

Modeling countermeasures for a balanced reopening in King County, Washington

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What do we already know?

Our [previous work](#) has estimated that COVID-19's effective reproductive number (R_e) in King County, WA fell below 1 at the end of March. These reductions have been made possible largely through physical distancing, which has caused tremendous economic hardship. To relax physical distancing while still avoiding a return to exponential growth of COVID-19, some locations, such as Taiwan, have successfully demonstrated the use of non-pharmaceutical interventions including rapid testing, home isolation, household/family quarantine, and contact tracing.

What does this report add?

We have applied our new agent-based model, Covasim, to simulate the delicate balance between increased levels of transmission expected with reopening and countermeasures such as test, trace, and quarantine. We begin by calibrating this model to King County data provided by the Washington State Department of Health. Data include daily counts of the number of tests, diagnoses and deaths in 10-year age bins. With schools closed and transmission continuing to occur among closest contacts (e.g. households), we estimate that **distancing and other measures have combined to reduce the transmission potential of COVID-19 on April 25th to 33% (30-37%) of early-pandemic levels.** Without additional countermeasures, we estimate (with significant caveats) that the **strength of the physical distancing program in the county as of April 25th could have supported a small absolute increase of 5% (0-13%) in both work and community transmission potential while avoiding a return to exponential growth.** These estimates are in the past due to the typical 2-to-3-week lag in the appearance of new COVID cases; as reopening has already begun, it is possible transmission has already exceeded this threshold. We next consider the extent to which additional countermeasures might balance increasing levels of work and community transmission associated with reopening. We find that **increased testing, contact tracing to home and work, and better compliance with household quarantine beginning on May 26th could counterbalance a two-fold increase in work & community transmission from the level estimated on April 25th.** This intervention is able to counterbalance a level of transmission that will still require some physical distancing and/or other precautions, such as wearing face masks, washing hands, keeping physical distance, and avoiding crowds.

What are the implications for public health practice?

These results suggest that a robust program of testing, household quarantine, and contact tracing will be required to balance the increase in disease transmission that would be associated with relaxing physical distancing in King County, WA.

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Executive summary

COVID-19 emerged as a public health threat in Washington State at the end of February, with the first death in the state reported at the end of that month. Since then, officials have been racing to contain the spread of the virus, including announcing the [closure of schools on March 12th](#), and culminating in a shelter in place order called “[Stay Home, Stay Healthy](#)” on March 23rd. These physical distancing measures have been effective in limiting the spread of COVID-19; however, sustained physical distancing is [proving to be difficult to maintain](#) and its economic costs are high. Because [95% of the population remains susceptible](#), countermeasures such as increased testing, home quarantine, and contact tracing will be required to prevent a return to exponentially growing numbers of new infections and deaths if physical distancing is relaxed. However, the extent to which these countermeasures are effective in balancing increases in transmission due to reopening has not been previously quantified.

In this report, we use our new agent-based model, [Covasim](#), to simulate the transmission of COVID-19 in King County. This model is different from the [compartmental model](#) IDM has used in the past to estimate the effective reproductive number, R_e . These two modeling approaches are complementary, and each has strengths and limitations. The mechanistic representation of households, contacts, schools, workplaces, and nuanced social interactions in Covasim allows us to explore reopening scenarios in ways that are not possible with compartmental models.

Disease transmission in work and community settings has reduced for two main reasons. First, people are leaving their homes less often due to the stay-at-home order. Second, essential workers and those needing to leave home are taking precautions such as wearing face masks, washing their hands, keeping physical distance, and avoiding crowds. In calibrating the model to data provided by the Washington Department of Health through May 17th, **we estimate that transmission potential averaged between work and community settings by April 25th is 33%** of what it would have been if everyone was conducting business-as-usual and not taking precautions. This estimated 67% reduction represents a combination of decreased mobility and additional personal precautions.

We used this calibrated agent-based model to quantify the potential impact of additional non-pharmaceutical interventions such as household quarantine and contact tracing. We estimate that the current effective reproductive number is approximately 0.78 (0.61 - 0.93) in King County, and these interventions will further reduce R_e . Therefore, increases in disease transmission at work and in the community (such as through some relaxation of social distancing or increased contacts) are possible while keeping R_e below a threshold value of 0.9, as long as they are done in conjunction with household quarantine and contact tracing, according to this analysis.

Two main findings come from this first application of our agent-based model. First, the **transmission potential in workplaces and in the community could have been increased from the level estimated on April 25th by 5% (0%-13%) to 38% while keeping R_e at or below 0.9.** While this result speaks to the success of the physical distancing interventions, the lower bound of 0% means there is a chance that even a small increase in transmission could drive R_e above 0.9. Delays inherent in COVID infections and disease reporting mean that **we must approach reopening with caution** so as to avoid a return to rapidly growing infections and deaths. For example, it is possible that recent reopenings that have

occurred since April 25th, but are not yet reflected in the data on cases and deaths, have already approached or exceeded this threshold.

Our second main result is that a comprehensive program consisting of increased testing, household and workplace contact tracing, and household quarantine could prevent epidemic growth while allowing a two-fold increase in disease transmission potential. Specifically, such a program is able to counteract an increase in the disease transmission potential from 33% of baseline estimated on April 25th up to 75% of baseline, effective on May 26th. This 75% level is below the 100% level that represents pre-COVID “business as usual,” but does not preclude a significant (greater than 75%) return to normal activities such as physical presence at work provided other personal precautions, like physical distancing, the wearing of face masks, and frequent handwashing, are used when individuals are away from home, in combination with environmental modifications such as physical barriers, improved ventilation, and space reconfiguration

Key inputs, assumptions, and limitations of our modeling approach

We used [Covasim](#), an agent-based model of COVID-19 transmission and interventions developed by IDM, to estimate the extent to which testing, tracing, and quarantine would enable the relaxation of physical distancing measures as part of reopening of the economy. Covasim includes demographic information on age structure and population size; realistic transmission networks in different social layers, including households, schools, workplaces, and communities; age-specific disease outcomes; and intrahost viral dynamics, such as viral-load-based transmission. Key inputs and assumptions of our modeling approach have been documented in our recent [methods article](#).

