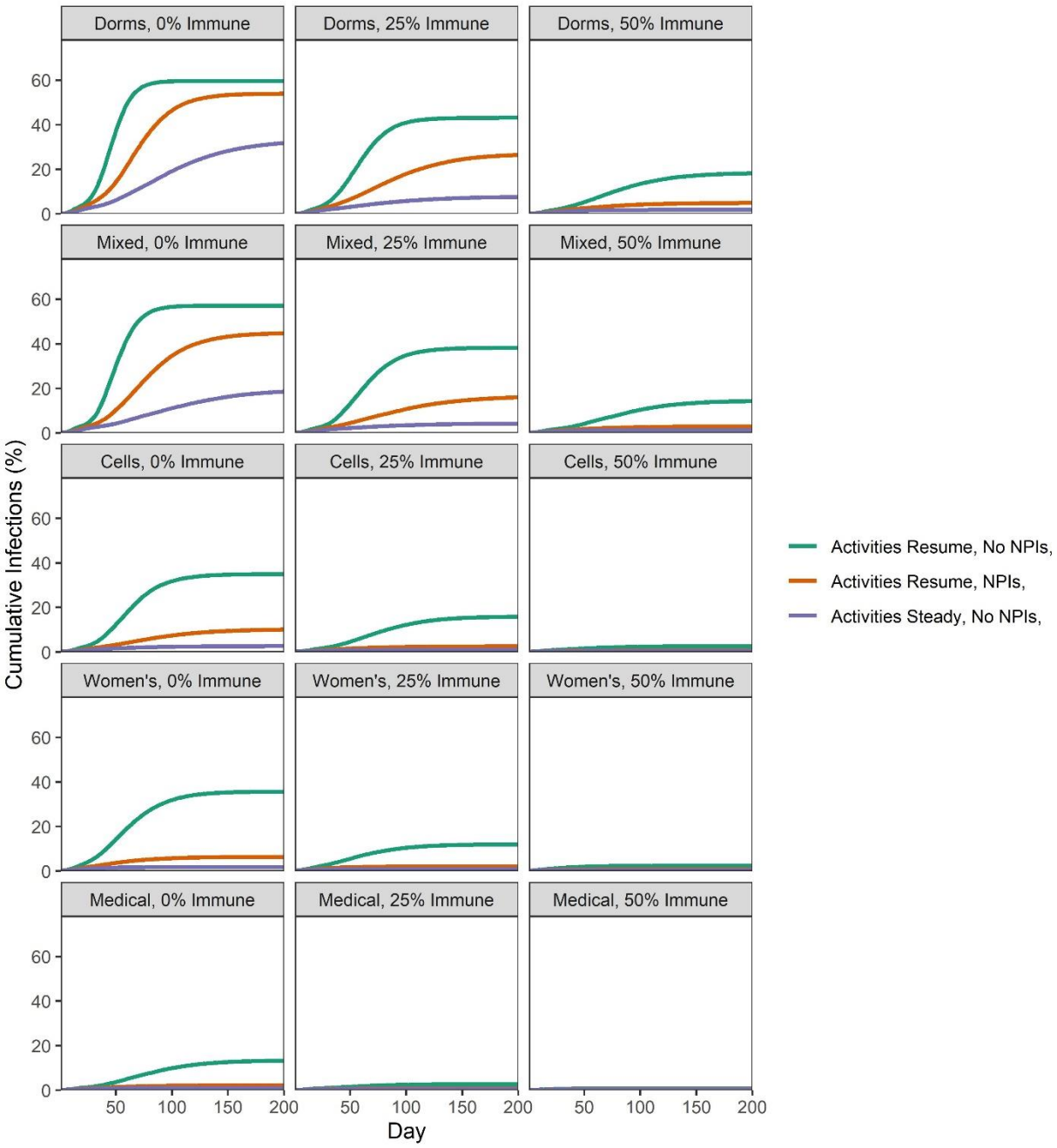


Figure shows average cumulative infections among residents across 500 model simulations over time for each scenario shown. In the best-case vaccine coverage scenario, coverage is 90%.

Figure S23: Cumulative resident infections over time with realistic vaccine coverage by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on repeated introductions of a new variant infection

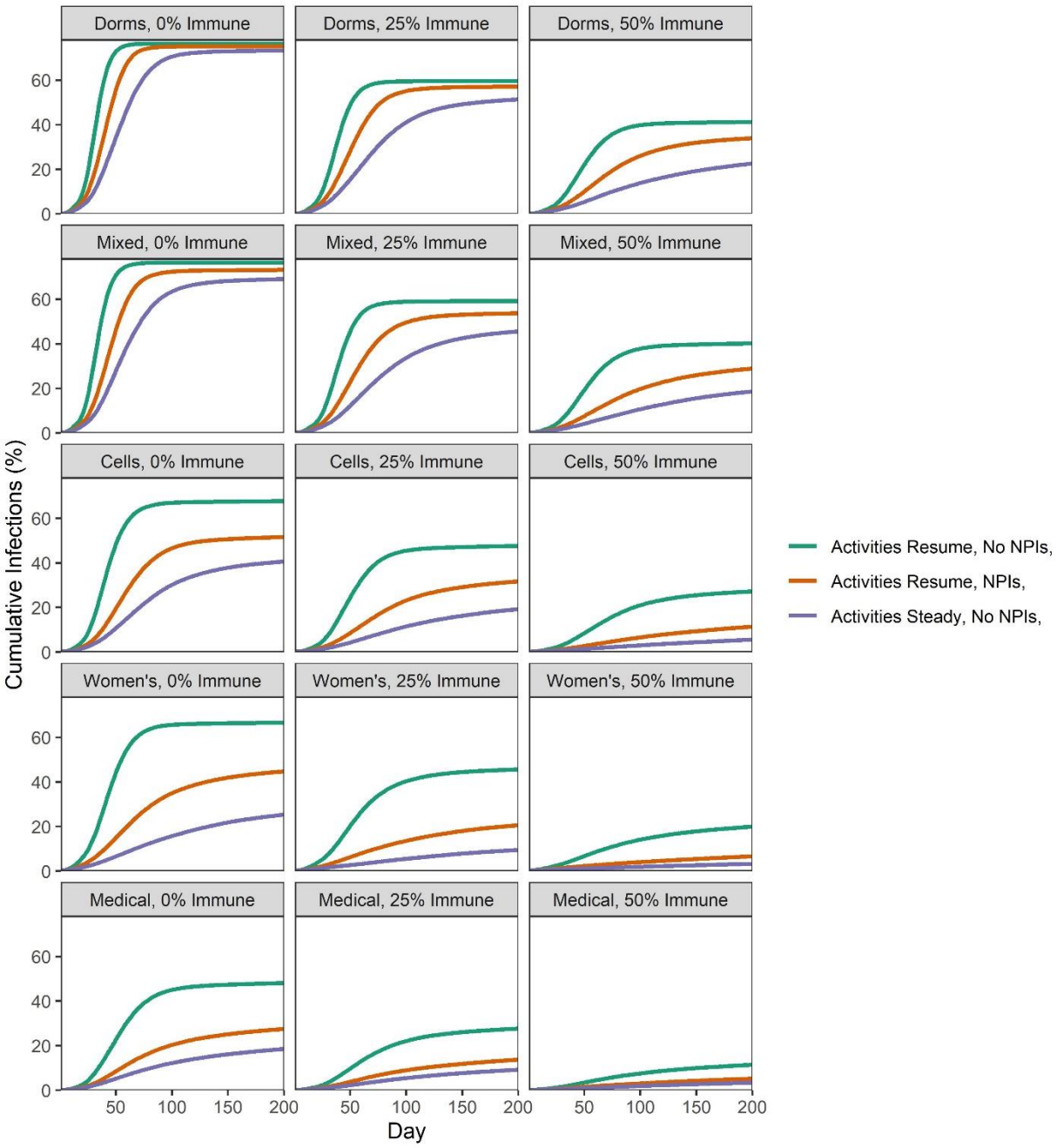


Figure shows average cumulative infections among residents across 500 model simulations over time with realistic vaccine coverage (< 90% and varies by age, see Table S5) and 0.1% daily incidence among susceptible staff members for each scenario shown.

