Physical distancing is working and still needed to prevent COVID-19 resurgence in King, Snohomish, and Pierce counties

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April 16, 2020 addendum: We added a discussion of our results' implications for the future.

What do we already know?

Physical distancing interventions have been the primary tools for suppressing COVID-19 transmission. Our previous analysis of case and mobility data showed there were significant reductions in the rate of transmission in King County, WA associated with the rollout of physical distancing policies. We also found that measured reductions in regional mobility were positively correlated with reduced transmission of COVID-19.

What does this report add?

We updated our daily estimates of the effective reproduction number using case data from WADoH through March 30 and regional mobility data through April 7. We estimate that the effective reproduction number in King County declined further through March 25 to somewhere between 0.3 and 1.2 (point estimate 0.73). This decline exceeded the short-term forecast in our previous report and reflects further reductions in COVID-19 transmission. In addition, the decline in transmission may not fully be explained by mobility covariates and may be evidence of additional beneficial changes at the household and individual levels. Finally, we quantify similar declines in transmission for Snohomish and Pierce counties.

What are the implications for public health practice?

Our collective efforts to limit physical interaction across society have stabilized the rate of spread of COVID-19, but the situation remains precarious with the effective reproductive number near and possibly varying above and below one. Continued adherence to physical distancing policies remains necessary to further reduce transmission; otherwise, rebound transmission is likely to occur.

Executive summary

To stem the spread of COVID-19, Washington State has instituted increasing levels of physical distancing policies, including closing schools, prohibiting large group gatherings, closing non-essential workplaces, and providing information to the public about how to modify behavior to reduce transmission during essential activities.

In this report, we update our quantitative assessment of the impacts of these policies on COVID-19 transmission in King, Snohomish, and Pierce counties. Relative to the last report, **we find that the epidemic has slowed further and that the effective reproduction number (R_e) in King County in late March was near and possibly below one**, with a point estimate of 0.73 and 95% confidence interval

ranging from 0.3 to 1.2 on March 25. Similar trends are observed for Snohomish and Pierce counties, although we estimate that changes in Pierce County lagged changes in the other two.

To estimate the R_e through April 7, we continued to leverage [Facebook Data for Good Project - Disease Prevention Maps](#), and we also looked at the impact of Governor Inslee's "Stay Home Stay Healthy" announcement. In King County, we see additional beneficial change co-occurring with the rollout of "Stay Home Stay Healthy" that is not reflected in our mobility covariate; this may represent delayed impacts of community distancing on reducing household transmission and additional behavior changes that reduce individual risk, but more evidence is needed to understand causes. Still, the overall nowcast predicts that R_e is no longer changing and remains near one. As a result, **while current levels of adherence to physical distancing policies are effectively controlling the rate of spread of COVID-19, the region is in a precarious state and must maintain distancing to prevent rebound transmission**.

These results remain encouraging for the people of King, Snohomish, and Pierce counties and speak to how we have been both responsive and responsible to each other during this epidemic. But continued progress and protection for everyone will require persistent adherence to physical distancing policies until more nuanced control options become available to maintain R_e less than 1 and prevent a resurgence in the rate of transmission.

Key inputs and assumptions

WA COVID-19 lab testing:
As described in our [previous report](#), we use lab testing data provided by Washington State Department of Health (WADoH) through the [Washington Disease Reporting System (WDRS)](#). Daily positive and negative COVID-19 tests were aggregated across testing facilities to county level by WADoH. Tests were assigned to days based on the specimen collection date. Note that we are using a version of this dataset compiled on April 3. Retrospective changes occasionally occur as data is compiled, and to hedge against this instability, **we use data only up to March 30.**

A key assumption of the model is that case data from February 28 to March 30 can be treated as a sample representative of community transmission in King and Snohomish counties and that the same is true for Pierce county from March 5 to March 30. In the models, daily changes in cases during these periods are correlated with changes in the number of active infections instead of changes in the availability or targeting of testing. The case-to-infection rate for each county, sometimes called the reporting rate, is assumed to be an unknown constant in this analysis and will eventually be treated as time-varying as we gather more data in the future.

In the data, the number of daily tests has been roughly stable since March 12, but was lower before then. Early in the outbreak, the constant reporting rate assumption may bias our point estimates of R_e and it contributes to the wider confidence intervals relative to later in the outbreak. For the purposes of this work in King, Snohomish, and Pierce counties, where the number of COVID-19 tests per day have generally increased or remained constant over these periods, we view the assumption of a constant

reporting rate as conservative. Scale-up of testing will be interpreted by the model as an increase in the number of COVID-19 infections.

