

COVID-19 Hospital Utilisation Planning model: updated description and parameters

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Abstract

This technical note summarises the current version of the hospital service demand model that is used by the Irish Epidemiological Modelling Advisory Group (IEMAG) reporting to the National Public Health Emergency Team (NPHE). The model is continually updated, so this note supersedes previous versions, and will be superseded by future updates.

Introduction

The COVID-19 hospital utilisation planning model was developed to assess likely acute hospital capacity requirements during the outbreak. The latest version, which provides demand estimates, is implemented in R and draws on a range of datasets to project service demand for acute hospitals. This note provides details of the data used in the model and the methods applied. In the current update, we additionally describe how the revised model incorporates assumptions about the rollout of the vaccination programme and how key parameters are calibrated to improve the fit between predictions and actual values of key outputs based on the latest available data.

Methods

The model is a numerical simulation that starts with county-level or national-level predictions of the number of cases diagnosed each day with COVID-19; these are based on epidemiological models. To project the service demand associated with a given epidemic scenario, assumptions are required about the numbers of patients who will experience varying levels of severity of the illness and receive relevant levels of treatment. The main required assumptions are age- and sex-specific probabilities of admission to hospital and critical care, as well as assumptions about length of stay by age group for each stage of the main care pathways. Given these assumptions, the model predicts the number of cases in each county or nationally requiring critical or non-critical acute hospital care on each day of the projection period. Assumptions about expected length of stay in hospital and critical care are used to remove individuals receiving each type of care on days after their hospital stays are expected to be completed. Aggregating across age/sex cells in these results yields predictions of county-level or national requirements for each type of treatment on each day.

For example, here is how county-level predictions of daily critical care demand are generated in the model:

$$1. \quad ICU_{r,t,d,s} = \sum_{j=A+LOS_PRE_d}^{A+LOS_PRE_d+100} (q_d p_d^1 l_{dj} C_{r,s,t-j}) + \sum_{k=A+LOS_PRE_d}^{A+LOS_PRE_d+100} (q_d p_d^2 l_{dk} C_{r,s,t-k})$$

In Equation 1, $ICU_{r,t,d,s}$ is the predicted number of people in requiring critical care from county r on day t from age/sex group d in epidemiology scenario s . A is the average lag between being identified as a case and being

admitted to hospital, LOS_PRE_d is the pre-critical care average length of stay in a general bed by age band. q_d is the share of all cases arising in age/sex group d . For scenarios that include the effects of the vaccination programme, this parameter is adjusted as described in the next subsection. p^1_d and p^2_d are age/sex-specific probabilities of a case being admitted to critical care that will ultimately end in survival or death, respectively. l_{dk} is the share of cases that remain in critical care on day j or k after being admitted to it, drawn from the first 100 days of the discrete distribution of actual historical lengths of stay, by age/sex group. $C_{r,s,t}$ is the predicted number of new cases in county r on day t from epidemiological scenario s , and j and k are indices to pick up the time since cases came into critical care units.

Similar methods are used to project the number of patients requiring non-critical care (“general”) beds. However, there are four sources of patients contributing to the utilisation of general beds: those requiring only non-critical care, pre-critical care patients (two groups, survivors and decedents) and post-critical care patients (survivors only). In principle one could add non-critical care patients who die in hospital. In practice, we include this latter group when generating the parameters for the first group listed. Equation 2 summarises the approach to estimating the number of general beds required each day:

$$2. \quad GEN_{r,t,d,s} = \sum_{m=A}^{A+100} (p_d^3 q_d g_{dm} C_{r,s,t-m}) + \sum_{n=A}^{A+LOS_PRE_d} (p_d^1 q_d C_{r,s,t-n}) + \sum_{x=A}^{A+LOS_PRE_d} (p_d^2 q_d C_{r,s,t-x}) + \sum_{y=A+LOS_PRE_d}^{A+LOS_PRE_d+100+LOS_POST_d} (p_d^1 q_d l_{dy} C_{r,s,t-y})$$

There are some additional parameters in Equation 2. $GEN_{r,t,d,s}$ is the number of people requiring non-critical care in county r on day t from age/sex group d in epidemiology scenario s . p^3_d is the age/sex-specific probability of a case being admitted for general hospital care only g_{dm} is the share of cases requiring only care in general beds that remain in hospital on day m after being admitted to it, drawn from the first 100 days of the discrete distribution of actual historical lengths of stay, by age/sex group. LOS_POST_d is the average length of stay in a general bed after receiving critical care, for age/sex group d , and m , n , x and y are time indices as in Equation 1.

