Report 40: Optimal scheduling rules for elective care to minimize years of life lost during the SARS-CoV-2 pandemic: an application to England

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Summary

Countries have deployed a wide range of policies to prioritize patients to hospital care to address unprecedent surges in demand during the course of the pandemic. Those policies included postponing planned hospital care for non-emergency cases and rationing critical care.

We develop a model to optimally schedule elective hospitalizations and allocate hospital general and critical care beds to planned and emergency patients in England during the pandemic. We apply the model to NHS England data and show that optimized scheduling leads to lower years of life lost and costs than policies that reflect those implemented in England during the pandemic. Overall across all disease areas the model enables an extra 50,750 - 5,891,608 years of life gained when compared to standard policies, depending on the scenarios. Especially large gains in years of life are seen for neoplasms, diseases of the digestive system, and injuries & poisoning.

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1. Introduction

Health systems worldwide have been struggling to provide life-saving hospital treatment when faced with surges in demand caused by the SARS-CoV-2 (henceforth COVID-19) pandemic. But even with surge capacity, many countries experienced shortages of critical care (CC) staff[1], as well as of general & acute (G&A) and CC beds[2,3] during the first peak of the pandemic. As a response, countries have deployed a wide range of policies to prioritize patients who require more urgent treatment or have a higher probability to benefit from treatment.

Prioritization policies have been used in pre-pandemic times due to constraints to the supply side of hospital care provision. For hospital admissions, prioritization normally means postponement or cancellation of planned procedures when high demand for emergency care is expected, for example in winter. During the first peak of the pandemic these policies led to the cancellation of elective procedures and rationed access to CC when the demand for emergency care threatened to exceed overall hospital capacity. For example, policies in Italy involved prioritizing intensive care to COVID-19 patients under 70 years who previously had no more than one admission per year for a chronic illness (e.g. exacerbated chronic obstructive pulmonary disease, advanced neoplasms and congestive heart failure)[5]. In England, the cancellation of non-urgent elective surgeries after 17th of March was combined with the prioritization to CC of those with high capacity to benefit as signaled by a low frailty score.[6,7] As the second wave progresses, several hospitals have been further pressured to evaluate capacity and cancel elective surgeries.[8–11]

While implemented to manage demand, these policies might not be optimal if they prioritize COVID-19 patients over other patients that have higher capacity to benefit. Also, when implemented, these policies generate a backlog of non-COVID-19 patients in need of care[12–14] that require prioritization rules that differ from pre-pandemic ones in order to be managed, since heterogeneity in disease progression over the postponement period might change their relative priority when compared to other patients. In England, the National Health Service (NHS) Confederation have projected waiting lists to reach 9.8 million by the end of this year,[15] highlighting how essential it is to identify ways to prioritize care and prevent hospitals being overwhelmed under the various constraints posed by the pandemic.[16]

Pre-pandemic prioritization and elective care scheduling rules are not sufficient in the presence of large surges of demand for emergency care like those brought about by the COVID-19 emergency hospitalizations since they don’t factor uncertainty in surges for emergency care nor the relative needs of COVID-19 patients vis a vis patient with other diseases. Failing to revise them may thus result in immediate or delayed deaths and increased morbidity among both non-COVID-19 and COVID-19 patients and an increase in the financial burden on health systems as delays in planned treatments accelerate disease progression and the need for more costly interventions.[17] It is therefore essential to develop optimal allocation rules for existing hospital capacity to treat COVID-19 and non-COVID-19 patients in order to minimize avoidable mortality, morbidity and costs caused by delays in planned care.

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The challenge for policymakers is to manage scarce hospital capacity and treat non-COVID-19 patients whilst maintaining the ability to respond to increased demand for emergency care by COVID-19 patients. These challenges are aggravated by the uncertainty about the number of COVID-19 patients that require care as well as the timing of the demand surges. To inform decisions about prioritization of care, policymakers need data-driven planning tools to better respond to the current crisis.

We develop a model to optimally re-schedule the backlogs of elective care and allocate hospital beds to elective and emergency patients in G&A and CC in England during the pandemic (from the 2nd March for 52 weeks), with the aim of minimizing Years of Life Lost (YLL) under alternative scenarios considering capacity constraints, demand for emergency care and epidemiological estimates of COVID-19 incidence and need for hospitalization (henceforth *Optimized Schedule)*. We consider a range of epidemiological scenarios that reflect varying stringency of non-pharmaceutical mitigation strategies, projected with a susceptible-exposed-infected-recovered (SEIR) dynamic transmission model of SARS-CoV-2. We use the model to simulate a set of prioritization policies that reflect those implemented in England (henceforth *Standard Policies*), including: (i) postponement of electives, (ii) prioritization to critical care based on frailty and (iii) re-scheduling patients to elective care using pre-pandemic prioritization rules. The YLL and cost effectiveness of the *Optimized Schedule* is compared to that of the *Standard Policies* under several epidemiological and capacity related scenarios. Our findings show that the *Optimized Schedule* leads to significantly lower YLL than the *Standard Policies* with especially notable gains for neoplasms, diseases of the digestive system, and injuries & poisoning. We further show that the *Optimized Schedule* is either dominant (lower costs and YLL) or cost effective when compared to the *Standard Policies*.

2. Methods

The development of an *Optimized Schedule* and the simulation of *Standard Policies* requires several steps. First, for each method of admission (elective and emergency) we project weekly cohorts of COVID-19 and forecast weekly inflows of non-COVID-19 patients in need of care, stratified by disease and age, and in addition we forecast the proportion of frail in each group, over a 52-week time horizon starting from the 2nd of March 2020 (week zero). Specifically, we estimate: (i) the number of non-COVID-19 patients in need of emergency and elective hospital care; (ii) the survival probability of patients admitted to hospital; (iii) the probability of being admitted as an emergency for patients waiting for elective care; and (iv) hospitalization costs.

In the *Optimized Schedule*, these forecasted weekly inflows of emergency and elective patients are the inputs to a deterministic linear programming (LP) model. In the model, patients in need of emergency care are exogenous (i.e., are always seen in hospital if there is capacity and always have priority over elective patients), while elective admissions are scheduled over the 52-week planning horizon with the objective of minimizing YLL. Admission decisions are taken on a weekly basis, and new patients are admitted to hospital in the middle of each week. Once admitted to hospital, in case of insufficient critical care resources to treat all patients in need, the model additionally allocates patients to critical care accounting for resource availability and probability of survival. The model considers capacity constraints on the supply side, including the maximum number of G&A/CC beds and staff (Senior Doctors, Junior

Doctors and Nurses) as well as recommended staff-to-bed ratios.[18,19] To reflect historical bed utilization rates, it is assumed that all the available capacity can be used, if needed, over the whole planning horizon. Full details of the model can be found in the Modelling section below.

The optimal scheduling rules and outcomes (YLL and costs) projected from the model for the different pandemic scenarios are compared to a range of *Standard Policies* that reflect those defined in England and in other European Countries.[6,7,20]

To model *Standard Policies,* we develop a simulation model in which "x%" of elective procedures are postponed over given weeks of the planning horizon, and when capacity is available, are re-scheduled in the same order of priority as when they were first scheduled (henceforth labelled as a first-in first-out (FIFO) rule-based system). Once admitted to hospital and when *Standard Policies* are switched on non-frail patients have priority in admission to CC. Full details of the model can be found in the Modelling section below.

The *Optimized Schedule* outcomes are compared with the *Standard Policies* over a range of scenarios using the aggregate incremental cost effectiveness ratio (ICER) calculated as:

$$ICER = \frac{\Delta Costs}{\Delta YLG} = \frac{Cost_{OPT} - Cost_{SP}}{YLL_{SP} - YLL_{OPT}}$$

with the subscripts *OPT=Optimized Schedule*, *SP=Standard Policy*. ΔYLG and $\Delta Costs$ denote, respectively, the incremental Years of Life Gained and incremental costs of the *Optimized Schedule* when compared to the *Standard Policies*. YLG and Cost are calculated across all disease groups and ages.

2.1 Data

We use several data sources, including combined administrative and modelling data, to create a unique dataset. This yields a comprehensive analysis of hospital elective and emergency admissions, waiting times, in-hospital mortality, YLL, and secondary care costs in England.

To model non-COVID-19 patients in need of care (CC and G&A) for both electives and emergencies and events once patients have been admitted to hospital (CC and G&A), we rely on administrative data on admissions to NHS acute hospitals in England between January 2015 and February 2020 from Hospital Episode Statistics (HES). HES provides information on inpatient and critical care admissions, including patient age, diagnoses, admission/discharge dates and methods (including death in hospital), the referral to treatment date and the healthcare resource group (HRG), the NHS diagnosis-related costing grouper.[21]

Projections of the weekly number of COVID-19 patients in need of emergency care are generated by an SEIR model (see further details in Section 2.3.1). To model care pathways of COVID-19 patients once admitted to hospital, we use individual-level clinical data from 614 patients admitted to hospital at Imperial College Healthcare NHS Trust (ICHNT) with SARS-CoV-2 infection between the 25th of February 2020 and the 5th of April 2020.[22]

Life expectancy is sourced from Office of National Statistics (ONS) life tables to calculate YLL.[23]

Each non-COVID-19 and COVID-19 patient is individually costed. We use the National Cost Collection dataset from 2015 to 2019,[24] which includes national and hospital level average unit costs of NHS patients in England using HRGs. HRGs classify patients with clinically similar treatments that use comparable levels of healthcare resources and assign them a unique cost. Every non-COVID-19 patient in HES belongs to an HRG which can be linked to a unit cost. For COVID-19 patients, we determine their HRGs using the HRG4+ 2020/21 Local Payment Grouper,[21] a software that uses each patient's managing hospital, area of admission (clinical vs surgical), age, sex, method of admission (emergency vs elective), discharge destination, length of stay (days), number of consultant assessment episodes, list of final diagnoses (ICD-10) and procedures (OPCS-4) to assign them an HRG.

We map secondary care demand to supply side capacity constraints. Staff numbers are estimated from the NHS Electronic Staff Record (ESR) dataset for 2020. ESR data hold monthly information on full time equivalents (FTEs) by staff type and area of work for over 1.2 million directly employed staff (about six percent of the UK's working population) covering 99% of NHS hospitals.

G&A bed availability is calculated using the March 2020 extract of the Quarterly Bed Availability and Occupancy Dataset (KH03 dataset),[25] which provides quarterly average daily numbers of available G&A beds for each hospital by consultant main specialty. CC beds are obtained using the Critical Care Monthly Situation Reports dataset for February 2020,[26] which provides the monthly total number of available adult CC beds per hospital. Both estimates are aggregated at the national level.

The number of monthly emergency admissions are obtained from the A&E Attendances and Emergency Admissions dataset from NHS England Statistics for the period March to June 2020.[27] These data are used to compare the robustness of the time series emergency forecasts.

2.2 Modelling

Admissions are categorized into groups based on primary diagnosis code and patient age (Appendix B). This results in a total of 42 disease-age groups for non-COVID-19 elective admissions, 45 groups for non-COVID-19 emergency admissions, and 3 groups for COVID-19 admissions. A binary frailty score is calculated for each patient. A patient is considered frail if they have an ICD-10 diagnosis included in Soong et al.'s frailty score[28], with the exclusion of *Anxiety & Depression* and *Incontinence* codes.

For each patient group, the following inputs are used: (i) the projected weekly number of new COVID-19 patients, the forecasted weekly number of non-COVID-19 emergency patients as well as the weekly number of patients in need of elective care; (ii) estimates of their probabilities of transitioning to various states once admitted (e.g. discharged, to CC or G&A, or died) with these probabilities being dependent on having waited a week prior to admission for elective patients; (iii) the probability of elective patients waiting to be admitted to elective care turning into emergencies while waiting; (iv) the forecasted initial number of elective patients waiting to be seen in hospital and hospitalized patients at the beginning of the time period of the analyses as well as estimates of the costs and YLL of these patients; and (v) supply side resources (i.e. G&A and CC beds, staff, and staff-to-bed ratios).

2.2.1 Patient Cohorts

To quantify the weekly inflows of patients (both COVID-19 and non-COVID-19) in need of elective and emergency hospital care, we first categorize patients into the following cohorts (Appendix Table B2):

(i) Cohort A: patients in need of elective care.
(ii) Cohort B: Non-COVID-19 patients in need of emergency inpatient care.
(iii) Cohort C: COVID-19 patients in need of emergency inpatient care.

This classification results in the following stocks and their corresponding flows in our modelling approach, for each patient group: (i) the stock of waiting patients, which increases with new weekly inflows of elective patients and decreases with outflows of patients admitted to hospital; (ii) the stock of elective patients hospitalized in G&A (CC), increasing each week with new elective admissions to G&A (CC) and decreasing with the transition of patients to CC (G&A) or with patients leaving the hospital (either recovered or dead); (iii) the stock of emergency patients hospitalized in G&A (CC), increasing each week with new emergency admissions to G&A (CC) and decreasing with the transition of patients to CC (G&A) or with patients leaving the hospital (either recovered or dead).

Using HES data of historical admissions, cohorts A and B are forecasted using local linear trend models with trigonometric seasonality and assuming historical hospital beds utilization rates (Appendix C1). Cohort C is modelled using a deterministic SEIR model to generate projected epidemic curves for two scenarios defined by the maximum value, R_{max}, of the reproduction number R_t attained over the projected period (beginning 1st September 2020): $R_{max} = 1.1$ and $R_{max} = 1.2$. We use explicit model compartments for three age groups and three degrees of severity (asymptomatic, mild and severe influenza-like-illness), hospitalizations, and deaths. The basic reproduction number, seed time of the epidemic, the start time of lockdown, and the reduction in transmission due to non-pharmaceutical interventions (NPIs) are calibrated to hospital occupancy data[29] from 20th of March to 30th of June. For each R_t we run an early lockdown scenario with a lockdown imposed on the 1st of December 2020 and a late lockdown scenario imposed on the 1st of January 2021, in order to simulate ongoing mitigation efforts. See Appendix D for model details and Figure D1 for the fitted initial epidemic and 4 projected scenarios. We calibrate the post-lockdown period to our desired R_{max} and project under the assumption of fixed NPIs, resulting in a single peak of infections, leading to herd immunity with respect to the fixed contact rates.

2.2.2 Transition Probabilities

To model patients' flows between the different states, we estimate various transition probabilities. Due to increased severity caused by delayed access to care, some patients waiting to be admitted for elective care may need emergency care and thus transition from Cohort A to B. In other words, these patients are removed from the stock of waiting patients and admitted to hospital as emergencies. This probability is estimated as a function of waiting time (days) using a Kaplan-Meier estimator (Appendix E1). We then calculate the mean of the weekly transition probabilities to be used in the model. Once patients are admitted for either elective or emergency care to either G&A or CC, they can transition to any of the following states: (i) discharge alive; (ii) move to CC or G&A; (iii) die; or (iv) remain in their current state (G&A or CC). The probabilities of transitioning between these states within a given number of days are estimated using multinomial logistic regressions, conditional on waiting time for electives (Appendix E2).