Figure S24: Cumulative resident infections over time with best-case vaccine coverage by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on repeated introductions of a new variant infection

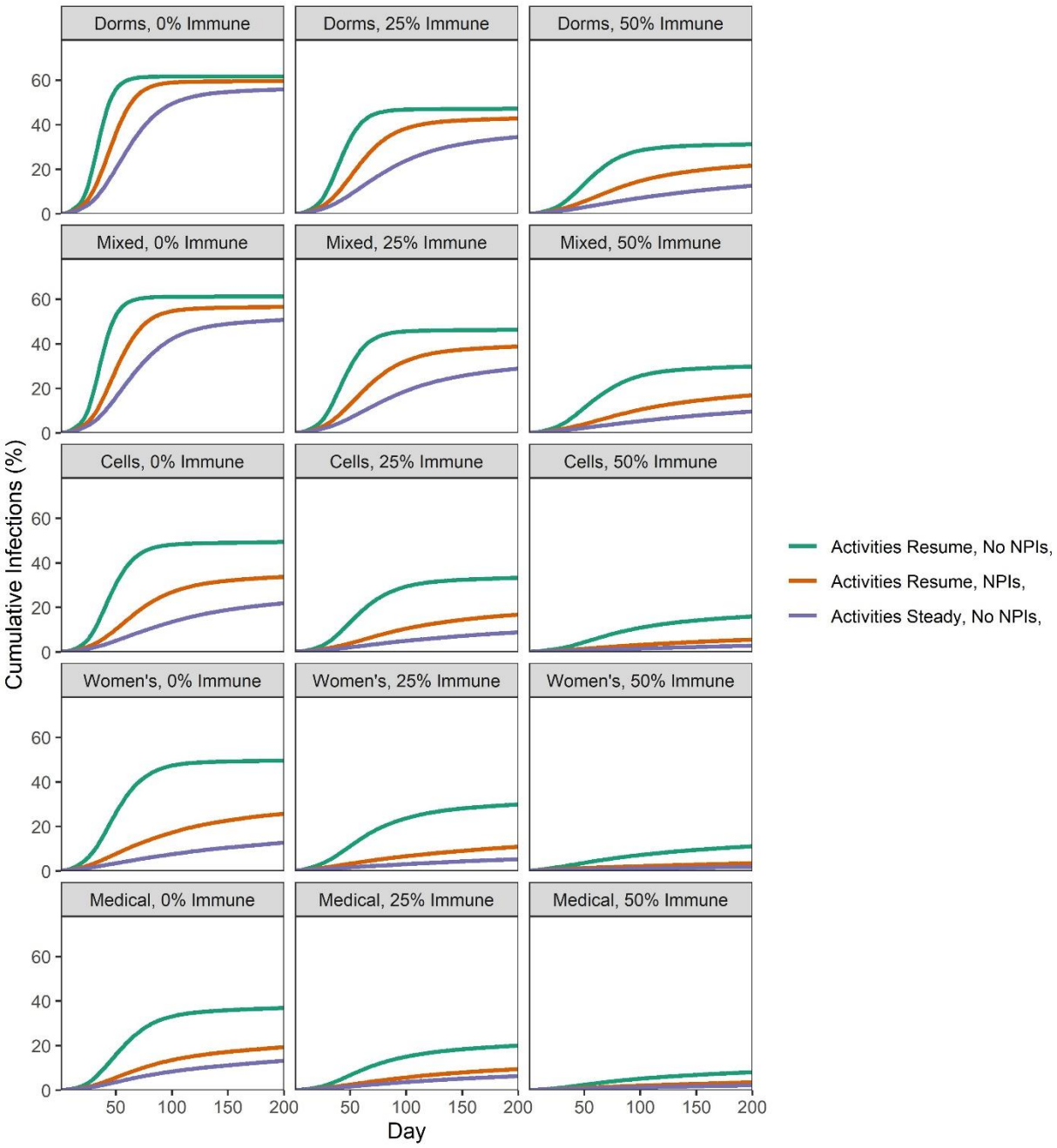


Figure shows average cumulative infections among residents across 500 model simulations over time with best-case vaccine coverage (90%) and 0.1% daily incidence among susceptible staff members for each scenario shown.

Figure S25: Cumulative resident infections over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection concurrent with vaccination scale-up