We simulated a representative sample of the 2.25 million King County residents in Covasim. While agent-based modeling is able to capture many details of populations and disease transmission, our work has important limitations and assumptions that could impact our findings. Specific limitations include:

- Results are sensitive to the current level of disease transmission (R_t). However, this level is uncertain and changes stemming from recent reopening activities are not visible in epidemiological data due to inherent delays. We have effectively assumed that there have been no changes over the past two weeks, and any changes that have occurred should be discounted from our results.
- Finding model input parameters to make the model outputs look like the data is challenging with agent-based models. We have identified many good combinations of parameter inputs, and use the top 50 for analysis. However, other parameter combinations may better explain the data, and the goodness-of-fit function we use does not capture all aspects of the underlay data.
- We find that the age of cases and deaths in the model is skewed to slightly younger ages than what is seen in the data. We believe this is because long-term care and assisted living facilities have not been modeled explicitly, and we are working on adding this functionality to the model.
- The model captures COVID-19 symptoms, but does not include other influenza-like illnesses. All individuals considered "symptomatic" in the model are infected with COVID-19. While we conduct diagnostic testing in individuals who do not have symptoms due to COVID and correctly capture the test positivity rate, we have not modeled the care seeking behavior of individuals who are COVID-like symptoms due to other respiratory conditions.

- While [our analysis from March 29th](#) showed that changes in mobility began early in March and increased in magnitude over time, here we have assumed that changes in transmission at work, school, home, and in the community took place at discrete points in time on March 4th, 12th, 23rd, and April 25th. These time points correspond to early work-from-home policies, school closures, the "[Stay Home, Stay Healthy](#)" order, and changes in social-distancing and mobility patterns, respectively.

These findings are also dependent on the following assumptions. While these are consistent with what we know about the current situation in King County, additional data would be required to confirm these values. Specifically:

- We have assumed for the status quo scenario that there is a two-day lag in diagnostic testing between swab and notification of results. We also considered the impact of shorter delays and presumptively² acting on testing rather than waiting for the return of results.
- After being diagnosed, individuals are assumed to reduce their daily infectivity by 70% for home contacts, 90% for community contacts, and 100% for school and work contacts.
- We considered opening the work and community layers of the model jointly. However, it is possible that these two may not move in a 1:1 fashion.
- **Results presented here come from “what-if” scenario analysis without consideration of or accounting for resource limitations** that would challenge implementation of these scenarios in practice. Even if resources were available, compliance with these policies may be challenging to enforce, especially if requiring individuals and their close contacts to quarantine presumptively.

Agent-based model calibration to data from King County, Washington

Calibration is the process of adjusting uncertain and location-specific model input parameters to make the model outputs match epidemiological data. For this analysis, we have used King County data from the [Washington Disease Reporting System](#) (WDRS) extracted on May 17th. Contained within these data are the daily numbers of negative and positive diagnostic tests (by date of swab) and deaths (by date of death), each in 10-year age groups. The similarity between the output of the model and the King County data is quantified by a goodness-of-fit function, described in detail in our [methods paper](#).

The uncertain and location-specific parameters we included in the calibration included the overall infectiousness of COVID-19 and testing parameters governing who is receiving the diagnostic tests. Additionally, we fit several transmissibility attenuation factors based on trigger events that have occurred since early March. We used a [Bayesian optimization algorithm](#) to choose sets of 14 model input parameters. More details on our calibration approach and specific calibration parameters can be found [here](#) and in **Appendix 3**, respectively.

The resulting fit of the Covasim model to epidemiological data is shown in **Figure 1**. The top panel shows the daily numbers of total tests performed and tests that came back positive (diagnoses). The number of diagnostic tests reported each day in data from King County is used as an input to the model, so the match is perfect. These tests are allocated across the population with different weights depending on

² By presumptive, we mean that the process begins when a symptomatic individual takes a COVID-19 diagnostic test (instead of waiting for the results to be returned). If the test comes back negative, the individual and household are released from quarantine.

whether or not the individual is experiencing symptoms. Individuals symptomatic with COVID-19 are more likely to receive a test than those who are uninfected, presymptomatic, or asymptomatic. We fit one constant weight before March 7th, and a separate constant weight from March 7th onwards.