2.2.3 Outcome Measures: YLL and Costs

We calculate the individual average cost of every non-COVID-19 patient at each hospital in England by linking 2019 reference cost and HES data matched at HRG level. We then compute a mean unit cost for each patient group type. As the cost of treating COVID-19 patients has not yet been determined, we calculate the HRGs for each of the ICHNT COVID-19 patients using the grouper and match them to the 2018-19 national cost schedule to obtain a mean unit cost of a COVID-19 patient. See Appendix F1 for more details.

Finally, we calculate the YLL for each age group in several steps. First, we derive the number of YLL per death by averaging the age specific life expectancy (LE) across all ages within each age group.[23] The YLL per death factors are subsequently multiplied by the number of deaths per age group estimated by the optimization model to provide the total YLL. YLL are used as the main outcome of the model. While it would have been preferable to use an outcome that combines both premature mortality and quality of life such as Quality-Adjusted Life Years (QALYs), QALYs are not systematically available across all disease groups and therefore could not be embedded in the analyses.

2.2.4 Optimized Schedule

We develop an LP model for the optimal weekly scheduling of patient admissions to all hospitals across England (Appendix A). With a 52-week planning horizon, the LP model aims to minimize YLL by scheduling patients to general and critical care. Specifically, the key decision variables of the model are (i) which patients to admit to hospital and when (admission scheduling) and (ii) which patients should be allocated critical care resources in case of scarcity. Emergency inflows of COVID-19 and non-COVID-19 patients are always admitted and treated upon arrival if capacity is available and using pre-pandemic bed utilization rates. The optimization model allocates capacity to patients in need of emergency care and schedules the admissions of patients that are waiting for elective care. When demand for care is above capacity, the model rations care in three ways. First, patients in need of elective care remain on the waiting list. Second, patients admitted to care in need of CC beds are denied CC until capacity is available and, while waiting, are treated in G&A, where they are assigned different transition probabilities. Third, for patients in need of emergency care that are denied treatment because there is no capacity to see all emergencies we consider two sets of assumptions: (i) that they die (Upper Bound case); or (ii) that they would be seen in extra emergency care capacity beyond the surge capacity implemented during the first wave of the pandemic (Lower Bound case). The optimization model is open source, and it solves within seconds on a standard computer. See Appendix A for further details. The source code is available on GitHub (https://github.com/ImperialCollegeLondon/OptimalScheduling4COVID).[30]

2.2.5 Standard Policies

Building on the same inputs as the optimization model, we model *Standard Policies* by developing a simulation model over the same 52-week planning-horizon in which patients are admitted to hospital according to their order of priority as determined pre-pandemic; in addition to this, the model accounts for the postponement of a fraction of elective admissions over given weeks of the planning horizon. For each simulated policy, we implement a postponement of 100% elective admissions (75% in alternative specification) during the weeks in which the *Standard Policy* is activated. Patients that have their elective procedures cancelled remain in the queue awaiting admission to hospital at the earliest possible time according to a FIFO rule. When capacity is not available, they are kept waiting and when space is available, they are admitted in order of original scheduled date that reflects their order of priority when care was scheduled. If several patients across different disease groups have the same scheduled date, we select an equal proportion of patients across all diseases to be admitted to care (uniform sampling). In addition, once admitted to care, and during the weeks in which the *Standard Policy* is on, CC is prioritized for non-frail patients (emergency and elective) belonging to each patient group. All other modeling assumptions are as in the *Optimized Schedule*.

We model four *Standard Policies* informed by actual admission policies in England between 17th of March and 23rd of April 2020, including prioritization of non-frail patients to critical care and postponement of non-urgent elective procedures. *Standard Policy* 1 assumes that all elective procedures were cancelled between 17th of March to 29th of April 2020 (weeks 3-8 in the model), as actually occurred.[20] *Standard Policy* 2 additionally allows for this policy to be implemented over the intervention horizon by switching the policy on and off contingent on specific trigger points given by projected incidence of COVID-19. The trigger points are chosen based on the incidence of COVID-19 observed when Standard Policy 1 was implemented in England. In particular, cancellation of all electives is triggered when the number of projected COVID-19 cases in need of hospital care surpasses 4,118 (the observed number of COVID-19 cases on 17th of March). Electives procedures are rescheduled starting from the week in which the number of projected COVID-19 cases decline and fall below 7,494 (the observed number of cases on 23rd of April). If the number of cases at the peak remains below 7,494 after electives are cancelled, then electives are rescheduled when the number of cases begins to decrease. *Standard Policies 3* and *4* are akin to 1 and 2 but consider 75% of electives postponement (Appendix G).

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2.3 Scenarios

For both the *Optimized Schedule* and the *Standard Policies,* we run several scenarios to reflect different epidemiological projections, capacity constraints and inflows of emergency admissions. The baseline scenario considers epidemiological projections of COVID-19 hospitalizations at R_t of 1.1 and pre-pandemic hospital capacity (staff and beds). The best-case scenario considers an R_t of 1.1 plus reduction in emergencies and expanded capacity. A reduction in the forecasted number of patients in need of emergency care is considered to reflect behavioral changes due to the pandemic and its mitigation strategies as well as potentially increased mortality at home. We reduce our forecasted emergency needs by 34%, using A&E attendance data to estimate the proportion of the reduction in emergency admissions throughout the pandemic (see Appendix C2). Capacity is *expanded* to reflect hospital interventions introduced to increase total capacity (e.g. field hospitals, recruitment of retired and student medical staff) by 16,500 beds and 38,462 staff.[31] The worst case scenario considers epidemiological projections of COVID-19 hospitalizations at R_t of 1.2, no reduction in emergency care needs, and no expanded capacity. Appendix Table H outlines the various constraints and assumptions modelled to compose the different scenarios used.

2.4 Sensitivity Analyses

We run sensitivity analyses by calculating the YLL per death for each age group by taking the difference between life expectancy at birth[32] and the midpoint of the age group, using projected life expectancy at birth in the UK of 81 years at 2020 (Appendix F2).[33] Results remain qualitative the same apart from all YLL outputs which are ~4% lower across all scenarios, proportional to the change in the YLL/death input data (full set of results available from authors upon request).

3. Results

3.1 Years of Life Lost and Healthcare Cost under Different Scenarios

When comparing the *Standard Policies* with the *Optimized Schedules* considering hospital activity for all patient groups, the (average and total) YLL is greater under the *Standard Policies* (Appendix Table I1). Looking at YLL by patient group, the *Standard Policies* tend to be associated with a higher YLL for all disease groups (ICD groups) across all scenarios. The top three ICD groups that exhibit the largest contributions to YLL in the *Standard Policies* (when compared with the *Optimized Schedule)* are neoplasms (C00-D48), digestive system disease (K00-K93), injuries and poisoning (S00-T98). Large differences are also observed for diseases of the circulatory system (I00-I99; for both Lower and Upper Bound cases), and for respiratory diseases (J00-J99; in the Upper Bound case) (Figure 1 for *Standard Policy 1;* Appendix Figure I1 for *Standard Policies 2-4*). The *Optimized Schedule* prioritizes these patients over COVID patients and thus exhibits higher YLL than *Standard Polices* for the latter in some scenarios. The differences in YLL between the *Optimized Schedule* and the *Standard Policies* are larger in scenarios where capacity constraints are more stringent and are particularly significant in the Worst-Case Late Lockdown Upper bound scenario. When existing capacity enables accommodating all emergencies (Best Case and Baseline scenarios) or when there is scope to invest in extra emergency care capacity beyond the existing levels, the value of prioritization is reduced as all patients can receive care with the existing capacity.

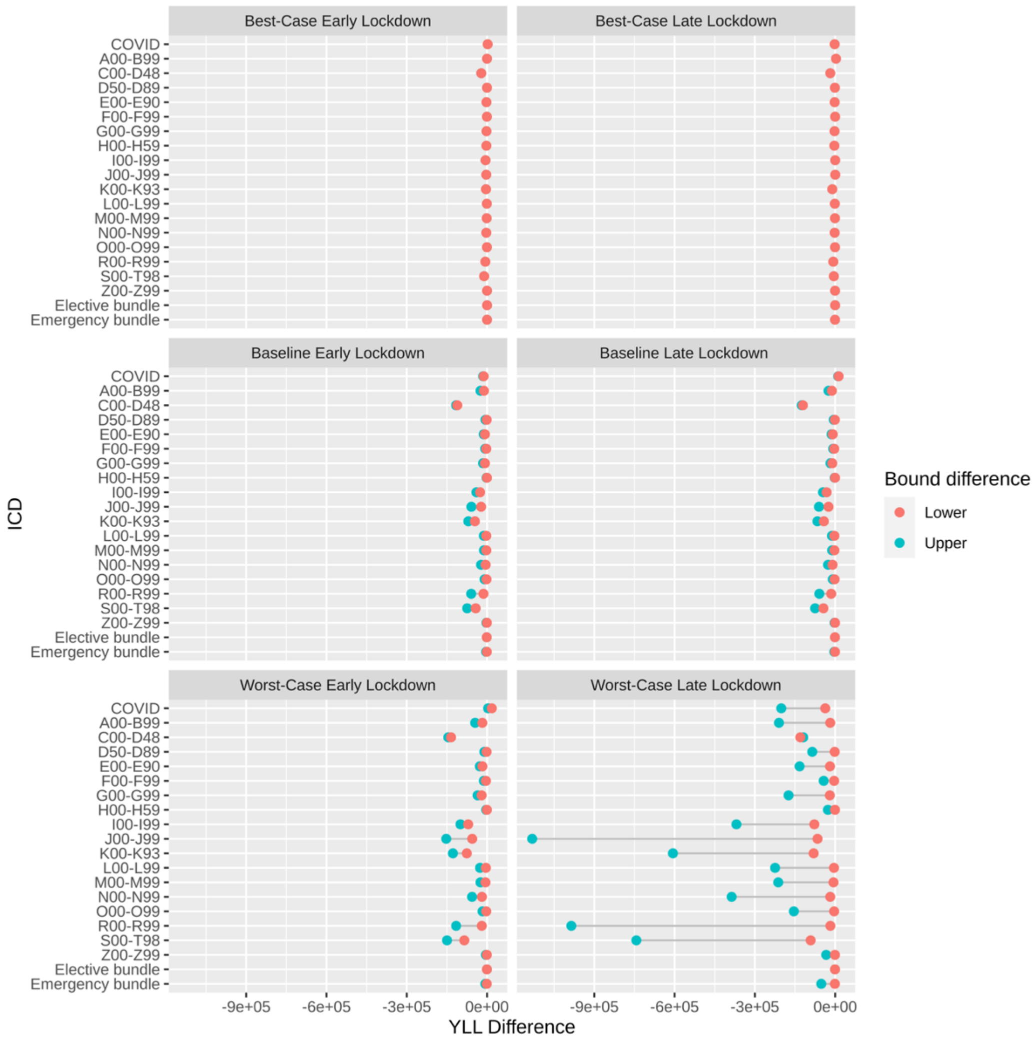


Figure 1. Comparison of *Standard Policy 1* and *Optimized Schedule* for Years of Life Lost (YLL) The difference in YLL for all admissions under *Standard Policy* 1 and *Optimized Schedule* ($YLL_{OPT} - YLL_{SP}$) over the 52-week planning horizon.

The significant health gains of the *Optimized Schedule* do not come at an increased cost in most scenarios (Figure 2 and Appendix Table I2). In fact, for most scenarios (Baseline and Best-Case), the *Optimized Schedule* is also cheaper than the *Standard Policies.*

For the few scenarios in which the *Optimized Schedule* is costlier than the *Standard Policies*, only minimal increased spending is required to increase YLG, with the extra costs being associated with an increased number of elective admissions and shifting from low priority to high priority patients. For the worst-case scenarios, the *Optimized Schedule* is cost effective for thresholds ranging between £57 and £1070 per YLG.

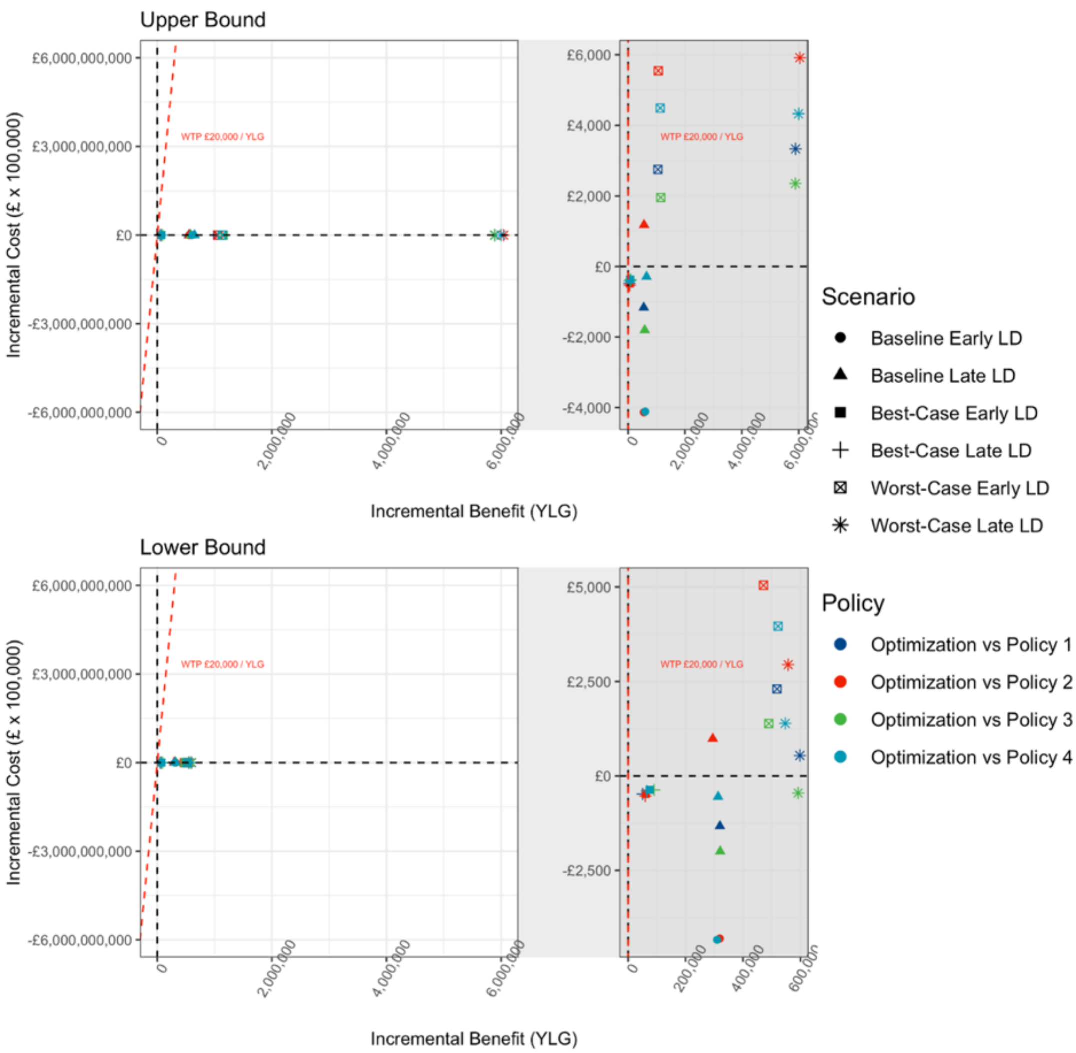


Figure 2: Incremental Cost-Effectiveness Ratios/Cost Effectiveness Plane. $Incremental\ Cost = Cost_{OPT} - Cost_{SP}$; $Incremental\ Benefit = YLL_{SP} - YLL_{OPT}$.

