The Case for Altruism in Institutional Diagnostic Testing

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Twitter Thread

1. Altruism is not only good for society—in an outbreak, it can also be self-serving. A thread on our modeling paper https://www.medrxiv.org/content/10.1101/2021.03.16.21253669v1 w/ @ivan_specht @KianSani @codeanticode and thanks @EmilyAnthes piece @NYT https://www.nytimes.com/2021/03/24/health/coronavirus-testing-sabeti-altruism.html 1/16
2. COVID-19 made clear that diagnostic testing is a highly effective tool to curb viral spread. A positive test result informs infectious individuals that they & their close contacts must self-isolate, reducing transmission. #covid19 #testing 2/16
3. As well-endowed institutions—e.g. schools, workplaces—sought to revive operations, they turned inwards, deploying vast resources to test their own members regularly, often w/clinical-grade tests, while surrounding communities suffered testing shortages & delays. 3/16
4. For example, the NFL spent $100m on daily testing w/24 hour return time, burning through ~1M mostly negative tests. In spite of this, they had outbreaks across a number of teams. They were not alone. 4/16
5. The White House outbreak & many others show failure of confined testing programs. By not testing the surrounding community, institutions miss a chance for social good &

remain blind to community cases that could breach the institution & spread like 🔥🔥 5/16

6. We hypothesized that institutions that only test themselves would be less safe than those that supported community testing. 6/16
7. We constructed an #epidemiological model to test this hypothesis, taking an agent-based approach & generating contact network for how agents interact. Beyond typical SEIR compartments, we have quarantine ones that agents enter when they or close contacts test positive. 7/16
8. We found that the deployment of diagnostic tests to members' close contacts outside the institution offered the best protection (overall lowest transmission) in practically all tested scenarios. #protection 8/16
9. Under baseline parameters—modeled on our affiliated institution, @ColoradoMesaU—using about 45% of tests outside the institution was the best way to stay safe. This proportion depends on variable model parameters including interaction and contact tracing levels. 9/16
10. Going beyond @ColoradoMesaU, our results were robust to a wide range of factors, such as local community prevalence, social mitigation efforts, testing capacity, and contact tracing adoption 10/16
11. For best performance, institutions would ask members to reliably report close contacts (e.g. family members, roommates) & know who is most crucial to test. But even w/o perfect reporting, our results show that overall transmission w/in institution & beyond is lower when testing is deployed inside & outside the institution. 11/16
12. Mathematically, our results are hardly surprising. It's intuitive that if institutions allocate most diagnostic tests to members' contacts, they will likely preempt the virus's emergence within their walls by establishing a 'barrier of defense.' 12/16
13. By leveraging a larger % of tests and resources towards strategic testing in surrounding communities, institutions can create circles of safety around them, & limit viral transmission both within and outside their institutional walls. 13/16
14. Our research justifies #altruistic—and more effective—testing strategies. Early in the pandemic, many institutions chose to devote considerable resources to testing themselves -and themselves only. This policy is neither the most ethical nor the most safe. 14/16
15. Epidemics are one of those rare instances where a seemingly selfless approach is, in fact, the most self-serving: institutions must test beyond their walls to stay safe behind them. 15/16
16. Thanks to our authors, full list: @ivan_specht, @KianSani, @BottiYolanda, @mhughes6510, @DrKHeumann, Amy Bronson, @MesaVeep, Emily Baron, @eparrie, @orglennon, and @ben_fry, @codeanticode, @PardisSabeti. 16/16

ABSTRACT

Amid COVID-19, many institutions deployed vast resources to test their members regularly for safe reopening. This self-focused approach, however, not only overlooks surrounding communities but also remains blind to community transmission that could breach the institution. To test the relative merits of a more altruistic strategy, we built an epidemiological model that assesses the differential impact on case counts when institutions instead allocate a

proportion of their tests to members' close contacts in the larger community. We found that testing outside the institution benefits the institution in all plausible circumstances, with the optimal proportion of tests to use externally landing at 45% under baseline model parameters. Our results were robust to local prevalence, secondary attack rate, testing capacity, and contact reporting level, yielding a range of optimal community testing proportions from 18% to 58%. The model performed best under the assumption that community contacts are known to the institution; however, it still demonstrated a significant benefit even without complete knowledge of the contact network.