Model calibration

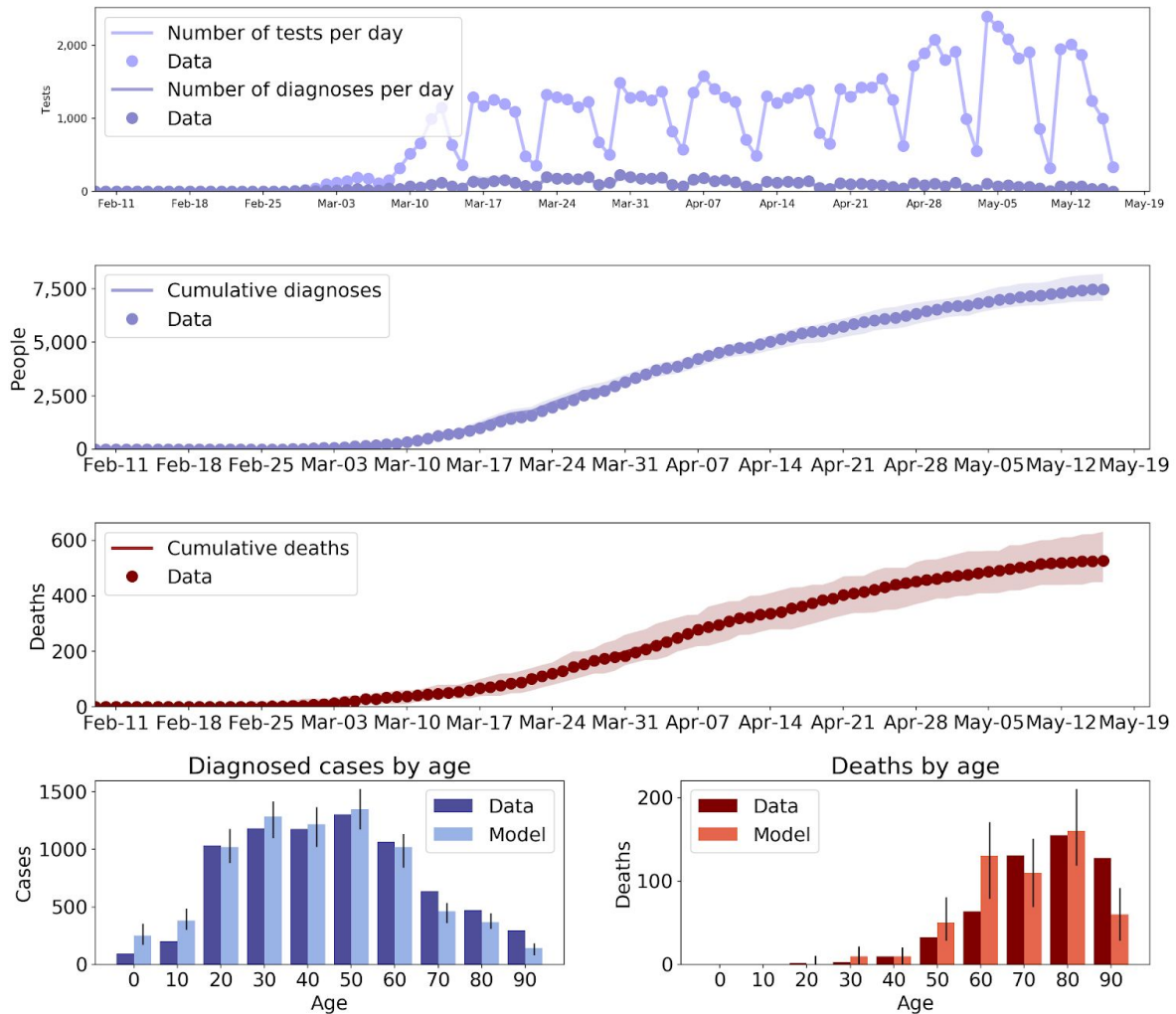


Figure 1: Calibration results comparing Covasim model outputs to data from King County. Solid lines represent the median of repeated runs of the model with 500 parameter sets and 20 random seeds. The shaded region indicates the lower and upper bound of the top 50 of these replicates. These intervals represent a combination of parametric and stochastic uncertainty.

The second and third panels show our fit to the cumulative number of diagnoses and deaths, respectively. The bottom two panels show age-specific trends in diagnoses and deaths using data aggregated over the entire time period. While the goodness-of-fit function specifically considers daily numbers of tests, diagnoses, and deaths, it currently considers all ages groups in aggregate. For age specifically, we have used best estimates from literature and hand-adjusted susceptibility by age to achieve this fit, which follows the age distribution of diagnoses and deaths reasonably well. Despite this, outputs from the model are slightly younger than the data. We suspect this is due to not fully modeling mixing between older populations in congregate settings such as long-term care and assisted living facilities. The discrepancy in the age distributions of cases and deaths should not significantly affect our

results, as this mismatch accounts for approximately 12% of the total number of cases and deaths. Hence, within the limitations of this approach and with the caveats we have noted here and elsewhere, we believe the model gives a reasonably good explanation for the observed data with respect to the analysis described later in this report.

Several key model outputs resulting from this calibration are shown in **Figure 2**. As of May 17th, 2020, our model results indicate that approximately 58,000 (47,500-69,500)³ people have been exposed to COVID-19, representing 2.6% of the population. New infections likely peaked at approximately 1,200 per day around the second week of March, and active infections peaked at approximately 9,800 in the last week of March. The effective reproductive number fell from a high of 2.0 (1.78 - 2.36) in late February to a present-day value of 0.78 (0.61 - 0.93). We also estimate a case fatality rate (CFR) of 6.92%, and an infection fatality rate (IFR) 0.9%. CFR is defined as the number of deaths from COVID-19 divided by the total number of people diagnosed with COVID-19. IFR is defined as the number of deaths from COVID-19 divided by the total number of people infected with COVID-19. Overall, we estimate that only about 13% of all King County COVID-19 cases have been diagnosed for the period between January 27th and May 17th.

[Previous COVID analyses by IDM](#) have used a susceptible-infected-recovered (SEIR) compartmental model to understand the current and historical trajectory of the epidemic in King County. SEIR models carefully capture and propagate uncertainty, and are therefore better positioned for estimating historical and present trends. In comparison, the agent-based modeling approach used here serves a different purpose: to estimate the impact of interventions such as home quarantine and contact tracing. Despite the significant methodological difference, results from the two approaches yield consistent results. See **Appendix 1** for a comparison.

In our calibration, we estimated the extent to which COVID-19 transmission changed at discrete time points in the work and community layers of the network. Schools closures started on March 12th and we assumed that there would be a 20% increase in the household transmission potential by March 23rd due to both adults and children spending more time at home. Key to results that will follow, we find that transmission in workplace and community layers fell by 75% (to 25% of their original pre-COVID levels) on March 23rd following the "[Stay Home, Stay Healthy](#)" order. Subsequent increases to 30% are estimated for the community layer and workplaces on April 25th. We assume that schools will remain closed for the duration of this analysis. We will be considering scenarios that increase transmission potential in work and community layers on May 26th from the 33% of baseline level estimated on April 25th. Please note that we have assumed that the 33% estimate is assumed to be held constant from April 25th to the increase in transmission on May 26th, when in reality changes might have occurred due to the initial phase of reopening.

³ Confidence intervals in this report represent the 10th and 90th percentile of the best 50 traces after repeated runs of the model with different sets of parameters and random number generator seeds. These parameters and random seeds allow us to propagate and consider the effect of both parametric and stochastic uncertainty (see Appendix 3).

