# Using a clinical prediction rule to prioritize diagnostic testing leads to reduced transmission and hospital burden: A modeling example of early SARS-CoV-2

Jody R. Reimer[1], Sharia M. Ahmed[2], Benjamin Brintz[2,3], Rashmee U. Shah[4], Lindsay T. Keegan[3], Matthew J. Ferrari[5*], Daniel T. Leung[2*]

[1]University of Utah, Department of Mathematics, Salt Lake City, UT, United States of America

[2]University of Utah School of Medicine, Department of Internal Medicine, Division of Infectious Diseases, Salt Lake City UT, United States of America

[3]University of Utah School of Medicine, Department of Internal Medicine, Division of Epidemiology, Salt Lake City UT, United States of America

[4]University of Utah School of Medicine, Department of Internal Medicine, Division of Cardiovascular Medicine, Salt Lake City UT, United States of America

[5]The Pennsylvania State University, Department of Biology, State College, PA, United States of America

*Corresponding MJF: mferrari@psu.edu; DTL: daniel.leung@utah.edu

Corresponding author:

Daniel T. Leung, MD, MSc, FIDSA

University of Utah School of Medicine

30 N 1900 E, Salt Lake City, UT 84132

Daniel.Leung@utah.edu

**Summary**

When the demand for diagnostic tests exceeds capacity, the use of a clinical prediction rule to prioritize diagnostic testing can have meaningful impact on population level outcomes, including delaying and lowering the infection peak, and reducing healthcare burden.

© The Author(s) 2021. Published by Oxford University Press for the Infectious Diseases Society of America. All rights reserved. For permissions, e-mail: journals.permissions@oup.com.

**Abstract**:

***Background:*** Prompt identification of infections is critical for slowing the spread of infectious diseases. However, diagnostic testing shortages are common in emerging diseases, low resource settings, and during outbreaks. This forces difficult decisions regarding who receives a test, often without knowing the implications of those decisions on population-level transmission dynamics. Clinical prediction rules (CPRs) are commonly used tools to guide clinical decisions.

***Methods:*** Using early SARS-CoV-2 as an example, we used data from electronic health records to develop a parsimonious 5-variable CPR to identify those who are most likely to test positive. To consider the implications of gains in daily case detection at the population level, we incorporated testing using the CPR into a compartmentalized model of SARS-CoV-2.

***Results:*** We found that applying this CPR (AUC: 0.69 (95% CI: 0.68 - 0.70)) to prioritize testing increased the proportion of those testing positive in settings of limited testing capacity. We found that prioritized testing led to a delayed and lowered infection peak (i.e., "flattens the curve"), with the greatest impact at lower values of the effective reproductive number (such as with concurrent community mitigation efforts), and when higher proportions of infectious persons seek testing. Additionally, prioritized testing resulted in reductions in overall infections as well as hospital and intensive care unit (ICU) burden.

***Conclusion:*** We highlight the population-level benefits of evidence-based allocation of limited diagnostic capacity.

**Key words: clinical prediction rule, transmission dynamics, diagnostic testing**

## Introduction

The ongoing COVID-19 pandemic has demonstrated the importance of rapid identification of infections in managing an epidemic, as it allows for rapid isolation of cases, contact tracing and quarantining of contacts, thereby limiting onward transmission. However, as seen at the onset of the current pandemic, diagnostic testing capacity is often limited in the emergence of novel infections, in low resource settings, or during outbreaks [1–3].When diagnostic testing is unavailable, clinical case definitions are used instead in clinical management and public health response [4]. The rationing of diagnostic testing may result in those with more severe disease or at higher risks of complications receiving tests, as definitive diagnosis is critical to guide care [5]. However, because of their symptoms, severely ill patients may also be less mobile, thereby limiting the indirect benefit of their diagnostic testing on reducing onward transmission. Therefore, tools are needed to guide clinicians in the face of limited testing capacity.

Clinical prediction rules (CPRs) are commonly used tools to help to guide clinical management decisions, such as who should undergo testing or receive limited clinical resources. They provide standardization and consistency in care between physicians, as well as improved diagnostic accuracy [6]. Some widely used CPRs include the Centor criteria [7] for diagnosis and treatment of strep pharyngitis, the Ottawa ankle rule [8] for appropriate use of X-ray in setting of ankle trauma, and the CURB65 score [9] for triage of patients with pneumonia. As CPRs are usually developed to improve patient care, their evaluation has been focused on their impact on patient-level outcomes; the impact of CPRs on population health, including on transmission dynamics of infectious pathogens, has not been widely studied.

Compartmental models such as the *susceptible-exposed-infected-removed* (SEIR) model, are often used to describe disease dynamics through a population. They combine epidemiological information (e.g. transmissibility, duration of infectiousness, reproductive number) to provide a picture of the population-level disease dynamics over time [10,11], to our knowledge, compartmental models have not yet been used to evaluate the impact of CPRs on population-level public health outcomes.

Many diagnostic models for SARS-CoV-2 now exist [12], each specific to a given population and time, typically focused on achieving optimal patient care. Using a single health system in Utah as a proof-of-concept, we developed a CPR and incorporated it into an SEIR model of the ongoing SARS-CoV-2 pandemic to evaluate the population-level impact that could have been achieved by using a CPR to prioritize testing early in the pandemic, when testing capacity was limited. Many countries, including the United States, have experienced shortages in diagnostic testing capacity, and these shortages will likely continue in many settings worldwide [13–15], and well as in future outbreaks of emerging pathogens. Our primary objective was to measure the impact that prioritized testing (using the CPR) could have had on the course of the SARS-CoV-2 pandemic, including the magnitude and timing of the outbreak peak as well as the associated impact on hospitalization and intensive care unit (ICU) burden. Additionally, we determined the conditions (e.g., test availability, test seeking volume, effective reproductive number) in which prioritized testing would have resulted in the greatest reduction of SARS-CoV-2 infections and hospitalizations. Potential benefits of CPR-guided testing continue to be relevant for surges in the SARS-CoV-2 pandemic, for future emerging infections, and for outbreaks of common infections (e.g., cholera, measles) in settings with limited diagnostic capacity.