Facebook mobility data:

We used data from the [Facebook Data for Good Project - Disease Prevention Maps](#) to track changes in population and mobility between regions over time. **These data are collected from mobile users with location services enabled and are aggregated to coarse geographic levels as anonymous counts of users; individual users cannot be identified.** On a typical day, data are captured from around 230,000 people across the Puget Sound region. For more about these data, see this [separate report](#). We emphasize we are not directly measuring reductions in social contact, but rather changes in mobility and the places where people are spending their days.

For this report, we used the same mobility covariate we [used previously](#), with several days of added data. The covariate captures location-specific changes between day and night population occupancy and is shown in Figure 1, below. For each 0.6 square kilometer tile we calculated the absolute value of the difference between day (9am to 5pm) and night (1am to 9am) population occupancy, divided by nighttime population occupancy for each tile. This absolute relative difference was then averaged across all tiles for each day, weighted by population occupancy. Note that data were available for the western part of King County, and that tiles with fewer than 10 observed users were excluded from the data for privacy concerns.

By the time Governor Jay Inslee announced his "Stay Home, Stay Health" order, the day-night population fluctuation in King County had reached a new steady-state, and the time trend has ceased declining. This should not necessarily be interpreted negatively, since mobility does not need to continuously decline in order for transmission to decline. Furthermore, the relationship between mobility and transmission can change over time, for example, early into social distancing already infected people can infect co-habitants. Over time we expect household transmission to decline, both as community transmission declines and as high-risk households are likely to have already been infected and thus no longer susceptible. Individual behavior changes, like improved hand hygiene, mask use, and other distancing behaviors may not be reflected in the saturated mobility covariate. For these reasons, we have also included an added effect of the "Stay Home, Stay Healthy" policy in the statistical model. Since we only have a few overlapping days of data, it is included as a constant effect only after March 23.
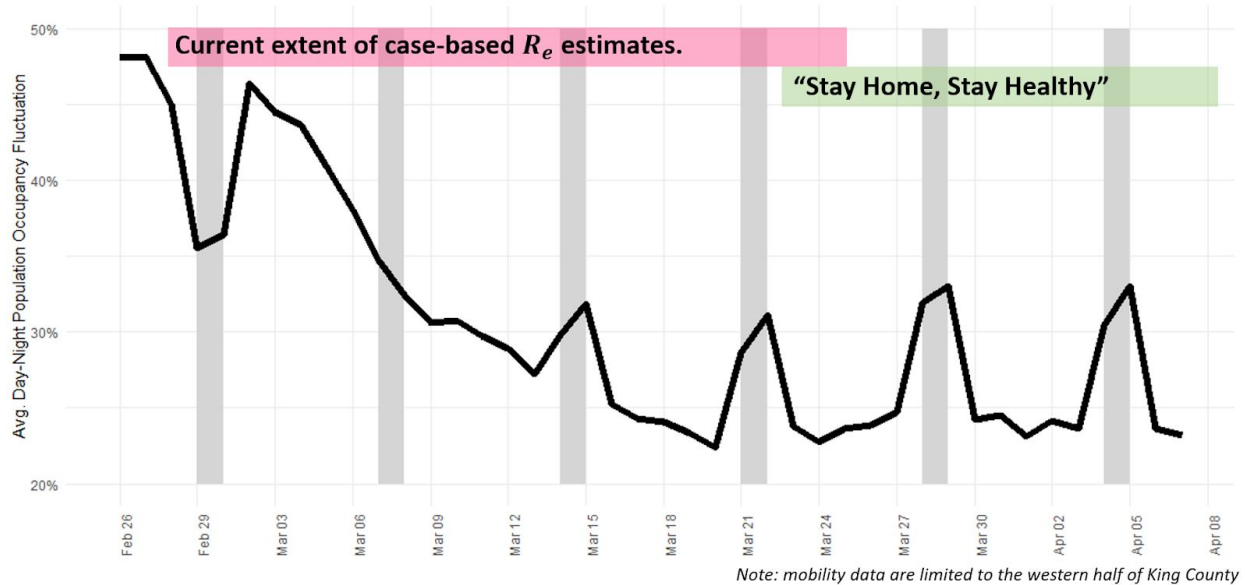
Figure 1: Black trend line shows the day-night population fluctuation covariate daily average since February 26th. There is an observable drop-off in this measure of mobility which started in early March and had apparently reached a "steady state" saturation point around the time that Stay Home, Stay Healthy was declared. The pink bar indicates the date range for which we can make estimates of R_e based on WDRS data.