Model estimates

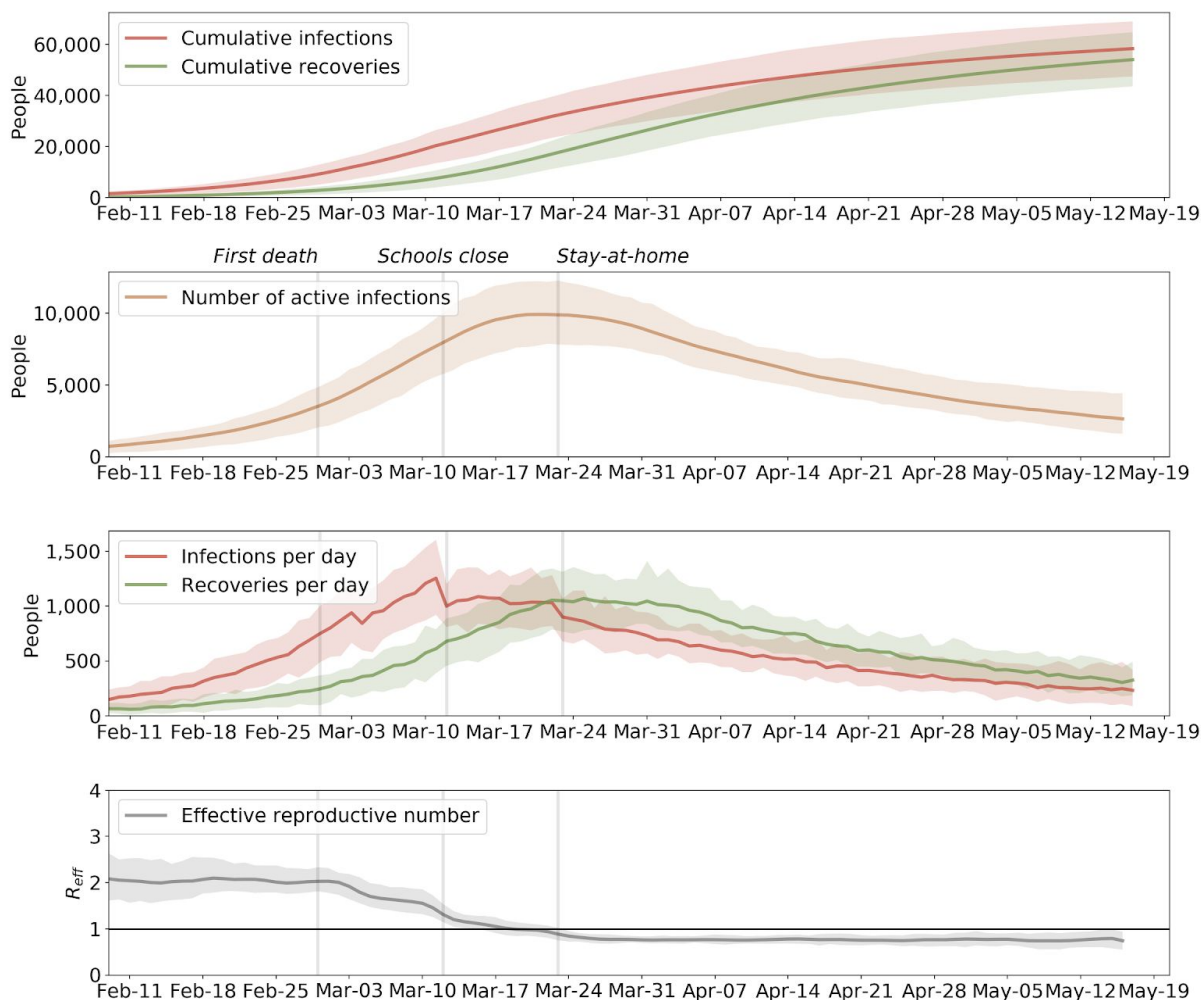


Figure 2: Model estimates showing key trends over time. Solid lines represent the median of repeated runs of the model with 500 parameter sets and 20 random seeds. The shaded region indicates the lower and upper bound of the top 25 of these replicates. These intervals represent a combination of parameter and stochastic uncertainty.

It is important to note that this 33% of baseline number represents a combination of 1) people spending more time at home, and 2) increased use of non-pharmaceutical interventions, such as frequent handwashing, the wearing of face masks, and physical distancing, when at workplaces or when in the community.

Balanced reopening and the need for countermeasures

In the absence of a vaccine, other mitigation efforts, including testing, tracing, and quarantine, will need to be used to control the spread of COVID-19 as physical distancing measures are relaxed and people begin to resume pre-COVID levels of activity.

The goal of this analysis is to quantify the delicate balance between relaxing physical distancing and increasing countermeasures so as to keep the epidemic under control. To do this, for a set of

intervention scenarios, we swept a range of values representing increasing levels of transmission potential at work and in the community beginning on May 26th. For each value, we computed the mean effective reproductive number⁴ by averaging over the period from May 26th through the end of the evaluation period, July 31st. We applied linear regression with the input of the transmission level and the output of the effective reproductive number to estimate the transmission potential that corresponds to an effective reproductive number of 0.9.

Figure 3 (left) shows the effective reproductive number over time for the baseline scenario in which the transmission potential in work and community layers is 33% of baseline levels. On May 26th, we simulated increased transmission in these layers at 40% and 50% levels without any additional testing, tracing, or quarantine countermeasures. These hypothetical increases in the transmission potential at workplaces and in the community correspond to people returning to work, spending time in the community, or using fewer personal precautions like masks. R_e is estimated to be below 0.9, so the 30% scenario always maintains epidemic control. We find that the 40% scenario has a mean R_e near 0.9, while the 50% of baseline transmission potential simulation has a mean R_e above 1.0, indicating a return to exponential growth without additional interventions.

Figure 3 (right) shows the mean R_e as a function of the percent of baseline transmission occurring in work and community layers, with these individual realizations as dots. We highlight the transmission level that corresponds to a value of $R_e=0.9$, our target level for this analysis.

For this scenario, we find that on May 26th we could increase the transmission potential from the 33% of baseline level to 36% of baseline while still maintaining epidemic control. Interventions, such as contact tracing, will enable control to be maintained at higher levels of work and community transmission. This result should be viewed with caution as it inherently assumes there have been no increases in transmission potential since April 25th. These changes, which are expected due to Phase 1 reopening, would not be apparent in epidemiological data due to lags in symptom onset and testing data, and thus would have been missed by our calibration procedure.

⁴ The effective reproductive number is the average number of secondary infections that are caused by each newly infected person. If it is below one, then the epidemic will gradually die out; if it is above one, it will increase exponentially unless herd immunity is reached; if it is at one, then the number of new cases will stay constant over time.

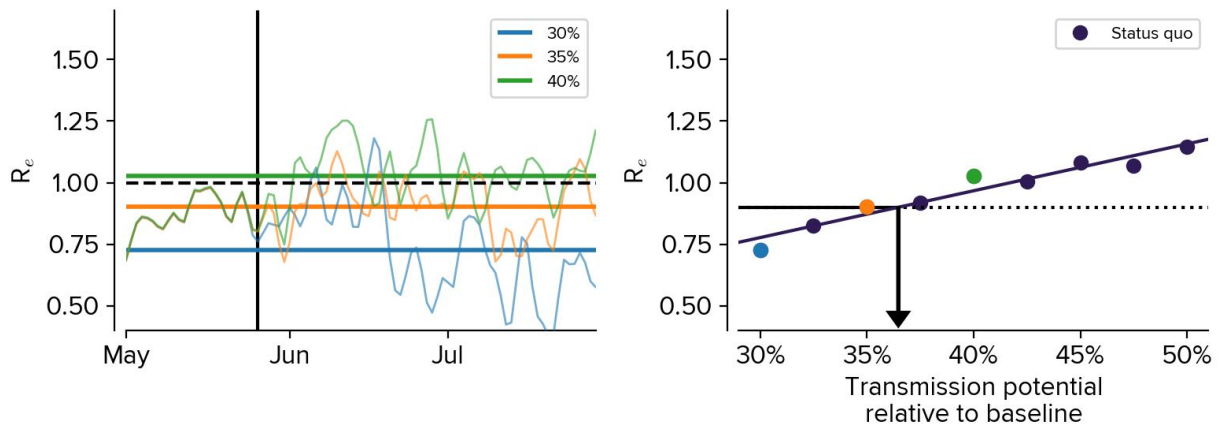


Figure 3: Finding the balancing point. **(Left)** Time-series view of the effective reproductive number for simulation realizations at three levels of work and community transmission on May 26th. Horizontal lines indicate the mean R_e from May 26th through July 31st. **(Right)** Mean effective reproductive number as a function of the transmission occurring in work and community layers relative to the baseline level of transmission occurring in these same layers. Increasing values on the x-axis of this figure correspond to increases in people at work and/or reductions in personal precautions like hand washing and masks. The maximum percent of baseline transmission for which this curve remains below $0.9 R_e$ is about 36% for this scenario⁵.