## Materials and Methods

### *Clinical prediction rule*

All patients tested for SARS-CoV-2 in the University of Utah Health (UHealth) system were eligible for our study. Data were gathered from a period where testing eligibility was based on presenting with at least one of cough, fever, shortness of breath, or a high risk of exposure given recent travel or contact with a laboratory-confirmed case (March 1, 2020 – April 6, 2020). We use the phrase *test eligible* to describe any person seeking a test who satisfies these conditions. We considered age, gender, state ranked area deprivation index, smoking status, reported symptoms, healthcare worker status, travel history, and exposure to a confirmed SARS-CoV-2 case as predictive variables. Random forest regression and logistic regression models were considered for our CPR. Our final CPR was a logistic regression model using the top 5 predictors to output the probability of an individual testing positive for SARS-CoV-2. Full details on data processing, the predictive variables, and the construction of the CPR are available in the Supplementary Materials S1. This study was reviewed by the University of Utah Institutional Review Board (IRB) and determined to be exempt.

### *Modeling daily testing*

We first explored the effects of prioritized versus indiscriminate testing per day (Fig. 1A). On a given day, we assumed a certain number, $N_{eligible}$, of people seek testing and are test eligible (have cough, fever, shortness of breath, or known exposure and seek testing). Of those who seek testing, a certain proportion $q$ would test positive for SARS-CoV-2 if given a test and the rest, $(1-q)$, would test negative. We assumed a limited number, $N_{tests}$, of SARS-CoV-2 tests were available daily. Using simulations (details in Supplementary Material S2),

we measured the proportion of test eligible, SARS-CoV-2 positive patients who received testing under the two testing regimes: prioritized and indiscriminate testing.

***SEIR modeling***

We also considered the effect of prioritized testing on disease spread in the population over longer time scales (months-to-years). We incorporated the same processes described above into a stochastic SEIR model parametrized for COVID-19. On each modeled day, we simulated the steps shown in Fig. 1B, with parameters as in Table 1. Further simulation details are in Supplementary Materials S3.

We ran simulations assuming a total population of 3.2 million, the approximate population of the state of Utah [16]. We assumed an initial condition of 15 people in the infectious class and all others in the susceptible class. We ran our simulations for a period of 2 years. For each set of parameters considered, we ran 1000 stochastic simulations and then calculated the mean value of each of the total susceptible ($S+T_S$), exposed ($E+T_E$), infectious ($I+ T_I$), and removed ($R+ T_R$) groups, as well as 95% prediction intervals.

We then calculated several metrics including the timing of the peak of the mean infection curve; the peak value of the mean infection curve; and the mean total number of infections by the end of the simulation. These metrics allowed us to compare expected outcomes between the models with indiscriminate testing and prioritized testing.

To highlight the associated implications for healthcare demand, we also modeled the daily occupancy of hospital beds and ICU beds (details in Supplmentary Material S3) We then calculated the mean number of people-days (i.e., the number of people on a given day) where demand for hospitalization exceeds Utah's capacity of 4,869 hospital beds and the number of people-days where demand for ICU beds exceeds Utah's capacity of 687 ICU beds

[18,19]. Note that these numbers are for total hospital and ICU beds, not those set aside for COVID-19 patients, and thus provide an upper bound for hospital capacity.

All analyses and simulations were conducted using R statistical software (version 3.6.0, [20]). All code is archived and available online at doi:10.5281/zenodo.3924186.

## Results

During the period March 1 – April 6, 2020, 1,983 patients were tested for SARS-CoV-2 at UHealth. After removing observations with missing covariate data, we obtained an analytic sample size of 1,928. Our final parsimonious 5-variable CPR had a cross-validated AUC of 0.69 (95% CI: 0.68 - 0.70). In all the results that follow, we used this 5-variable CPR. We explored using additional variables but found this only marginally improved predictive ability (AUC up to 0.71; Fig. S1 and Table S2), at the expense of requiring much greater data entry effort by clinicians. We also considered alternative versions of the CPR in light of varying predictor availability in different clinical contexts. We explored models excluding symptoms, including vital signs, and including a race/ethnicity variable (Table S1). Again, these did not meaningfully improve predictive ability (AUC up to 0.72; Table S2). Finally, we explored using random forest regression to fit the models, but logistic regression estimates had consistently higher AUCs.

When comparing indiscriminate testing to prioritized testing, the absolute difference in the number of people infected with COVID-19 who were tested was greatest for intermediate levels of testing availability, achieving the greatest benefit to disease detection when between 40-60% of test eligible people received testing (vertical difference between solid lines in Fig. 2). However, the proportional increase in the number of people infected with COVID-19 who were tested was greatest for low testing capacity, with the largest fold changes seen when <20% of test eligible people received testing (dotted line in Fig. 2). For

example, if the rate of SARS-CoV-2 positivity among test eligible people was 5% and there was test capacity for only 10% of those test eligible people, we would expect to see a nearly 3-fold increase in the number of patients testing positive on a given day if using prioritized testing instead of indiscriminate testing (Fig. 2A). These results were sensitive to the proportion of SARS-CoV-2 positive patients who are test eligible, with greater differences between prioritized and random testing strategies seen for low rates of SARS-CoV-2 positivity (compare Fig. 2A-2E). Results were robust to the total number of test eligible persons.

Using our stochastic SEIR compartmental model, we show that prioritized testing delays the timing and reduces the prevalence at the infection peak and reduces final size of the pandemic (Fig. 3, Table 2). For our base parameter set, prioritized testing as compared with indiscriminate testing resulted in a 30 day delay in the timing of the infection peak and a 22% decrease in the peak number of infections.

The differences in the timing and numbers of infections between a model with prioritized versus indiscriminate testing were greatest for lower values of the effective reproductive number, $R_e$ (Fig. 3, Table 2). When alternate CPRs with similar AUC values were considered, results varied only marginally (Table S2). Alternate CPRs with higher AUC values did not necessarily perform better on all metrics (Table S3). Increasing the proportion of infectious test eligible people ($w_I$) had a positive impact on the magnitude of the differences between the indiscriminate and prioritized testing models (Fig. 3, Table 2). Increasing the number of tests available ($N_{tests}$) increased the differences for low values of $N_{tests}$ but then had reduced benefits for higher values (Table 2), consistent with Fig. 2. Varying the delay in test results, $\theta$, from 0 to 4 days, we observed only small differences in overall disease dynamics (Table 2). Increasing $\eta$ from 0.2 to 0.5 (i.e., those awaiting test results isolate less effectively) did not notably increase the effect of varying $\theta$ (Table S3).