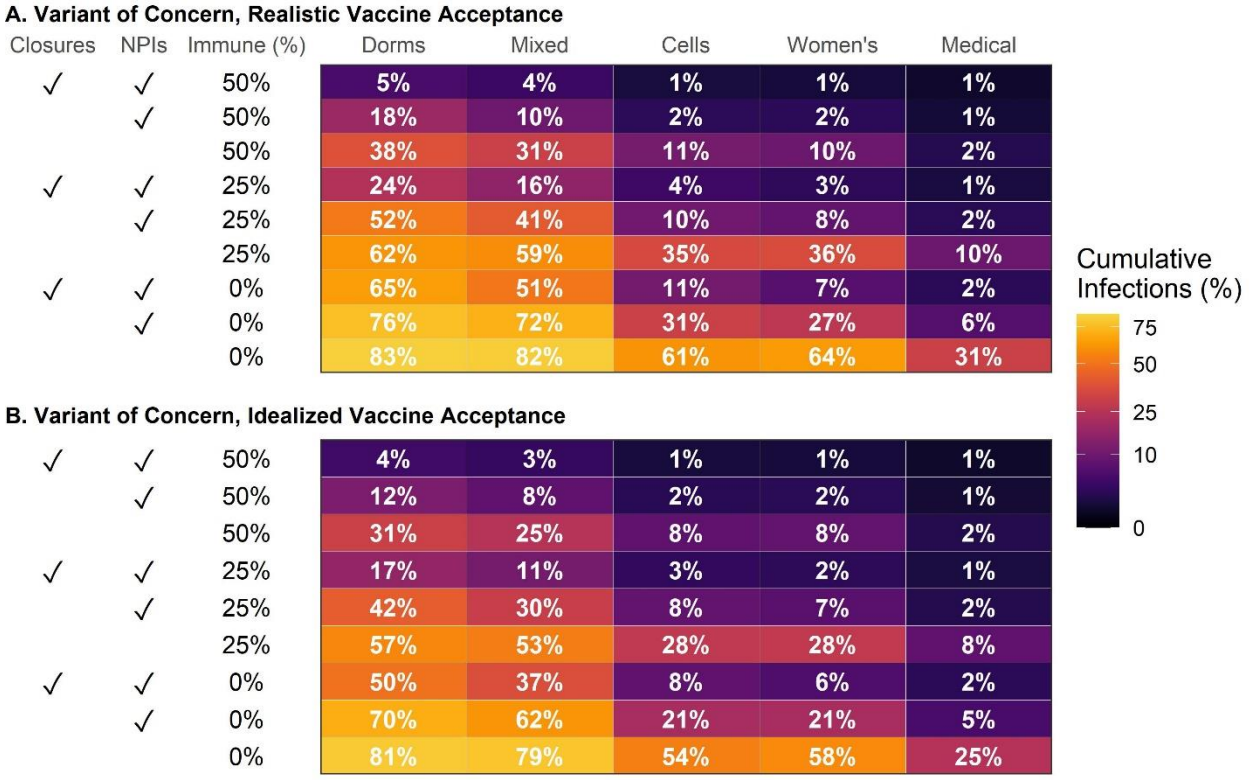


Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. Vaccination of residents is modeled as beginning on the same day that an infection is introduced to the prison (in the main analysis, vaccination is scaled-up prior to introduction). “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S26: Cumulative resident cases requiring hospitalization over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection concurrent with vaccination scale-up

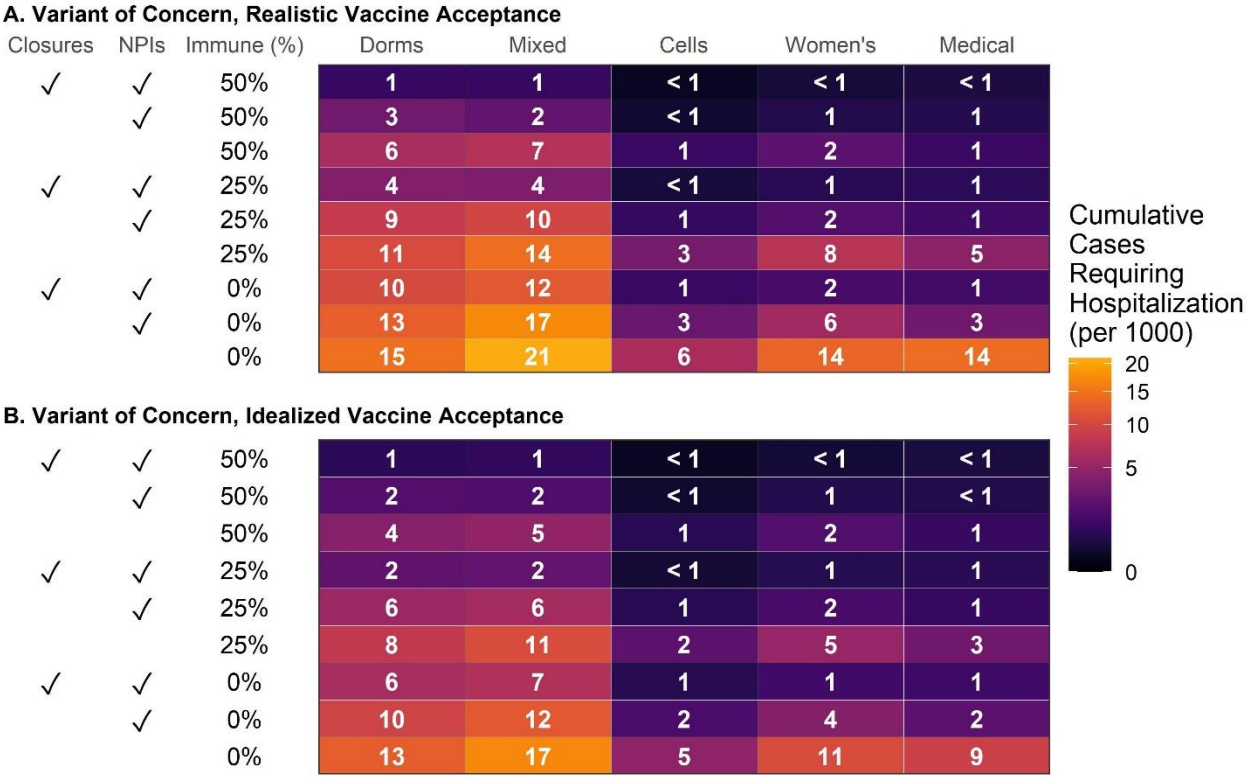


Figure shows average cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days for each scenario shown. Vaccination of residents is modeled as beginning on the same day that an infection is introduced to the prison (in the main analysis, vaccination is scaled-up prior to introduction). "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S27: Cumulative resident infections over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection and 80% staff vaccination coverage

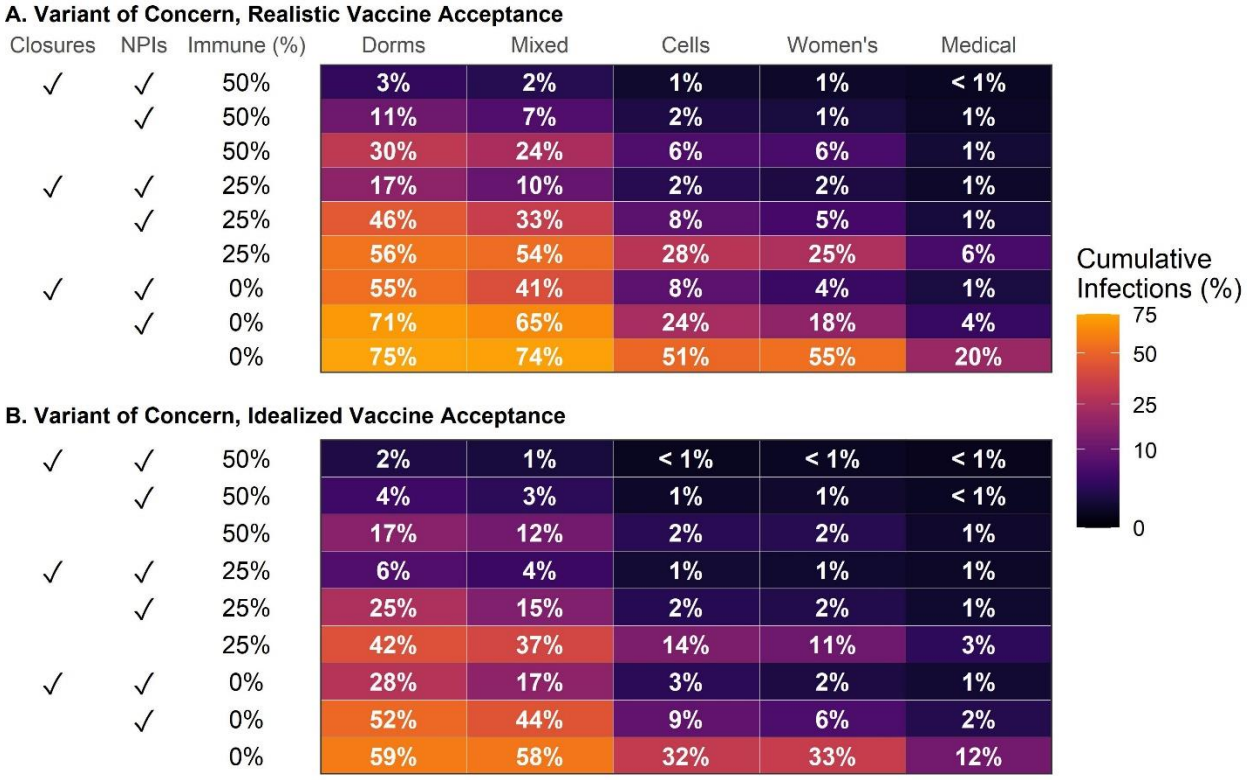


Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. Staff vaccination coverage is set at 80% (compared to 40% in the main analysis). "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S28: Cumulative resident cases requiring hospitalization over 200 days by in-person activity status, widespread use of NPIs, and baseline immunity, conditional on introduction of a single new variant infection and 80% staff vaccination coverage