An example scenario balancing increased transmission with countermeasures

The level of mitigation necessary is dependent on the extent to which transmission increases in work and community layers. To explore this tradeoff, we considered a scenario in which transmission in these layers increased to 75% on May 26th. Without mitigation, we see a rapid return to exponential growth in infections, and the number of daily infections exceeds the previous peak by mid-June (see the black trace in the top panel of **Figure 4**). The daily number of tests remains about constant, as shown in the black trace in the bottom panel of the figure. The effective reproductive number jumps from 0.9 to 1.6 soon after the reopening. To mitigate this exponential growth and bring the effective reproductive number back down below 1.0, we found that the following hypothetical combination was sufficient:

- Schools remain closed.
- Home isolation for diagnosed individuals, and quarantine of other household members (with 90% compliance), beginning presumptively on the day of testing.
- 70% of workplace contacts are found and quarantined after a 2-day delay.
- Individuals in quarantine are tested for COVID-19. The daily probability of testing is 90% if symptomatic and 10% otherwise.
- Quarantine lasts for 14 days. For those in quarantine we assume transmission is reduced. Relative to pre-quarantine, transmission after quarantine is: household=80%, community=30%, work=0%. Similarly, if an individual is diagnosed, we assume their transmission potential is reduced, relative to pre-diagnosis: household=30%, community=10%, and work 0%. Percentages are applied to the per-day probability of transmission for each contact.

With this testing, tracing, and quarantine intervention in place, the result is shown in the violet color in **Figure 4**. Because the effective reproductive number is approximately 1.0, the top panel shows that the

⁵ For the purpose of this analysis, we swept the reopening level through 14 levels between 0.3 and 0.7, and report the greatest level at which $R_e \leq 0.9$. In the future, we will perform a regression and report the opening level at which the regression crosses $R_e = 0.9$. This 36% number is different from the 38% we report elsewhere as this is just one of the 50 input parameter configurations we evaluated.

daily number of new infections remains constant. The number of daily tests increases, as shown in the bottom panel, because of two reasons. First, this scenario has twice as much testing, so the daily rate increases from about 2,000 to 4,000 per day. Second, the intervention includes testing of individuals who are in quarantine. This intervention is sufficient to bring the effective reproductive number back down to approximately 1.0 despite the increase of the transmission potential in work and community layers.

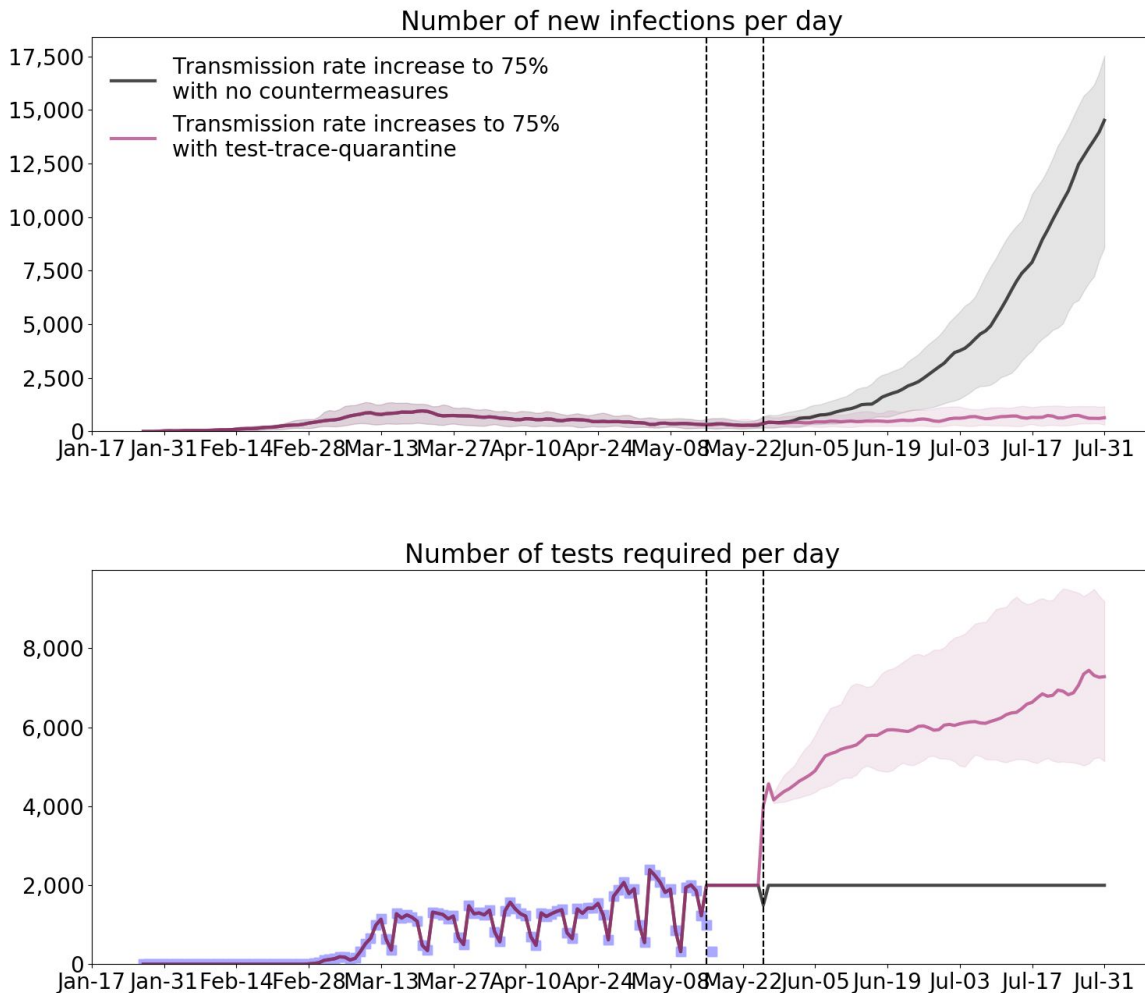


Figure 4: Increasing work and community transmission to 75% of baseline levels while maintaining status quo (black) and with test-trace-quarantine+more testing (violet). The top panel shows the daily number of infections growing exponentially after the day of reopening in the case of status quo countermeasures while test-trace-quarantine intervention maintains a general trend of decreasing daily infections. The bottom panel shows the number of daily tests used by the two scenarios with King County data overlaid for the historical period through May 10th indicated by purple squares.