Finally, we explored the impact of prioritized testing on hospital and ICU bed occupancy, basing our parameters on the outbreak in Utah. We demonstrated that prioritized testing resulted in reductions in the number of people-days (i.e., sum of the number of people on each day needing a hospital/ICU bed) where demand exceeded capacity for both hospital and ICU beds (Table 2). For our base parameter set, prioritized testing as compared with indiscriminate testing resulted in 63% and 96% reductions in the number of people-days above hospital and ICU capacity, respectively.

## Discussion

The availability of diagnostic testing may be limited during either the initial phase of an outbreak with an emerging pathogen, or even in later phases in under-resourced settings resulting in rationing of diagnostic tests, which can have unintended population-level implications. Using SARS-CoV-2 in Utah as a proof-of-concept, we found that a CPR to prioritize testing positively impacts both the number of laboratory-confirmed cases per day, as well as long-term disease dynamics when testing is scarce. We incorporated our model of prioritized testing into an SEIR model and showed the value of our CPR, with appreciable delays in the timing and height of the infection peak, decreases in the total number of infections, and reductions in the number of people-days above hospital and ICU capacity. This novel combination of analytic methods allowed us to highlight both the individual- and population-level benefits of the CPR.

In spite of our CPR having only moderate discriminatory performance (AUC=0.69), our results show that prioritizing diagnostic testing, even based on less-than-perfect CPRs, still has a meaningful impact on individual and population disease burden. Furthermore, future predictive models built following more extensive and improved data collection (e.g.

standardized collection by clinicians over a longer time) may improve CPR performance, thereby further improving the impact of prioritized testing on community disease burden.

When considering the individual-level impact of the CPR on test-eligible individuals, we found that prioritized testing yielded the greatest absolute gains for intermediate testing capacity (capacity to test between 40-60% of test eligible people), and highest proportional gains for low testing capacity. Improved diagnostic triage through prioritized testing leads to diagnosis of individuals earlier in their course of disease, with potential for benefit through earlier initiation of therapies or medical monitoring, and isolation or contact-tracing precautions [21].

At the population level, we found notable impact of prioritized testing on COVID-19 dynamics, leading to reductions in infections, hospitalizations, and ICU utilization, as well as delaying the infection peak, providing more time for health systems to prepare for the surge. The magnitude of this impact was sensitive to several key parameters. For example, when $R_e$ was lowered, as may happen with the introduction of other public health interventions such as social distancing, the effects of prioritized testing increased. This suggests a synergistic effect between prioritized testing and other non-pharmaceutical interventions, since implementing prioritized testing concurrently with other non-pharmaceutical interventions that reduce $R_e$, can help to maximize potential gains. Increasing the proportion of infectious people who seek testing ($w_I$) increases the effects of prioritized testing because of the indirect benefit (reduction of $R_e$) of isolating those individuals quickly. This may occur in populations with a higher proportion of symptomatic individuals, such as older populations [22] or those with other known risk factors [23]. Alternatively, the proportion of infectious individuals seeking testing could be increased intentionally through interventions such as contact tracing or campaigns to encourage test-seeking behavior.

For any given level of testing, when SARS-CoV-2 is prevalent and comprises a large fraction of the test eligible population, either testing strategy can be impactful in reducing transmission by speeding up isolation. For any given level of testing, when SARS-CoV-2 is prevalent but only a small fraction of the test eligible population, prioritized testing using the CPR leads to greater population level benefit. Thus, in settings with both SARS-CoV-2 and high prevalence of influenza-like illness (e.g., a possible fall and winter scenario), prioritized testing may be of increased value.

Use of prioritized testing is most useful in situations with limited test capacity, as the benefits of prioritized testing become negligible when test demand does not exceed test availability. While some health systems had increased their testing capacity to meet demands, as the US experiences new surge in cases demand for testing has continued to increase. Further, many countries and regions with lower resources may continue to have limited capacity for testing. Investment in a system of prioritized testing may be more cost-effective than the manufacturing or purchasing of more tests to meet demand. Additionally, this approach can be useful in future pandemic preparedness as a similar approach implemented in a timely manner may help maximize finite testing resources during the initial stages of a future outbreak, until adequate, affordable testing is available.

Our study has several limitations. Our CPR was derived using data from a single health system servicing primarily non-Hispanic white patients, with test eligibility criteria that followed CDC guidance from early in the pandemic; thus, as with other diagnostic CPR for SARS-CoV-2 [12], our CPR should not be considered as generalizable and requires validation in other settings. For different populations or for later time periods in Utah, the CPR should be updated with the most appropriate available data. Furthermore, specific population subgroups (age, gender, etc.) may benefit from individualized CPRs, and this was not explored in this analysis. Instead, we highlight the generalizability of the approach we

have presented, and that the individual and population level impacts of prioritized testing are robust to the specific CPR used (Table S3). Secondly, there are several logistical challenges. Implementation of such a prioritization system would require its incorporation into a telephone or web-based triage, or through a health worker-based assessment. Additionally, our model assumes that all individuals seeking testing would present at the same time. In most clinical settings, the implementation of such a CPR would involve the use of a probability threshold, set based on data from the previous day(s) and the expected number of test eligible people. The optimal setting of this threshold, given stochastic testing demands and infection dynamics, would be an area for future exploration during clinical trials. Third, we did not consider the implications of the sensitivity and specificity of SARS-CoV-2 tests; low sensitivity and specificity in the diagnostic tests would reduce the utility of testing in general, and thus also of prioritized testing. Finally, our SEIR model was chosen as a tool to demonstrate the relative impact of the CPR using a generalizable framework familiar to our intended audience, and thus omitted explicit consideration of some SARS-CoV-2 transmission mechanisms (e.g., superspreader events). As knowledge about any emerging pathogen continues to evolve, additional details which could help with detailed forecasting can and should be included for specific populations, appropriate for a specific time and place.

The limited availability of SARS-CoV-2 testing has hampered disease mitigation efforts in many locations. By incorporating a diagnostic CPR into a transmission dynamics model, we have demonstrated the potential efficacy of prioritized testing for delaying and reducing peak infections and the consequent healthcare demand. By highlighting parameter regimes in which these effects are greatest, we have suggested situations in which it may be most efficacious to consider using a CPR to prioritize testing of testing shortages caused by the emergence of a novel infectious disease such as SARS-CoV-2.