Modeling approach

We fit a COVID-specific transmission model to daily case counts. The key modeling assumption is that individuals can be grouped into one of four disease states - susceptible, exposed (latent) but non-infectious, infectious, and recovered. In addition, we assume:

- COVID-19 has a latent period that lasts about 4 days during which infected people are not yet capable of transmission. The choice of a 4 day latent period implicitly assumes that people become infectious on average roughly 1 day before the typical 5-day symptomatic incubation period ends.
- After the latent period, those exposed to COVID-19 are infectious for about 8 days.
- The probability of testing an infected individual is unknown but roughly constant for the modeled period in each county.

We use a multi-step approach to generate daily estimates of R_e, the effective reproductive number. Technical details can be found in the appendix, but concisely, we assume that case data can be scaled up by $1/p$, where p is reporting rate, in order to coarsely approximate the total number of infected individuals. Since COVID-19 infections last roughly 8 days, we expect the number of infecteds to vary with an approximately 8 day timescale, and we smooth the coarse approximations accordingly. A similar procedure is repeated for the number of latently infected individuals (this time smoothing to a roughly 4 day time scale). Comparison of the rates of change of these estimates can then be used to estimate R_e using the transmission model equations in the appendix. Finally, since the reporting rate is unknown,

this procedure is repeated for a range of reporting rates from 0 to 1, and the mean R_e and uncertainty is collected across all reporting rates.

This procedure gives us high variance, daily estimates of R_e in King, Snohomish, and Pierce counties up to March 25. We are unable to estimate R_e from March 26 to 30 because of COVID-19's 4-day latent period.

Updated estimates of effective reproductive number for King County

In our previous report, we made R_e estimates for King County based on epidemiological data up to March 18. Adding data up to March 30 allows us to extend this estimate to March 25 where we infer that R_e is likely between 0.3 and 1.2 (95% confidence interval) with point estimate of 0.73. This is lower than our March 18 estimate, and it suggests that transmission slowed from March 19 to March 24 more significantly than we previously projected (see Appendix 2). Still, on March 25, we are not definitively below the critical $R_e = 1$ threshold for declining transmission. Daily estimates are shown in black with two standard deviation error bars in Figure 2.
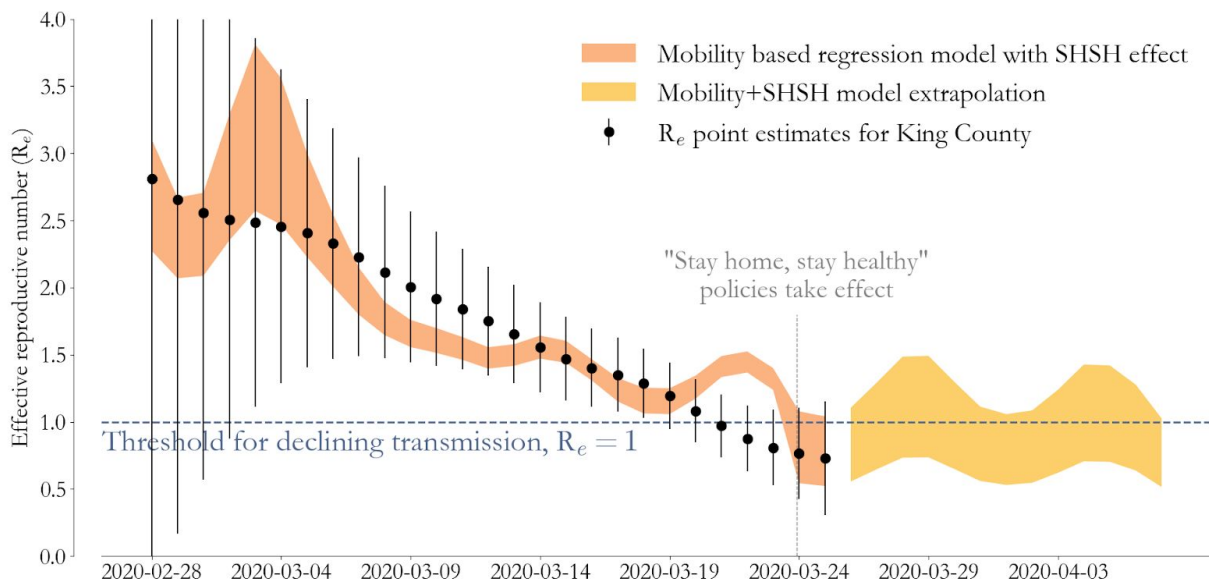