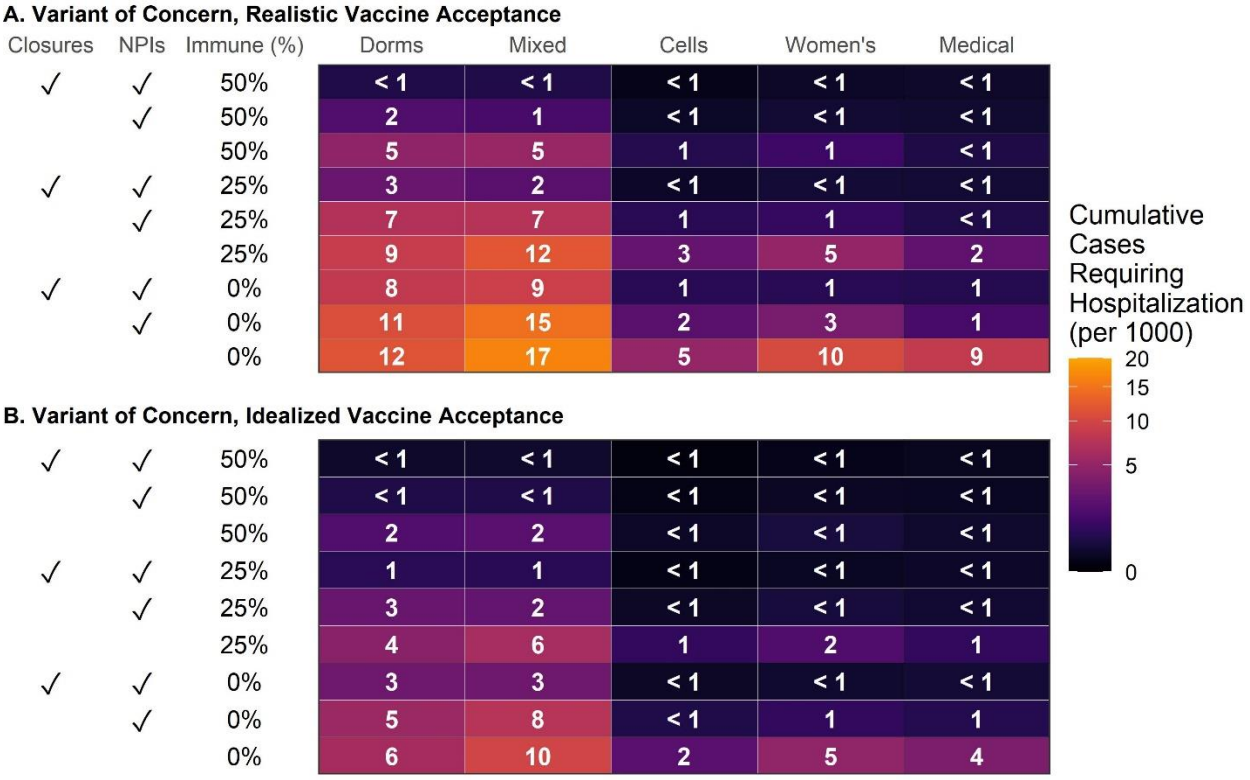


Figure shows average cumulative severe cases (requiring hospitalization) among residents across 500 model simulations over 200 days for each scenario shown. Staff vaccination coverage is set at 80% (compared to 40% in the main analysis). "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S29: Cumulative resident infections over 200 days with in-person activities opened and varying effectiveness of NPIs and baseline immunity, conditional on introduction of a single new variant infection

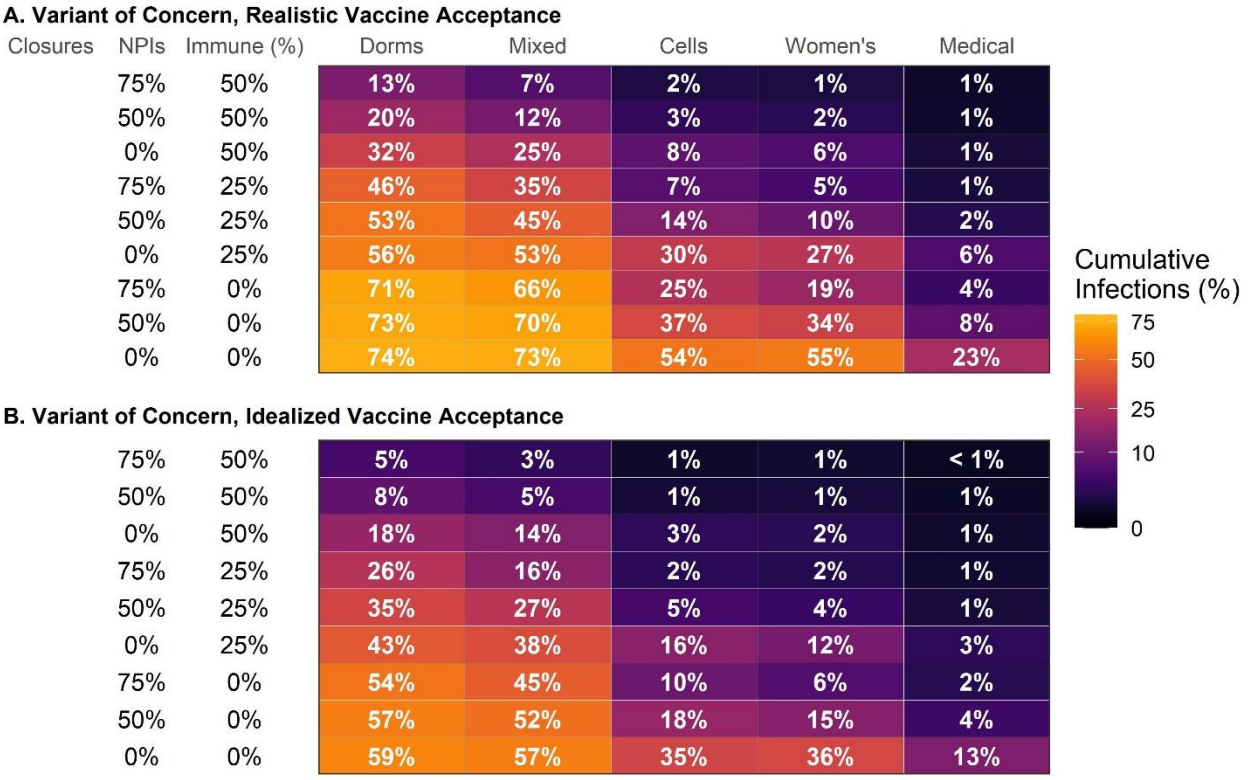


Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. In-person activities re-open in all scenarios, but the effectiveness of NPIs is varied (compared to 75% in the main analysis). The 0% effective NPIs scenarios corresponds to the scenario with no NPIs in the main analysis. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S30: Cumulative resident cases requiring hospitalization over 200 days with in-person activities opened and varying effectiveness of NPIs and baseline immunity, conditional on introduction of a single new variant infection