**NOTES**

**Author contributions**: JRR, SMA, LTK, MJF, and DTL conceptualized this study. JRR, SMA, and RUS curated the data. JRR and SMA conducted the formal analyses. MJF and DTL acquired funding for this study. JRR, SMA, BB, MJF, and DTL developed the methodologic approach used in this study. JRR, SMA, BB, and LTK wrote the software for this study. LTK, MJF, and DTL supervised the work in this study. JRR developed all visualizations for this study. JRR and SMA wrote the first draft of this manuscript. All authors reviewed and edited this manuscript. **Acknowledgments:** We thank the medical students who participated in the chart review process: Margaret Bale, Ben Berger. Jordan B. Peacock, William West, Alyssa Brown, Brendan Crabb, Sara Mann, and Valerie Martin. All code is archived and freely available at doi:10.5281/zenodo.3924186.

**Funding**: LTK is supported by the University of Utah 3i Seed award 26798; LTK also reports grants from Pfizer, Benten Dickson, CDC, and FEMA, outside the submitted work. Funding for MJF was provided by the joint NSF-NIH-NIFA Ecology and Evolution of Infectious Disease award DEB 1911962; MFJ was funded by grants to develop models to support vaccination strategies for measles and rubella in LMICs, outside the submitted work. RUS is supported by a grant from National Heart Lung and Blood Institute (K08HL136850) and a donation from Women As One. Funding for SMA, BB, LTK, and DTL was provided by NIH grant R01 AI135114 (to DTL).

**Competing interests**: The authors have no competing interests to report.

## References


1. Sealy TK, Erickson BR, Taboy CH, et al. Laboratory Response to Ebola - West Africa and United States. MMWR Suppl **2016**; 65:44–49.

2. World Health Organization. Coronavirus disease 2019. Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019. Accessed 28 June 2020.

3. Zaki AM, van Boheemen S, Bestebroer TM, Osterhaus ADME, Fouchier RAM. Isolation of a Novel Coronavirus from a Man with Pneumonia in Saudi Arabia. N Engl J Med **2012**; 367:1814–1820.

4. Centers for Disease Control and Prevention: National Notifiable Disease Surveillance System. Coronavirus Disease 2019 (COVID-19): 2020 Intermin Case Definition, Approved April 5, 2020. 2020. Available at: https://wwwn.cdc.gov/nndss/conditions/coronavirus-disease-2019-covid-19/case-definition/2020/. Accessed 25 June 2020.

5. Rosenberg ES, Tesoriero JM, Rosenthal EM, et al. Cumulative incidence and diagnosis of SARS-CoV-2 infection in New York. Ann Epidemiol **2020**; 48:23-29.e4.

6. Wallace E, Johansen ME. Clinical prediction rules: Challenges, barriers, and promise. Ann Fam Med **2018**; 16:390–392.

7. Fine AM, Nizet V, Mandl KD. Large-scale validation of the centor and mcisaac scores to predict group A streptococcal pharyngitis. Arch Intern Med **2012**; 172:847–852.

8. Bachmann LM, Kolb E, Koller MT, Steurer J, Ter Riet G. Accuracy of Ottawa ankle rules to exclude fractures of the ankle and mid-foot: Systematic review. Br Med J **2003**;

326:417–419.

9. Lim WS, Van Der Eerden MM, Laing R, et al. Defining community acquired pneumonia severity on presentation to hospital: An international derivation and validation study. Thorax **2003**; 58:377–382.

10. Garnett GP, Cousens S, Hallett TB, Steketee R, Walker N. Mathematical models in the evaluation of health programmes. Lancet **2011**; 378:515–540.

11. Metcalf CJE, Lessler J. Opportunities and challenges in modeling emerging infectious diseases. Science (80- ) **2017**; 357:149–152.

12. Wynants L, Van Calster B, Bonten MMJ, et al. Prediction models for diagnosis and prognosis of covid-19 infection: Systematic review and critical appraisal. BMJ **2020**; 369.

13. Why US coronavirus testing barely improved in April - Vox. Available at: https://www.vox.com/2020/5/1/21242589/coronavirus-testing-swab-reagent-supply-shortage. Accessed 28 June 2020.

14. Canipe C, Hartman T, Suh J. The COVID-19 testing challenge. Available at: https://graphics.reuters.com/HEALTH-CORONAVIRUS/TESTING/azgvomklmvd/. Accessed 28 June 2020.

15. Coronavirus Test Obstacles: A Shortage of Face Masks and Swabs - The New York Times. 2020. Available at: https://www.nytimes.com/2020/03/18/health/coronavirus-test-shortages-face-masks-swabs.html. Accessed 30 June 2020.

16. U.S. Census Bureau QuickFacts: Utah. Available at:

https://www.census.gov/quickfacts/UT. Accessed 28 June 2020.

17. Lemaitre JC, Grantz KH, Kaminsky J, et al. A scenario modeling pipeline for COVID-19 emergency planning. medRxiv **2020**; Available at: http://medrxiv.org/content/early/2020/06/12/2020.06.11.20127894.abstract.

18. American Hospital Directory. Individual Hospital Statistics for Utah. 2020. Available at: https://www.ahd.com/states/hospital_UT.html. Accessed 25 June 2020.

19. Harvard Global Health Institute. US Hospital Capacity. 2020. Available at: https://globalepidemics.org/hospital-capacity/. Accessed 25 June 2020.

20. R Core Team. R: A Language and Environment for Statistical Computing. 2019; Available at: https://www.r-project.org/.

21. Brown LB, Miller WC, Kamanga G, et al. Predicting partner hiv testing and counseling following a partner notification intervention. AIDS Behav **2012**; 16:1148–1155.

22. Wu JT, Leung K, Bushman M, et al. Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China. Nat Med **2020**; 26:506–510.

23. Yang J, Zheng Y, Gou X, et al. Prevalence of comorbidities and its effects in coronavirus disease 2019 patients: A systematic review and meta-analysis. Int J Infect Dis **2020**; 94:91–95.

24. coronavirus.utah.gov. Overview of COVID-19 Surveillance. 2020. Available at: https://coronavirus.utah.gov/case-counts/. Accessed 25 June 2020.