3.2 Number of Elective & Emergency Admissions

Across all scenarios, the *Optimized Schedule* accommodates more elective admissions than the *Standard Policies* since there is no postponement of elective procedures, and admission scheduling is determined by the patient's probability of survival and the likelihood of the patients needing emergency care while waiting for elective care. This also leads to a lower number of total emergency admissions under the *Optimized Schedule*. Indeed, in the Baseline (Early and Late Lockdown), Best-Case scenario (Early and Late Lockdown) and Worst-Case scenario Early Lockdown, the *Optimized Schedule* leads to fewer non-COVID-19 patients in need of emergency care (and thus fewer non-COVID-19 emergency admissions) than the *Standard Policies* (Appendix Table I3). The ICDs for which the difference in elective (emergency) admissions is the highest (lowest) are: K00-K93 Diseases of the digestive system, C00-D48 Neoplasms, N00-

N99 Diseases of the genitourinary system and S00-T98 Injury, poisoning (Figure 3 for *Standard Policy 1*, Appendix Figure I2 for *Standard Policies 2-4*).

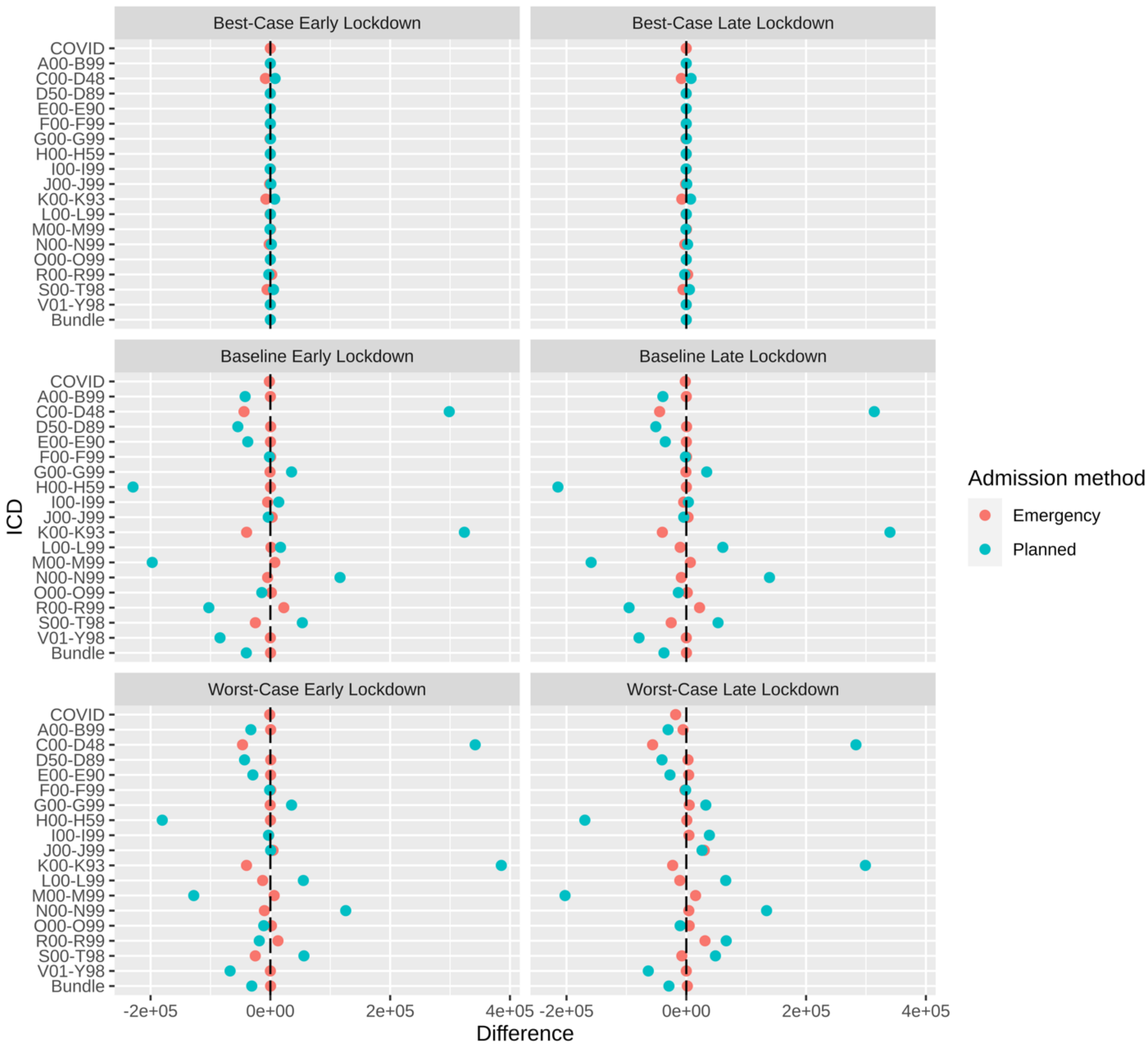


Figure 3: Difference in Elective and Emergency Admissions between Optimized Schedule and Standard Policy 1, by ICD. $Difference = Admissions_{OPT} - Admissions_{SP}$.

In the Worst-Case scenarios, especially in Late Lockdown, capacity constraints are more severe than in the Baseline and Best-Case scenarios. As a consequence, and relative to other scenarios, more patients will require emergency care while waiting for elective care in both the *Optimized Schedule* and the *Standard Policies*. Therefore, due to fewer available resources, the *Optimized Schedule* and the *Standard Policies* differ less in terms of number of emergency admissions in the Worst-Case Late Lockdown scenario (Appendix Table I3).

Notice that there are no denials in emergency admissions in the Best-Case scenario for all *Standard Policies* and the *Optimized Schedule*. However, this is not the case in any other scenario, where emergency patients may be denied admission due to the capacity shortages. The numbers of emergency admission denials are higher for the *Standard Policies* than the *Optimized Schedule* (Figure 4 for Best- and Worst Case, Appendix Figure I3 and Table I3 for Baseline-Case).

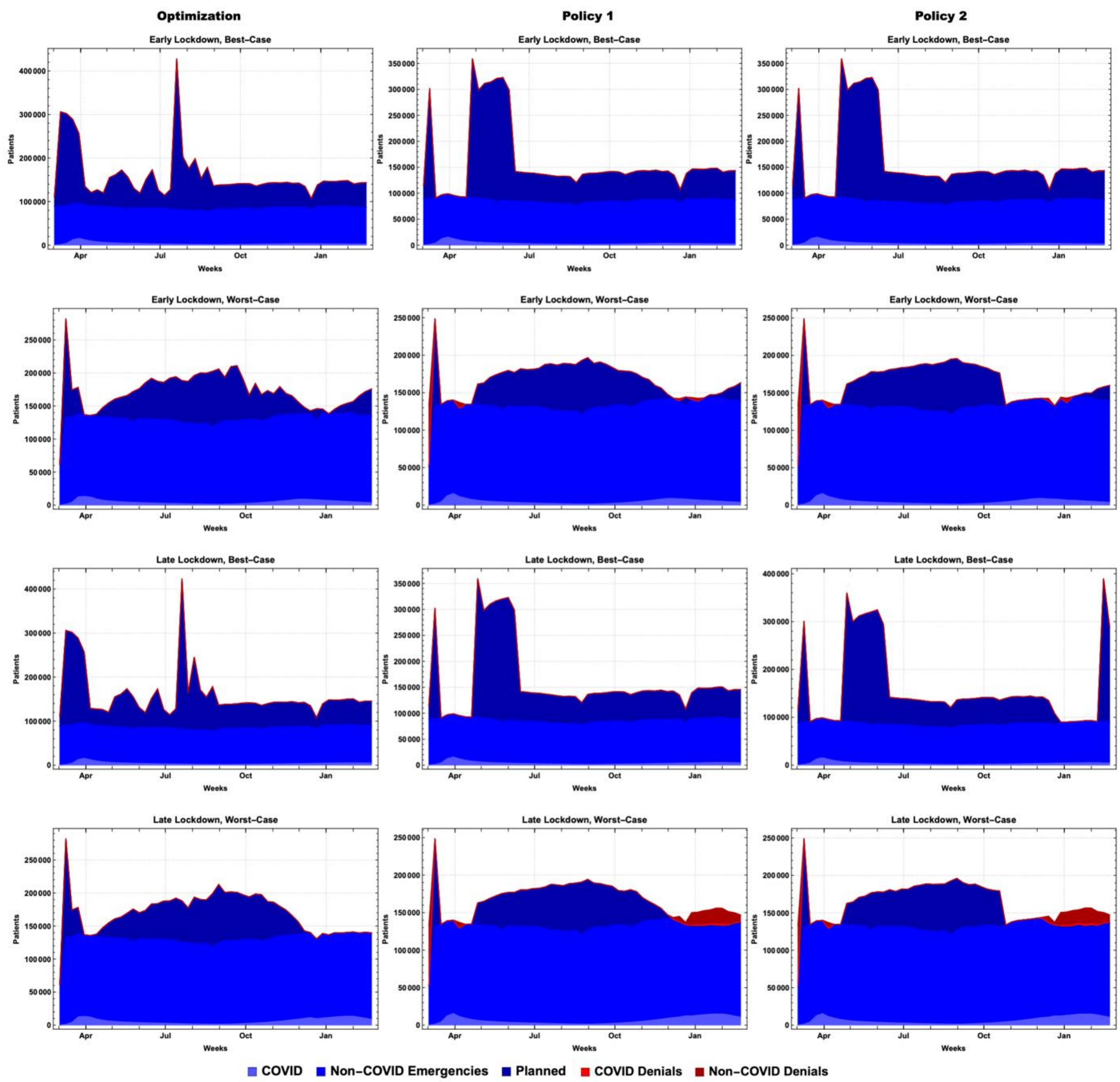
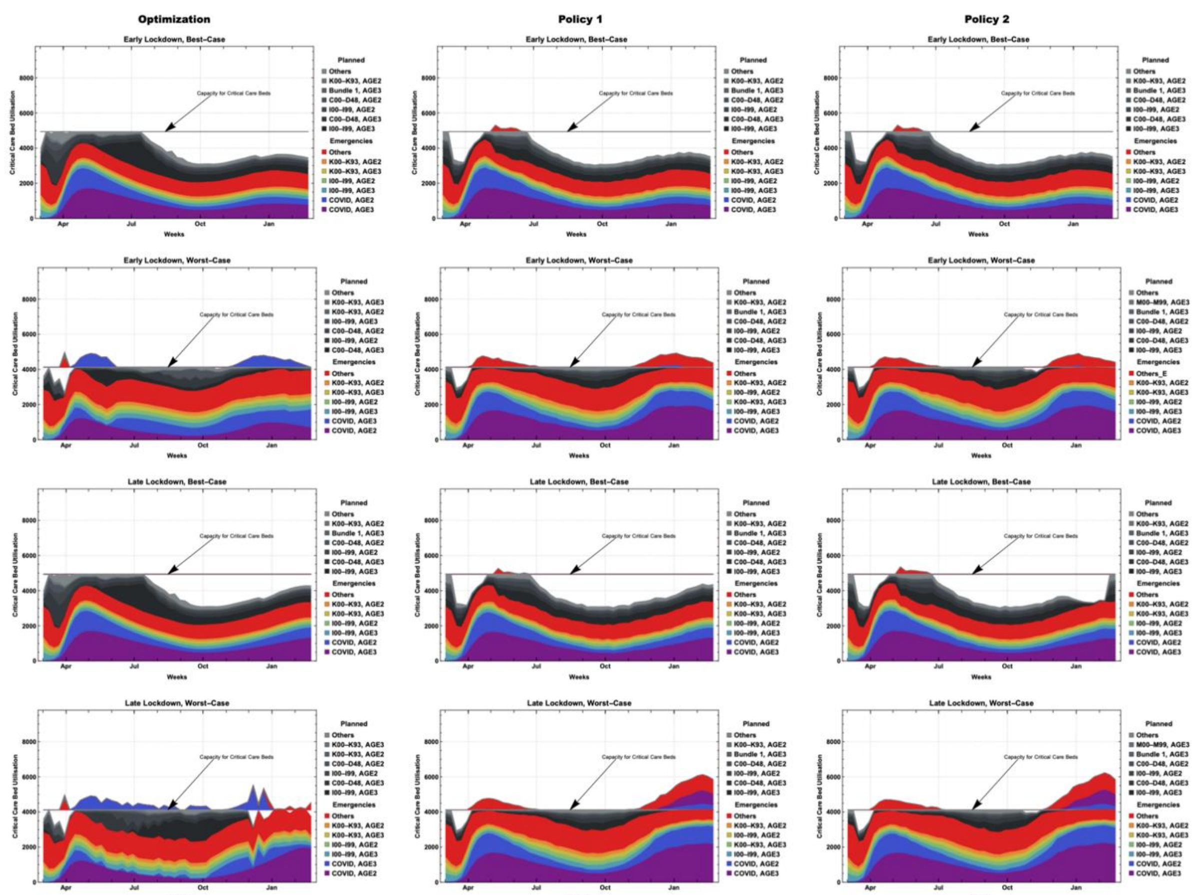


Figure 4. Comparison of *Standard Policies* and *Optimized Schedule* for admissions and admission denials over the planning horizon.