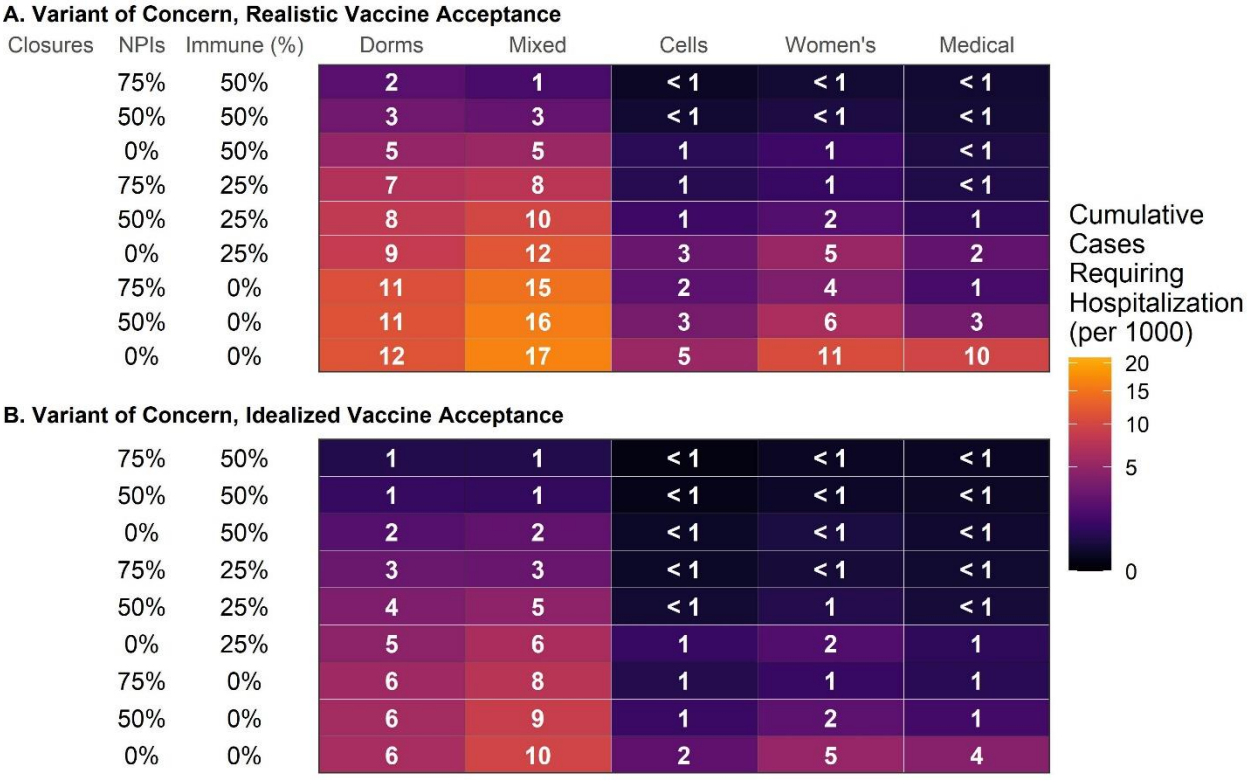


Figure shows average cumulative severe cases requiring hospitalization among residents across 500 model simulations over 200 days for each scenario shown. In-person activities re-open in all scenarios, but the effectiveness of NPIs is varied (compared to 75% in the main analysis). The 0% effective NPIs scenarios corresponds to the scenario with no NPIs in the main analysis. "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S31: Sensitivity analysis on daily infection importation rate: comparison of cumulative resident infections over 200 days for prisons with resumption of in-person activities and realistic vaccine coverage, varying baseline immunity, NPI usage, and whether variant infection is imported once or repeatedly