INTRODUCTION

During any societal crisis, altruism has the potential to both satisfy moral duty and maximize "utility," leading to the best possible outcome for the greatest number of people. It gains newfound urgency and utility during a pandemic, when important decisions must be made around allocating scarce resources, such as tests, therapies, and vaccines. In these instances more than ever, our own interests—our health, safety, and well-being—become highly interdependent on those of others. Specifically for communicable diseases, testing is patently a public good because a positive result can reduce others' exposure and suffering by guiding isolation and quarantine practices.

Considerations of altruism and its efficacy have resurfaced in various COVID-19 response plans worldwide. As the disease began to spread in the U.S., it forced schools and businesses to cease in-person operations to mitigate its spread. To reopen, many of these institutions rushed to test their own members, enacting several-times-per-week or even daily testing protocols in hopes of preventing outbreaks [16, Paltiel]. Countless institutions spent millions on internal testing programs. Some universities, for instance, spent upwards of $1-2 million per week to test students and staff, often using clinical-grade diagnostics.[2,3] Meanwhile, communities surrounding these institutions continued to struggle with ongoing clinical testing shortages and long delays for results. For institutional testing programs that considered supporting community testing, however, legal and regulatory barriers served as an additional deterrent from doing so.

To turn inward is a common and understandable approach during any crisis, but these expensive self-focused testing programs still left institutions blind to community cases that could potentially enter and spread like wildfire. For example, the NFL spent $100 million in total throughout the 2020-21 season on nearly one million daily tests for around 7,500 institutional members. Yet, the League still experienced various outbreaks. They were not alone; outbreaks occurred within many similar testing programs, as the world witnessed most prominently at the White House in Fall 2020.

We are now faced with the question of whether the confined use of significant resources to enable high-frequency testing within individual institutions alone is the most appropriate or effective way to contain a virus. We hypothesized that if institutions test *altruistically*—that is, designate a substantial portion of their testing capacity outside the institutions—it would not only be good for their communities, but also for them. That is, there would be lower case

counts in these institutions themselves had their programs incorporated the testing of close contacts of its members into its testing strategy, thereby detecting potential COVID-19 encroachment.

This paper seeks to ascertain whether a self-focused or an altruistic testing approach is a more effective mitigation strategy. We develop a simple-yet-reasonable epidemiological model to answer this question, comparing results under varying local community prevalence levels, social mitigation efforts, testing capacity, and contact tracing adoption. We then discuss the significant real-world implications of our findings concerning how institutions might better allocate their available testing capacity

EPIDEMIOLOGICAL MODEL

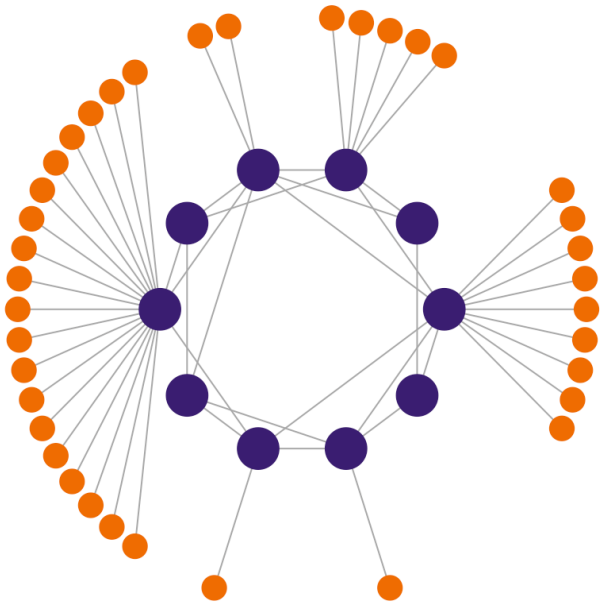
To test our central claim, we build an agent-based epidemiological model of a hypothetical "institution" such as a workplace, school, or similar organization, accounting for interactions between the institution and its surrounding community. We construct a social network that describes a hypothetical institution and then use that network as the basis for simulating the spread of COVID-19. For a full, mathematically rigorous methods section, see **Appendix A**; here, we provide an intuitive, high-level description. We model two distinct groups: (1) institution members and (2) all of their first-degree close contacts outside the institution (hereafter referred to as the "periphery"). We assume that the periphery remains unchanged throughout the simulation.