3.3 Admission to Critical Care

In the Baseline scenario, the *Optimized Schedule* denies CC to a small fraction of patients (2.2% and 2.6% over the 52 weeks under Early and Late Lockdown, respectively), most of which (83% and 85%, respectively) are COVID-19 patients aged 65+-years-old (Appendix Figure I4). In the Worst-Case scenarios, the share of patients denied CC increases to 4.8% and 6.4% under Early and Late Lockdown, respectively; also, in this case, 92% and 83% (respectively) of patients that are denied CC stem from COVID-19 aged 65+ (Figure 5). Therefore, the *Optimized Schedule* shows that it may be advantageous (to minimize YLL) to prioritize non-COVID patients for access to CC. In particular, it is interesting to notice that in the Worst-Case Late Lockdown *Optimized Schedule,* patients with neoplasms and diseases of the circulatory system are given access to CC while COVID-19 patients aged 65+-years-old are denied CC. All patients who are denied CC receive treatment in G&A in both *Standard Policies* and *Optimized Schedule*. See Appendix Figure I5 for G&A bed utilization under these scenarios.

Comparing the *Optimized Schedule* with *Standard Policies*, the former has a higher average elective occupancy in CC and in G&A. It also tends to admit more non-COVID-19 patients to CC than the *Standard Policies*. In the Best-Case scenario, the *Optimized Schedule* admits all patients to CC requiring it, while *Standard Policies* deny CC to patients during the weeks following the postponement of elective admissions (Appendix Table I3).



Bundle 1 includes ICD codes A00-B99, E00-E90, F00-F99, H60-H95, O00-O99, P00-P96 and Q00-Q99. Age 1, 2 and 3 correspond to age brackets <25, 25-64 and 64+ respectively.

Figure 5. CC bed utilization by patient group over the planning horizon.

4. Discussion and Policy Implications

We develop an optimal scheduling tool for hospital care that, if implemented, saves lives when compared to the healthcare policies implemented in several countries. In most of the assessed scenarios, the tool also leads to decreased hospital costs, except in scenarios with severe capacity constraints. In those scenarios, the health gains of the *Optimized Schedule* imply minimal extra spending, the extra costs being associated with an increased number of elective admissions and shifting care from low priority to high priority and costlier patients.

The different outcomes are caused by two factors: (i) the *Optimized Schedule* is data-driven, admits patients in an optimal way based on the relative probability of survival across the different disease groups and maximizes the use of hospital capacity while *Standard Policies* rely on prioritization rules implemented pre-pandemic and admits patients based on uniform sampling and the timing of their arrival in the care pathway; (ii) *Standard Policies* prescribe a blanket postponement of electives, while the *Optimized Schedule* only delays electives if the dynamic capacity needs exceed hospital capacity over the course of the pandemic. How well the *Optimized Schedule* fairs with regards to the *Standard Policies* depends on the severity of the capacity constraints and of the pandemic scenario.

As shown by Table 1, the years of life gained (YLG) increase in proportion with the severity of the considered scenarios, suggesting that optimal scheduling of electives is increasingly beneficial as resources become scarcer. The Table reports the gains in years of life of the *Optimized Schedule* compared to *Standard Policy 1* across the different scenarios. The analysis shows that in the Best-Case scenarios, when enough resources are available to treat all patients in the system, the *Optimized Schedule* outperforms the *Standard Policy* by only 1.1-1.4%. This differential benefit increases with the severity of the pandemic scenarios, reaching a 8.2%-76% increase in YLG for the Worst-Case Late Lockdown scenario.

Table 1. Absolute and relative difference in YLG between the *Optimized Schedule* (OPT) and *Standard Policy 1* (SP1) across the scenarios (LB: lower bound; UB: upper bound).

Scenario	Δ $YLG_{OPT\text{-}SP1}$ (LB/UB)	Δ% $YLG_{OPT\text{-}SP1}$ (LB/UB)
Best-Case Early Lockdown	61’454 / 61’454	1.4% / 1.4%
Best-Case Late Lockdown	50’750 / 50’750	1.1% / 1.1%
Baseline Early Lockdown	319’402 / 558’662	6.2% / 11%
Baseline Late Lockdown	319’747 / 552’940	6.0% / 10%
Worst-Case Early Lockdown	518’162 / 1’051’544	8.5% / 17%
Worst-Case Late Lockdown	597’895 / 5’891’608	8.2% / 76%

When capacity constraints allow to accommodate all surges in emergency care needs due to COVID-19, YLL and costs are always higher under *Standard Policies*. The *Optimized Schedule* accommodates all emergencies and still exhibits lower YLL and costs associated with elective patients than those associated with the *Standard Policies*. In contrast, the *Standard Policies* lead to higher YLL and unit costs across most

ICDs associated with delayed treatment and subsequent emergency admission, with the biggest losses being incurred for neoplasms, diseases of the digestive system, and injuries & poisoning.

In addition to this, our optimization model shows that prioritizing non-COVID-19 patients to CC could result in lower YLL. In particular, in the Worst-Case scenarios, to minimize YLL the *Optimized Schedule* prioritizes access to CC to patients with neoplasms and diseases of the circulatory system over elderly COVID-19 patients.

Our findings are of relevance for policymakers globally. In England, fears over premature mortality and morbidity associated with the cancellation of elective procedures heightened policy discussions on the increasing needs of patients for elective care.[4] This has resulted in NHS England directing hospitals to resume elective care to target levels in August 2020. This directive, provided before the second peak, is becoming near impossible to meet with surge demands from COVID-19 and winter pressures.[34,35] Thus, our findings are timely for the NHS as they have the potential to support the NHS in re-scheduling delayed elective procedures while coping with further peaks of the pandemic. We achieve this through a model that minimizes YLL under the competing constraints faced by the health system. While we have shown the benefits of our *Optimized Schedule* tool with an application to the context of the NHS in England, the model can be used in any other health systems globally: it is open source and runs efficiently with limited computing resources. It can also be adapted for use at hospital level, and to strategically plan care in the context of other pandemics or in post-pandemic periods.

Despite our model being data-driven, it can also be run in low-income settings where resources are limited and historical data on hospital activity is scarce. Where data are not available, our findings outline key prioritization principles that save lives that can be embedded in national policies in low-income settings, where efficient use of resources is key. These are: (i) prioritizing patients to elective care according to their capacity to benefit, considering the effect of waiting times on disease progression; (ii) postponing electives for which disease progression is mild and that have lower chances of being admitted to emergency care; (iii) prioritizing access to emergency care and CC based on capacity to benefit, rather than by default prioritizing COVID-19 over non-COVID-19 patients; and (iv) when handling unavoidable backlogs, admitting elective patients based on their capacity to benefit from care rather than applying FIFO scheduling. These principles, if implemented, also have the potential to save costs for health systems.

Despite its strengths and important policy implications, our analysis has several limitations. Given data limitations, a number of assumptions are made. First, COVID-19's impact on staff shortages and infection control measures (e.g., ward closures) are not modelled, which likely underestimates the impact of COVID-19 on hospital capacity. Second, referrals for elective care are assumed to remain constant at pre-pandemic levels. We now know that primary care attendance and referrals were reduced during the first peak of the pandemic.[36] This has two implications for the analyses: we do not account for YLLs due to reduced care seeking behavior by patients, and the types of procedures requested by patients and GPs are likely to differ during the pandemic period, which may impact the costs and life years saved by the different policies. A third assumption is that patients within each broad age and disease category are considered as homogenous in the severity of disease and progression along the disease pathway. This fails to account for the heterogeneity in disease progression and outcomes for different patient subgroups. Furthermore, the model does not consider competing risks. The hospital dataset records usage on discharge; therefore, the data analysis does not account for patients who would have died before receiving elective care. Furthermore, some patients who have been scheduled for elective care may subsequently die of COVID-19 due to hospital acquired infection; this is not accounted for in any model. Also, patients scheduled for elective care may not have an emergency admission observed but may have a different disease progression due to the change in severity of their illness. In the absence of an indicator that would enable capturing severity in a meaningful way across ICDs, we account for the latent severity by modelling transition probabilities as a function of waiting times. Severity is also captured through some patients being forecasted to need care earlier than others. Thus, this analysis may underestimate the life years lost and cost of care.

We do not allow for capacity restrictions due to the need of isolating patients in hospital to avoid nosocomial infections. Due to a lack of available data on mental health service use, community care, social care, dental care, primary care and other services, this study is restricted to examining care delivered by acute hospitals. While these services may not be used to deliver COVID-19 care during the pandemic and were not the focus of government policy, these services may have still been restricted due to staff shortages and attempts by the health service to reduce nosocomial transmission. While some services are unlikely to have a significant impact on life years lost in the short term, a reduction in access to care for patients with severe mental health conditions particularly, may have resulted in increased morbidity and should be a focus of future research.

In both the *Optimized Schedule* and *the Standard Policies,* we use Years of Life Lost as our main outcome. None of the models incorporate preferences of either patients and the public or medical professionals (such as the clinical guide on surgical prioritization by the Royal College of Surgeons of England).[37] Furthermore, we do not examine the impact of the *Standard Policies* or the *Optimized Schedule* on existing health inequalities or health equity. Those living in deprived socioeconomic areas and those from black and minority ethnic groups have an increased risk of mortality from COVID-19.[38,39] To date, data are not available as to whether the same groups have been more or less likely to have unmet care needs due to policy changes or changes in care seeking behavior. Further research is needed to ensure that the *Optimized Schedule* does not inadvertently increase health inequalities, and is acceptable to clinicians, patients and the public. If data are available, however, the model can be readily adapted to run with the objective of minimizing health inequalities.

While these are important caveats that can impact the magnitude of the YLL and costs, they are likely to affect the *Optimized Schedule* and the *Standard Policies* models in a similar way, thus not impacting the validity of the comparison across the two.

The presented model attempts to minimize the detrimental health impact of unprecedented hospital capacity shortages during the pandemic. The model is an attempt to operationalize the principles of best use of NHS resources as embodied in the NHS England strategic plan “The NHS Five Year Forward View”[40] and in National Institute for Health and Care Excellence (NICE) fundamental operating principles.[41] More generally, the model is of relevance to health systems globally seeking to prioritize hospital care to address the needs of all patients, substantially improving on short sighted measures that focus on COVID-19 patients to the detriment of the health of other patients.

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6. References

1. As virus spikes, Europe runs low on ICU beds, hospital staff [Internet]. [cited 2020 Nov 15];Available from: https://apnews.com/article/international-news-virus-outbreak-italy-barcelona-france-d7a43368a17f0abaff4d563151b84127

2. Coronavirus: “Intensive care staff shortage” highlighted by virus - BBC News [Internet]. [cited 2020 Nov 15];Available from: https://www.bbc.co.uk/news/av/uk-wales-52421544

3. Europe’s hospitals could soon hit capacity with covid-19 patients - The Washington Post [Internet]. [cited 2020 Nov 15];Available from: https://www.washingtonpost.com/world/europe/covid-coronavirus-europe-hospitals-capacity/2020/10/31/fe074b56-188a-11eb-8bda-814ca56e138b_story.html

4. Wu K, Smith CR, Lembcke BT, Ferreira TBD. Elective Surgery during the Covid-19 Pandemic. N Engl J Med 2020;383(18):1787–90.

5. Vergano M, Bertolini G, Giannini A, et al. Raccomandazioni Di Etica Clinica Per L ’ Ammissione a Trattamenti Intensivi E Per La Loro Sospensione , in Condizioni Eccezionali Di Squilibrio Tra Necessita e Risorse Disponibili. Soc Ital di Anest Analg Rianim e Ter intensiva [Internet] 2020;(May):207–11. Available from: http://www.siaarti.it/SiteAssets/News/COVID19 - documenti SIAARTI/SIAARTI - Covid19 - Raccomandazioni di etica clinica.pdf

6. NICE G. Assess frailty COVID-19 rapid guideline : critical care in adults (Last update : 27 March 2020). Nice [Internet] 2020;2020. Available from: https://www.nice.org.uk/guidance/ng159

7. Improvement NE and N. IMPORTANT AND URGENT – NEXT STEPS ON NHS RESPONSE TO COVID-19. 2020;21(1):1–9.

8. Coronavirus: Three of NI’s five health trusts cancel planned surgery - BBC News [Internet]. [cited 2020 Nov 15];Available from: https://www.bbc.co.uk/news/uk-northern-ireland-54921936

9. Covid-19: Elective surgery cancelled at Craigavon Hospital - BBC News [Internet]. [cited 2020 Nov 15];Available from: https://www.bbc.co.uk/news/uk-northern-ireland-54801326

10. Coronavirus: Weston General Hospital halts admissions - BBC News [Internet]. [cited 2020 Nov 15];Available from: https://www.bbc.co.uk/news/uk-england-somerset-52796589

11. Triggle N. Do the NHS accounts add up? BBC News. 2007;

12. Lim H, Kwon H-J, Lim J-A, et al. Short-term Effect of Fine Particulate Matter on Children’s Hospital Admissions and Emergency Department Visits for Asthma: A Systematic Review and Meta-analysis. J Prev Med Public Health 2016;49(4):205–19.