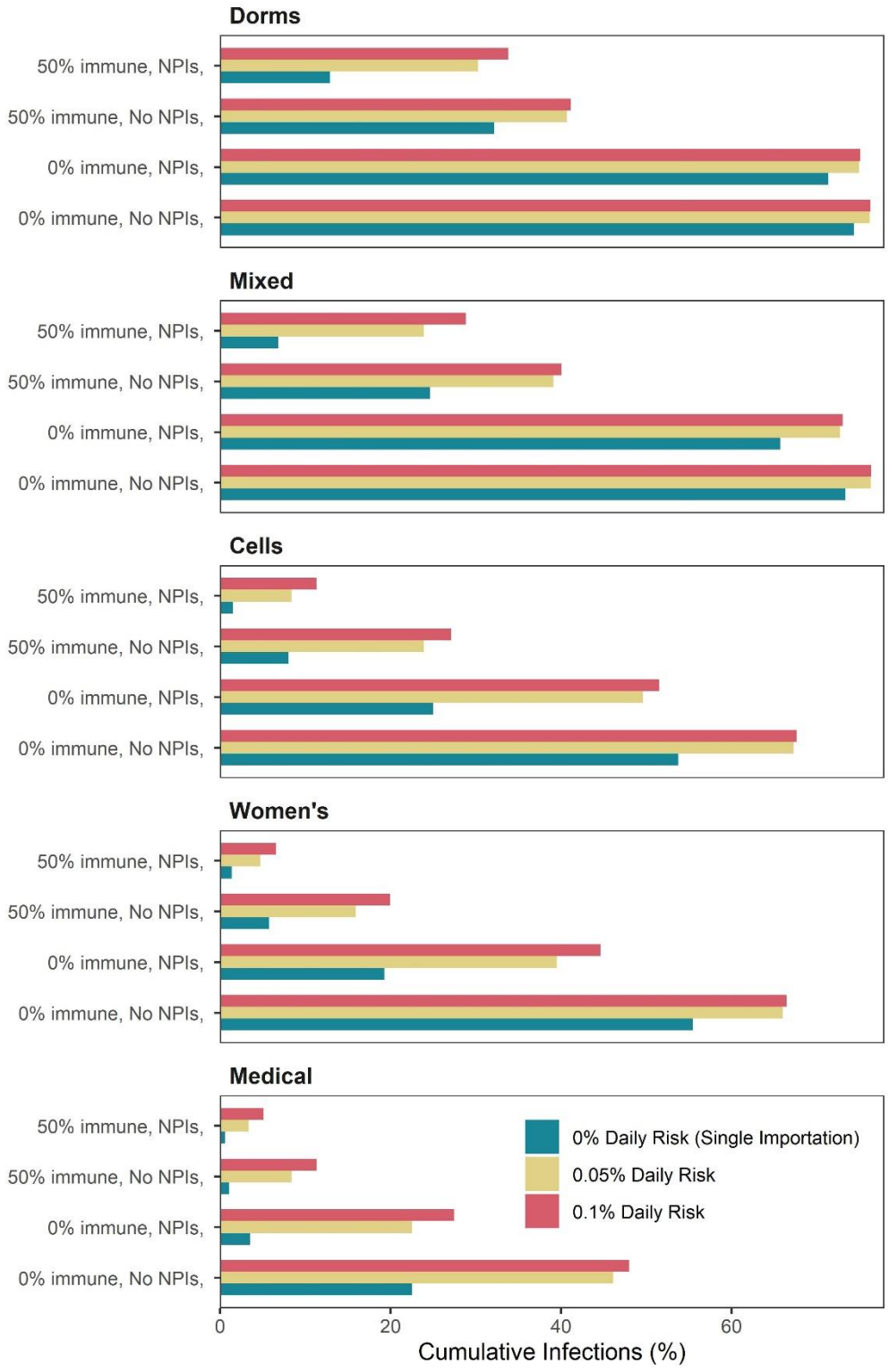


Figure shows average cumulative infections among residents across 500 model simulations over 200 days with no importations after day 1 (main analysis; single importation), 0.05% daily incidence among susceptible staff members (sensitivity analysis; 0.05% daily risk), and 0.1% daily incidence among susceptible staff members (main analysis; 0.1% daily risk) for each scenario shown. In the realistic vaccine coverage scenario, vaccine coverage varies by age (see Tables S1 and S5). Panels are distinguished by the type of prison modeled.

Figure S32: Cumulative resident infections over 200 days by in-person activity status, widespread use on NPIs, and baseline immunity, conditional on continual importation of variant infections with 0.05% daily incidence

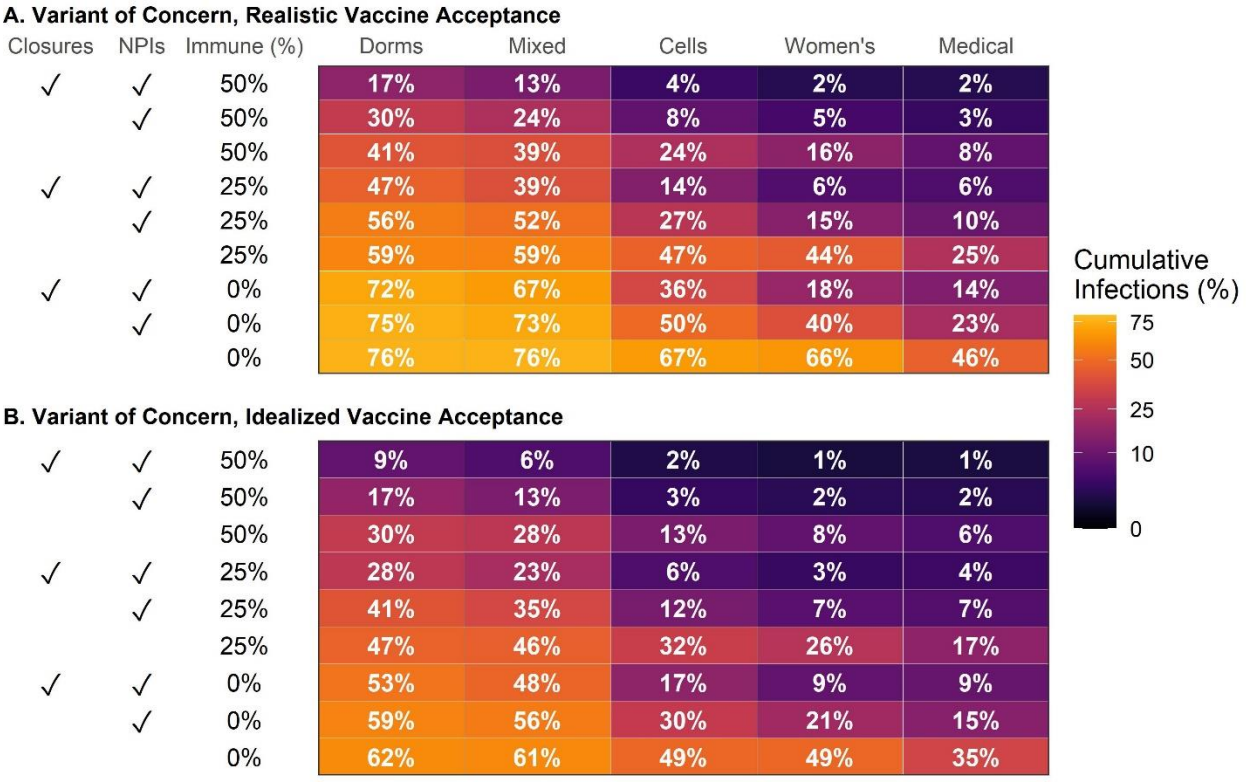


Figure shows average cumulative infections among residents across 500 model simulations over 200 days with 0.05% daily incidence among susceptible staff members for each scenario shown (compared to 0.1% daily incidence in the main continued importations analysis shown in Figure 4). "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S33: Cumulative resident infections over 200 days by in-person activity status, widespread use on NPIs, and baseline immunity, conditional on introduction of a single variant infection with reduced staff and activity transmission