Predictions based on national-level SEIR models are estimated using the same method, but the relevant models omit the county-level indices in the matrices for the input case predictions and service demand outcomes.

County-level demands for care are mapped on to hospitals using a matrix showing the historical probability of a COVID-19 hospitalised case from each county being treated in each hospital. The care provided in each hospital is assigned to a hospital group, providing projections of daily demand for each level of care in these regional groupings as well. We do not routinely include hospital-group-level predictions in our weekly updates, but they are available on request.

The latest version of the model does not generate predictions of the supply of hospital services.

Modelling the effects of the vaccination programme on the age-sex composition of cases

If the SEIR projections we use as inputs are adjusted to reflect vaccination, and vaccination is broadly in descending order by age, our results should reflect three channels of effects on service demand: fewer cases, reduced probability of admission to care and shorter average lengths of stay. The latter two channels arise because older groups exhibit much higher probabilities of admission and hospital lengths of stay for Covid. Vaccinating older groups before the others reduces these metrics over time, implying reductions over time in the acute care beds required for a given number of Covid cases. Modelling this requires a daily schedule of expected cumulative effective vaccinations over the projection period. This can be used to adjust the future age distribution expected for new cases each day in the CHUP model (parameter q_d discussed in the previous section) when projecting the numbers of cases requiring hospitalisation and critical care. In practice, the same projection of effective vaccinations over time is used for the SEIR models and for projecting service demand.

Data and parameter assumptions

In this section, the main sources of data are outlined and their use in the model is described. Appendix 1 provides a summary description of data sources that are used to inform the model. Appendix 2 gives further information on how some of the data sources are processed to arrive at parameter estimates.

Epidemic curves

Epidemic predictions used in the model are provided by the IEMAG modelling subgroup. The main set of scenarios currently used in the model are county-level predictions from a SEIR model of the number of new cases confirmed on each day. The predictions are based on the methodology outlined in the IEMAG Technical Note "[A population-level SEIR model for COVID-19 scenarios \(updated\)](#)", 12 November 2020.

An example of a list of scenarios is listed in Table 1. The scenarios illustrate growth in COVID-19 cases under different assumptions about how individual behaviours react to the prevailing set of public health restrictions.

TABLE 1: Typical range of epidemic scenarios

Scenarios
A: Assume $R=0.5$ for 12 weeks
B: Assume $R=0.7$ for 12 weeks
C: Assume $R=0.9$ for 12 weeks
D: Assume $R=1.1$ for 12 weeks
E: Assume $R=1.2$ for 12 weeks
F: Assume $R=1.4$ for 12 weeks
G: Assume $R=1.6$ for 12 weeks
H: Assume $R=1.8$ for 12 weeks
I: Assume $R=2.2$ for 12 weeks
J: Assume $R=2.6$ for 12 weeks

Care intensity and duration parameter assumptions: treatment probability, treatment lags and average lengths of stay

For modelling purposes, the focus is on three COVID-19 patient groups:

- (i) persons with moderate illness who require non-critical hospital care;
- (ii) those with severe illness who spend time in critical care but subsequently recover; and
- (iii) those who are admitted to, and later die in, critical care.

In principle, each COVID patient group could have varying lengths of stay at different points along the care pathway, i.e. hospital bed only, pre-critical care, critical care and post-critical care. In practice, the numbers per day for the two critical care groups have tended to be relatively small, so we currently use averaged parameters and merge the two groups. We are also aware that some people will die in the general hospital setting without being admitted to critical care, or after being discharged from critical care. Here too, due to relatively small numbers of cases per day for many demographic groups we include these cases in a wider category of those who are hospitalised but do not require critical care.

To account for age and sex variations in severity and treatment, average rates for three metrics by sex and 10-year age band up to 80+ are calculated from the Health Protection Surveillance Centre (HPSC) CIDR database. The metrics used, which are assumed to remain stable during the prediction period, are

- (i) shares of total reported Covid cases made up by each demographic group (average over a rolling two-week window for historical dates, with the final two weeks of historical data used for the prediction period). This is adjusted to reflect the planned rollout of vaccination in future periods, as discussed above. The historical shares of cases by age band are illustrated in FIGURE 1;
- (ii) shares of new reported cases that require hospital treatment but not critical care treatment (based on cases since the start of January 2020), by demographic group; and
- (iii) shares of diagnosed cases that require critical care treatment (based on cases since the start of January 2020), by demographic group.