How much mitigation is necessary?

For any particular level of increase in workplace and community transmission, a variety of different interventions could be used to restore the effective reproductive number to a level below 1.0. Instead of asking which combinations of interventions will balance a specified increase in transmission, we turned the problem around. For a specific intervention, we ask what level of transmission in work and community settings will result in an effective reproductive number just below 1.0. For this analysis, we

have selected a threshold value of $R_e=0.9$ in order to provide some buffer in the event of disruptions in testing or contact tracing, superspreader events, and other potential factors that could jeopardize containment efforts.

With this approach, we explored four possible mitigation scenarios⁶, which build on each other:

1. **Status quo:** Maintains current levels of testing (2,000 per day) with no additional mitigation efforts. Test results are returned in 2 days.
2. **Household quarantine:** On a positive diagnostic test, an individual will be quarantined along with 90% of household members⁷.
3. **+ presumptive quarantine:** Individuals and members of their household (90% compliance) are quarantined when one member is being tested..
4. **+testing, tracing, and quarantine to workplaces:** 90% of a person's household contacts are quarantined when the test is taken and tracing of workplace contacts starts (70% quarantined after 2 days). We assume that community contacts cannot be traced. Individuals in quarantine have a daily probability of receiving a diagnostic test. If symptomatic, the daily probability is 90%. For those without symptoms, the daily probability is 10%. Tests applied in quarantine are additive to daily test capacity.
5. **+ faster and more testing:** In addition to the scenarios implemented in (4), we assume 2 times the number of daily tests are available for finding new cases and the mean delay from symptom to test is reduced by a factor of 2.

Figure 5 shows one bar for each of these four scenarios. The height of the bar is the transmission level in work and community layers that drives the effective reproductive number to 0.9 on average. Increases in transmission above these bars risks a return to exponential growth. We report mean values, but due to uncertainty, a safer estimate would come from the bottom of each error bar.

First, without any additional countermeasures, we estimate that a small increase in work and community transmission potential was possible from the level set in the model on April 25th while avoiding a return to exponential growth. While the model shows that the potential transmission could be up to 38%, we urge caution in acting on this result as recent efforts to reopen as part of Phase 1 are not explicitly included in our counterfactual scenario. Transmission increases due to these activities will not be visible in epidemiological data for another week or two. This is a simple result stemming from the fact that the point estimate of the R_e was sufficiently below 0.9 before simulating reopening on May 26th.

Second, we found that high compliance (90% assumed) with household quarantine is able to counteract slightly higher levels of transmission in work and community layers, allowing an increase over status quo to above 40% of “normal” pre-COVID values. Acting quickly by presumptively quarantining the household on test instead of waiting for results gives a small additional gain. The benefits of presumptive quarantine would need to be carefully weighed against the risk of individuals not seeking COVID tests to avoid burdening household members with quarantine. Quarantining presumptively gains

⁶ To be clear, these are just exploratory scenarios. We have not considered the feasibility of implementing these scenarios.

⁷ We assume that undiagnosed individuals in quarantine will reduce their community contacts by 70%. However, because all household members are quarantined together, there is a continued risk of household transmission. We have assumed that quarantined individuals will take precautions to reduce their chance of infection by 20%.

the one or two days it typically takes to return test results. However, the delay from the beginning of the infectious period to receiving diagnostic results is already very long, nearly two-thirds of household contacts will already be infected before results are returned. Presumptive quarantine, contact tracing, and public health messaging to reduce the delay between symptom onset and testing are needed jointly.

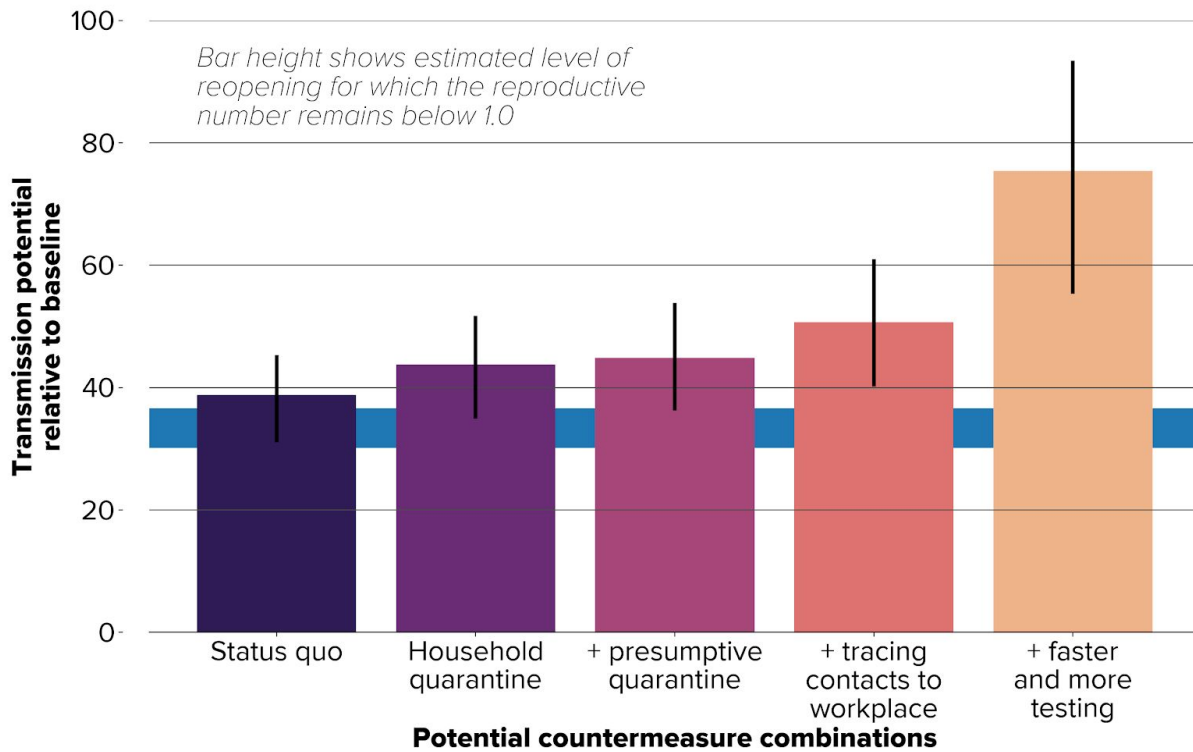


Figure 5. For each possible countermeasure described fully in the text above, we plot the level at which work and community transmission can be sustained while keeping the effective reproductive number below 0.9. Countermeasures combine incrementally from left to right. Greater transmission levels can be balanced by more powerful and resource-intensive interventions. The blue dashed line shows the interval 30-37%, our estimate of the percentage of work and community transmission occurring relative to baseline. Bar height is the mean of 50 samples, and error bars show 10% to 90% percentile.