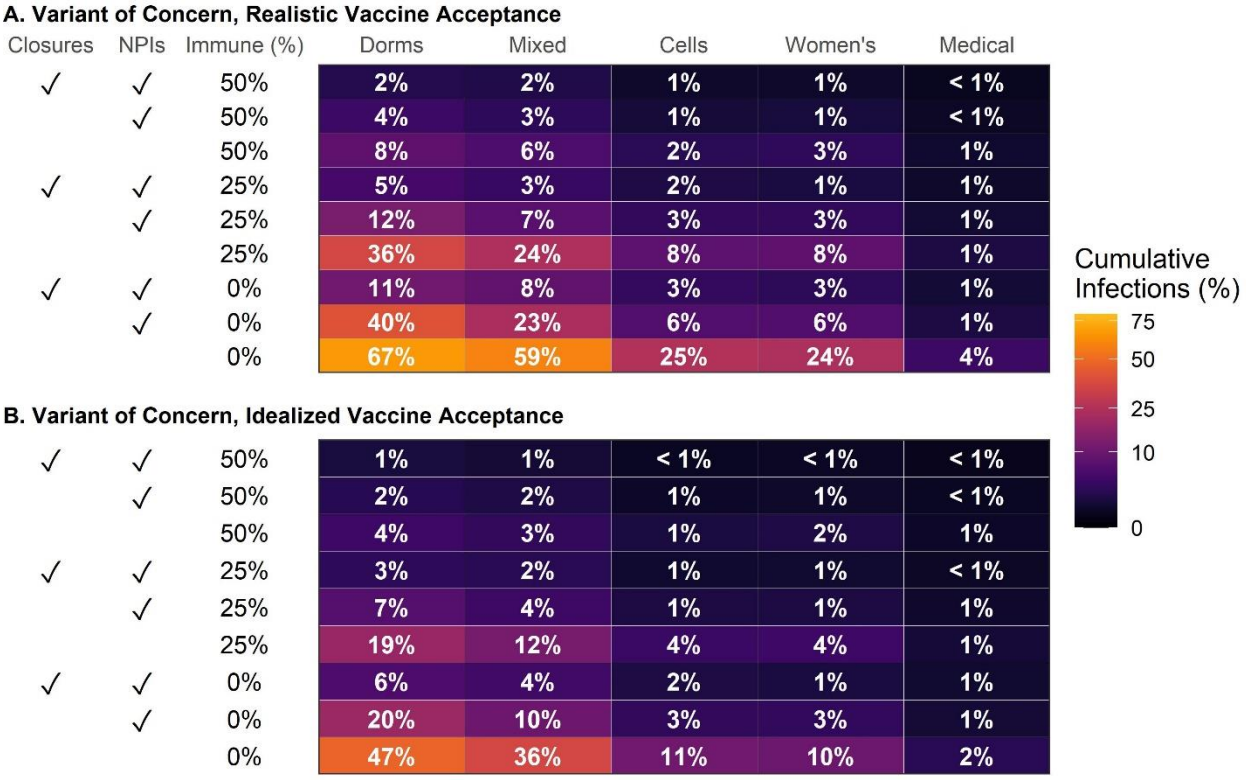


Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. The probability of infection per infected activity contact and staff-staff and staff-resident effective contact rates are halved compared to the main analysis. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).

Figure S34: Cumulative resident infections over 200 days by in-person activity status, widespread use on NPIs, and baseline immunity, conditional on continual importation of variant infections with reduced staff and activity transmission

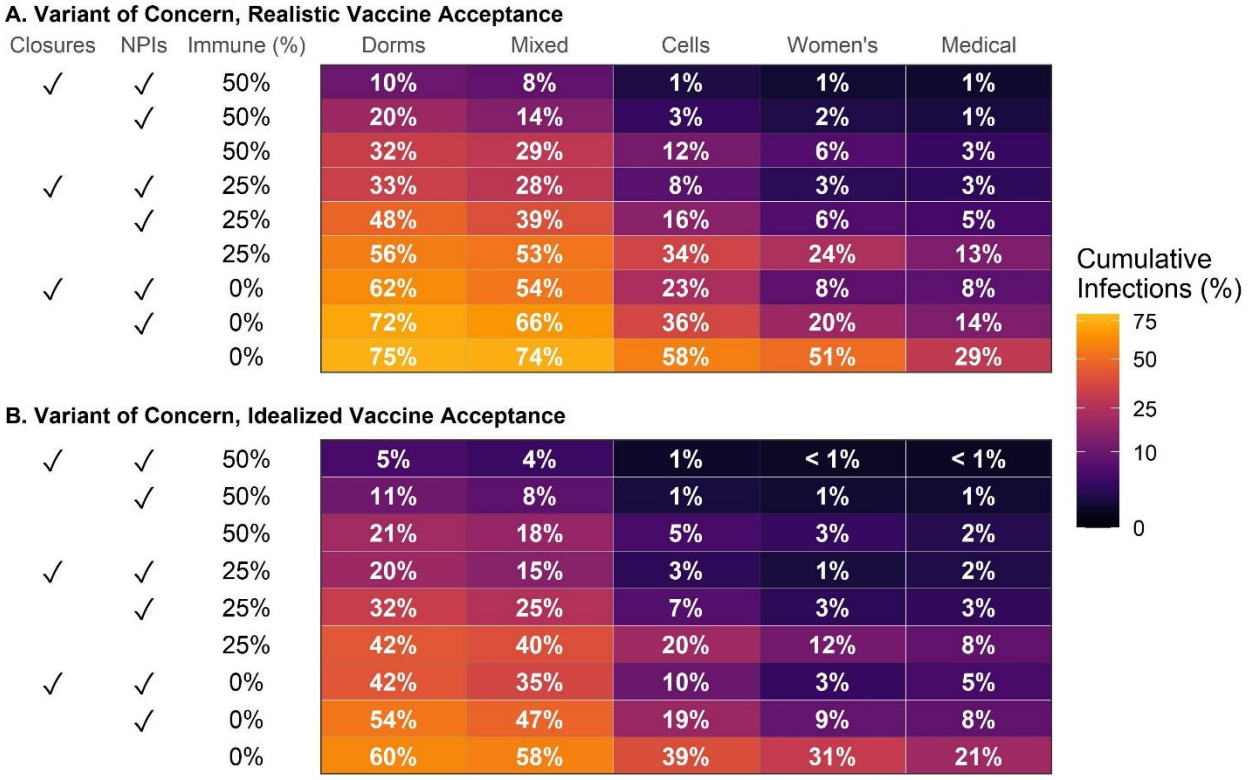


Figure shows average cumulative infections among residents across 500 model simulations over 200 days with 0.1% daily incidence among susceptible staff members for each scenario shown. The probability of infection per infected activity contact and staff-staff and staff-resident effective contact rates are halved compared to the main analysis. "Idealized" vaccine acceptance is the same as "best-case" vaccine acceptance in the main text (90% across all ages).

Figure S35: Distribution of cumulative resident infections over 200 days by in-person activity status, use of NPIs, and baseline immunity, conditional on introduction of a single variant infection

2.5th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
		50%	< 1%	< 1%	< 1%	< 1%	< 1%
✓	✓	25%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	25%	1%	< 1%	< 1%	< 1%	< 1%
		25%	1%	< 1%	< 1%	< 1%	< 1%
✓	✓	0%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	0%	3%	< 1%	< 1%	< 1%	< 1%
		0%	74%	1%	< 1%	< 1%	< 1%

B. Variant of Concern, Idealized Vaccine Acceptance

✓	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
		50%	< 1%	< 1%	< 1%	< 1%	< 1%
✓	✓	25%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	25%	< 1%	< 1%	< 1%	< 1%	< 1%
		25%	< 1%	< 1%	< 1%	< 1%	< 1%
✓	✓	0%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	0%	< 1%	< 1%	< 1%	< 1%	< 1%
		0%	2%	1%	< 1%	< 1%	< 1%

Cumulative Infections (%)
100
75
50
25
10
0

10th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	50%	1%	< 1%	< 1%	< 1%	< 1%
		50%	2%	1%	< 1%	< 1%	< 1%
✓	✓	25%	2%	1%	< 1%	< 1%	< 1%
	✓	25%	3%	2%	< 1%	< 1%	< 1%
		25%	57%	54%	< 1%	< 1%	< 1%
✓	✓	0%	3%	3%	< 1%	< 1%	< 1%
	✓	0%	73%	66%	< 1%	< 1%	< 1%
		0%	75%	75%	1%	2%	< 1%

B. Variant of Concern, Idealized Vaccine Acceptance

✓	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
	✓	50%	< 1%	< 1%	< 1%	< 1%	< 1%
		50%	1%	1%	< 1%	< 1%	< 1%
✓	✓	25%	1%	< 1%	< 1%	< 1%	< 1%
	✓	25%	2%	< 1%	< 1%	< 1%	< 1%
		25%	44%	2%	< 1%	< 1%	< 1%
✓	✓	0%	2%	1%	< 1%	< 1%	< 1%
	✓	0%	52%	3%	< 1%	< 1%	< 1%
		0%	60%	59%	< 1%	1%	< 1%