Figure 2. *Daily estimates of the effective reproductive number are computed using WDRS case detection data (black dots, 2 standard deviation error bars). Facebook mobility data can be used to explain R_e variation by fitting a log-linear regression model with a mobility-based covariate and a "Stay Home, Stay Healthy" (SHSH) intercept (95% CI in orange). The fitted relationship between R_e and mobility can be used to extrapolate past inherent delays in the case data due to COVID-19's latent infection period (95% CI in yellow). Recent case data and the extrapolation highlight that further reductions in the rate of transmission may be required to reduce the rate of new COVID-19 cases and that relaxed adherence to physical distancing policies will likely lead to rebound transmission.*

These point estimates, based entirely on the WDRS case data and necessarily smoothed over time by our inference method, have relatively large uncertainty that comes from multiple sources: changes in behavior, under-reporting, and randomness in transmission. Auxiliary data, like those we have captured

on mobility from Facebook, can be used to generate more confident and responsive R_e estimates that can be extended past COVID delays and into real-time. This is shown in orange and yellow in Figure 2. Facebook mobility data is used to estimate the change in population flux between day and night over time (see the Key Inputs section for details), and we combine this mobility metric with a "Stay Home, Stay Healthy" specific effect in a log-linear model fit to the R_e point estimates. **The fitted estimate of R_e on March 25 is 0.75 (with 95% confidence interval from 0.5 to 1.0), consistent with the case data alone but with higher certainty.** While this suggests that while R_e has a high probability of being below 1, it is still not definitive.

Connecting the case data to the mobility data allows us to extrapolate ('nowcast') into the days masked by COVID-19's latent period, after March 25 in this case. The 95% confidence interval for this extrapolation is shown in yellow, where using this measure of mobility we find that increased mobility over the weekends drives increases in R_e, moving our daily estimate above and below 1 regularly. We urge caution in interpretation of the mobility-based nowcasted R_e projections, as in past work we have found resulting projections to be sensitive to the mobility covariate used, and we still do not have enough data to be confident which mobility measure best explains transmission reductions.

Since our last report, we have added a term in the model to capture the effect of "Stay Home, Stay Healthy". Adding this intercept term improves agreement with the epidemiological data over using the mobility covariate alone because it allows the model to better fit the decline in transmission in the last few days. This suggests that additional effects, such as reduced household transmission and individual behavior changes may also be contributing to declining COVID-19 transmission in King County. In general we do not expect direct correspondence between steady-states in mobility and in transmission, and as we collect more case data, we will be able to learn more about the impact of particular physical distancing policies on COVID-19.

Pierce and Snohomish counties show similar trends
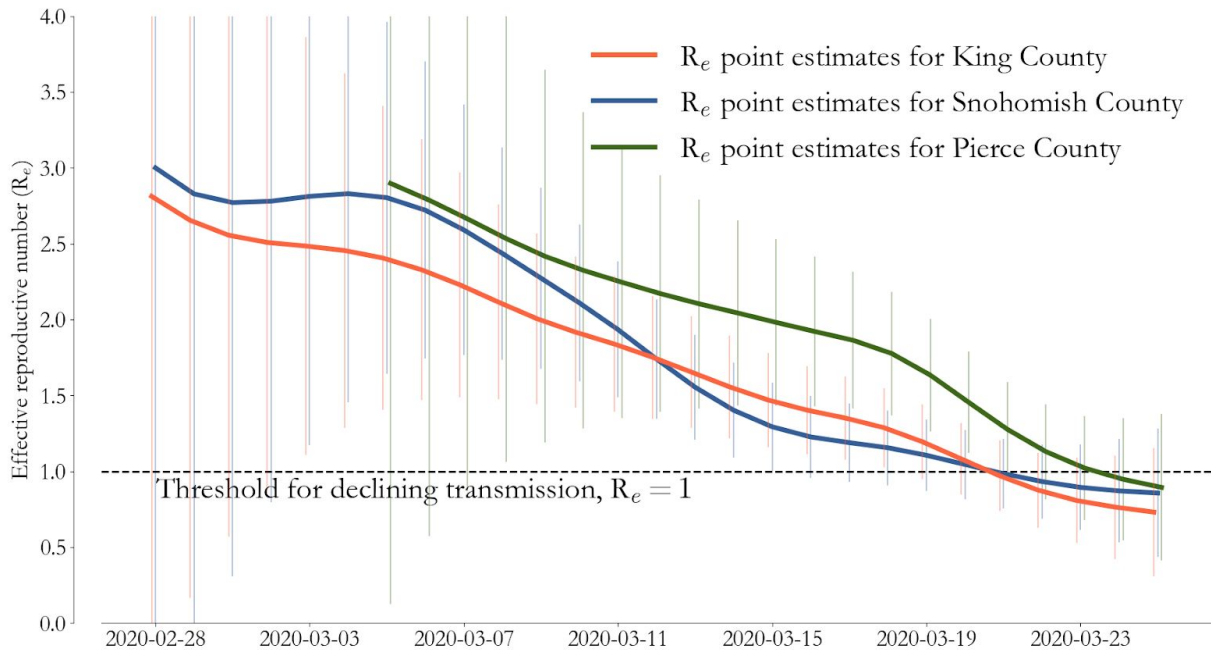

