OHSU COVID Forecast Model

The OHSU model is built on a standard SIR framework by which individuals move between Susceptible, Infected, and Recovered compartments. The model is calibrated using statewide hospital census levels reported by the Oregon Health Authority (OHA).\(^1\) The statewide hospital census is used for calibration instead of case counts or deaths because of the importance of the hospital census as a resource constraint, to avoid the lag incumbent with using deaths, or the disadvantages of case counts being dependent on testing practices.

The model uses empirically estimated (and literature reviewed) assumptions about various parameters of hospitalization for COVID. In particular, it uses an assumption for the percent of diagnosed COVID-19 cases needing hospitalization, time from infection to hospitalization, percent of hospitalized cases using the intensive care unit (ICU), and the length of stay for ICU and non-ICU admissions. The underlying speed of the virus spread is based on assumptions about parameters of the virus absent interventions to prevent spread. Specifically, based on literature reviewed estimates, the model assumes a 5-day doubling period and a 14-day recovery period, which together equates to an R-nought of 3.08. As diagnosed cases represent only a portion of infections, an ascertainment rate from CDC surveillance studies of 3.5 is applied to estimate the true number of infections in the community (e.g., every diagnosed case represents 3.5 infections in our community). The model uses assumptions about the date of first case in Oregon to start the virus spread process.

The model produces an intervention effect which represents how much slower than expected the virus is growing. This approach is described in a paper which describes how to implement optimal control theory to epidemiologic problems (Linn, 2010). The approach introduces a parameter that reflects that effectiveness of policy (or spread prevention behaviors in general) and shows that it can be estimated through maximum likelihood. The intervention effectiveness parameter also provides a mechanism for projected future policy changes. The intervention effect is estimated on a weekly level and thus uses 7 days of worth of census levels for each data point. Due to the complexity of the model, a closed form measure of uncertainty is not available and unfortunately, simulation based measures have not yet been developed. So unfortunately, we are not able to provide a confidence interval for the forecasts. Instead we perform various sensitivity analyses that allow readers to see the impact of changes in various assumptions.

The model incorporates vaccination rates by removing people from the susceptible compartment and adding them to the recovered compartment. This is done by using state reports of the number of people receiving a first dose on certain dates and then using assumptions about the efficacy (measured as a percent) and the number of days until immunity is reached. Previously infected individuals are assumed to be vaccinated in proportion to their relative share of the population. The model also uses assumptions about the length of time to second dose (based on current vaccines in use) and the percent of individuals who may decline second doses. For future projections, the model uses expected vaccine volumes and age priority assumptions stated in official OHA documents, and an estimate for the percent of people who ultimately accept vaccination.

\(^1\) Data available for download at: https://public.tableau.com/profile/oregon.health.authority.covid.19#!/vizhome/OregonCOVID-19HospitalCapacitySummaryTables_15965754787060/HospitalizationbySeveritySummaryTable
Although the model adjusts the hospitalization rate (per case) assumption to reflect the age profile of the population that has been vaccinated, there are two related limitations worth mentioning. First, the model does not account for the age profile of previously infected individuals. If previously infected were mostly high risk, a lower hospitalization rate would be expected. Second, this method does not account for the specific underlying conditions of individuals vaccinated. If higher risk people are more likely to be vaccinated in each age group, the model may underestimate how much vaccination reduces the hospitalization rates.

The model incorporates virus variants by adjusting the underlying transmission rate of the virus in circulation. To do so, estimates from genetic sequencing from GISAID are used to determine the proportion of infections that are attributable to variants with different transmission rates\(^2\). The model then uses a weighted average of standard (“wild”) and variant virus to estimate the current and historical R-naught. The California variant is assumed to grow 20% faster than the wild type and the UK variant is assumed to grow 50% faster\(^3\). In addition, to forecast future transmission rates, the model simulates the dynamic between strains based on the current prevalence and the assumed transmission rates. An alternative scenario trends the various strains to using curve fitting functions.

References:

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\(^2\) Estimates from NextStrain found at: [https://nextstrain.org/groups/spheres/ncov/oregon](https://nextstrain.org/groups/spheres/ncov/oregon)