Finally, the most comprehensive package of countermeasures we considered is able to balance a doubling of disease transmission potential at work and in the community (from 33% to 75%) . While we do not see a return to full normal given these intervention scenarios, these results do not preclude more than a 75% return to normal activities provided other precautions, such as the mandatory use of face masks or voluntary hotel isolation programs (which could further limit household transmission), are used broadly. However this set of potential countermeasures represents a significant improvement in testing capacity, speed, and efficiency paired with TTQ policies affecting both households and workplaces. Note that a more conservative estimate would come from the bottom of the error bar, near 56%.

Conclusions

We used a new agent-based model of COVID-19 transmission and interventions in King County, Washington, to estimate the extent to which several quarantine and contact tracing interventions could counteract increased disease transmission at work and in the community. These transmission increases are expected as physical distancing and stay at home orders are relaxed because [95%](#) the population remains susceptible to COVID.

We calibrated this model to age-stratified epidemiological data, including tests, diagnoses, and deaths. Results of this calibration suggest that work and community transmission has fallen dramatically compared to the beginning of the outbreak. Compared to this baseline, we estimate that transmission at work and in the community has fallen by 67% (to 33%).

Our results have two main findings. First, under “status quo” operations, we estimate that the effective reproductive number is approximately 0.78 (0.61-0.93) in King County, and therefore a small increase in work and community transmission is possible while avoiding a return to exponential growth. Second, a fairly comprehensive (but non-exhaustive) package of countermeasures including pairing an expanded and improved testing system with presumptive household quarantine and workplace tracing was able to support a more than doubling of the disease transmission potential at work and in the community (from 33% to 75%). These changes in transmission were assumed to occur on May 26th. However, even with these countermeasures, transmission can return only to 75% of initial levels, far from the 100% that represents “normal” full employment without personal precautions. However, some of the difference between 75% and 100% could be made up for by wearing face masks, maintaining physical distance, frequently washing hands, environmental modifications, and/or other countermeasures.

These findings do not account for additional non-pharmaceutical interventions, like face masks or voluntary away-from-home isolation, that may enable more people to physically return to work, if taking appropriate precautions. At the same time, implicit in our results is an assumption that nothing has changed with respect to disease transmission over the past few weeks. Any changes or increases in transmission that may have happened during this period would not be apparent in case or death data due to lags inherent to COVID infections and the reporting processes. In fact, there have been [significant increases in traffic](#), likely related to reopening activities or distancing fatigue. We urge strong caution and a slow and incremental approach to reopening.

This analysis leverages the physical mechanisms and detail of the Covasim agent-based modeling tool to inform decision making. However, like all modeling analyses, this work is subject to many assumptions and limitations, some of which are described above. In particular, this report is agnostic to other variables which will undoubtedly impact health policy choices, including cost, logistics, and supply constraints. We are conducting this research in support of public health partners who are better suited to account for these constraints.

Appendix 1: Comparison to IDM transmission modeling results

This report introduces the use of Covasim, an agent-based model, for the analysis of COVID-19 transmission and interventions in King County. This model increases the resolution and realism of the modeling efforts compared to other models such as compartmental frameworks (e.g., SEIR). This change in methodology is necessary for more detailed analyses such as the ones presented in this report. Our calibration results are consistent with [previous results](#), which used compartmental models, see **Figure S1**. In the top panel, the mean COVID-19 prevalence estimated by Covasim (dashed black) is in agreement with RAINIER-based estimates (red). Similar consistency in the results can be seen for estimates of cumulative incidence (center panel) and the effective reproductive number (bottom panel). Of these, the Covasim result is higher in prevalence, but similar in cumulative incidence and R_e . This discrepancy is likely explained by longer recovery periods assumed in Covasim, since this model takes into account the fact that people with severe and critical disease take longer to recover.