13. NHS hospital waiting lists could hit 10 million in England this year | Hospitals | The Guardian [Internet]. [cited 2020 Nov 15];Available from: https://www.theguardian.com/society/2020/jun/10/nhs-hospital-waiting-lists-could-hit-10-million-in-england-this-year

14. Covid-19 Victoria: hospitals advised to reduce elective surgery as doctors warn of overcrowding | Melbourne | The Guardian [Internet]. [cited 2020 Nov 15];Available from: https://www.theguardian.com/australia-news/2020/jul/09/covid-19-victoria-hospitals-advised-to-reduce-elective-surgery-as-doctors-warn-of-overcrowding

15. NHS Confederation. Road to Recovery [Internet]. NHS Confed. [cited 2020 Dec 6];Available from: https://www.nhsconfed.org/news/2020/06/road-to-recovery

16. Hunter DJ. Trying to "Protect the NHS" in the United Kingdom. N Engl J Med [Internet] 2020 [cited 2020 Nov 15];NEJMp2032508. Available from: http://www.nejm.org/doi/10.1056/NEJMp2032508

17. Griffin S. Covid-19: Waiting times in England reach record highs. BMJ [Internet] 2020 [cited 2020 Nov 15];370:m3557. Available from: http://dx.doi.org/10.1136/bmj.m3557

18. Safe medical staffing | RCP London [Internet]. [cited 2020 Nov 15];Available from: https://www.rcplondon.ac.uk/projects/outputs/safe-medical-staffing

19. Staffing levels | Advice guides | Royal College of Nursing [Internet]. [cited 2020 Nov 15];Available from: https://www.rcn.org.uk/get-help/rcn-advice/staffing-levels

20. NHS. Operating framework for urgent and planned services in hospital settings during COVID-19. 2020;

21. HRG4+ 2020/21 Local Payment Grouper V2 (COVID-19) - NHS Digital [Internet]. [cited 2020 Nov 15];Available from: https://digital.nhs.uk/services/national-casemix-office/downloads-groupers-and-tools/local-payment-2020-21

22. Perez-Guzman PN, Daunt A, Mukherjee S, et al. Clinical Characteristics and Predictors of Outcomes of Hospitalized Patients With Coronavirus Disease 2019 in a Multiethnic London National Health Service Trust: A Retrospective Cohort Study. Clin Infect Dis [Internet] 2020 [cited 2020 Nov 15];Available from: https://academic.oup.com/cid/advance-article/doi/10.1093/cid/ciaa1091/5885151

23. Office for National Statistics. Past and projected period and cohort life tables, 2018-based, UK - Office for National Statistics [Internet]. [cited 2020 Dec 6];Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/bulletins/pastandprojecteddatafromtheperiodandcohortlifetables/1981to2068

24. NHS England » National Cost Collection for the NHS [Internet]. [cited 2020 Nov 15];Available from: https://www.england.nhs.uk/national-cost-collection/

25. Statistics » Bed Availability and Occupancy [Internet]. [cited 2020 Nov 15];Available from: https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/

26. Statistics » Critical Care Bed Capacity and Urgent Operations Cancelled [Internet]. [cited 2020 Nov 15];Available from: https://www.england.nhs.uk/statistics/statistical-work-areas/critical-care-capacity/

27. Statistics » A&E Attendances and Emergency Admissions [Internet]. [cited 2020 Nov 15];Available from: https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/

28. Soong J, Poots AJ, Scott S, et al. Quantifying the prevalence of frailty in English hospitals. BMJ Open [Internet] 2015 [cited 2020 Nov 15];5(10):8456. Available from: http://bmjopen.bmj.com/

29. Statistics » COVID-19 Hospital Activity [Internet]. [cited 2020 Nov 15];Available from: https://www.england.nhs.uk/statistics/statistical-work-areas/covid-19-hospital-activity/

30. ImperialCollegeLondon/OptimalScheduling4COVID: Code for the report “Optimal scheduling rules for elective care to minimize years of life lost during the SARS-CoV-2 pandemic” [Internet]. [cited 2020 Nov 16];Available from: https://github.com/ImperialCollegeLondon/OptimalScheduling4COVID

31. McCabe R, Schmit N, Christen P, et al. Adapting hospital capacity to meet changing demands during the COVID-19 pandemic. BMC Med [Internet] 2020;18(1):329. Available from: https://doi.org/10.1186/s12916-020-01781-w

32. Expectation of life, principal projection, UK [Internet]. Off. Natl. Stat. [cited 2020 Nov 15];Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/expectationoflifeprincipalprojectionunitedkingdom

33. Claxton K, Martin S, Soares M, et al. Methods for the estimation of the National Institute for Health and care excellence cost-effectiveness threshold. Health Technol Assess (Rockv) 2015;19(14):1–503.

34. NHS England » Elective letter [Internet]. [cited 2020 Nov 16];Available from: https://www.england.nhs.uk/publication/elective-letter/

35. Mass cancellations of NHS operations inevitable this winter, say doctors | Society | The Guardian [Internet]. [cited 2020 Nov 15];Available from: https://www.theguardian.com/society/2020/oct/23/mass-cancellations-of-nhs-operations-inevitable-this-winter-say-doctors

36. Use of primary care during the COVID-19 pandemic | The Health Foundation [Internet]. [cited 2020 Nov 15];Available from: https://www.health.org.uk/news-and-comment/charts-and-infographics/use-of-primary-care-during-the-covid-19-pandemic

37. COVID-19 documents - FSSA [Internet]. [cited 2020 Nov 15];Available from: https://fssa.org.uk/covid-19_documents.aspx

38. Deaths involving COVID-19 by local area and socioeconomic deprivation - Office for National Statistics [Internet]. [cited 2020 Nov 15];Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsinvolvingcovid19bylocalareasanddeprivation/deathsoccurringbetween1marchand31july2020

39. Updating ethnic contrasts in deaths involving the coronavirus (COVID-19), England and Wales - Office for National Statistics [Internet]. [cited 2020 Nov 15];Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/articles/updatingethniccontrastsindeathsinvolvingthecoronaviruscovid19englandandwales/deathsoccurring2marchto28july2020

40. NHS. Next steps on the NHS five year forward view: Ambitions in the plan will be challenging to deliver. 2017.

41. NICE. Our principles [Internet]. [cited 2020 Dec 6];Available from: https://www.nice.org.uk/about/who-we-are/our-principles

42. Harvey AC. Forecasting, Structural Time Series Models and the Kalman Filter [Internet]. Cambridge University Press; 1990 [cited 2020 Nov 15]. Available from: https://www.cambridge.org/core/product/identifier/9781107049994/type/book

43. Durbin J, Koopman SJ. Time Series Analysis by State Space Methods [Internet]. Oxford University Press; 2012. Available from: https://oxford.universitypressscholarship.com/view/10.1093/acprof:oso/9780199641178.001.0001/acprof-9780199641178

44. Helske J. KFAS : Exponential Family State Space Models in R. J Stat Softw [Internet] 2017;78(10). Available from: http://www.jstatsoft.org/v78/i10/

45. khauck2606/DAEDALUS: An integrated economic-epidemiological model to project closure strategies differentiated by economic sector for maximizing economic production in the presence of SARS-CoV-2 [Internet]. [cited 2020 Nov 15];Available from: https://github.com/khauck2606/DAEDALUS

46. mrc-ide/sircovid [Internet]. [cited 2020 Nov 15];Available from: https://github.com/mrc-ide/sircovid

47. Business Impact of COVID-19 Survey (BICS) results - Office for National Statistics [Internet]. [cited 2020 Nov 15];Available from: https://www.ons.gov.uk/economy/economicoutputandproductivity/output/datasets/businessimpactofcovid19surveybicsresults

48. Diekmann O, Heesterbeek JAP, Roberts MG. The construction of next-generation matrices for compartmental epidemic models. J R Soc Interface [Internet] 2010 [cited 2020 Nov 15];7(47):873–85. Available from: https://royalsocietypublishing.org/doi/10.1098/rsif.2009.0386

49. Therneau TM. Survival Analysis [R package survival version 3.2-7]. 2020 [cited 2020 Nov 15];Available from: https://cran.r-project.org/package=survival

50. Slides and datasets to accompany coronavirus press conference: 23 April 2020 - GOV.UK [Internet]. [cited 2020 Nov 15];Available from: https://www.gov.uk/government/publications/slides-and-datasets-to-accompany-coronavirus-press-conference-23-april-2020

7. Appendices

Appendix A: Optimization Model

A1. Overview of the Model Structure

We develop a linear programming model to optimally schedule the admission of patients to hospital under different pandemic scenarios. Figure A1 offers a schematic overview of the model structure.

Model inputs. Focusing on the entire NHS in England, we first characterize (i) the initial situation (at $t = 0$) in terms of the available resources (Ξ) and the current allocation of patients (waiting vs in-hospital patients, in CC vs G&A, etc.). We divide patients into different patient groups and subdivide each group on the basis of severity. For each subgroup, we provide as inputs (ii) their resource requirements (Δ) as well as transition matrices (Π) representing the probabilities of endogenous transfers of patients between severity groups (e.g., patients needing emergency care while waiting for elective care, or patients in G&A requiring CC). For $t > 0$, based on the scenarios we are investigating (e.g. lockdown), we observe (iii) new exogenous inflows of patients (Φ). Investments to increase capacity could additionally be accounted for in a strategic planning problem (possible model expansion).

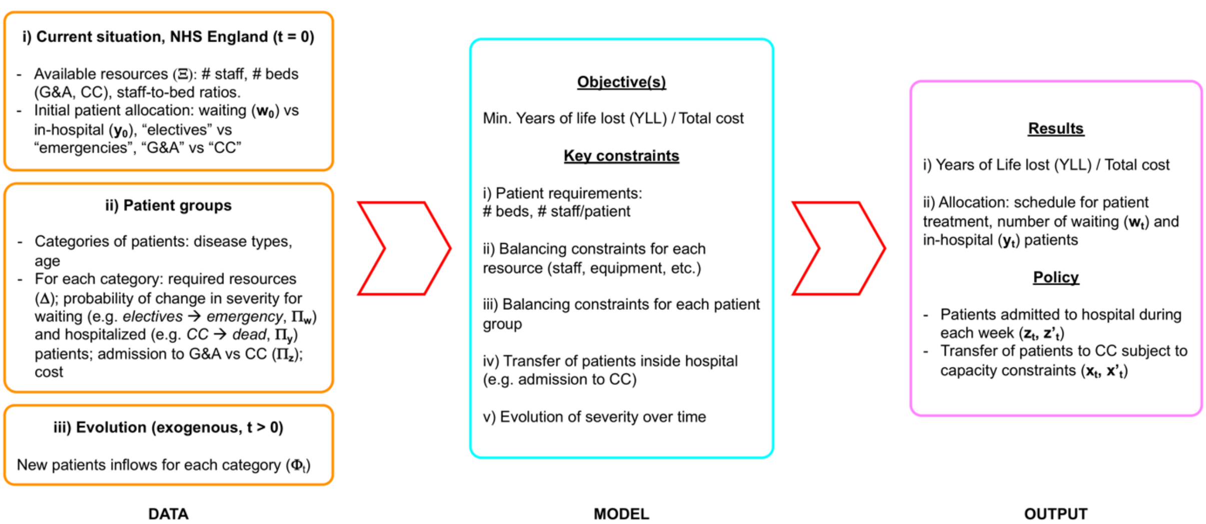

Figure A1 – Conceptual input-output overview of the LP model

Model outputs. During each week, the model optimizes the allocation of patients, i.e., how many patients of each group to admit to hospital (z_t, z_t') as well as the in-hospital transfers of patients(x_t, x_t'). Crucially, we account for the possibility of capacity shortages, which, for instance, have affected patients' welfare negatively during the first peak of the COVID-19 outbreak; that is, the model considers that admission to hospital or to CC might be denied to patients in need. The objectives are the minimization of total YLL (the model can also be used to minimize total cost). The key constraints are the capacities and resource balances.

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A2. LP Model Formulation

In this section we detail the sets, parameters, decision variables and constraints of the LP optimization model. Figures A2 and A3 offer a schematic representation of the system's evolution for any given week t. Week t begins at time t and ends at time $t+1$. Patient inflows are observed at the middle of each week (time $t+0.5$), when also decisions on hospital admissions are made (z_t). The evolution of newly admitted patients during their first 3.5 days in hospital is mapped by the decision variables x'_t. During the following weeks, the transition of patients across severity states is mapped by the decision variables x_t (see Figure A3). The number of waiting (w_t) and hospitalized (y_t) patients is assessed at each time instant $t \in \{0, \ldots, t, \ldots, T\}$. The model is initialized with the number of waiting and hospitalized patients at the beginning of the planning horizon $t = 0$ (w_0, y_0).

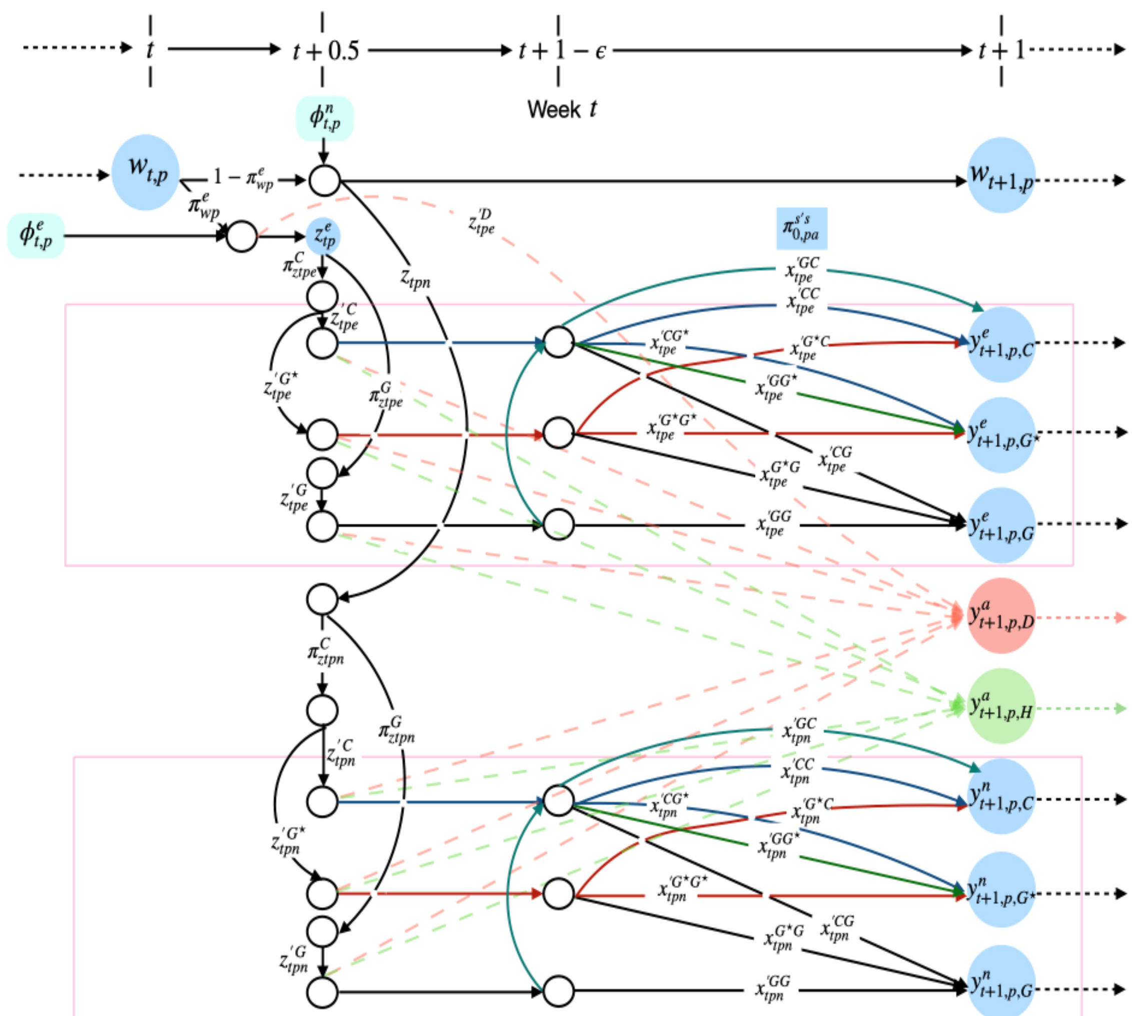

Figure A2 - Schematic overview of the system evolution of incoming patients at half-week for any given week t.