We then assess the effect of redistributing some of the institution's testing capacity to the periphery, assuming for simplicity that diagnostic testing in the community is rare before the institution's intervention. The model provides critical insight into the optimal proportion of tests to redistribute, given several baseline assumptions about viral dynamics, prevalence, and more. Moreover, we assume no knowledge of the institution and the periphery beyond what institutional administrators/health officers might reasonably gather, such as the number of individuals, their frequent contacts, and the number of tests conducted. As such, our model gives a general framework by which institutions may assess possible testing protocols' effectiveness.

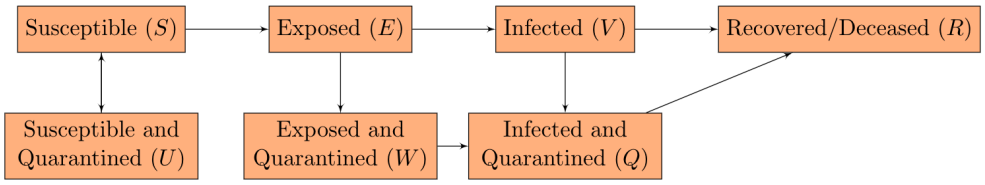
Modeling viral propagation between an institution and its periphery requires detailed information on how the agents involved interact with each other. A typical means to capture this information is a simple undirected graph, in which two nodes (*i.e.*, people) share an edge if and only if those two people interact during the modeled period. In a real-world context, we might construct this graph by, for example, surveying members of the institution and its surrounding community about their social interactions. In this paper, however, we assume knowledge only of the mean and variance in contact numbers inside and outside the institution, which is likely more feasible to estimate in most contexts.

We proceed by modeling N agents who interact according to a random graph, in which node degrees follow an overdispersed Negative Binomial distribution fit to the observed mean and variance (see **Appendix A** for the random graph generation algorithm) [Mossong]. To account

for institution-periphery interactions, we assign each agent a number of regular contacts made outside the institution, drawn from a different Negative Binomial distribution. See **Figure 1a** for an example of a contact network generated via this method. This contact network may or may not be fully known to the institution; we include a model parameter that captures the extent to which agents report their contacts (see **Appendix B**).



(a)



(b)

Figure 1*: (a) Example of a contact network representing members of the institution (large, purple nodes) and their contacts in the periphery (small, light orange nodes). Here we have 10 institution members who make an average of about 4 contacts within the institution and 4 contacts outside the institution. (b) Flowchart of compartments and possible state transitions.*

