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 state sources. Hospital census is used opposed to case counts, because they avoid inconsistencies in testing from affecting infection estimates.

To convert the hospital census into the number infected, 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 cases needing hospitalization, time to hospitalization (from infection), percent of 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. Based on literature reviewed estimates, the model uses a 5 day doubling period which combined with a 14 day recovery period equates to an R-nought of 3.08. The hospitalization rate parameter is based on hospitalized individuals per case. In order to convert cases to infections, the ascertainment rate, based on CDC surveillance studies of 3.5 is applied. 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 (Lawley, 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.

The projection of the intervention effect uses patterns of fear and fatigue that have been evident in Oregon and across the US. These patterns have followed a wave like pattern (modeled as a sine curve). The wavelength and range have been estimated using data from Oregon. Notably, the pattern across the US showed that larger spikes in cases per day produced longer wavelengths before fatigue began. This extended fear cycle for Oregon is implemented by extending the estimated full cycle fear and fatigue by approximately 50% reflecting the extended fear cycles found primarily on the East Coast during the spring.

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 day until it 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 as expected vaccine volumes, from various sources, age priority assumptions stated in official documents, and an estimate for the percent of people who ultimately accept vaccination.

The model adjusts the hospitalization rate (per case) assumption to reflect the population that has been vaccinated. The adjustment does not account for the age profile of previously infected individuals. It

also does not account for the specific conditions of the individuals vaccinated. If higher risk people are more likely to be vaccinated in each age group, it may tend to underestimate the reduction in the hospitalization rate that results.

The model incorporates virus variants by adjusting the underlying transmission rate of the virus in circulation. As stated above, the model starts with an R-nought of 3.08 and uses estimates from genetic sequencing to determine the share of virus of variant with different transmission rates. It then uses a weighted average as the current R-nought of the virus. The model uses projections about the share of the virus, and the transmission rate of variants, to project future transmission rates.

References:

Lin, F., Muthuraman, K., & Lawley, M. (2010). An optimal control theory approach to non-pharmaceutical interventions. *BMC infectious diseases*, *10*(1), 1-13.