25. University of Wisconsin School of Medicine and Public Health. 2015 Area Deprivation Index v2.0. Available at: https://www.neighborhoodatlas.medicine.wisc.edu/. Accessed 21 May 2020.

26. James G, Witten D, Hastie T, Tibshirani R. An Introduction to Statistical Learning. New York: Springer, 2013.

27. Kaitlin K, Smith T, Sadler B. Random Forest vs Logistic Regression: Binary Classification for Heterogeneous Datasets. Data Sci Rev **2018**; 1:9.

28. Zhang Y, Keegan LT, Yuqing Q, Samore MH. The real time effective reproductive number for COVID-19 in the United States. medRxiv **2020**;

29. Sanche S, Lin YT, Xu C, Romero-Severson E, Hengartner N, Ke R. High Contagiousness and Rapid Spread of Severe Acute Respiratory Syndrome Coronavirus 2. Emerg Infect Dis **2020**; 26:1–8.

30. The Atlantic. The Covid Tracking Project. 2020. Available at: https://covidtracking.com/. Accessed 25 June 2020.

**Figure captions:**

**Fig. 1.** Effects of prioritized testing on daily testing outcomes and incorporation into an SEIR model. **(A)** Schematic comparing the testing of a subset of test eligible people using either indiscriminate testing or prioritized testing. Red figures would test positive for SARS-CoV-2 and blue figures would test negative. Gray figures are not seeking tests. For prioritized testing, people are arranged and then tested according to their probability of testing positive, as determined by the clinical prediction rule. **(B)** Visual depiction of how prioritized testing was incorporated into the daily stochastic SEIR model. Step 1: People in each compartment seek testing with probability $w_S$, $w_E$, $w_I$, and $w_R$. Individuals waiting for test results are in states $T_S$, $T_E$, $T_I$, $T_R$. Step 2: Following testing, daily SEIR dynamics occur with transmission rate $\beta$, incubation rate $\sigma$, and removal rate $\gamma$. Those waiting for test results (states $T_S$, $T_E$, $T_I$, $T_R$) have reduced transmission by a factor of $\eta$. Step 3: A proportion of those in states $T_S$, $T_E$, $T_I$, $T_R$ receive their test results, after an average delay of $\theta$ days.

**Fig. 2.** Effect of prioritized testing compared to indiscriminate testing on the percentage of SARS-CoV-2 positive, test eligible people, who are tested. The horizontal axis allows for comparison between different testing capacities. The vertical axis refers to the percent of SARS-CoV-2 positive, test eligible people. Dotted lines denote the fold change between the grey and green lines. The percent of SARS-CoV-2 positive people (proportion $q$) of those who are test eligible is 5% in **(A)**, 25% in **(B)**, 50% in **(C)**, and 75% in **(D).**

**Fig. 3.** Comparison of SEIR curves between models with prioritized versus indiscriminate testing for decreasing values of the effective reproductive number, $R_e$, **(A)-(E),** and decreasing rates of test seeking among infectious individuals $w_I$, **(F)-(H)**. Solid line are the mean of 1000 stochastic simulations with prioritized testing, and the dotted

lines are the mean for the model with indiscriminate testing. Shaded regions denote corresponding middle 95$^{th}$ percentiles of simulations. **(A)** $R_e$ = 2.5, **(B)** $R_e$ = 2.25, **(C)** $R_e$ = 2.0, **(D)** $R_e$ = 1.75, **(E)** $R_e$ = 1.5, **(F)** $w_I$ = 0.029, **(F)** $w_I$ = 0072, **(F)** $w_I$ = 0.144. *Note that **(D)** and **(G)** have the same parameters but have both been included to show sequential change as we vary $R_e$ and $w_I$.

**Fig. 4.** Comparison of simulated demand for daily hospital and ICU occupancy between models with prioritized versus indiscriminate testing. The solid line are the mean of 1000 stochastic simulations with prioritized testing, and the dotted lines are the mean for the model with indiscriminate testing. $R_e$ decreases from 2.5 to 1.5 in increments of 0.25 in plots **(A)** through **(E)**.

**Table 1.** Summary of the parameters and their sources, where available, as used in our stochastic SEIR model. The final column depicts the range of values presented for our sensitivity analysis. For full details on model parametrization, see Supplementary Material S4.

| Symbol | Interpretation | Value | Source(s) | Other values considered |
|---|---|---|---|---|
| $w_S$ | Proportion of individuals in states S,E,I,R who are test eligible each day | 0.0013 | Estimated. Details in S4 | - |
| $w_E$ | | 0.0013 | | - |
| $w_I$ | | 0.072 | | 0.029–0.144 |
| $w_R$ | | 0.00084 | | - |
| $N_{tests}$ | Number of tests available daily | 1000 | - | 500, 3000, 5000 |
| σ | Incubation rate | 1/5.2 | (18,19) | - |
| γ | Recovery (“removal”) rate | Uniform random variable over 1/7 to 1/4 | (20–23) | - |
| $R_e$ | Effective reproductive number | 1.75 | - | 1.5–2.5 |
| β | Frequency dependent transmission rate | $\gamma * R_e$ | (24) | - |
| θ | Average test result delay | 2 days | - | 0–4 |
| η | Reduction in transmission due to isolation | 0.2 (i.e., isolation reduces transmission by 80%) | (27) | - |

**Table 2.** Effects of prioritized testing on the SEIR infection dynamics over a range of parameter values. All parameter values are as stated in the text, except where stated otherwise in this table. Each column compares the mean results from 1000 stochastic simulations of the model with prioritized testing to one with indiscriminate testing. Bolded entries denote the results for the base parameter set described in the text (i.e., $R_e$ =1.75, $w_I$ = 0.072, $N_{tests}$=1000, θ=2), and are repeated for reference in each subsection. NA values exist where hospital or ICU demand did not exceed capacity for either the prioritized or indiscriminate testing model.