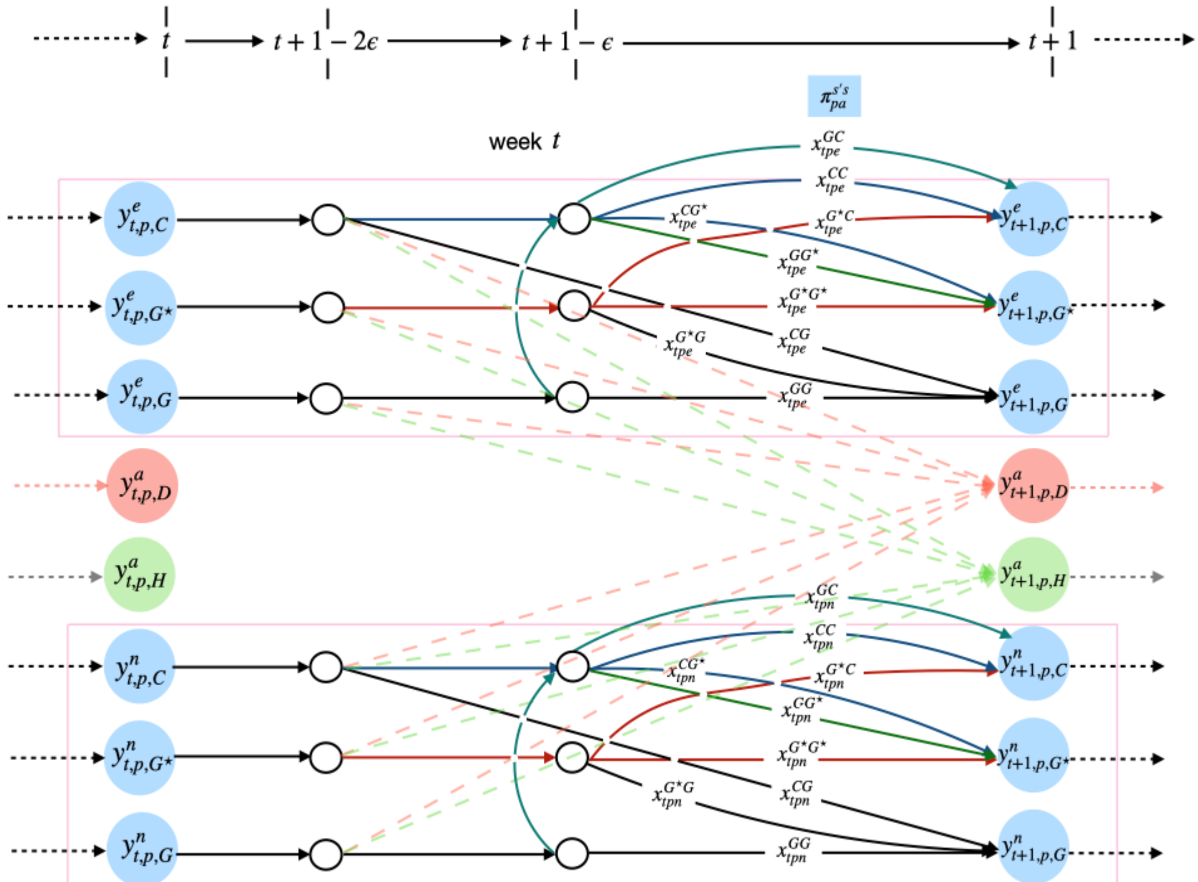

Figure A3 – Schematic representation of the system evolution of hospitalised patients during a week for any given week t.

Table A1. Sets and their elements

Set name (index)	**Elements**
TIMES ($\mathcal{T}$)	$\{0, \dots, t, \dots, T = 52\}$ Time periods (weeks)
RESOURCES ($\mathcal{R}$)	$\{0, \dots, r, \dots, R\}$ Resources (CC beds, G&A beds, staff)
PATIENT GROUPS ($\mathcal{P}$)	$\{0, \dots, p, \dots, P\}$ Patients divided by disease type and age group
ADMISSION TYPE ($\mathcal{A}$)	$\{e, n\}$, where e is emergency and n is elective admission
SEVERITY STATE ($\mathcal{S}$)	$\{G, C, G^{*}, H, D\}$, where G is G&A, C is CC, $G^{*}$is G&A for patients who have been denied CC, H is recovered, D is dead

Table A2. Parameters with description

Parameter	Units	Description
ϕ_{tp}^{a}	[# patients]	New patients' inflow (exogenous) for each patient group $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$ during each week $t \in \mathcal{T}$
$\pi_{w,p}^{e}$	[-]	Probability of transfer from elective n to emergency e for each waiting patient group $p \in \mathcal{P}$
$\pi_{z,tpa}^{s}$	[-]	Fraction of patients from each patient group $p \in \mathcal{P}$ of type $a \in \mathcal{A}$ requiring admission to $s \in \mathcal{S}$ at the beginning of each week $t \in \mathcal{T}$
$\pi_{0,pa}^{ss'}$	[-]	Probability of transfer in the first 3.5 days from severity state $s \in \mathcal{S}$ to $s' \in \mathcal{S}$ for each patient group $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$
$\pi_{y,pa}^{ss'}$	[-]	Probability of transfer (weekly transitions) from severity state $s \in \mathcal{S}$ to $s' \in \mathcal{S}$ for each patient group $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$
$\delta_{0,psa}^{r}$	[# items]	Requirement of resource $r \in \mathcal{R}$ for each patient group $p \in \mathcal{P}$ in severity state $s \in \mathcal{S}$ and admission type $a \in \mathcal{A}$ (first 3.5 days)
δ_{s}^{r}	[# items]	Requirement of resource $r \in \mathcal{R}$ for patients in severity state $s \in \mathcal{S}$ (weekly)
ξ_r	[# items]	Capacity of resource $r \in \mathcal{R}$ (weekly)
λ_p	[# years]	Years of life lost (YLL) for each patient group $p \in \mathcal{P}$
γ_{pa}	[GBP]	Unit cost of care for each patient group $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$

Table A3. Decision variables with description. All variables are continuous and non-negative unless otherwise indicated

Variable	Units	Description
w_{tp} [(1)]	[# patients]	Elective patients of group $p \in \mathcal{P}$ *waiting* for care at time $t \in \mathcal{T}$
z_{tpa}	[# patients]	Patients of group $p \in \mathcal{P}$ and admission type $a \in \mathcal{A}$ *admitted* to hospital in week $t \in \mathcal{T}$
z'^{s}_{tpa}	[# patients]	Patients of group $p \in \mathcal{P}$ and admission type $a \in \mathcal{A}$ *admitted* to severity state $s \in \mathcal{S}$ in week $t \in \mathcal{T}$
y_{tpa}^{s} [(1)]	[# patients]	Patients of group $p \in \mathcal{P}$ and admission type $a \in \mathcal{A}$ *in* hospital and *in* severity state $s \in \mathcal{S}$ at time $t \in \mathcal{T}$
$x_{tpa}^{ss'}$	[# patients]	Patients of type $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$ *transferred from* severity state $s \in \mathcal{S}$ *to* $s' \in \mathcal{S}$ during week $t \in \mathcal{T}$ (weekly transitions)
$x'^{ss'}_{tpa}$	[# patients]	Patients of type $p \in \mathcal{P}$ of admission type $a \in \mathcal{A}$ *transferred from* severity state $s \in \mathcal{S}$ *to* $s' \in \mathcal{S}$ during week $t \in \mathcal{T}$ (first 3.5 days)

[(1)] for $t = 0$, $w_{tp} = w_{0p}$ and $y_{tpa}^{S} = y_{0pa}^{S}$, where w_{0p} and y_{0pa}^{S} are input parameters

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A2.2 Constraints

The model is expressed by the objective function [1] and the constraints [2]-[15].

$$\min \quad YLL = \sum_{t\in\mathcal{T}}\sum_{p\in\mathcal{P}}\sum_{a\in\mathcal{A}}\lambda_p\left(y^D_{tpa} + z'^D_{tpa}\right) \qquad [1]$$

s.t.

$$w_{t+1,p} = \phi^n_{tp} + \left(1-\pi^e_{w,p}\right)w_{tp} - z_{tpn} \qquad \forall t \neq T, \forall p \quad [2]$$

$$z_{tpe} + z'^D_{tpe} = \phi^e_{tp} + \pi^e_{w,p}w_{tp} \qquad \forall t \neq T, \forall p \quad [3]$$

$$z'^C_{tpa} + z'^{G^*}_{tpa} = z_{tpa}\pi^C_{z,tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [4]$$

$$z'^G_{tpa} = z_{tpa}\pi^G_{z,tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [5]$$

$$y^s_{t+1,pa} = \sum_{s'\notin\{H,D\}}\left(x^{s's}_{tpa} + x'^{s's}_{tpa}\right) \qquad \forall t \neq T, \forall p, \forall s, \forall a \quad [6]$$

$$x'^{s's}_{tpa} = \pi^{s's}_{0,pa}z'^{s'}_{tpa} \qquad \forall t \neq T, \forall p, \forall s' \in \{G,C,G^*\}, \forall s \in \{G,H,D\}, \forall a \quad [7]$$

$$x'^{CC}_{tpa} + x'^{CG^*}_{tpa} = \pi^{CC}_{0,pa}z'^C_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [8]$$

$$x'^{GC}_{tpa} + x'^{GG^*}_{tpa} = \pi^{GC}_{0,pa}z'^G_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [9]$$

$$x'^{G^*C}_{tpa} + x'^{G^*G^*}_{tpa} = \pi^{G^*C}_{0,pa}z'^{G^*}_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [10]$$

$$x^{s's}_{tpa} = \pi^{s's}_{y,pa}y^{s'}_{tpa} \qquad \forall t \neq T, \forall p, \forall s' \in \{G,C,G^*\}, \forall s \in \{G,H,D\}, \forall a \quad [11]$$

$$x^{CC}_{tpa} + x^{CG^*}_{tpa} = \pi^{CC}_{y,pa}y^C_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [12]$$

$$x^{GC}_{tpa} + x^{GG^*}_{tpa} = \pi^{GC}_{y,pa}y^G_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [13]$$

$$x^{G^*C}_{tpa} + x^{G^*G^*}_{tpa} = \pi^{G^*C}_{y,pa}y^{G^*}_{tpa} \qquad \forall t \neq T, \forall p, \forall a \quad [14]$$

$$\sum_{p\in\mathcal{P}}\sum_{a\in\mathcal{A}}\sum_{s\in\mathcal{S}}\left(\sum_{s'\in\{H,D\}}\delta^r_{0,psa}\,x'^{ss'}_{tpa} + \sum_{s'\notin\{H,D\}}\frac{\delta^r_s}{2}x'^{ss'}_{tpa} + \delta^r_s y^s_{tpa}\right) \leq \xi_r \qquad \forall t, \forall r \quad [15]$$

Unless stated otherwise, each parameter bound by a "∀" ("$\forall t$") is assumed to range over all values of its associated set (e.g., "$\forall t$"should be read as "$\forall t \in \mathcal{T}$" , whereas "$\forall p$" abbreviates "$\forall p \in \mathcal{P}$").

The model minimizes the total YLL [1] over a 1-year planning horizon (52 weeks).

In the middle of each week t, a new exogenous inflow of patients in need of elective care (ϕ^n_{tp}) is observed, which adds to the cohort of waiting patients at the end of the previous week (w_{tp}). Note that at $t = 0$, we have a stock of patients waiting for care (w_{0p}) that are people that at the beginning of week zero were waiting for elective care but had not yet been admitted to hospital. Some of these elective patients are admitted to hospital during week t (z_{tpn}); patients in need of elective care not admitted to the hospital remain in the waiting list [2]. Patients waiting for elective care are at risk of needing emergency care while waiting with probability $\pi_{w,p}^{e}$. These patients are immediately admitted into hospital, together with the new inflow of patients in need of emergency care (ϕ_{tp}^{e}). In case of capacity shortages, admission to hospital might be denied to patients in need of emergency care. In the model, we assume these patients (z'^{D}_{tpe}) either die if no extra emergency capacity is made available in the NHS (Upper Bound case) or are admitted to newly created emergency care capacity (Lower Bound case) [3]. This assumption is relaxed in a sensitivity analysis in which we assume these patients survive, hence providing upper/lower bounds for our results relative to this assumption.

At the moment of admission to hospital, patients can be assigned a G&A (G) or a CC (C) bed based on the parameter $\pi_{z,tpa}^{s}$. The variables z'^{s}_{tpa} define the severity state $s \in \mathcal{S}$ that patients are admitted to. Patients needing CC are assigned a C bed if available (z'^{C}_{tpa}); in case of capacity shortages, CC admission might be denied to a patient in need; this patient is admitted to a specific G&A state (G^{*}) where he/she evolves according to a new set of transition probabilities [4]. If capacity becomes available, patients in G^{*} that have neither died nor been discharged are assigned a C bed. Patients needing G&A care are assigned a G bed [5].

Once in hospital, patients can transition between these severity states, and they can also recover (H) or die (D). At week 0, there is already a stock of patients in hospital care (y_0) that corresponds to patients that were admitted to hospital prior to week 0 and that had not been discharged from hospital by then. The number of patients in a given severity state $s \in \mathcal{S}$ at the end of week t ($y_{t+1,pa}^{s}$) is equal to the sum of the patients who remained in state s during that week plus the transitions from other states $s' \in \mathcal{S}$ to s during week t [6]. In particular, equations [7]-[10] and the decision variables $x'^{s's}_{tpa}$ map the transitions across severity states of newly admitted patients in their first 3.5 days of hospitalization; symmetrically, the set of equations [11]-[14] and the decision variables $x_{tpa}^{s's}$ map transitions across severity states in the following weeks.

The transition of a patient from state s' to state s is defined by the matrix $\pi_{0,pa}^{s's}$ for the first 3.5 days [7] and by the matrix $\pi_{y,pa}^{s's}$ $[11]$ in the following weeks. Admission to CC is an exception to this: [8], [9], [12] and [13] enforce that in case of capacity shortages, CC might be denied to a patient in need; this patient transitions to a specific G&A state (G^{*}) where he/she evolves according to a new set of transition probabilities. If space in CC becomes available in the following weeks, this patient might be admitted to CC [10][14].

Patients in G&A and CC are allocated 1 bed and staff resources (nurses, doctors) based on specific staff-to-bed ratios. Equation [15] ensures that the total consumption of bed and staff resources does not exceed the available capacity (ξ_r). To do this, patients are divided into three distinct categories: (i) patients leaving the hospital in the first 3.5 days consume an amount of resources proportional to their length-of-stay ($\delta_{0,psa}^{r}$); (ii) newly admitted patients who remain in hospital after the first 3.5 days consume resources for a half-week ($\delta_{s}^{r}/2$); (iii) in the following weeks, patients use resources for full-week periods (δ_{s}^{r}).

Appendix B: Patient Group and Cohort Identification

Patients are grouped using their ICD-10 root group (Table B1) and age group (0-24, 25-64, and 65+ years). For example, ICD-10 code C15 for malignant neoplasm of the oesophagus falls under the root ICD group C00 – D49: Neoplasms. This medically classifies diseases in broad categories (e.g. respiratory diseases, cancer, etc.) and thus captures any heterogeneity within the needs for emergency or elective admissions for that set of diseases.