Figure 3. *Daily estimates of the effective reproductive number computed using WDRS case detection data for King (red), Snohomish (blue) and Pierce (green) counties with two standard deviation error bars. Trends across all three counties generally agree, demonstrating that social distancing has been more widely effective. Still, estimates suggest that all three counties are in a similar, precarious position near $R_e = 1$.*

We repeated the analysis of the WDRS data for Snohomish and Pierce counties. We use a truncated analysis period in Pierce County because testing ramp-up happened somewhat later than in Snohomish and King. Overall, as shown in Figure 3, we find that all three counties have similar trends in R_e based on each county's epidemiological data, with R_e starting at roughly 3 early on and declining to about 1 by March 25. While this suggests widespread adherence to physical distancing across all three counties, it also highlights the danger of our current position since reduced adherence within a county will lead to rebound transmission and increased importation to its neighbors. Moreover, we see that King and Snohomish have more closely related R_e trends than Pierce, where declines in R_e lagged by roughly a week. This hints at more general heterogeneity across counties in Washington that we plan to quantify in the future.

April 16, 2020 addendum: Model based projections for King County depend entirely on future behavior

Given estimates of R_e over time in King County, the associated COVID-19 transmission model (see Appendix 1) is fully specified, and we can use the model to estimate the daily number of reported cases over time under the assumption that testing capacity remains roughly unchanged. Critically, pushing these estimates into the future requires us to make some assumptions about how we expect R_e to change in the future. As we noted above, since the relationship between mobility, policy, and COVID-19

transmission is still unclear, we cannot be confident in these expectations. That said, comparisons across different future scenarios illustrates the precarious situation in King County.
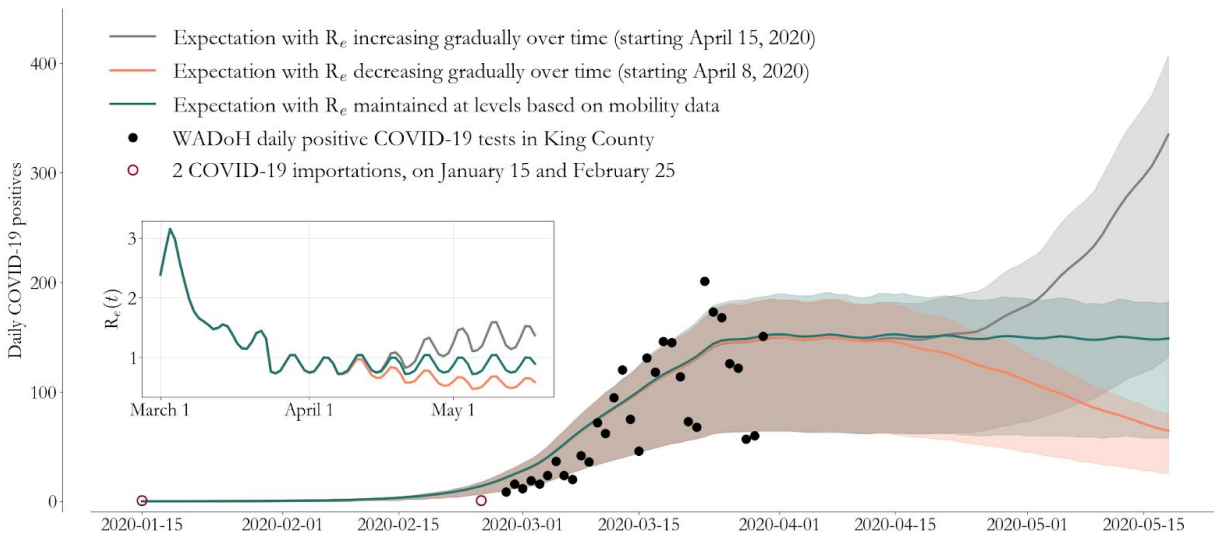