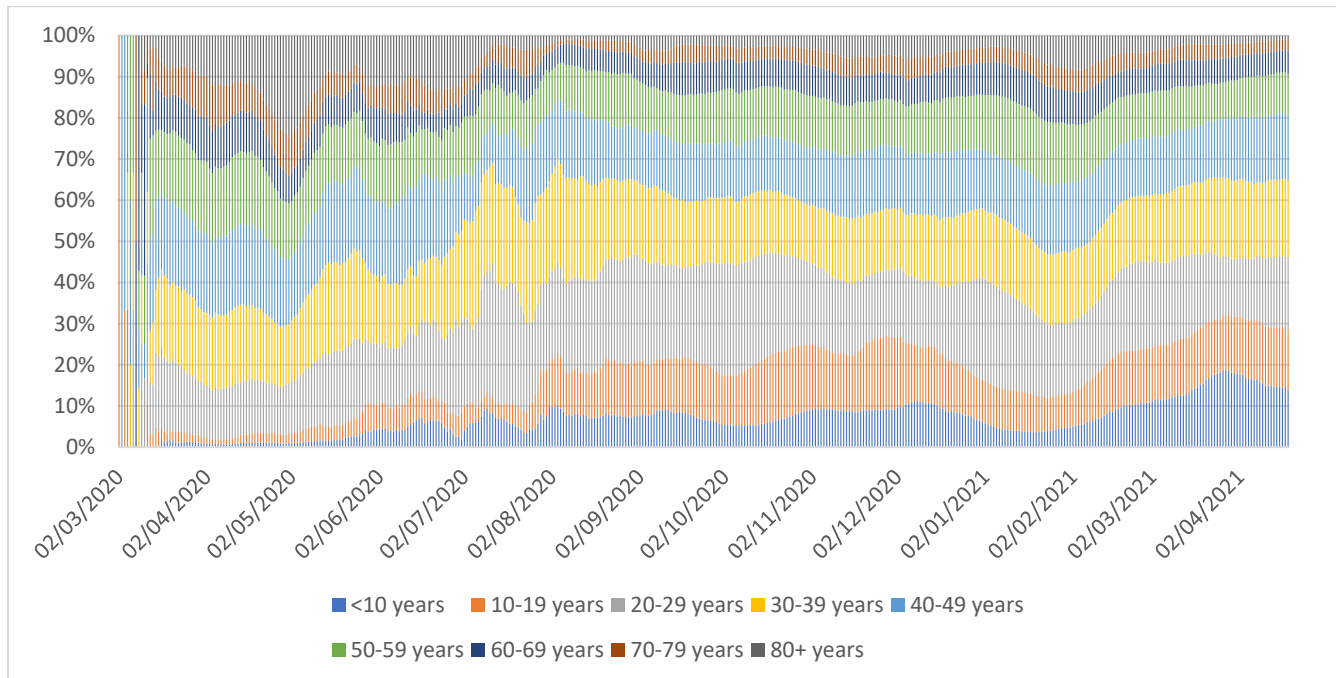


FIGURE 1: Share of new Covid cases by age group in previous 14 days, 2/3/2020 to 19/4/2021. Source, ESRI analysis of HPSC CIDR file.

Increases in the oldest age bands for all these parameters are strongly associated with increases in predicted service demand from the model. The first set of parameters (i) above indicating the age/sex distribution of cases are assumed to remain constant during the prediction period at values equal to their recent history. Initial assumptions on admission probabilities are taken from CIDR data for confirmed cases by sex and age band. The admission probabilities for general admissions and critical care are then calibrated by scaling them by constant factors across age-sex groups to minimise the absolute prediction error for total admissions in the most recent week. At times when there are relatively small numbers of daily admissions (i.e. averaging <5 admissions to critical care per day), a 28 day window is used.

The historical values before the calibration factors are applied are shown in Table 2. We omit the most recent two weeks of case notifications from this analysis to allow for reporting lags. At present, after model calibration a weighted average by population yields a probability of 4.2% of cases requiring only a general hospital bed (scaling factor 0.87) and 0.68% of cases requiring critical care (scaling factor 1.2).