Table B1. ICD root group identification

ICD-10 Chapter	Disease Category
A00–B99	Certain infectious and parasitic diseases
C00–D48	Neoplasms
D50–D89	Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism
E00–E90	Endocrine, nutritional and metabolic diseases
F00–F99	Mental and behavioural disorders
G00–G99	Diseases of the nervous system
H00–H59	Diseases of the eye and adnexa
H60–H95	Diseases of the ear and mastoid process
I00–I99	Diseases of the circulatory system
J00–J99	Diseases of the respiratory system
K00–K93	Diseases of the digestive system
L00–L99	Diseases of the skin and subcutaneous tissue
M00–M99	Diseases of the musculoskeletal system and connective tissue
N00–N99	Diseases of the genitourinary system
O00–O99	Pregnancy, childbirth and the puerperium
P00–P96	Certain conditions originating in the perinatal period
Q00–Q99	Congenital malformations, deformations and chromosomal abnormalities
R00–R99	Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified
S00–T98	Injury, poisoning and certain other consequences of external causes
V01–Y98	External causes of morbidity and mortality
Z00–Z99	Factors influencing health status and contact with health services

Patients are further grouped into cohorts depending on the type of care needed. Patients are broadly categorized as needing emergency or elective care. For those waiting for elective care, their disease might deteriorate and consequently, these patients might need emergency treatment while waiting for elective care. Some ICD groups in our dataset, however, have too few observations to run robust empirical analyses. Thus, the ICDs representing the lowest 5% of the frequency distribution of patients in need of care separately are aggregated together for both electives and emergencies (Table B2). This leaves 15 and 14 ICD groups for non-COVID-19 emergency admissions and elective patients in need of care, respectively, plus one COVID-19 emergency ICD group. Admitted patients are also stratified by age (0-24, 25-64 and 65+ years).

Table B2. Bundling of elective and emergency ICDs

Elective Bundling	Emergency Bundling
A00 – B99: Infectious and parasitic diseases	D50 – D89: Disease of blood, immune mechanism disorders
E00 – E89: Endocrine, nutritional, metabolic diseases	H00 – H59: Disease of eye and adnexa
F01 – F99: Mental, behavioural, neurodevelopment disorder	H60 – H95: Diseases of ear, mastoid process
H60 – H95: Diseases of ear, mastoid process	P00 – P96: Conditions originating in perinatal period
O00 – O99: Pregnancy, childbirth, puerperium	Q00 – Q99: Congenital malformations, deformations and chromosomal abnormalities
P00 – P96: Conditions originating in perinatal period	Z00 – Z99: Factors influencing health status, health services
Q00 – Q99: Congenital malformations, deformations, chromosomal abnormalities	

In summary, each patient in our dataset falls into one of three cohorts: i) non-COVID-19 patients waiting for elective care that do not require emergency treatment while waiting (Cohort A); ii) non-COVID-19 patients in need of emergency care, including those patients that require emergency care while waiting for electives care due to progressed disease severity for the same condition for which they need elective care (Cohort B); iii) COVID-19 patients in need of emergency care (Cohort C).

Appendix C: Forecasting

C1. Forecasting Cohorts of Hospital Care Need

In order to estimate the number of non-COVID-19 patients in need of both elective and emergency care (i.e. the expected number of new weekly occurring patients that are expected to enter the care pathway and those that are admitted to emergency care), we fit local linear trend models with trigonometric seasonality to weekly historical data on hospital admissions for emergency patients for the various groups from January 2015 to February 2020, and we forecast from March 2020 to March 2021. For elective referrals we use weekly referrals from January 2015 to March 2019, and subsequently forecast from April 2019 to March 2021. As HES data only records a patient's referral date once the patient has been admitted to hospital, to account for the full patient cohort, we use a maximum waiting time of a year. The local linear trend model has several advantages over alternative approaches. It can deal easily with weekly seasonality, it can cope well with missing observations, has good forecasting ability and can be easily interpreted.

In a local linear trend model with trigonometric seasonality,[42,43] the observed number of admissions in a specific group y_t in week *t* is decomposed into an unobserved stochastic trend μ_t, an unobserved seasonal component γ_t and an unobserved measurement error ε_t:

$$y_t = \mu_t + \gamma_t + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2).$$

The stochastic trend μ_t has the form of a unit root process with a drift which is also modelled using a unit root process:

$$\mu_{t+1} = \mu_t + \nu_t + \xi_t \qquad \xi_t \sim \mathrm{N}\left(0, \sigma_\xi^2\right)$$
$$\nu_{t+1} = \nu_t + \zeta_t \qquad \zeta_t \sim \mathrm{N}\left(0, \sigma_\zeta^2\right)$$

The term μ_t allows the level of the trend to change, while the drift ν_t modifies the slope of the trend over time.

The seasonal term has the form:

$$\gamma_t = \sum_{j=1}^{[s/2]} \gamma_{jt},$$

where $s = 52.18$ is the period and is equal to the average number of weeks in a year accounting for leap years, and

$$\gamma_{jt+1} = \gamma_{jt} cos\lambda_j + \gamma_{jt}^* sin\lambda_j + \omega_{jt}$$
$$\gamma_{jt=1}^* = -\gamma_{jt} sin\lambda_j + \gamma_{jt}^* cos\lambda_j + \omega_{jt}^*$$
$$\lambda_j = \frac{2\,\pi\,j}{s}.$$

The parameters γ_{jt} and $\gamma_{jt=1}^*$ capture the seasonality of the series and allow for complex seasonal patterns, while ξ_t , ζ_t, ω_{jt} and ω_{jt}^* are white noise errors which are mutually uncorrelated. Estimation is done by maximum likelihood using the KFAS package in R.[44] Admissions needs forecasts and 95% forecasting intervals (FI) are constructed.

We forecast patients in need of care split by admission method (elective or emergency), disease group, and age band. We priginally aimed to also stratify these forecasts by frailty. However, due to the small number of frail patients, we were unable to run forecasts for frail patients. Therefore, we instead forecast the proportion of patients in need of care who are frail. Analogously, while our goal was to run forecasts for patients in need of both G&A and CC (for both elective and emergency care settings), the number of patients in CC is considerably small for some patient groups. So, we run forecasts for volumes of patients in need of G&A, and for proportions of patients in need of care that need CC. These proportions are forecasted using a local linear trend model with trigonometric seasonality. The dependent variable used in the estimation is not the proportion of interest p_t but $y_t = \ln\left(\frac{1-p_t}{p_t}\right)$. Forecasts for p_t and the corresponding forecasting intervals are obtained from forecasts and forecasting intervals of y_t, respectively, by $p_t = \frac{1}{1+e^{y_t}}$.

These weekly proportions are then applied to the forecasted volumes of patients in need of elective care (cohort A) and emergency care (cohort B) for each patient group in order to obtain the number of patients in need of care split by elective vs. emergency setting, patient group (disease, age, and frailty), and G&A vs. CC entry point.

C2. Adjusting for Emergency Needs reductions

Changes in care seeking behavior, changes in the prevalence of certain conditions and deaths at home have reduced the number of A&E attendances and emergency admissions during the pandemic, but our forecasts of emergency needs do not account for such changes. Therefore, we modify our forecasts for emergency admissions in the light of the changes in the patterns observed in the total hospital admission in England. In order to calculate the percentage reduction in emergency admission, we estimate a local linear trend model with trigonometric seasonality to monthly historical data (i.e. s = 12 in the sum of trigonometric terms) between August 2010 and February 2020. We then forecast emergency admissions and forecasting interval (FI) for the next four months and compute the percentage difference between the forecasted and the observed emergency admissions. The results are reported in Table C1 below.

Table C1. Forecasted versus actual emergency attendances from March to June 2020

Month	Forecasted Emergency Attendances	Lower 95% FI	Upper 95% FI	Actual Emergency Attendances	Percentage Difference	Lower 95% FI	Upper 95% FI
March	556,899	550,285	563,512	427,921	– 30%	– 29%	– 32%
April	530,080	523,467	536,694	326,581	– 62%	– 60%	– 64%
May	550,247	543,634	556,861	398,407	– 38%	– 36%	– 40%
June	534,958	528,344	541,571	437,535	– 22%	– 21%	– 24%

We found that the forecasted emergency needs reduced by around 34% during the first peak of the pandemic.

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Appendix D: Epidemiological Projections for COVID-19 Hospitalizations

Epidemic projections are made using the integrated epidemic/economic model Daedalus [45], in which the population consists of 4 age groups: pre-schoolers, school-age children, working-age adults, and retired. The working-age population is further divided into 63 economic sectors plus non-working adults. Each of these groups is further divided into 8 subgroups with respect to disease status: the susceptible, the exposed, the asymptomatic infectious, the infected with mild symptoms, the infected with influenza like symptoms, the hospitalized, the recovered, and the dead, whose population at time t is denoted, respectively, by $S_i(t)$, $E_i(t)$, $I_i^{asym}(t)$, $I_i^{mild}(t)$, $I_i^{ILI}(t)$, $H_i(t)$, $R_i(t)$, and $D_i(t)$. Disease dynamics follow a SEIR model as follows:

$$\dot{S}_i(t) = -S_i(t)\lambda_i(t)$$
$$\dot{E}_i(t) = S_i(t)\lambda_i(t) - \sigma E_i(t)$$
$$\lambda_i(t) = \beta \sum_{j=1}^{7} M_{ij} \frac{I_j(t)}{w_j}$$
$$I_j(t) = \dot{\mathrm{I}}_{\mathrm{i}}^{\mathrm{asym}}(t) + \dot{I}_i^{mild}(t) + \dot{I}_i^{ILI}(t)$$
$$\dot{\mathrm{I}}_{\mathrm{i}}^{\mathrm{asym}}(t) = \sigma(1 - \mathrm{p_{sym}})\mathrm{E_i}(t) - \gamma_1 \mathrm{I_i^{asym}}(t)$$
$$\dot{I}_i^{mild}(t) = \sigma p_{sym}(1 - p_{ILI})E_i(t) - \gamma_1 I_i^{mild}(t)$$
$$\dot{I}_i^{ILI}(t) = \sigma p_{sym} p_{ILI} E_i(t) - \gamma_2 I_i^{ILI}(t) - h_i I_i^{ILI}(t)$$
$$\dot{H}_i(t) = h_i I_i^{ILI}(t) - \gamma_3 H_i(t) - \mu_i H_i(t)$$
$$\dot{D}_i(t) = \mu_i H_i(t)$$
$$\dot{R}_i(t) = \gamma_1 \left(I_i^{asym}(t) + I_i^{mild}(t)\right) + \gamma_2 I_i^{ILI}(t) + \gamma_3 H(t).$$

The indices *i* and *j* incorporate a community of 4 age groups (0-4, 5-19, 20-64, 65+ years) and the 63 sectors of the economy, each comprising a subset of the 20-64-year-old population. The degree $x_i \in [0,1]$ to which a sector is open determines the working sector population, with $x_i = 1$ yielding the pre-lockdown scenario (fully functioning). The value of x_i can be changed at discrete time intervals. All populations are subject to contacts in the community, with additional contacts made in the workplace. Opening certain sectors (schools, transport and hospitality/entertainment venues) also induces additional community contacts.

All model parameters are consistent with the real-time modelling used at Imperial College London.[46] Infections are divided into asymptomatic (“asym”), symptomatic (“sym”) and influenza-like-illness (“ILI”). P_{sym} denotes the proportion of infections that are symptomatic, and p_{ILI} the proportion of symptomatic infections that are influenza-like. Recovery rates are denoted by the letter γ, and age-stratified hospitalization and death rates are denoted h_i and μ_i, respectively.

We fit four parameters to English hospital occupancy data [29] from 20th of March to 30th of June 2020, namely t_0 (epidemic onset), R_0 (basic reproduction number), t_1 (lockdown onset) and δ (reduction in transmission during lockdown due to NPIs). Economic closure during lockdown, x_{min}, is estimated from ONS [47], alongside changes in contact rates due to working from home. For simplicity, and in order for projections to remain independent of hospitalization constraints, our projections retain the economic configuration, and we calibrate a fixed post-lockdown value of δ to yield our desired maximum value R_{max} of the reproduction number R_t. Calibration is performed using the next-generation operator eigenvalue method [48], for values of $R_{max} = 1.1$ and $R_{max} = 1.2$. A further value of δ is calibrated to $R_{max} = 1$ and used to impose a second lockdown on 1st December 2020 (Early) or 1st January 2021 (Late). This second lockdown is exogenous to the hospital capacity model, whilst representing a realistic mitigation strategy. We therefore have four different scenarios, comprising all combinations of R_{max} and onset of second lockdown.

Figure D1 presents the fitted initial epidemic and 4 projected scenarios.

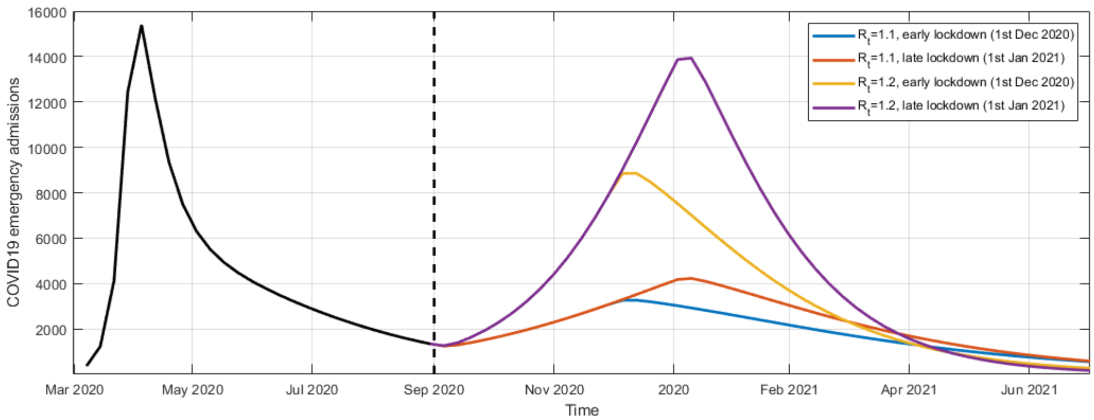

Figure D1. Fitted initial epidemic and 4 projected scenarios.

Appendix E: Transition Probabilities

We estimate transition probabilities for both patients waiting to receive care and those admitted to hospital.

E1. Patients in Need of Emergency Care due to Prolonged Waiting to Receive Care (π^{e}_{wp})

It is possible that patients waiting for elective care need emergency care due to prolonged waiting times imposed by prioritization rules and/or the various scenarios (e.g. postponement of elective admissions lead to delayed access to care for those patients). The longer patients wait, the more likely they are to need emergency care. We identify these types of patients as those that had an emergency admission for the same ICD as their elective admission while they were waiting for elective care. Specifically, we calculate the waiting period as the difference in time between the date (*rttperstart_elective* in HES) the patient entered the care pathway (i.e. when they are first referred to a consultant for a new condition) and the date the patient is admitted for emergency care for the same ICD (*admidate_emergency* in HES).

