Comments on roadmap scenario modelling

What follows is a comparative analysis on the **projections** afforded by agent-based stochastic scenario modelling under different roadmaps of phased unlocking, in relation to the **predictions** of the most likely outcomes afforded by dynamic causal modelling.

Headlines

- **The scenario modelling projections are, under all scenarios considered, substantially more pessimistic than the dynamic causal modelling predictions** (when considering long-term forecasts until September, after which conditional uncertainty precludes any precise predictions).

- **The explanation for this discrepancy is most likely the failure of the scenario modelling to account for prevalence-dependent lifting of restrictions and fluctuations in transmission risk**. In most other respects, the agent-based stochastic and dynamic causal models share many features.

- **The implication is that if unlocking phases are timed in a way that is sensitive to the incidence and prevalence of infection, a surge in fatalities (and hospital admissions) is unlikely** and a return to levels of unlocking seen last summer can be realised within the provisional dates laid out by the government.

- **Dynamic causal modelling of prevalence-dependent lifting of restrictions suggests that a return to 80% mobility and retail activity might be achieved sooner rather than later** – by early April.

These conclusions are based upon a comparative analysis of the modelling in terms of strong and weak points.

Strong points:

- Scenario-based **projections** are based upon informed and sophisticated agent-based stochastic modelling, where the model parameters have been optimised using a wealth of multimodal data. Fine-grained empirical priors on (age-stratified) contact rates – down to the level household transmission – are an integral part of the model, lending them a high degree of face validity.

- There has been a careful consideration of vaccine rollout, in terms of differential efficacy and uptake (in comparison to the coarse-grained approach used in the dynamic causal modelling – of estimating the delivery and efficacy using case and death rates).

- The scenario-based modelling has considered seasonal fluctuations in transmission risk

(e.g., using variations in humidity).

- The modelling is conditioned upon a carefully structured roadmap of discrete levels of unlocking, each associated with a particular reproduction ratio based upon empirical estimates.

- A wide range of unlocking (roadmap) scenarios and vaccination efficacies have been considered, with a particular focus on sterilising immunity (i.e., precluding infection and implicitly transmission).

Weak points

- Because the scenarios considered are pre-specified in terms of dates, there is no opportunity to model the effect of context-sensitive unlocking in response to incidence and prevalence data.

- Each level of restrictions has been assigned an R-number, whose validity might be questionable. Sometimes, the assumed R-number – for any given level of restriction – is based upon 'consensus' estimates. Ideally, they should have been based upon Bayesian model averages, where each estimate is weighted by the evidence for the model under which the estimate was made.

- Modelling unlocking with a linear piecewise approximation (with discrete R-numbers) is a plausible approach to scenario modelling but is not a plausible model of mitigated outcomes, where all variables are continuous (including contact rates, and transmission risk).

- The scenario modelling rests upon a large number of assumptions; particularly, relating to the efficacy of vaccination and the impact of nonpharmacological interventions. This contrasts with dynamic causal modelling where all unknown parameters are estimated from the data with a quantified uncertainty. For example, the efficacy of vaccination in precluding transmission was already estimated to be 48% in early February because this efficacy a parameter was included in the model. Similarly, for the phase and amplitude of seasonal fluctuations.

- The scenario modelling fails to accommodate non-seasonal fluctuations in contact rates and mobility and – more importantly – transmission risk, which subsumes increased transmissibility due to new variants.

Comparative predictions of hospitalisation

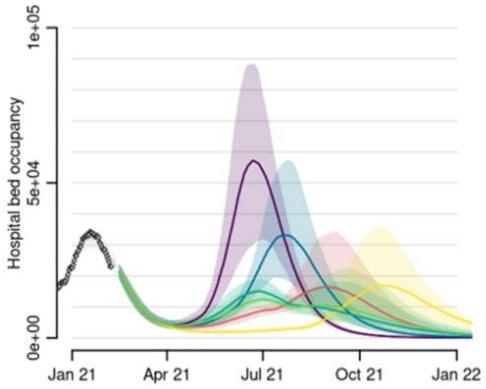


Figure 1B: projections of hospital occupancy from Imperial College London, suggesting a substantial resurgence in admissions over the summer. This contrasts with projections from Warwick University that accommodate seasonality.

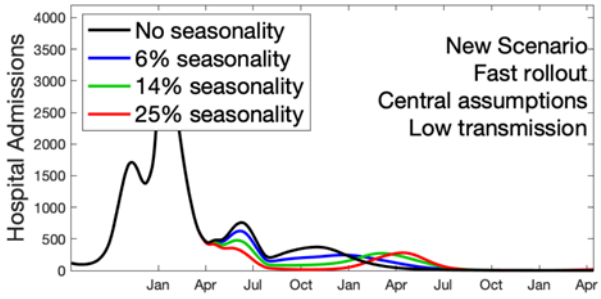


Figure 1B: projections from Warwick University of hospital admissions under different levels of seasonality modelling. The best-case scenario in this instance suggests a slight resurgence of hospital admissions in April, falling to low levels by August. This is similar to the predictions based on dynamic causal modelling that estimates seasonal fluctuations from the data.