TABLE 2 Historical probabilities of three classes of hospital attendance by age band and sex, HPSC CIDR data from 1 January to 8 February 2020

Parameter		Age bands								
		0- 9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
Female	Hospitalisation only	1.3%	1.0%	1.7%	2.5%	2.3%	2.9%	6.8%	19.8%	26.6%
	Critical care	0.04%	0.04%	0.06%	0.12%	0.34%	0.52%	1.41%	1.61%	0.40%
Male	Hospitalisation only	1.6%	0.7%	1.0%	1.7%	2.7%	4.8%	8.7%	24.0%	35.1%
	Critical care	0.06%	0.06%	0.07%	0.18%	0.45%	1.17%	2.42%	3.17%	0.94%

The second block of assumptions indicates how many days on average elapse between diagnosis and each level of care for those that receive it, and how long on average individuals receiving each type of care stay in the relevant facilities. We currently assume that individuals receive continuous care at a given level up to their length of stay. No provision is made for later readmission or transfer between hospitals. The first two parameters are assumed to be fixed across all cases, but the length of stay in a post-critical care bed is allowed to vary by age band (see Table 3 for the most recent set of assumptions). The current assumption for the gap between cases being classified as events and admitted to hospital is two days, and the assumed pre-critical care stay in general beds for severely ill patients is six days. These parameters are calibrated to maximise the correlations between actual and predicted daily total admissions (for the former) and actual and predicted daily critical care admissions (for the latter) over the most recent 60 days of data.

TABLE 3: Age-specific parameters for average hospital length of stay for post-critical care in a general bed (days)

Parameter	Age band								
	0 to 9	10 to 19	20 to 29	30 to 39	40 to 49	50 to 59	60 to 69	70 to 79	80+
ALOS post-critical care general bed	2	2	2	2	5	5	9	10	17

The most significant length of stay assumptions affecting estimates of bed occupancy are the assumed length of stay in a general hospital bed for those not requiring critical care and the length of stay in a critical care bed for those requiring that level of treatment. Historically these parameters have been skewed, with long tails representing the minority of cases with much longer than average lengths of stay. To allow for this, we assume the historical discrete distributions of length of stay for these two categories of care will be followed in future projections. These historical distributions of the shares of cases remaining in general beds or critical care each day from 1 to 100 days after admission are illustrated in Figures 2 and 3 below. The distribution of lengths of stay in general hospital beds from HIPE discharges and the distribution of length of stay in critical care beds from CIDR are drawn from data over the period since 1 December 2020 to help capture the densities of the tails as far as possible. Then the lengths of stay distributions are calibrated by adding or subtracting days of stay from the actual distributions to minimise the absolute prediction error for the daily utilisation of hospital beds and critical care beds. Data on actual bed occupancy comes from the morning NOCA extract on the number of Covid cases receiving critical care and from the earliest HSE Daily Operations Report each day on the numbers of infectious COVID patients in general hospital beds. At present, the calibration subtracts two days from the length of stay distribution for general beds and adds six days for critical care beds.

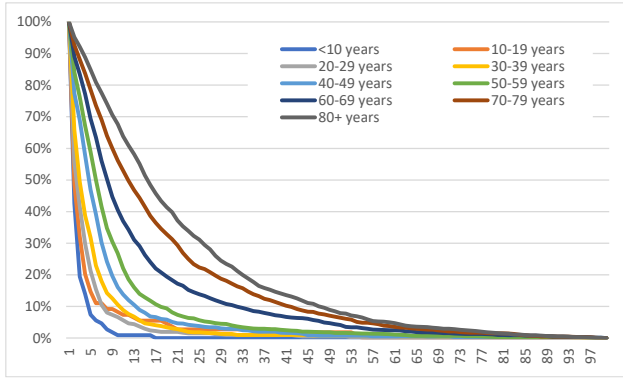


FIGURE 2: Share of Covid cases not requiring critical care remaining in general hospital beds by days elapsed since admission. Source: ESRI analysis of HPO HIPE file

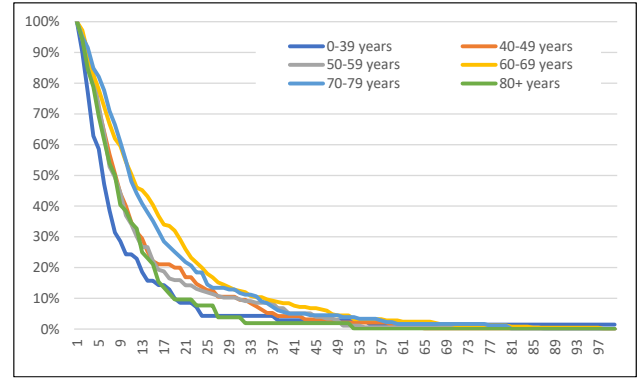


FIGURE 3: Share of Covid cases remaining in critical care by days elapsed since critical care admission. Source: ESRI analysis of HPSC CIDR file