Figure 4. *Model based projections under 3 scenarios, shown in the inset. Gradual increase in effective reproductive number (grey), maintenance (green), and gradual decrease (red) lead to dramatic changes in projections of COVID-19 cases in King County (50% confidence intervals for each scenario). Since we do not yet understand the relationship between mobility data, policy choices, and COVID-19 transmission, we cannot say with confidence which scenario is most likely.*

This is shown in Figure 4. We compare 3 scenarios (inset), gradual increase in R_e associated with relaxed physical distancing policy (grey), R_e remaining near 1 inline with the steady-state in the mobility data (green), and R_e gradually declining further potentially as a result of behavior changes like hand washing and face masks that are not captured by our mobility covariate (red). **In the main figure, all three scenarios rise with the case data from King County (black dots), but they diverge from one another rapidly as a consequence of modest differences in** R_e. At our current state, with R_e at or just below 1, small increases in transmission cause exponential growth in COVID-19 cases in King County.

Limitations

Like all modeling work, this analysis is not without significant limitations. To list a few:
- We have assumed the reporting rate is constant during the period of data evaluated.
- The fitting procedure does not yet incorporate mortality data.
- We have not adjusted for testing specificity (ill patients in hospital vs. general public).
- Age or other heterogeneity in acquisition or transmission is not modeled.
- Mobility is only a proxy for transmission, and its association with transmission changes over time.
- We have not explored the effects of importations into the region.

Conclusions

These results show that COVID-19 transmission in King County has continued declining from March 18 to March 25, where we estimate that the reproductive number is between 0.3 and 1.2 with point estimate

of 0.73 based on epidemiological data alone. These are encouraging results, but we still cannot say with certainty that R_e is below one, and we emphasize that COVID-19 transmission will only be stably under control when R_e is substantially lower than 1.

In Snohomish and Pierce counties, we also found declines in COVID-19 transmission that were largely consistent with findings in King County. But in all three counties, we cannot say with certainty that R_e is above or below 1.

Finally, we used mobility data to improve our model by explaining variance in King County's COVID-19 transmission. We found that changes in day-to-night population fluctuation alone cannot explain the decline, and we augmented our model with a specific effect for changes co-occurring with the "Stay Home, Stay Healthy" announcement. In doing so, we showed that additional beneficial changes occurred concurrent with the announcement, but it is not yet clear if that change is a result of specifics of the policy or of broader changes in household transmission and individual behavior over time in King County.

The mobility-based SHSH model allows us to nowcast King County's reproductive number closer to today (up to April 7). These results are inconclusive: R_e fluctuated around one, with highs due to increased mobility on the weekends. As we better understand the relationship between transmission and mobility, nowcasts will become more certain. But, as it is, our model emphases King County's precarious position on the cusp of COVID-19 transmission increase.

Appendix 1: Estimating the reproductive number from case data

We use the following SEIR model:

$$
\begin{aligned}
S_t &= S_{t-1} - \beta(m)S_{t-1}(I_{t-1} + z_{t-1}) \, \varepsilon_t \\
E_t &= \beta(m)S_{t-1}(I_{t-1} + z_{t-1}) \, \varepsilon_t \; + \; (1 - 1/D_e)E_{t-1} \\
I_t &= E_{t-1}/D_e \; + (1 - 1/D_i)I_{t-1} \\
C_t &\sim Binom(I_t, p) \\
log(\beta(m)) &= \theta_0 + \theta_1 m_1 + \theta_2 m_2
\end{aligned}
$$