| | Delay in peak timing (days) | Reduction in peak height (people) (%) | Reduction in total infections (people) | Reduction in people-days above hospital capacity (%) | Reduction in people-days above ICU capacity (%) |
|---|---|---|---|---|---|
| $R_e$ | | | | | |
| 2.5 | 8 | 21,192 (7%) | 6,478 (0%) | 21,619 (5%) | 145,802 (72%) |
| 2.25 | 10 | 27,197 (12%) | 9,891 (0%) | 35,371 (10%) | 138,734 (76%) |
| 2.0 | 13 | 24,418 (14%) | 17,081 (1%) | 48,960 (20%) | 128,623 (83%) |
| **1.75** | **30** | **25,592 (22%)** | **38,415 (2%)** | **62,794 (63%)** | **108,918 (96%)** |
| 1.5 | 36 | 22,855 (43%) | 101,938 (5%) | NA | 45,747 (100%) |
| $w_I$ | | | | | |
| 0.029 | 10 | 12,592 (9%) | 29,584 (1%) | 27,768 (20%) | 108,691 (88%) |
| **0.072** | **30** | **25,592 (22%)** | **38,415 (2%)** | **62,794 (63%)** | **108,918 (96%)** |
| 0.144 | 45 | 49,559 (74%) | 54,434 (2%) | 40,246 (100%) | 98,663 (100%) |
| $N_{tests}$ | | | | | |
| 500 | 21 | 20,832 (15%) | 24,751 (1%) | 45,297 (33%) | 111,538 (90%) |
| **1000** | **30** | **25,592 (22%)** | **38,415 (2%)** | **62,794 (63%)** | **108,918 (96%)** |
| 3000 | 21 | 24,499 (46%) | 141,657 (6%) | NA | 49,329 (100%) |
| 5000 | 4 | 2,910 (8%) | 127,200 (7%) | NA | NA |
| θ | | | | | |
| 0 | 25 | 25,734 (23%) | 38,314 (2%) | 63,136 (73%) | 107,319 (97%) |
| **2** | **30** | **25,592 (22%)** | **38,415 (2%)** | **62,794 (63%)** | **108,918 (96%)** |
| 4 | 23 | 24,646 (21%) | 40,993 (2%) | 61,139 (63%) | 108.912 (95%) |

Figure 1

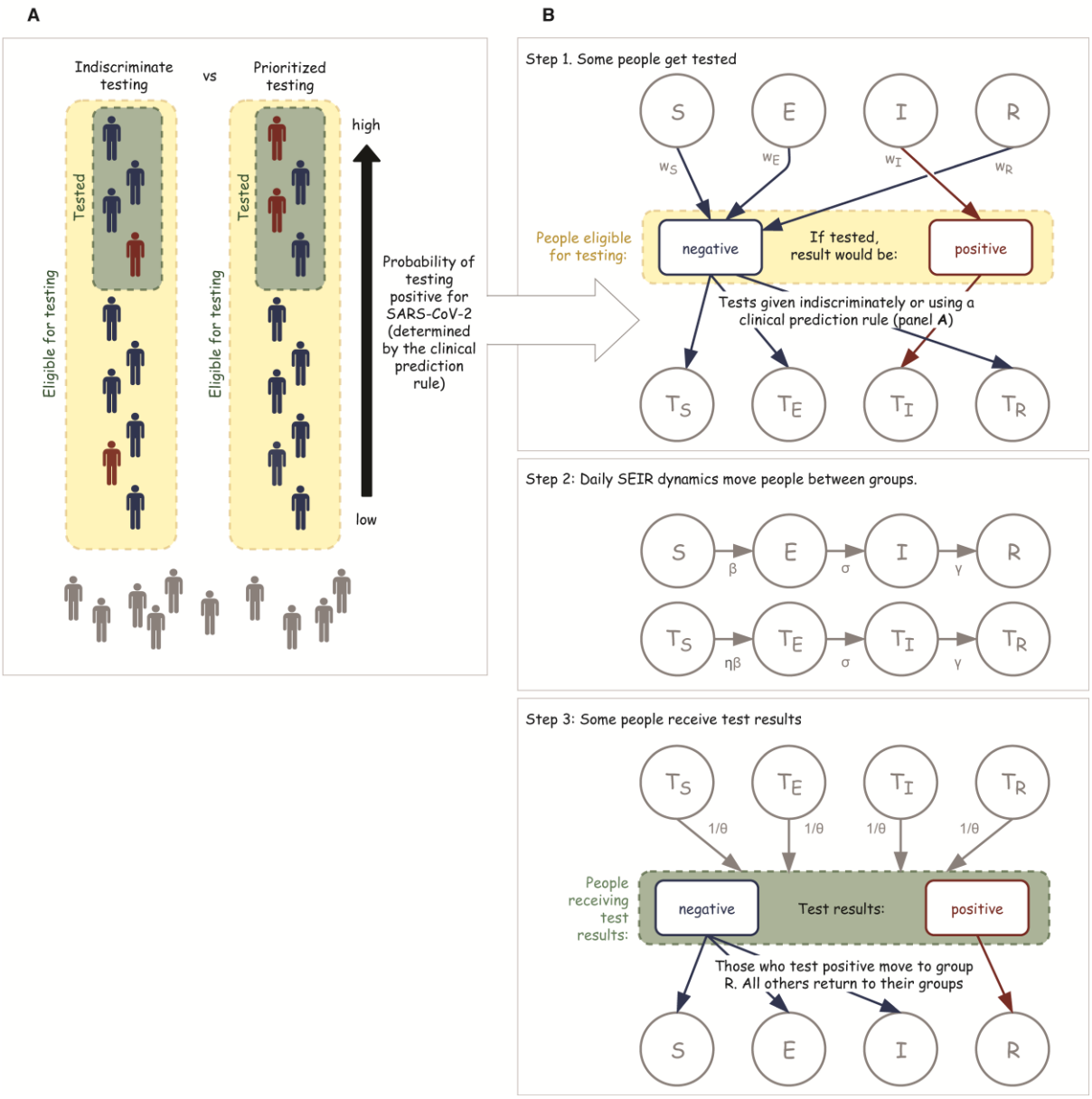

A
Indiscriminate testing
vs
Prioritized testing
Tested
Eligible for testing
high
low
Probability of testing positive for SARS-CoV-2 (determined by the clinical prediction rule)
B
Step 1. Some people get tested
S
E
I
R
People eligible for testing:
negative
If tested, result would be:
positive
Tests given indiscriminately or using a clinical prediction rule (panel A)
Step 2: Daily SEIR dynamics move people between groups.
Step 3: Some people receive test results
People receiving test results:
Test results:
Those who test positive move to group R. All others return to their groups