Region-hospital group mapping of admissions

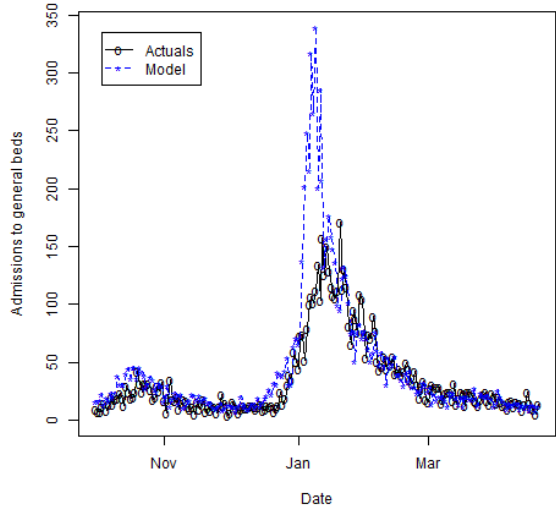
The model contains a matrix showing the share of each region’s hospitalised COVID cases that are assumed to go to each hospital in the country (see Table A3 in Appendix 1). This matrix was generated using Hospital In-Patient Enquiry microdata, and it indicates the historic probability of a COVID-19 hospitalised case from each county being treated in each hospital. We use the matrix to assign cases from counties to hospitals and we then add up the cases from hospitals into hospital groups. To allow for any recent changes that might have arisen in the pattern of bed occupancy compared to historical data, we calibrate the shares each hospital group represents in the total number of infectious Covid patients in general beds and of all Covid patients in critical care beds to match their actual shares for the most recent available seven days. The resulting calibration factors are used to adjust projected bed-days in future periods.

Outputs

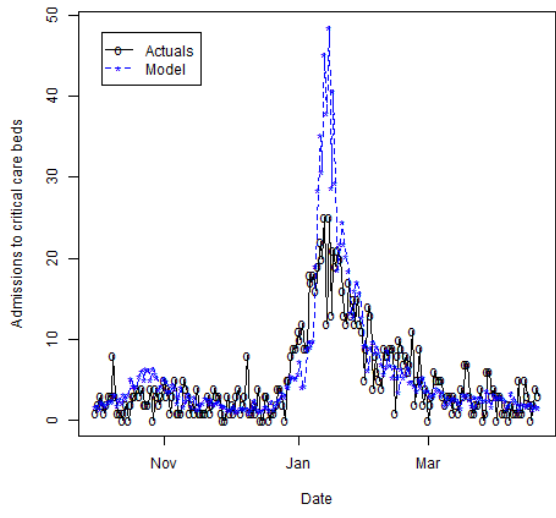
The main output used to display projected service demand due to COVID-19 is a set of tables containing weekly averages for new cases, acute non-critical COVID bed days and critical care COVID bed days. All results are rounded to the nearest 10 cases.

Figure 4 shows a comparison of actual vs. predicted hospital admissions for all Covid beds and Covid critical care beds for two periods: since 1 October 2020 and the most recent 60 days available.

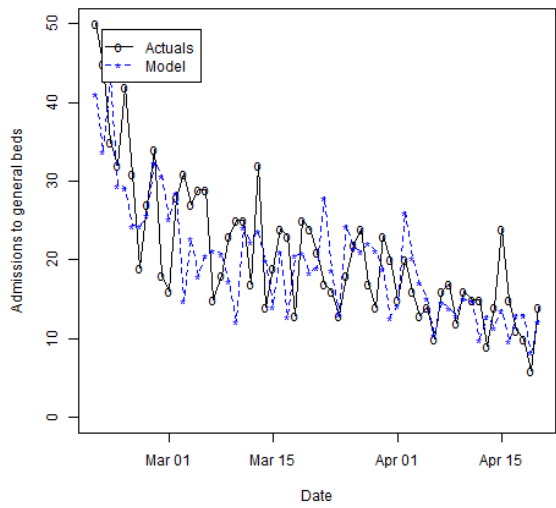
Comparison of model to actual general bed admissions for Covid: October 1st 2020 onwards



Comparison of model to actual critical care admissions for Covid: October 1st 2020 onwards



Comparison of model to actual general bed admissions for Covid: Most recent 60 days



Comparison of model to actual critical care admissions for Covid: Most recent 60 days