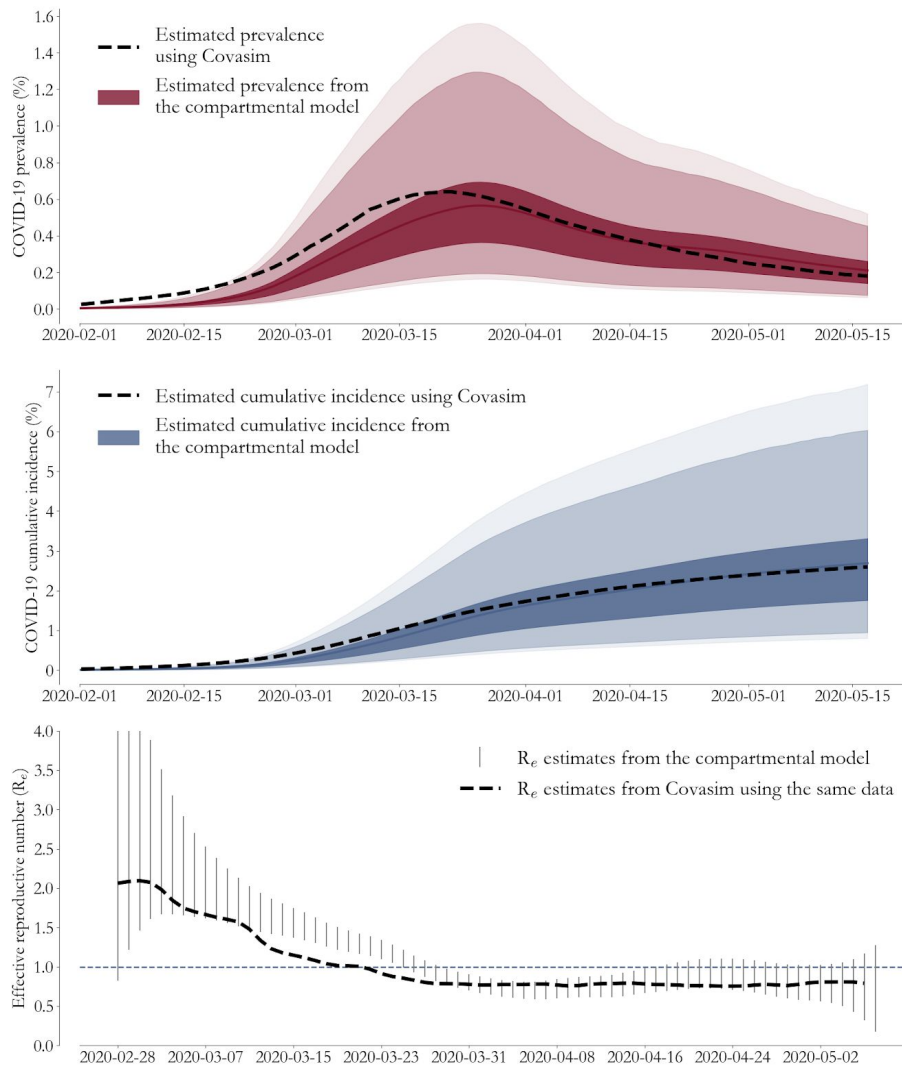


Figure S1: Comparison between Covasim and a RAINIER-based model used in other IDM COVID-19 transmission modeling estimates. Covasim estimates are shown by dashed black lines, whereas RAINIER-based estimates are represented by solid lines (50% CI dark, 95% CI light, 99% CI lightest) on the top two panels, and by 2 standard deviation error bars in the bottom panel.

Appendix 2: Delays between exposure, infectiousness, and testing limit the potential impact of interventions

A key factor in modeling the test, trace, and quarantine intervention is the delays between exposure, onset of symptoms (if any), and diagnostic testing. **Figure S2** shows our modeling assumptions for these distributions for the calibrated model. The first two distributions come from literature⁸ whereas the delay from symptom onset to diagnostic testing stems from daily testing probabilities that are higher for symptomatic individuals than asymptomatic, presymptomatic, and uninfected individuals. This distribution can be compared to self-reported data obtained from WDRS as shown in the final panel of Figure S2. This King County distribution has a median of 4 days, and may be biased due to recall and other systematic errors.

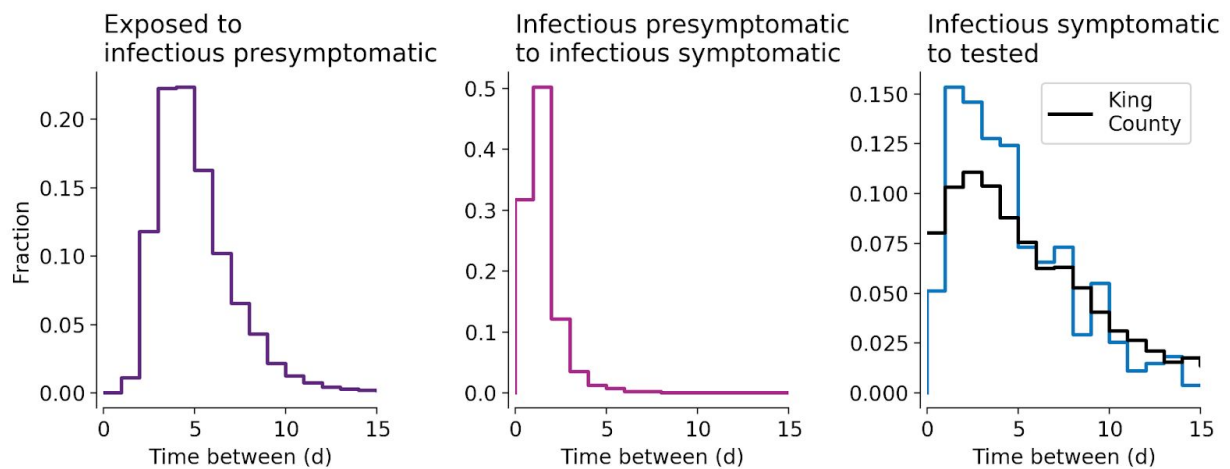


Figure S2: Distribution of the time people in the simulation spend between different disease states (exposed, infectious presymptomatic, infectious symptomatic) until tested. The third panel additionally shows the distribution of delays from self-reported onset of symptoms to date of diagnostic testing for King County (black).

⁸ See Table 1 of the [Covasim methods article](#)

Appendix 3: Calibration of model parameters

To fit Covasim to epidemiological data from King County, we simultaneously adjusted a total of 14 model parameters, see **Table S1** and bold values in **Table S2**. These parameters include the underlying probability of transmission per contact per day, and the number of infections seeded at the beginning of the simulation on Jan. 27th. We also calibrate two testing parameters that determine the extent to which diagnostic tests are consumed by individuals symptomatic with COVID. We calibrate one constant value before March 8th, one from March 8th to April 27th, and another after April 27th.

Finally, we calibrate several transmissibility attenuation factors that are applied on different environments (i.e., households, schools, workplaces, and community) at trigger event days that have occurred since early March. These events are:

- **March 4th**: Early work-from-home policies
- **March 12th**: School closures
- **March 23rd**: “Stay home, Stay healthy” order
- **March 30th**: Changes in social-distancing and mobility patterns
- **April 25th**: Changes in social-distancing and mobility patterns

Parametric fitting is done using [Bayesian optimization](#). We use uniform priors for each of the parameters. The optimization algorithm outputs samples that characterize the parameter space. For the results in this report, we use 50 samples of the parameter space to propagate parametric uncertainty through model simulations. These 50 samples (input parameter configurations) are selected along with the seed of the random number generator to ensure a good and reproducible fit to historical data.

Table S1: Calibrated model parameters.

Description	Median Value (10th, 90th percentiles)
Basic probability of transmission per contact per day	0.012 (0.011, 0.014)
The number of infections seeded on January 27	38.5 (11.2, 58.3)
Odds ratio of a symptomatic person being tested (vs. an asymptomatic or uninfected person), used from January 27 th to March 8 th	250
Odds ratio for testing, as above, used from March 9 th to April 27 th	69 (49, 91)
Odds ratio for testing, as above, used from April 27 th through end of simulation	57 (27.3, 78)

Table S2: Estimated transmission rates relative to baseline. Increases in household transmission are driven by school and workplace closures. Bold values were calibrated. Reporting median, 10th percentile and 90th percentile of top 50 parameter sets. Numbers in the text are derived from the mean of workplace and community layers values for each date.

	Before Mar. 04	Mar. 04	Mar. 12	Mar. 23	Mar. 30	Apr. 25 onward
Households	100%	100%	110%	120%	120%	120%
Schools	100%	100%	0%	0%	0%	0%
Workplaces	100%	71% (56%, 83%)	41% (33%, 47%)	26% (23%, 28%)	33% (27%, 34%)	32% (27%, 34%)
Community	100%	65% (53%, 84%)	40% (30%, 49%)	23% (22%, 28%)	29% (26%, 33%)	29% (26%, 33%)