Figure 2

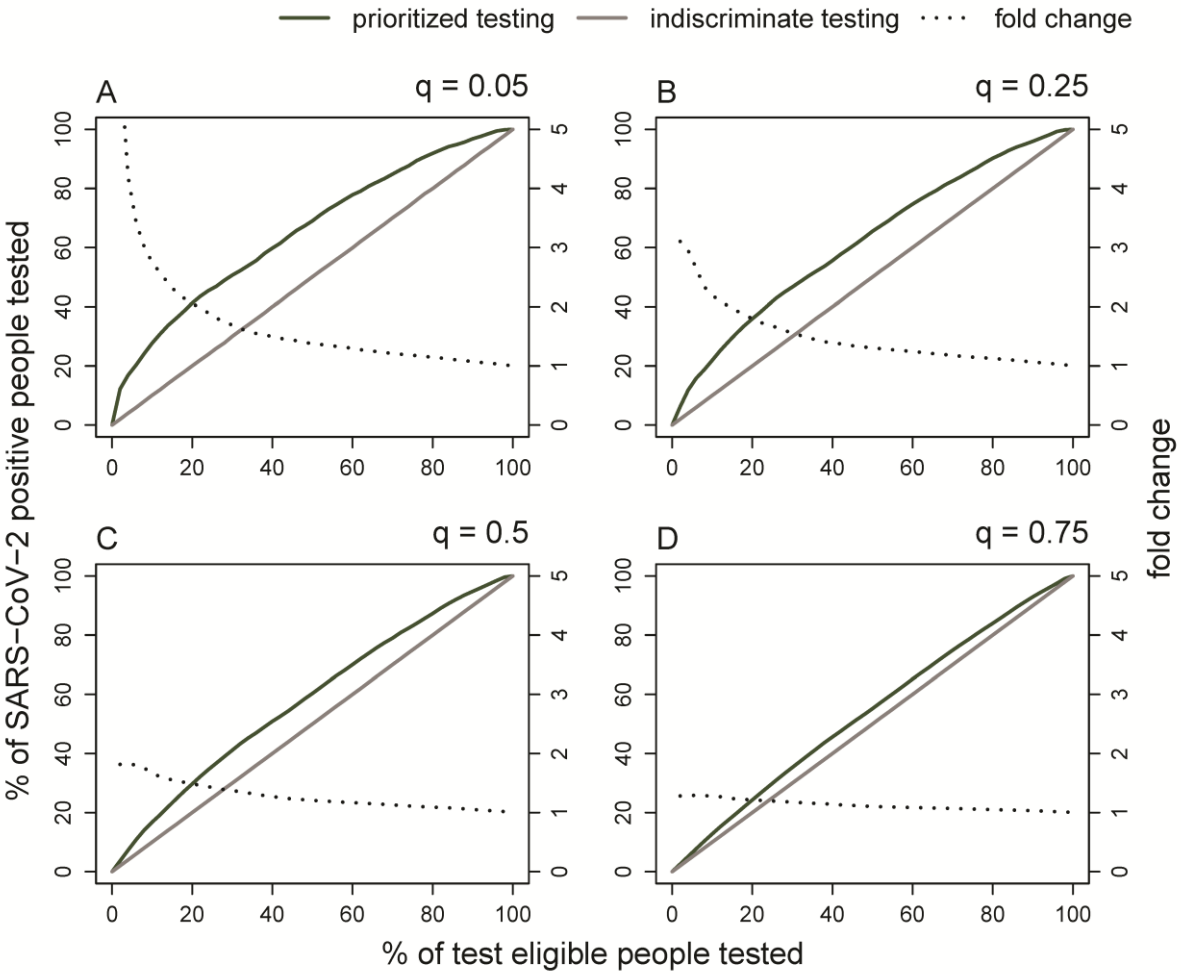

prioritized testing
indiscriminate testing
fold change
A
q = 0.05
B
q = 0.25
C
q = 0.5
D
q = 0.75
% of SARS−CoV−2 positive people tested
fold change
% of test eligible people tested