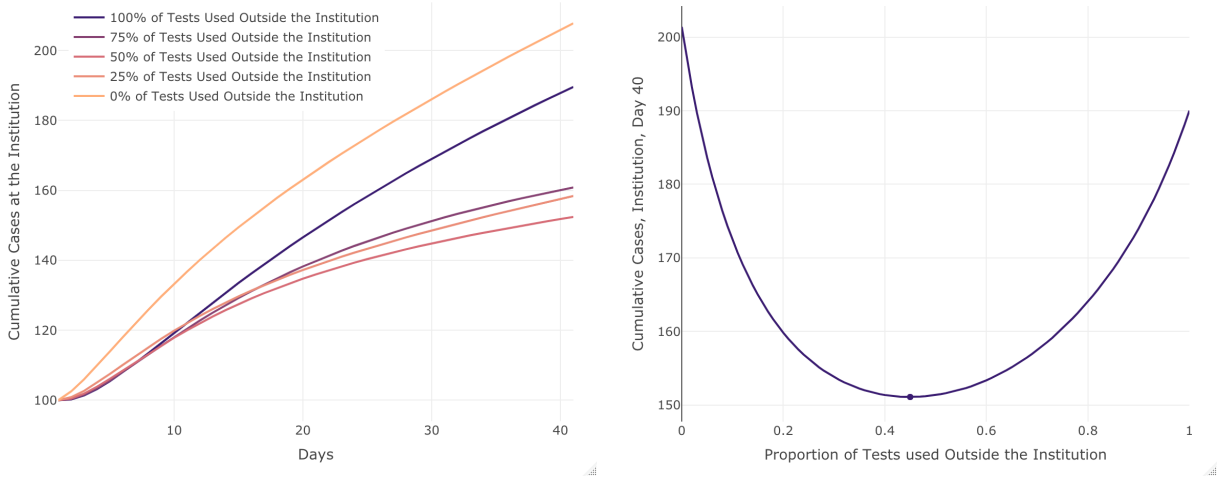
Having established a graphical contact network, we experiment with different testing strategies to simulate the spread of COVID-19. As a first step, we assume that the periphery exhibits an epidemiological steady-state, computed based on the proportion of tests distributed there. By steady-state, we mean that the probability of an individual in the periphery being in a certain epidemiological state remains constant over the course of the simulation (see **Appendix D** for a more detailed treatment of this assumption). Within the institution, by contrast, we set the initial infection rate very low in comparison to the periphery, reflective of the fact that many institutions returning to in-person activities have rigorous testing/quarantining protocols. For these agents, we model viral states probabilistically via an adapted *N*-intertwined mean-field

approximation (NIMFA). In its original form, the NIMFA states that at a given time, the rate of transmission from agent *j* to adjacent agent *i* is proportional to the product of the marginal probabilities that *i* is susceptible and that *j* is infectious. This approximation significantly reduces computational complexity without significantly influencing results [Qu].

We extend this method to model testing-based interventions. First, we allow the outgoing transmission rate to vary between agents as a partial means of modeling overdispersion (with the rest coming from the node degree distribution). To account for quarantine compartments, we set the time-dependent rate at which agent *j* enters quarantine proportional to the product of the marginal probabilities that *j* is infectious and that *j* receives a test. In turn, this latter probability depends on the test distribution strategy, the probability that *j* has not previously tested positive, and the number of adjacent nodes in *j*'s contact network. Finally, accounting for the fact that COVID-19 cases exhibit an exposed (but not yet infectious) stage, we arrive at a new, more detailed compartmental model, in which agents transition between epidemiological states as depicted in **Figure 1b.**

RESULTS

We first applied our model to a mid-sized university (N = 10,000), using real data we gathered at Colorado Mesa University (CMU). CMU established a testing program in summer 2020 initially focused on university students and staff, and began supporting testing in the greater Mesa County community later that year. Contact tracers determined that the mean and variance of the number of close contacts within the institution were 2.3 and 2.4, respectively, and outside the institution were 0.2 and 1.9, respectively. They also found that the prevalence on campus at the beginning of the Spring 2020 semester was approximately 1%, and that they planned to conduct about 0.12 diagnostic tests per day per person. Supplementing our own data collection with that of the local public health authority, we compiled a complete set of parameters specific to CMU (see **Appendix D**) and ran the model accordingly.