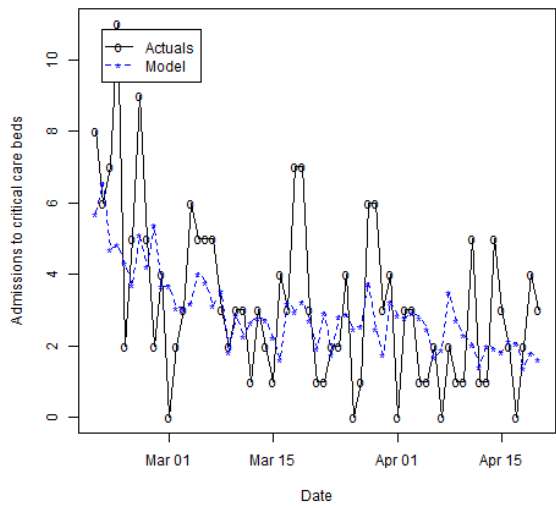


FIGURE 2: Comparisons of actual to predicted Covid admissions to all beds and to critical care, for the most recent 60 days and period since 1 October 2020, CHUP model v7.19.

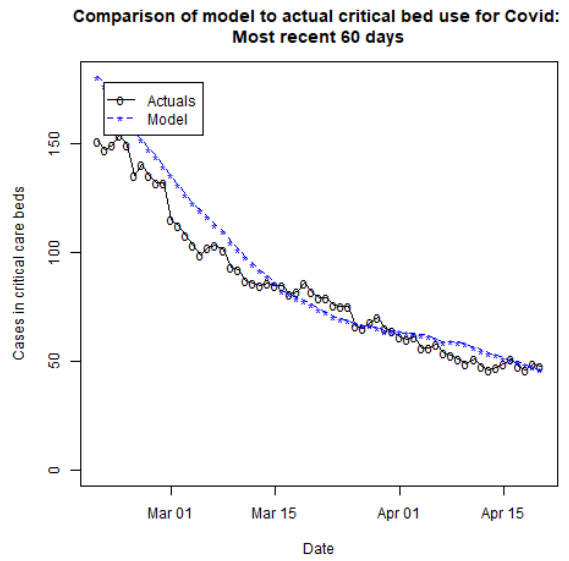
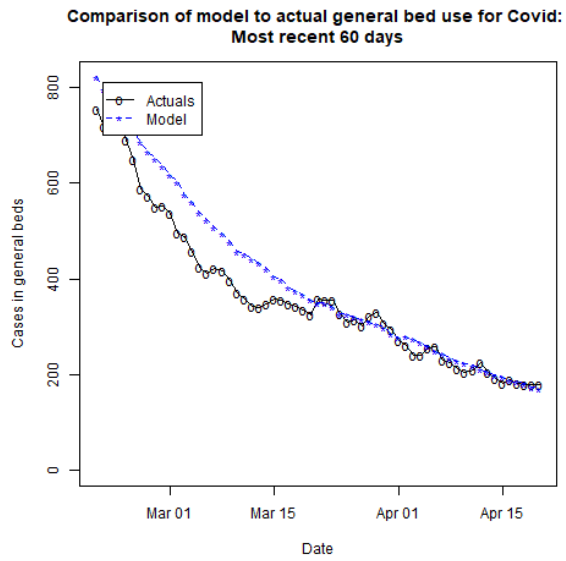
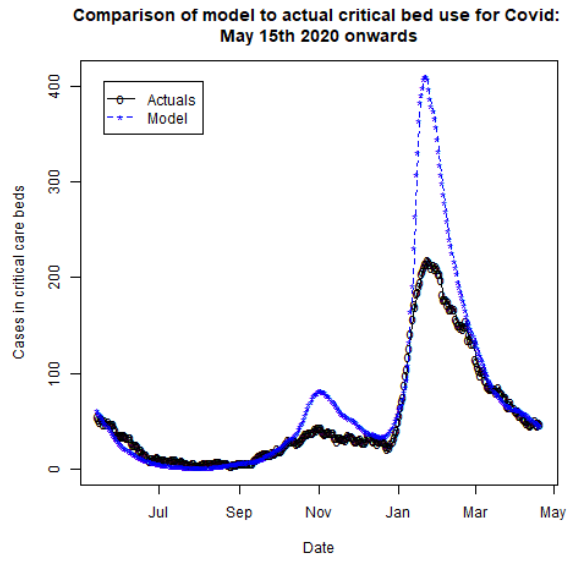
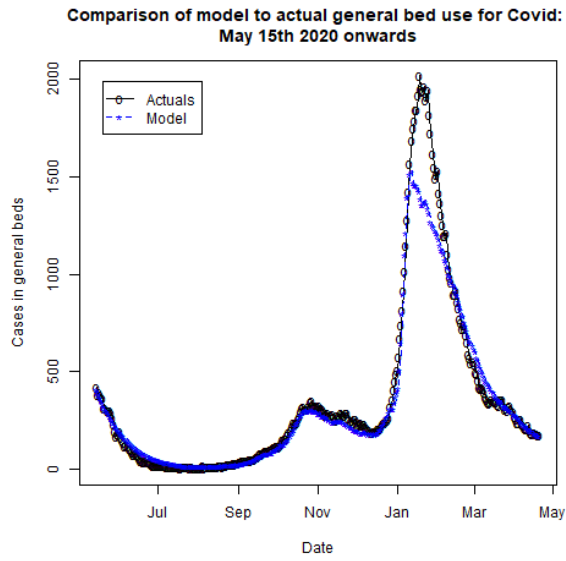