Where S_t, I_t, and E_t are the number of people who are susceptible, infected and exposed at time t. ε_t has a zero-mean log-normal distribution, and p is the case detection rate. We assume $D_e = 4$ days for the latent period, $D_i = 8$ days for the infectious period, and z_t is non-zero only on January 15th, 2020 and February 25th, 2020, corresponding to the two large Washington clades on Nextstrain. $\beta(m)$ is the transmission rate per day, m_1 represents the mobility covariate, m_2 represents the SHSH covariate that is zero before March 23 and one after, and θ_0, θ_1, and θ_2 represent the coefficients used to calculate the infection rate by regressing the movement covariate against case-based estimates.
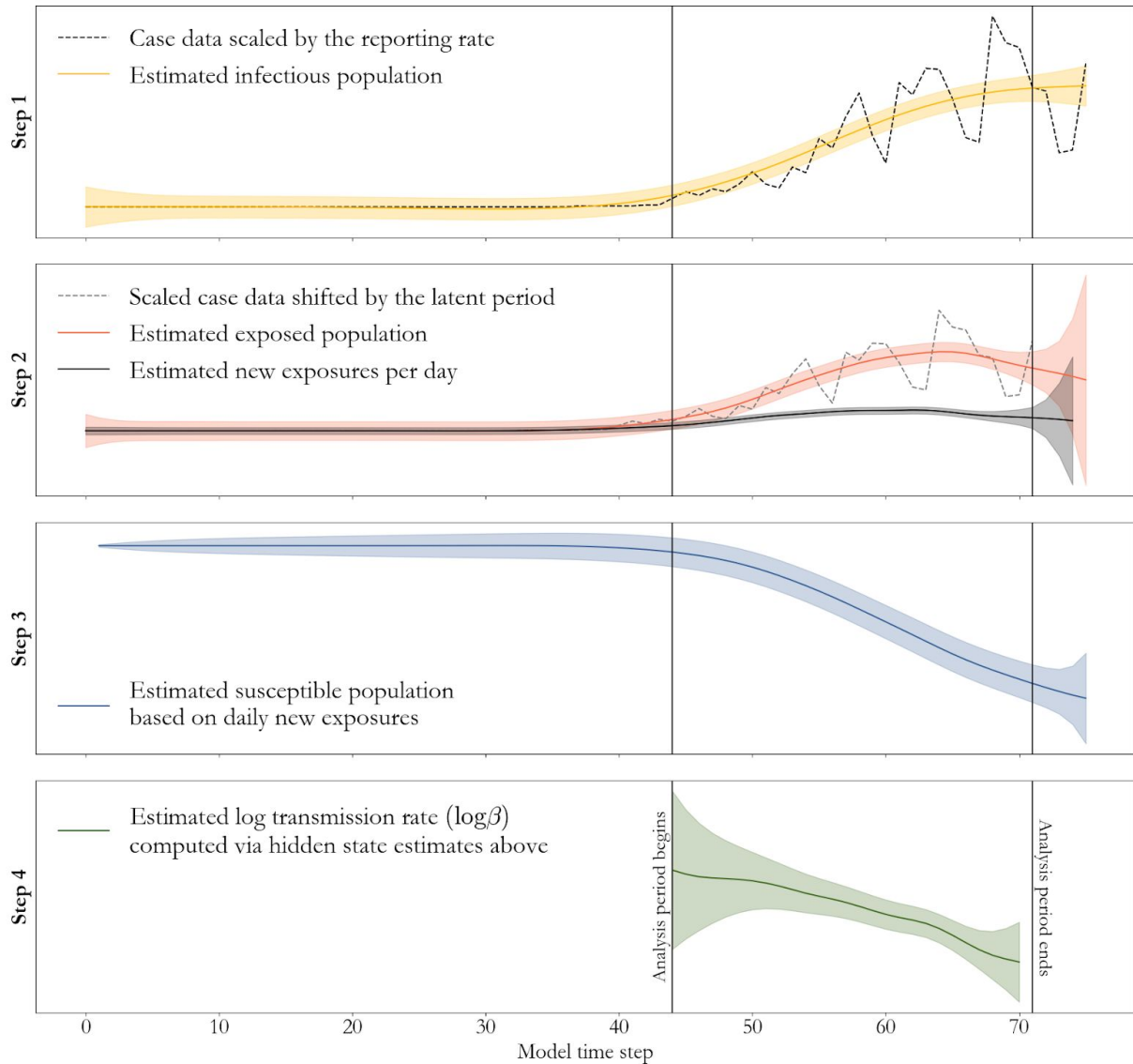
Figure S1. *Unknown parameters such as infection rate are inferred using RAINIER in a multi-step process. **Step 1** - case data is scaled by an inferred reporting rate and smoothed to timescale D_i to obtain I_t. **Step 2** - case data is shifted by D_e, scaled and smoothed to timescale D_e to obtain an estimate for E_t and calculate new exposures. **Step 3** - the susceptible population on a given day is then calculated by subtracting the new exposures from the previous day's susceptible population. **Step 4** - calculation of transmission rate via hidden states.*

Unknown parameters such as the transmission rate $\beta(m)$ are estimated from daily case data. As shown in Figure S1, this is a multi-step process. The critical steps are 1 and 2. In step 1, case data is scaled by a proposed reporting rate and smoothed to timescale D_i to construct an approximation of I_t. Then, in step 2, the same case data is shifted by D_e, scaled (by D_e/pD_i) , and smoothed to timescale D_e to construct an approximation of E_t. Finally, in steps 3 and 4, corresponding approximations for S_t and $log(\beta(t))$ are constructed using the SEIR equations. This algorithm estimates $log(\beta(t))$ conditional on the reporting rate, and it can therefore be used to numerically integrate out reporting rate dependence.