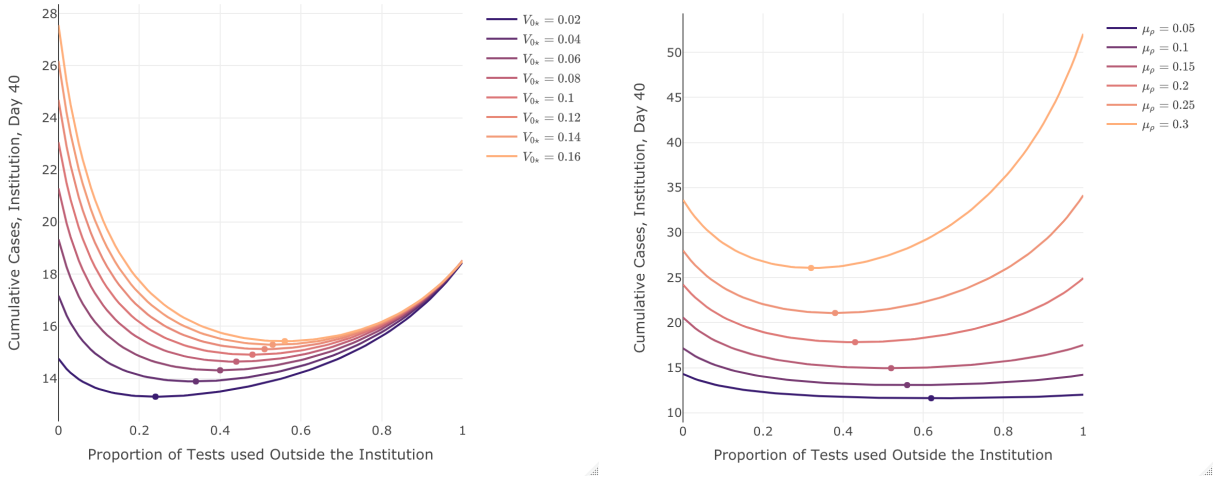


(a) **(b)**

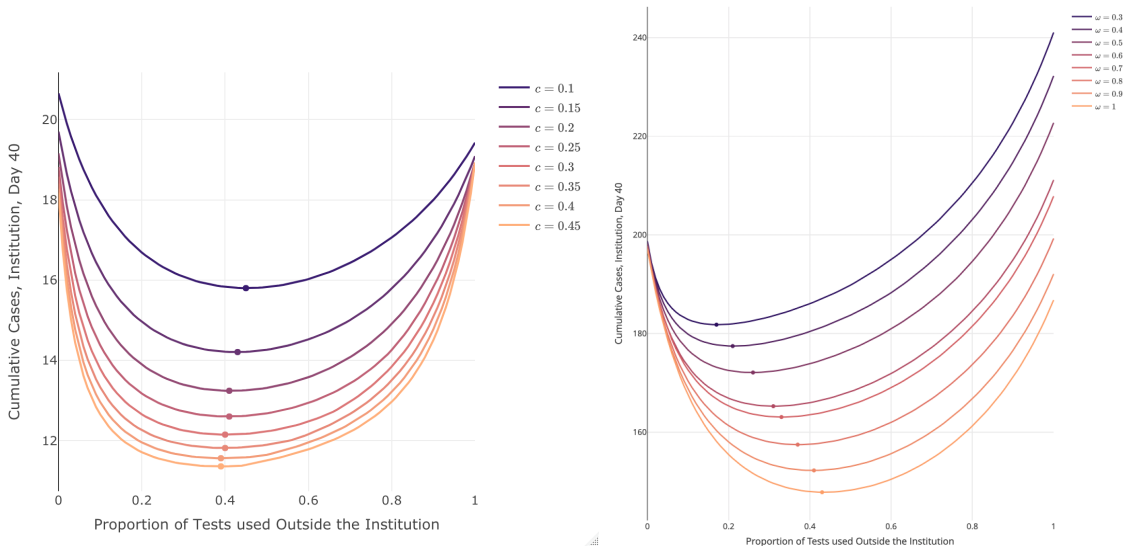
***Figure 3**: (a) Modeled cumulative cases over time at CMU under 5 possible testing strategies; (b) cumulative cases on day 40 as a function of the proportion of tests deployed to the periphery, with the minimum at 45% peripheral testing*