Figure 3

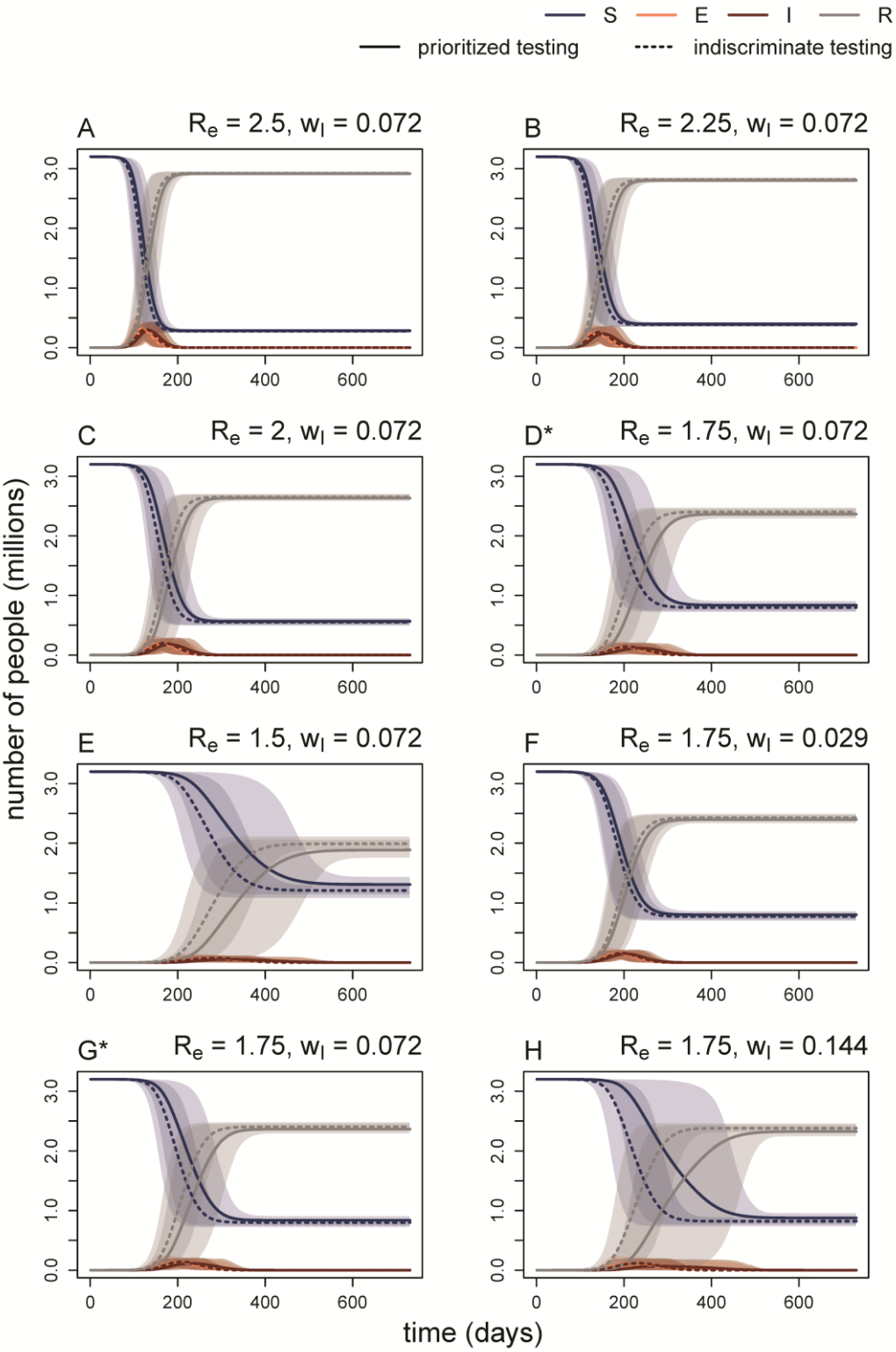
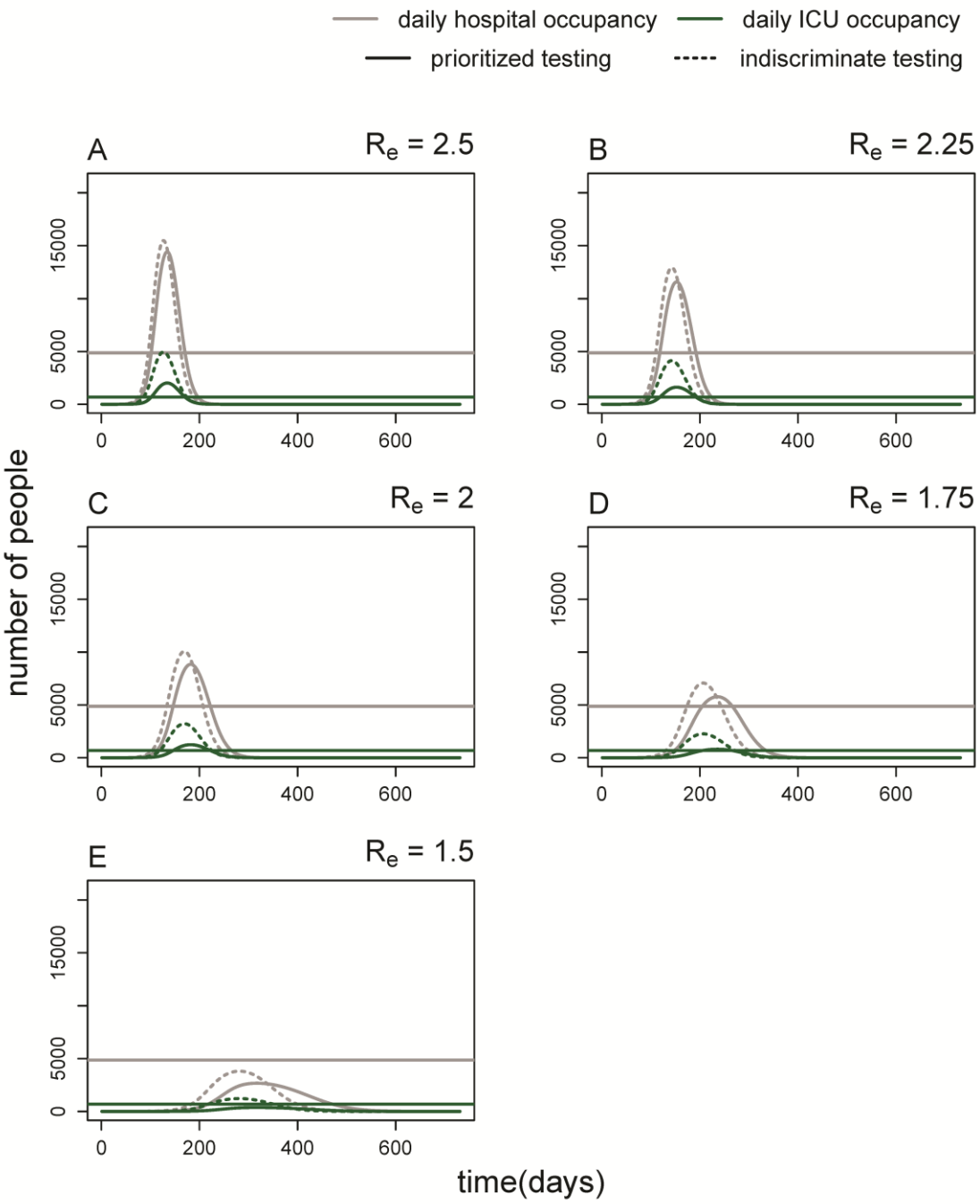

S
E
I
R
prioritized testing
indiscriminate testing
A
$R_e$ = 2.5, $w_I$ = 0.072
B
$R_e$ = 2.25, $w_I$ = 0.072
C
$R_e$ = 2, $w_I$ = 0.072
D*
$R_e$ = 1.75, $w_I$ = 0.072
E
$R_e$ = 1.5, $w_I$ = 0.072
F
$R_e$ = 1.75, $w_I$ = 0.029
G*
$R_e$ = 1.75, $w_I$ = 0.072
H
$R_e$ = 1.75, $w_I$ = 0.144
number of people (millions)
0.0
1.0
2.0
3.0
0
200
400
600
time (days)

Figure 4


daily hospital occupancy
daily ICU occupancy
prioritized testing
indiscriminate testing
A
$R_e$ = 2.5
B
$R_e$ = 2.25
C
$R_e$ = 2
D
$R_e$ = 1.75
E
$R_e$ = 1.5
number of people
time(days)
0
5000
15000
200
400
600