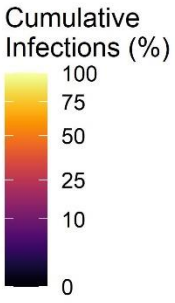
25th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	1%	1%	< 1%	< 1%	< 1%
	✓	50%	2%	2%	< 1%	< 1%	< 1%
		50%	35%	3%	< 1%	1%	< 1%
✓	✓	25%	3%	3%	< 1%	< 1%	< 1%
	✓	25%	50%	10%	< 1%	1%	< 1%
		25%	58%	57%	1%	4%	< 1%
✓	✓	0%	62%	9%	< 1%	1%	< 1%
	✓	0%	74%	71%	< 1%	3%	< 1%
		0%	76%	76%	64%	63%	< 1%

B. Variant of Concern, Idealized Vaccine Acceptance

✓	✓	50%	1%	< 1%	< 1%	< 1%	< 1%
	✓	50%	1%	1%	< 1%	< 1%	< 1%
		50%	3%	2%	< 1%	< 1%	< 1%
✓	✓	25%	2%	2%	< 1%	< 1%	< 1%
	✓	25%	7%	2%	< 1%	< 1%	< 1%
		25%	45%	43%	1%	2%	< 1%
✓	✓	0%	5%	3%	< 1%	< 1%	< 1%
	✓	0%	57%	49%	< 1%	1%	< 1%
		0%	61%	60%	3%	13%	< 1%



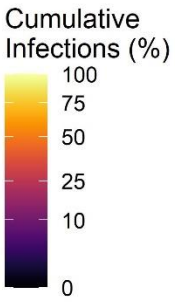
50th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	2%	2%	< 1%	< 1%	< 1%
	✓	50%	9%	3%	1%	1%	< 1%
		50%	39%	35%	3%	3%	< 1%
✓	✓	25%	11%	5%	2%	1%	< 1%
	✓	25%	55%	46%	3%	3%	< 1%
		25%	59%	59%	43%	36%	1%
✓	✓	0%	70%	59%	3%	3%	< 1%
	✓	0%	75%	72%	35%	15%	1%
		0%	76%	76%	66%	65%	32%

B. Variant of Concern, Idealized Vaccine Acceptance

✓	✓	50%	1%	1%	< 1%	< 1%	< 1%
	✓	50%	2%	2%	< 1%	< 1%	< 1%
		50%	24%	14%	1%	1%	< 1%
✓	✓	25%	3%	2%	< 1%	< 1%	< 1%
	✓	25%	34%	12%	1%	1%	< 1%
		25%	46%	45%	18%	6%	1%
✓	✓	0%	41%	10%	1%	1%	< 1%
	✓	0%	59%	54%	3%	3%	< 1%
		0%	61%	61%	47%	46%	2%



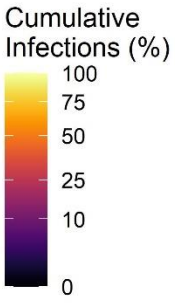
75th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	4%	3%	1%	1%	< 1%
	✓	50%	22%	10%	2%	2%	1%
		50%	41%	39%	16%	8%	1%
✓	✓	25%	37%	20%	3%	2%	1%
	✓	25%	57%	52%	12%	7%	1%
		25%	60%	60%	46%	45%	10%
✓	✓	0%	73%	67%	17%	5%	1%
	✓	0%	75%	73%	47%	35%	4%
		0%	77%	77%	68%	67%	44%

B. Variant of Concern, Idealized Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	2%	2%	< 1%	1%	< 1%
	✓	50%	7%	3%	1%	1%	< 1%
		50%	29%	26%	3%	3%	1%
✓	✓	25%	11%	5%	1%	1%	1%
	✓	25%	40%	30%	3%	3%	1%
		25%	48%	46%	30%	22%	3%
✓	✓	0%	51%	35%	3%	3%	1%
	✓	0%	60%	56%	21%	9%	2%
		0%	62%	62%	49%	49%	29%



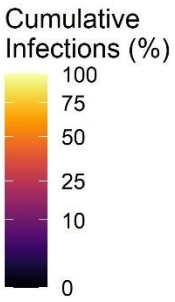
90th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	8%	5%	2%	2%	1%
	✓	50%	30%	19%	4%	3%	2%
		50%	42%	41%	25%	16%	3%
✓	✓	25%	47%	34%	6%	4%	3%
	✓	25%	58%	54%	23%	14%	4%
		25%	61%	60%	48%	48%	22%
✓	✓	0%	74%	69%	29%	9%	5%
	✓	0%	76%	74%	50%	43%	12%
		0%	77%	77%	69%	68%	47%

B. Variant of Concern, Idealized Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	4%	2%	1%	1%	1%
	✓	50%	13%	7%	2%	2%	1%
		50%	31%	29%	8%	5%	3%
✓	✓	25%	20%	10%	2%	2%	1%
	✓	25%	43%	36%	7%	5%	3%
		25%	48%	47%	33%	30%	10%
✓	✓	0%	55%	45%	7%	4%	4%
	✓	0%	61%	57%	28%	18%	8%
		0%	63%	62%	50%	51%	34%



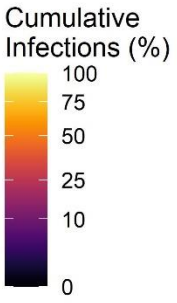
97.5th Percentile

A. Variant of Concern, Realistic Vaccine Acceptance

Closures	NPIs	Immune (%)	Dorms	Mixed	Cells	Women's	Medical
✓	✓	50%	16%	8%	3%	3%	3%
	✓	50%	36%	26%	7%	5%	3%
		50%	43%	42%	28%	22%	6%
✓	✓	25%	51%	41%	12%	6%	5%
	✓	25%	59%	56%	31%	20%	7%
		25%	61%	61%	50%	51%	26%
✓	✓	0%	75%	71%	38%	16%	10%
	✓	0%	76%	75%	52%	50%	22%
		0%	78%	78%	70%	69%	49%

B. Variant of Concern, Idealized Vaccine Acceptance

✓	✓	50%	7%	4%	2%	2%	2%
	✓	50%	19%	14%	3%	3%	3%
		50%	33%	31%	14%	11%	4%
✓	✓	25%	31%	20%	4%	3%	3%
	✓	25%	45%	40%	13%	9%	4%
		25%	49%	48%	35%	35%	16%
✓	✓	0%	57%	49%	14%	7%	6%
	✓	0%	61%	58%	32%	26%	13%
		0%	63%	63%	51%	53%	38%



The results in this figure can be interpreted as possible outcomes given the base-case parameter values and model assumptions for a given scenario and prison that could occur due to randomness. In prisons with mostly dorms and low baseline immunity, large outbreaks occur when activities are re-opened absent NPIs in almost all 500 simulations. There is more variation in cumulative infection risk in prisons with dorms and high immunity and in prisons with cells and low immunity, indicating that these types of prisons could experience more variation in outcomes. Across all settings except those with mostly cells and high baseline immunity, resumption of in-person activities without NPIs led to a substantial increase in cumulative infections in the vast majority of simulations.

Figure shows average cumulative infections among residents across 500 model simulations over 200 days for each scenario shown. “Idealized” vaccine acceptance is the same as “best-case” vaccine acceptance in the main text (90% across all ages).