Our initial model results based on the CMU parameters provide strong evidence in support of an altruistic testing strategy. We observe that the projected number of cases 40 days after the beginning of the modeled period is lowest when CMU deploys 45% of its tests to the periphery (see **Figure 3**). This strategy reduces the institutional case count by 25% as compared to a self-focused testing strategy (*i.e*. 0% peripheral testing). However, our data from CMU—which inform our baseline parameters—are likely subject to several biases. While CMU administrators attested that they believe the data to represent the student body fairly well, students who contracted the virus (as every individual in our dataset did) are likely to have higher degrees of social interaction than those who did not, leading to a positive bias. On the other hand, CMU informed us that certain close contacts were likely not reported or otherwise not included in some cases, introducing a negative bias.

Because of the potential limitations and biases of our CMU data, and because our model relies on numerous parameters that vary widely between institutions, we proceeded by demonstrating robustness to and characterizing the influence of several factors on our results. These include four key factors: local community prevalence, social mitigation efforts, testing capacity, and contact tracing adoption (see **Figure 4**). Of course, there are more factors to assess, including distributions in numbers of contacts, variance in transmissibility, and initial prevalence within the institution. For an assessment of these factors, see **Appendix C**, or, for an interactive sensitivity analysis, visit https://ispecht.shinyapps.io/covid19-diagnostic-precision/.



(a) **(b)**



(c) **(d)**

Figure 4*: Cumulative cases on day 40 as a function of the proportion of tests deployed to the periphery, with minima marked, under different values of (a) the initial prevalence in the periphery (V_{0^*}), (b) the secondary attack rate (rho), (c) the testing capacity (C), and (d) the proportion of contacts traced (omega)*

We first assessed sensitivity to the prevalence of COVID-19 among members of the periphery (V_{0^*}). While the 6% positivity rate in Mesa County in January 2020 was reflective of national statistics at the time, different institutions face significantly higher or lower caseloads in their surrounding communities, representative of factors such as density and public health resources that varied from place to place. Moreover, rates have naturally varied over the course of the outbreak. We observe that under higher values of V_{0^*}, the effectiveness of redistributing tests to the periphery grows, with the optimal proportion increasing from 36% when V_{0^*} = 2% to 83% when V_{0^*} = 16% (see **Figure 4a**). This finding is unsurprising, given that the probability of any individual test detecting a case in the periphery grows with higher values of V_{0^*}. In turn, the resulting quarantine (of both the peripheral member and their contact in the institution) minimizes the probability of the virus breaching the institution.

Next, we turned to social mitigation efforts. While several model parameters capture these efforts, we focus on the secondary attack rate (SAR) for institution members—that is, the probability of transmission between an infectious individual and a susceptible one. Individuals may decrease the proportion of contacts they infect by, for example, wearing masks and socially distancing—thereby decreasing the observed SAR. Many institutions employ different mitigation measures, but altruism remains an effective strategy under a wide range of values for the observed SAR specifically for institution members, denoted *mu_rho* (see **Figure 4b**). For *mu_rho* = 0.05, the optimal proportion of peripheral testing lies at 67%; this proportion decreases to 45% when *mu_rho* = 0.3. This again falls in line with our expectations, as for higher *mu_rho* values, a single case within the institution has much greater potential to spread, limiting peripheral testing effectiveness and lowering the optimal proportion of tests to be

administered outside the institution. On the other hand, when *mu_rho* is low, a single case within the institution will likely not give rise to an outbreak. This makes institutional testing less essential, leaving more capacity to establish a 'barrier of defense' in the periphery to prevent cases from breaching the institution in the first place.