These reporting-rate independent point estimates of $log(\beta(t))$ can finally be used to estimate θ_0, θ_1, θ_2, and the variance in transmission in a standard log-normal regression problem given covariates m_i. In this report, we use 2 covariates, one based on Facebook mobility data (see the Key Inputs section) and another that is zero until March 23 and one afterwards, indicating what times are pre- and post- the "Stay Home, Stay Healthy" announcement in WA.

Appendix 2: Comparison of current and previous estimates and nowcasts

We can compare the estimates of R_e for King County from Figure 1 of our previous report to the update in Figure 2 above. This is done in Figure S2. The daily R_e estimates were similar through March 18 and the additional data in this report supports our conclusion of continued decline in the rate of transmission. With the additional data and an updated mobility covariate, our mobility-informed estimates of R_e trend lower, and the addition of a second intercept term to model changes following the announcement of "Stay Home, Stay Healthy" further improves the regression model's fit for the last few data points albeit with increased uncertainty.
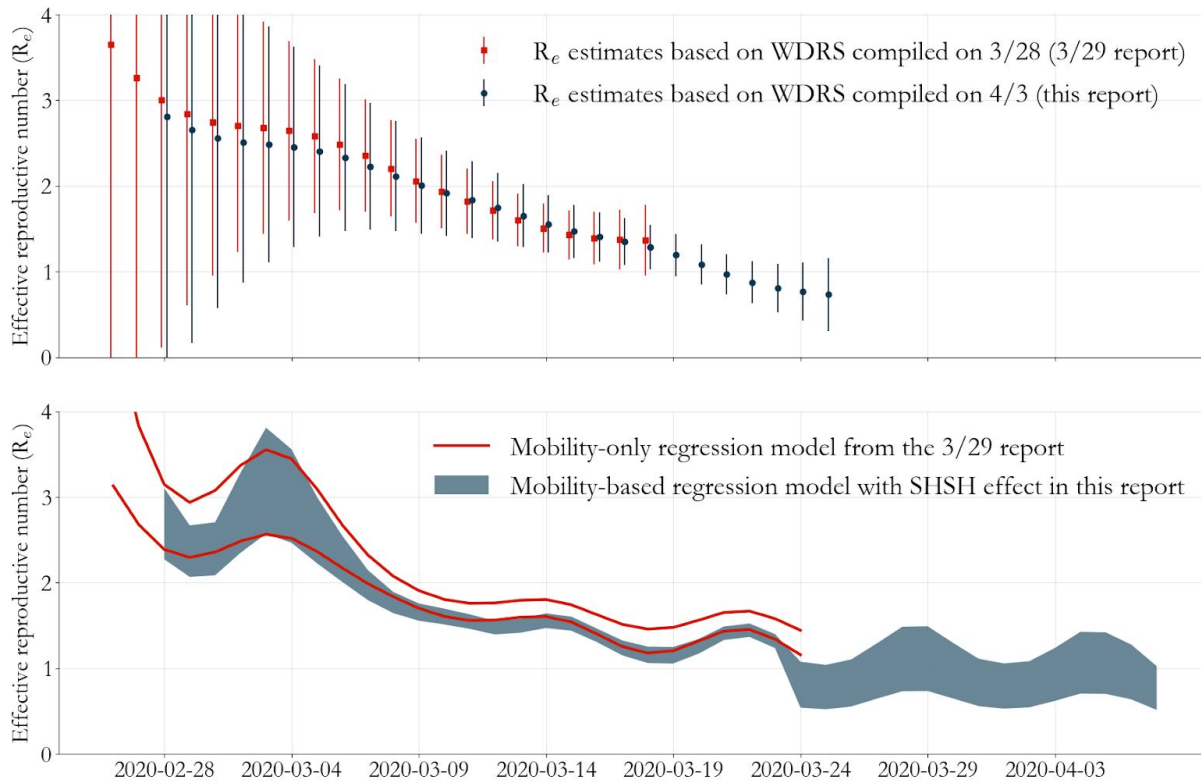

Figure S2. *As case data is updated, we refine our R_e estimates. (Top panel) Estimates from our previous report based on epidemiological data from a WDRS dataset compiled on March 28 (red squares) are compared to our current estimates (blue dots). Error bars are 2 standard deviations. (Bottom panel) Mobility based nowcast from our previous report (95% CI in red) is compared to our most recent nowcast (95% CI in blue). Downwards shift on March 24 is due to the SHSH intercept.*