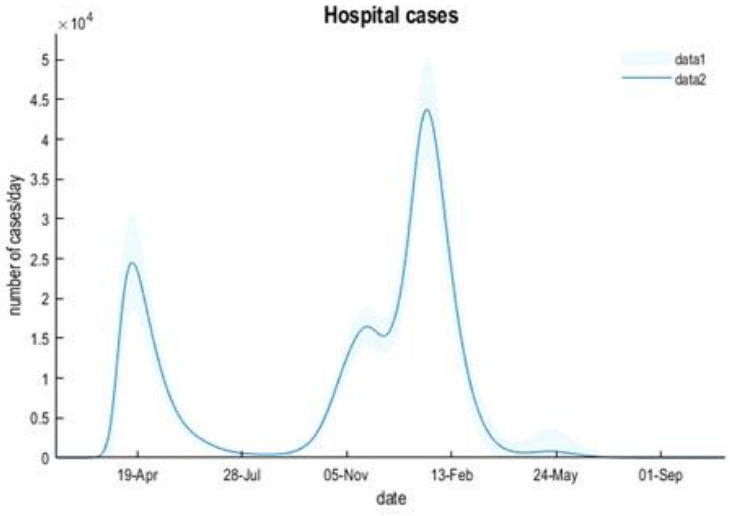


Figure 1C: UCL predictions based upon dynamic causal modelling of hospital occupancy, suggesting COVID-related hospital admissions should return to levels seen last summer by August. These predictions are based upon an expressive model that includes seasonal fluctuations in transmission risk and mobility.

Conclusion

The scenario modelling above is state of the art, with many fine-grained and empirically informed aspects. As such, it provides a quantitative and reliable point of reference for plausible outcomes under idealised and prespecified interventions. However, these projections should not be read as the most likely outcomes – or the outcomes that can be attained with a context-sensitive unlocking that responds adaptively, in real-time, to levels of prevalence.

When one includes adaptive mitigations at a coarse-grained level (i.e., a prevalence-dependent changes in contact rates) a different picture emerges that is more optimistic and plausible (see Figure 1). The key difference is the absence of a resurgence during the first phases of unlocking over the spring and summer. Figure 2 illustrates a remarkable consilience between the predicted unlocking – based upon past responses to changes in prevalence – and the tentative dates anticipated by the government's roadmap. The predictions of mobility and lockdown in the lower left panel are based entirely on model parameter estimates, with no foreknowledge of the roadmap.

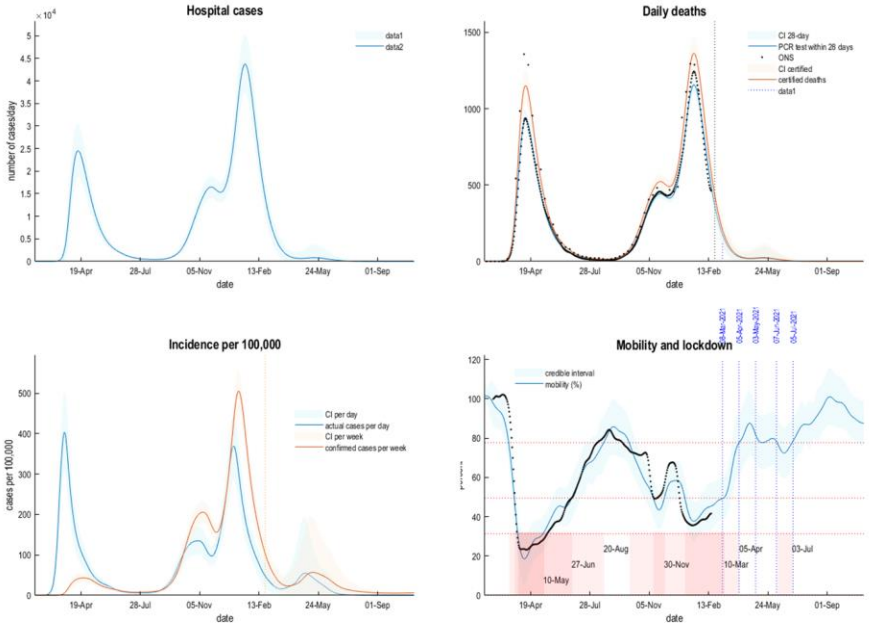


Figure 2: predictions from the [UCL long-term forecasting dashboard], reproducing the hospital occupancy predictions in Figure 1C and supplementing them with equivalent predictions of incidence (measured in terms of estimated true incidence per hundred thousand per day and notification rates per week). The reduction in incidence and subsequent hospitalisation is reflected in the low death rates that are predicted to fall to low levels by July. The final (lower right) panel shows predictions of mobility (based upon Google mobility data – retail activity), with various threshold crossings. The vertical blue lines are the anticipated dates under roadmap 3 of the Imperial College scenario modelling. The black dots are smoothed empirical data.