We then focused on *c*, the number of tests administered by the institution per day per person. An intuitive way to think about this parameter is that on average, an institution member receives a diagnostic test every 1/*c* days. We found that test redistribution to the periphery remains an effective strategy even for relatively low values of *c*, such as *c* = 10% (see **Figure 4c**). Counterintuitively, the optimal proportion of peripheral testing *increases* from 43% to 63% as *c* decreases from 45% to 10%. This result reflects the fact that under our baseline CMU parameters, institution members average about 10 times more contacts within the institution than outside it. As such, the size of the periphery is small, limiting the possible pathways for the virus to breach the institution. Our results tell us that such limited tests would best be used to prevent the virus from entering the institution via these pathways. Note that we also investigated different proportions of contacts within and outside the institution; for an analysis, see **Appendix C**.

Finally, we accounted for the fact that institution members may not report all of their contacts in the periphery, or may have contacts that the institution cannot test due to factors such as geographic disparity. We captured the proportion of reported, testable contacts with the parameter *omega*. As our results suggest, contact reporting need not be perfect for peripheral testing to help curb viral spread (see **Figure 4d**). Even if institution members report only 30% of their contacts, the optimal proportion of peripheral testing remains at 24%; this proportion increases to 56% as the fraction of reported contacts grows to 100%. This result makes sense because the most socially-active—and therefore riskiest—members of the institution have many peripheral contacts, at least some of which will likely be known to the institution even under imperfect contact tracing (e.g. familial contacts). A positive test from even just one of these contacts will send the original institution member into quarantine, allowing the 'barrier of defense' strategy to remain an effective means of protecting the institution.

DISCUSSION

Our model supports our hypothesis that the altruistic approach—in which institutions test beyond their walls—is the most effective protection strategy. In every instantiation of the model, we observe that deploying some proportion of diagnostic tests to the periphery significantly reduces the cumulative caseload at the end of a 40-day period. The optimal proportion of peripheral testing is 45% under baseline parameters and ranges from 18% to 58% under different levels of social interaction, testing, and contact tracing.

Our methods serve as a general framework for modeling one specific population within the context of another, and we hope that further research may help refine the intricacies of such dynamics. We also hope our work provides justification for institutions to consider implementing an altruistic testing strategy, and for legal and regulatory bodies to create a path for them to do so. We encourage institutions to partner with local public health authorities to

support testing or connect members of the periphery with the appropriate testing provider, as Colorado Mesa University and the University of California Davis have done.

Our results urge a fundamental rethinking of how institutions with substantial testing capacity approach safety amid outbreaks. Epidemics are one of those rare instances where a seemingly selfless approach is, in fact, the most self-serving: institutions must help test beyond their walls to stay safe within them.

CODE AVAILABILITY

Code used to implement the model and generate **Figure 3a** is available at github.com/broadinstitute/covid19-diagnostic-precision.

CONFLICTS OF INTEREST

Pardis C. Sabeti is a co-founder and shareholder of Sherlock Biosciences and is a non-executive board member and shareholder of Danaher Corporation. Andrés Colubri and Pardis C. Sabeti are inventors on patents related to diagnostics and Bluetooth-based contact tracing tools and technologies filed with the USPTO and other intellectual property bodies.

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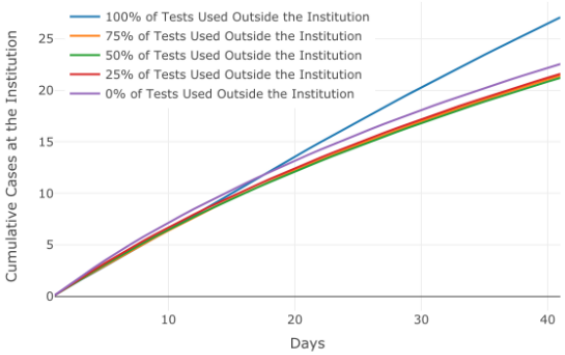
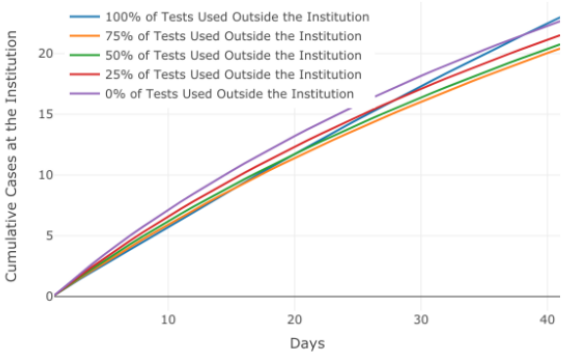
Appendices