FIGURE 2: Comparisons of actual to predicted Covid general beds and critical care beds, most recent 60 days and period since 15 May 2020, CHUP model v7.19.

Appendix 1 – Parameter values for the current set of scenarios used in the model and description of key data used to inform model inputs

Data Sources

TABLE A1 Data Sources informing the CHUP model

Data Source	Data	Data Description	Data collected
IEMAG Disease modelling subgroup	Epidemic Curves	National and county level predictions from SEIR model of number of new COVID-19 cases per day	Weekly updated
ESRI Demographic Model	Population Data	Local authority level single year of age and sex population estimates for 2020	
CIDR Database	Daily confirmed cases	Number in each county and share of total by age group, rolling 14-day average	Weekly updated
	Probability of Hospital and ICU Admission	10-year age bands and sex	
	Diagnosis to admission lag, in days	Average	
	Pre-Critical Care Length of Stay	Average	
	ICU Length of Stay	Frequencies, averages, survivor/decedent breakdowns, and age breakdowns	
HIPE Database	Hospital Allocation Matrix	Historic probability of a COVID-19 hospitalised case from each county being treated in each Tier 1 public hospital	Weekly updated
	General hospital Length of Stay	Frequencies, averages, survivor/decedent breakdowns, and age breakdowns	
	Post-Critical Care Length of Stay	Average	
HSE Daily Operations Report	COVID-19 Confirmed Cases	Count of COVID-19 admissions and symptomatic cases by hospital	Daily updated
NOCA ICU-BIS	COVID-19 Occupied Critical Care Beds	Count of COVID-19 admissions and confirmed occupied critical care beds by hospital	Daily updated

Allocation matrix of confirmed COVID-Cases

Table A3 represents a matrix populated with data from an analysis of HIPE microdata that indicates the historic probability of a COVID-19 hospitalised case from each county being treated in each public hospital over the course of the pandemic to date. The matrix is continually updated with latest available data on case flows to hospitals recorded in the HIPE database.

TABLE A3 Matrix of the historical probability of a COVID-19 case from each county being treated in each hospital as of 20th January 2020

HIPE Hospital ID																										
County	4	5	7	21	22	37	41	100	101	103	105	203	235	236	303	403	404	405	501	503	506	601	602	701	702	705
Carlow	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.94	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cavan	0.00	0.01	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.06	0.82	0.01
Clare	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.00	0.10	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Cork	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	0.69	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Donegal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.93	0.04	0.00	0.00	0.00
Dublin	0.00	0.19	0.13	0.13	0.10	0.24	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Galway	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kerry	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.90	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kildare	0.64	0.02	0.01	0.02	0.20	0.01	0.08	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Kilkenny	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.06	0.89	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Laois	0.06	0.00	0.00	0.03	0.00	0.00	0.06	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.71	0.00	0.00	0.00	0.00	0.00
Leitrim	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.04	0.00	0.00	0.83	0.00	0.08	0.00
Limerick	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Longford	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Louth	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00
Mayo	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.88	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Meath	0.00	0.03	0.00	0.00	0.15	0.08	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.25	0.01	0.45
Monaghan	0.00	0.02	0.00	0.00	0.02	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.42	0.42	0.02
Offaly	0.00	0.00	0.02	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.09	0.00	0.00	0.80	0.04	0.00	0.00	0.00	0.00	0.00	0.00
Roscommon	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.25	0.03	0.09	0.03	0.09	0.00	0.00	0.47	0.00	0.00	0.00
Sligo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
Tipperary	0.00	0.01	0.00	0.01	0.00	0.02	0.00	0.02	0.03	0.00	0.53	0.00	0.04	0.00	0.28	0.00	0.00	0.00	0.02	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Waterford	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.90	0.02	0.00	0.05	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Westmeath	0.00	0.00	0.00	0.04	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.28	0.47	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Wexford	0.00	0.00	0.06	0.00	0.00	0.01	0.02	0.11	0.01	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wicklow	0.11	0.00	0.82	0.00	0.00	0.01	0.03	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix 2 – Data Preparation