Because scenario modelling **projections** do not pretend to be **predictions**, they do not have any predictive validity. However, because the dynamic causal modelling is a data assimilation scheme that furnishes predictions, one has to address predictive validity: in brief, the predictive validity of the dynamic causal modelling of the first wave was remarkably accurate, in terms of unlocking and predictions of the timing of the secondary wave in November. However, it failed to predict the subsequent resurgence over Christmas until fluctuations in transmission rate and mobility were included. Given that the dynamic causal has now been equipped with the expressivity necessary to explain resurgence of viral spread, one might hope that the predictions in Figure 2 will be realised.

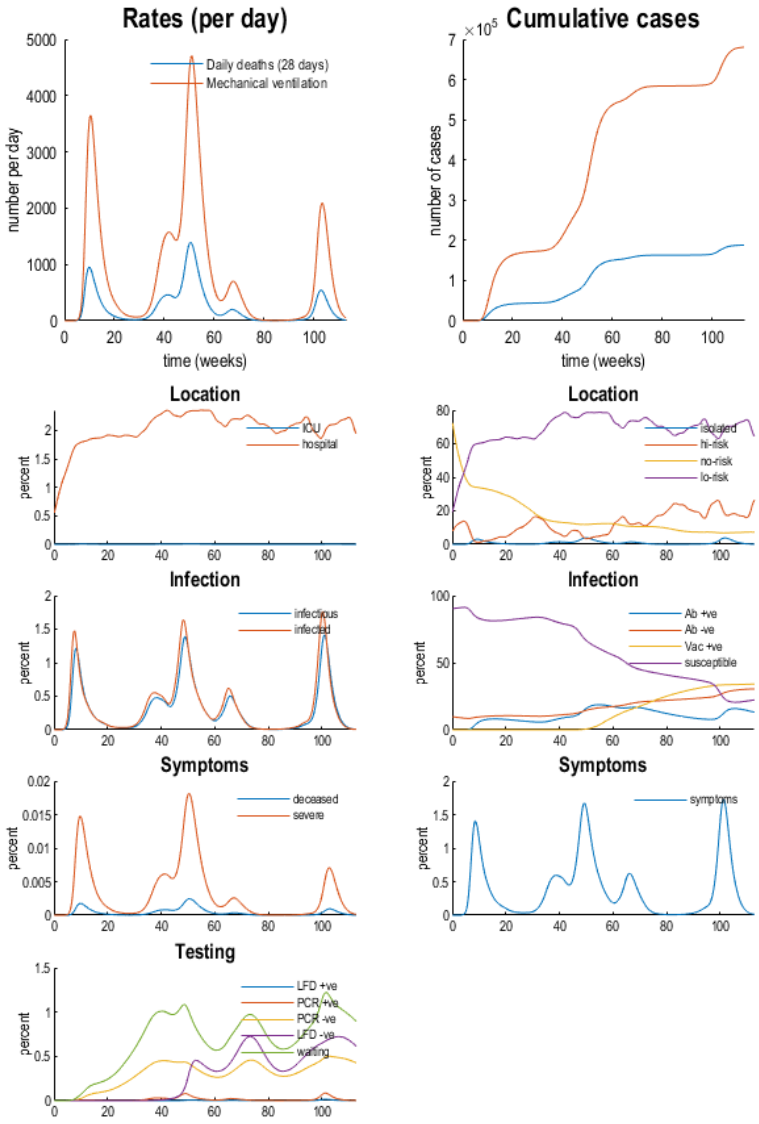
Postscript

The convergence between the scenario and dynamic modelling is most marked for the Warwick projections that allow for a nontrivial (25%) seasonality. The Imperial scenario modelling allowed for a small effect of seasonality (+/- 10%). When estimated empirically, seasonal fluctuations in transmission risk are **considerably higher**: in the summer transmission risk is estimated to be 7.9% and in the winter

15.5% which means a 51.2% decrease in the summer months. When one adds in smooth fluctuations, the transmission risk looks like the following (upper right panel):

Fluctuations in the infection fatality ratio, transmission risk, contact rates and case fatality ratios taken from the most recent UCL national dashboard.

In principle, this seasonality effect means that there is a serious risk of another wave next winter that may or may not be mitigated by reducing contact rates. The only way that the dynamic causal model can generate a wave next winter is by reducing the efficacy of vaccination (in terms of precluding infection and implicitly transmission) **to very low values of 25%** (the current DCM estimates are around 60%). The graphics below show the daily deaths and underlying latent states under this low vaccine efficiency assumption. Note that this results in about 25% of the population having immunity by the end of the year (yellow line in the **infection** panel), despite vaccinating nearly everyone. These predictions are over an interval ending in **April 2022** (i.e., about week 120).



Standard graphical output of long-term DCM predictions using maximum a posteriori parameter estimates based on current data – but reducing the estimated efficacy of vaccination from 60.9 % to 25%.

Note that in these simulations, the proportion the population who remains susceptible (here about 25%) are not necessarily exposed to the virus because viral spread will, hopefully, be contained.

The above analyses suggest that pessimistic projections of the Imperial – and to a lesser extent Warwick – groups, into next year, may in part be due to an underestimation of seasonality effects on transmission risk and the efficacy of vaccination.