(a) $\omega = 0.25$



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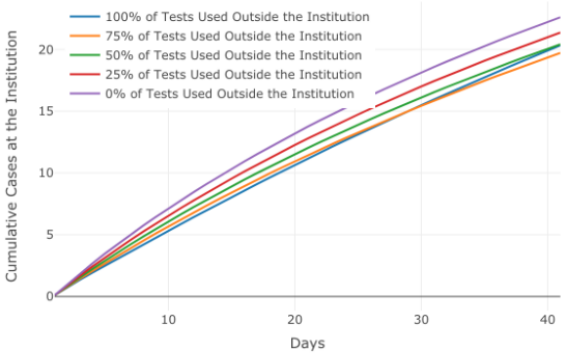
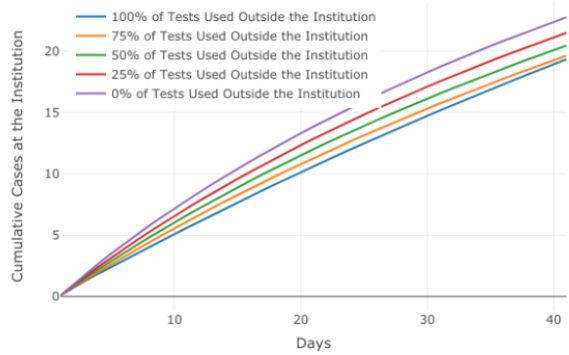
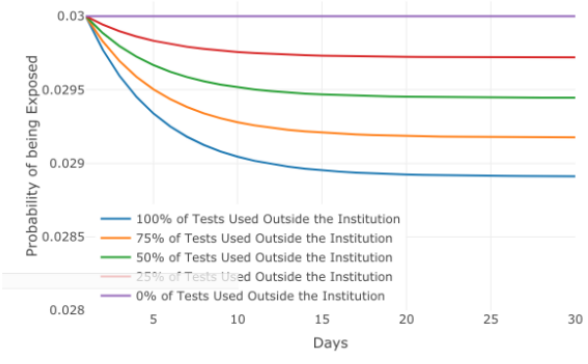


(c) $\omega = 0.75$

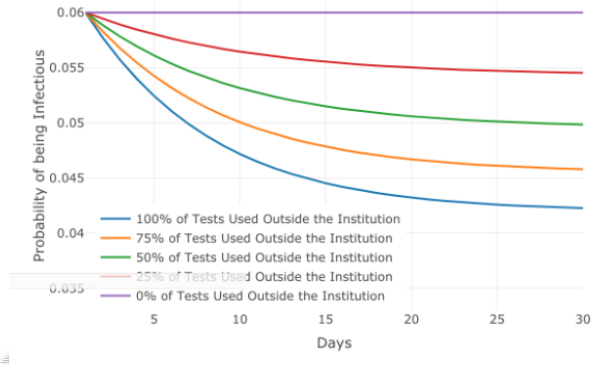


(d) $\omega = 1$

Figure S8: Modeled numbers of infectious persons in the institution over time, under a sample of 4 different possible values for ω.



(a)



(b)

Figure S9: Modeled probabilities of an agent in the periphery being (a) exposed and (b) infectious over time starting with the implementation of community testing at time 0.