Hospital admissions by age and sex band

```
preserve
keep age_10yr gender_name count_case patient_type hospital_admission icu_admission case_id
maxdate_flag event_day
order age_10yr gender_name count_case patient_type hospital_admission icu_admission
sum event_day
collapse (sum) count_case hospital_admission icu_admission if event_day >=306 & event_day <
`r(max)'+14, by(age_10yr gender_name)
sort gender_name age_10yr
export excel using "C:\Users\keeganc_ext\Desktop\CIDR\CHUP_PARAMS_20042021.xlsx",
sheet("Admission_10yr_Jan_on") sheetmodify cell(A2) firstrow(varlabels)
putexcel set CHUP_PARAMS_20042021.xlsx, sheet(Admission_10yr_Jan_on) modify
putexcel A1 = "10-year age groups", bold
putexcel A33 = "Source: HPSC CIDR Data"
putexcel A34 = "Note: Case notifications capped two weeks prior to file date to allow for case
hospitalisations to be recorded"
restore
```

Actual number of general admissions and beds occupied by day

HSE Daily Operations Report data at hospital level are loaded from the earliest extract file each day, and we use the fields “Number of confirmed COVID 19 cases Admitted on site” for occupancy and “No New Admissions COVID19 Positive previous 24hrs” for admissions.

Actual number of critical care admissions and beds occupied by day

NOCA data at hospital level are loaded from each morning extract file, and we use the fields nCovidConf for occupancy and nAdmitCovidConf for admissions.

Region-Hospital Matrix

The Region-Hospital Allocation Matrix is updated based on latest available HIPE microdata. The matrix is based on data analysis of discharged COVID-confirmed cases since 1st September 2020 using STATA 15:

```
Levelsof hospital if ED_247 ==1, local(levels)
foreach l of local levels {
preserve
collapse (count)count_case if hospital == `l' & admdate_N > 86, by(pop_region_1)
rename count_case h_`l'
merge 1:1 pop_region_1 using region_hosp_matrix, nogenerate
save region_hosp_matrix, replace
restore
}

use region_hosp_matrix, clear
egen N_total = rowtotal(h_705 – h_4)
foreach var of varlist h_705 – h_4 {
replace `var' = 0 if `var' ==.
gen p`var' = `var'/N_total
```

```

}
egen P_total = rowtotal(ph_705 – ph_4)
preserve
keep pop_region_1 N_total ph_705 – ph_4
order pop_region_1 ph_705 – ph_4 N_total
sort pop_region1
export excel using “C:\Users\keeganc_ext\Desktop\CIDR\region_hosp_matrix.xlsx”, ///
sheet (“region_hosp_ED247_HIPE_Apr”) firstrow(variables) sheetmodify
restore

```

Length of Stay in ICU

Parameters estimates for ICU LOS are taken from the latest available HPSC CIDR microdata. Analysis is undertaken in STATA 15. Although not shown, this code is also adjusted for age group analysis.

```

local row = 2
foreach i in 06mar2020 01apr2020 01may2020 01jun2020 01jul2020 01aug2020 01sep2020
01oct2020 01nov2020 01dec2020 01jan2021 01feb2021 01mar2021 {
sum los_new if date_of_discharge_from_icu_1_D >= td(`i')
putexcel set CHUP_PARAMS.xlsx, sheet(ICU LOS) modify
putexcel A1 = "Discharged since"
putexcel B1 = "Mean LOS"
putexcel C1 = "Standard Deviation"
putexcel D1 = "Min"
putexcel E1 = "Max"
putexcel F1 = "Obs"
local ++row
putexcel A`row' = `i'
putexcel B`row' = `r(mean)'
putexcel C`row' = `r(sd)'
putexcel D`row' = `r(min)'
putexcel E`row' = `r(max)'
putexcel F`row' = `r(N)'
bootstrap r(mean), reps(500): sum los_new if date_of_discharge_from_icu_1_D >= td(`i')
putexcel G1 = "Lower Bound - Bootstrap"
putexcel H1 = "Higher Bound - Bootstrap"
matrix table_`i' = r(table)
matrix a_`i' = table_`i'[5,1]
putexcel G`row' = matrix(a_`i')
matrix b_`i' = table_`i'[6,1]
putexcel H`row' = matrix(b_`i')
}

```