For our optimization model in Appendix A, we calculate the probability (π_p) that an individual within patient group *p* who is not admitted as an elective in a certain week may be admitted as an emergency in that week conditional on having already waited for a certain time period:

$$Pr\{WT \leq wt + 1 | WT \geq wt\}$$

where WT is the length of time between the referral to treat date and the emergency admission and wt is the length of time the individual has already waited pre-admission. The probability of switching in week $wt + 1$ is calculated using survival analysis methods as:

$$Pr\{WT \leq wt + 1 \mid WT \geq wt\} = \frac{1 - Pr\{WT \geq wt + 1\}}{Pr\{WT \geq wt\}} = \frac{1 - S(wt + 1)}{S(wt)},$$

where $S(t), t \geq 0$, is the survival function. Assuming we have independent and identically distributed observations on N individuals, with censoring time independent of the survival time, the required probability can be estimated using $\frac{1-\hat{S}(wt+1)}{\hat{S}(wt)}$, where $\hat{S}(wt)$ is the Kaplan-Meier estimator of the survival function. The estimation is done using the package Survival in R. [49]

We calculate these probabilities at weekly intervals of waiting time over a ten-week period (i.e. *wt* = 7, 14, 21 ,..,70). Then the average of these probabilities is used as input into the optimization model to give an estimate of this incidence across a range of *wt*.

Ideally, we would have estimated the transition probabilities stratified for every patient group defined by the ICDs, age groups and frailty scores outlined in Appendix B. However, due to small sample sizes in some of those groups, Kaplan-Meier estimates would not be precise. Therefore, we bundle some ICDs together for both emergency and elective admissions. Specifically, we bundle the ICDs representing the lowest 5% of the frequency distribution of electives as well as emergency patients in need of care. While the same criterion is applied for electives and for emergencies, the bundled groups do not match between electives and emergencies (Appendix Table B2). Thus, in estimating the transition probabilities we pool all patients in the elective bundle. Then we further refine that transition probability by combining it with the forecasted proportions of each ICD/age group out of the total number of patients in the bundle. The latter is accomplished using a local linear trend model with trigonometric seasonality subject to suitable transformations to account for the fact that a proportion is between zero and one (Appendix C1). In particular, the probability of transitioning from a waiting fo elective care to needing emergency care is applied to the cohort of patients in need of elective care (cohort A). Then, we apply the forecasted proportions who move from the electives to the emergency bundle of patients to this newly calculated stock of patients transitioning, in order to ascertain the number of patients in each ICD group that move from needing elective (cohort A) to emergency (cohort B) care.

E2. Patients Admitted to Hospital ($\pi_{y,ap}^{SS'}$)

Upon admission to hospital, patients in need of elective and emergency care can move between different states in their immediate care pathway. A patient can be admitted to G&A, then transition to being discharged (i.e. recovery), CC or die. Similarly, a patient can be admitted to CC (either directly or through G&A), then transition into recovery, (return) to G&A or die. For each G&A and CC starting state, the end states are mutually exclusive and jointly exhaustive outcomes.

Most patients admitted to G&A or CC beds stay for less than a week. Since our time unit is a week, estimating the transition probabilities at the end of the week would lead to an over-estimate of their patients' expected time in hospital. Therefore, we split the first week in half and estimate the transition probabilities for patients in the first half of the week (i.e. at 3.5 days from admission). For patients that remain in G&A longer than 3.5 days we estimate the probability of dying, being discharged from hospital, being transferred to CC or continue staying in a G&A bed by the end of day 10.5 of their admission. In the optimization model, the transition probabilities at 3.5 days are used as transition probabilities at the end of the first week from admissions. The transition probabilities at 10.5 days are then used for all subsequent weeks. For the stock of patients already in hospital at the start of the pandemic, the transition probabilities at 10.5 days apply.

The transition probabilities at 3.5 days are estimated using a multinomial logit. We estimate the transition probabilities at 10.5 days using a multinomial logit for individuals who stay longer than 3.5 days.

We make the following assumptions in this analysis.

First, patients in need of emergency care, both non-COVID-19 (cohort B) and COVID-19 (cohort C), are admitted without waiting. Therefore, their in-hospital transition probabilities are not conditioned on waiting time. For patients admitted for elective care, the transition probabilities are estimated conditional on waiting times.

Second, we do not include patients that need emergency care while waiting for elective procedures in the calculations of elective (cohort A) transition probabilities. Thus, it is possible that we underestimate some of the probabilities of transitioning into more severe states (e.g. CC or death).

Third, in the absence of data during the COVID-19 epidemic, we assume that the in-hospital transition probabilities estimated for non-COVID-19 patients pre-pandemic remained unchanged after the start of the pandemic.

Fourth, given the above assumption may be reasonable when hospital capacity is far from being exhausted but too strong under full capacity constraints (i.e., hospitals operating at capacity will see patients who would normally be admitted to CC remaining in G&A beds), we make the following simplifying assumptions for non-COVID-19 patients denied CC (these are the patients in group G^*):

(i) The probability of an individual i dying at time t if denied CC when in need is at least as large as the probability of dying if timely admitted to CC such that:

$$Pr_t^i\{dying|denied\ CC\} = \frac{1}{2}\left(Pr_t^i\{dying|CC\} + 1\right)$$

(ii) The probability that a patient who has been denied CC, is discharged alive is half of the smaller between the probability of not dying if denied CC and the probability that a patient who is in CC is first discharged to G&A and then discharged alive:

$$Pr_t^i\{discharged\ alive|denied\ CC\} = \frac{1}{2}min\left\{1 - Pr_t^i\{dying|denied\ CC\}, Pr_t^i\{discharged\ alive|G\&A\}\ Pr_t^i\{G\&A|in\ CC\}\right\}$$

(iii) The probability of an individual i remaining in G&A at time step t is 1 minus both of the above probabilities:

$$Pr_t^i\{G\&A|denied\ CC\} = 1 - Pr_t^i\{dying|denied\ CC\} - Pr_t^i\{discharged\ alive|denied\ CC\}.$$

Patients initially denied CC are in need of CC in subsequent weeks and can therefore be admitted to CC at all subsequent weekly time steps if capacity becomes available. If capacity does not become available, these patients will stay in G&A and the transition probabilities conditional on being denied CC apply to them.

Lastly, for the case of COVID-19 patients, we calculate the above transition probabilities as previously described directly from the available data.

Appendix F: Costs and Years of Life Lost

F1. Estimating Unit Costs

To calculate the cost the care provided in hospital, we link HES data with reference costs via their HRG. Patients are first matched via hospital and HRG using 2018-19 organizational reference cost data. If they could not be matched, they are then linked via just the HRG using the 2018-19 national reference cost schedule. We attempt to match any additional unmatched patients on either hospital and HRG using organizational or national reference cost data from 2017-18, then 2016-17, and then 2015-16. Due to data limitations, the majority of HES data could not be costed in years 2015-17. We therefore calculate average costs per patient group using admissions from 2017-19, where only fewer than 1% of admissions are not costed. There are no significant differences between average costs calculated using 2017-19 data and 2015-19 data. While it is possible that our cost estimates may be biased due to these missing matched patients, the small percentage of unmatched patients suggests that this bias is likely negligible.

Since HRGs do not yet exist for COVID-19 patients, we estimate their hospitalization costs by building our own HRGs using the HRG4+ 2020/21 Local Payment Grouper publicly available from NHS Digital.[21] The grouper is a computer program that assigns an HRG by considering various patient-level information and is the same software used by the NHS to generate HRGs in the HES data. We therefore take the following individual-level information from administrative discharge records of COVID-19 patients from ICHNT and feed them into the grouper to create individual HRGs for each patient: managing hospital, area of admission (clinical vs surgical), age, sex, method of admission (emergency vs elective), discharge destination, length of stay (days), number of consultant assessment episodes, list of final diagnoses (ICD-10) and procedures (OPCS-4), among others. An average unit cost as well as distributions of unit costs per patient group are then calculated for each cohort.

F2. Years of Life Lost

To calculate the unit YLL for each age group, we take the unweighted average of the age specific life expectancy across all ages in that group. The unit YLL per death for each age group is subsequently multiplied by the number total number of deaths of the group (irrespective of the age distribution if the patients are within the group) estimated by the optimization model to provide the total YLL.

This is summarized using the equation below:

$$YLL_i = (Life\ Expectancy - Age\ Group\ midpoint_i) \times Total\ umber\ of\ deaths_i$$

With $i = \{< 25, 25 - 64, 64\}$ denoting the age group.

As a sensitivity analysis, we also calculate the unit YLL in the following way. Using the life expectancy (LE) at birth for the UK in 2020 (81.15 years)[32] we derive the unit YLL per death for each age group by taking the difference between LE and the midpoint of the age group (i.e. at 12.5, 44.5 and 73 years). For example, for the age group 64+, the YLL per death is 8 (i.e., 81.15 –73, where 73 is the midpoint of the age group). Table F1 below summarizes the unit YLL per death across the age groups considered.

Table F1: Unit YLL per death across the three age categories

Age Group *i*	**Unit YLL per death using LE at birth**	**Unit YLL per death using age specific LE**
<25	68.85	69.9
25-64	36.65	38.5
64+	8.15	8.9

Appendix G: Standard Policies

We use the following *Standard Policies* implemented by the English government in our simulated scenarios: prioritization of patients to CC and the postponement of scheduled elective procedures.

On the 20th of March 2020, England's National Institute for Health and Care Excellence (NICE) published a critical care prioritization guideline for adults during the COVID-19 pandemic.[6] The guidelines (Figure G1) suggest how to prioritize admission of adult patients to critical care. In general, NICE suggested to assess each patient using a frailty assessment according to age. Those over 65 years of age without long-term disabilities, learning disabilities, or autism are to be assessed using the Clinical Frailty Scale (CFS) score. Physicians are suggested to use an individualized assessment of frailty and not the CFS score for patients under 65-years-old with long-term disabilities, learning disabilities, or autism. Those who are deemed to be less frail (e.g., CFS score < 5) and would like CC treatment would be referred to CC if their condition worsened. Those who are identified as frailer (e.g., CFS score of 5+) are further assessed whether CC was appropriate (measures undefined by NICE; presumably left to the physicians' discretion). If so, then these patients could still be admitted to CC if their condition deteriorated. If not, then these patients would receive end-of-life care.

To mirror this policy change, we include a prioritization rule to CC whereby in weeks where CC capacity will be full, patients are prioritized based on their frailty score. That is, patients who are not frail are prioritized over patients who are frail.

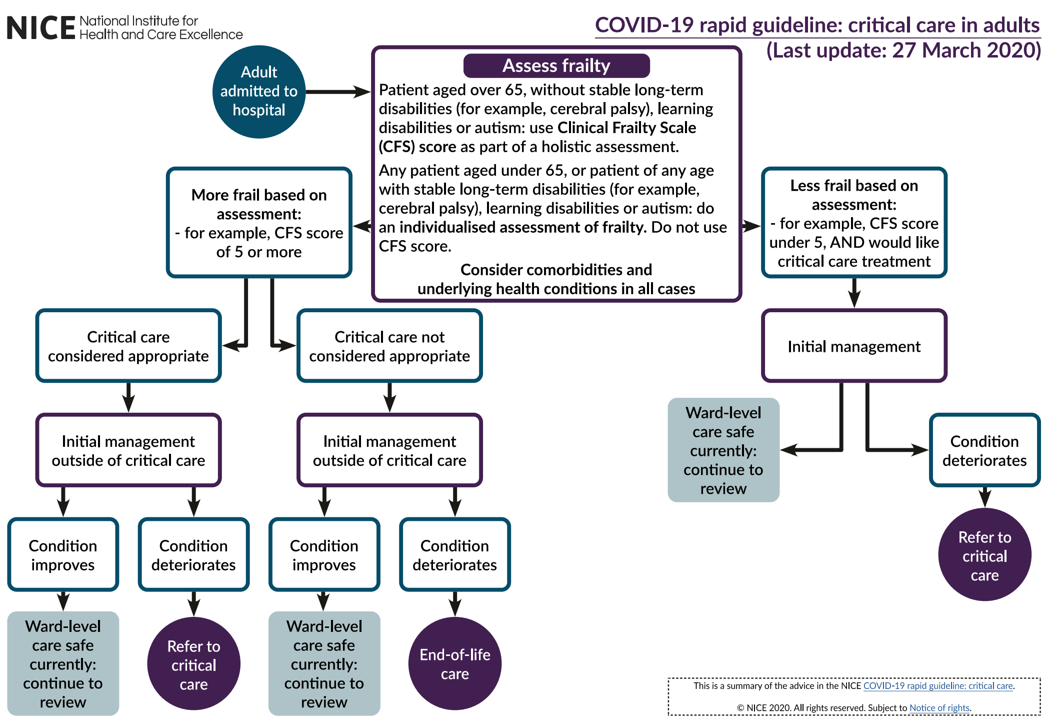

Figure G1. NICE prioritization of adults into critical care during COVID-19 pandemic guidelines[6]

Furthermore, in a letter to NHS staff on the 17th of March 2020, NHS England's Chief Executive and the NHS Chief Operating Officer informed hospitals to cancel all non-urgent elective operations from April 15th at the latest. This was implemented for hospitals to free up the maximum possible capacity in anticipation of upcoming surges in demand due to COVID-19 patients. On the 23rd of April, 2020, it was announced that hospitals should re-start other services.[50] Therefore, we leverage these decisions to model four *Standard Policies*.

In *Standard Policy 1*, we mimic the implementation of the policy described above that occurred in England between 17th of March and 23rd of April (weeks 3-8) and that consists of prioritization of patients to critical care based on frailty and postponement of non-urgent elective operations. *Standard Policy 1* assumes that the policy was only enacted during the actual time-period (weeks 3-8) and the postponement of 100% of elective procedures. *Standard Policy 2* considers potential policy implementation during future pandemic peaks by switching the policy on and off depending on the number of predicted COVID-19 cases in the population. We switch the policy on (postponement of 100% of electives) when the number of predicted COVID-19 cases surpass 4,118 (the observed number of cases on 17th of March). The policy is switched off when the number of predicted COVID-19 hospitalizations begin to decline and falls below 7,494 (the observed number of cases on 23rd of April). If the number of cases never reaches the peak 7,494 after the policy is switched on, then it is switched off when the number of hospitalizations begins to decrease. Therefore, for $R_t = 1.1$, the policy switches on between weeks 3-8 and 44-50 for Late Lockdown and between weeks 3-8 only for Early Lockdown. Likewise, for $R_t = 1.2$, the policy switches on between weeks 3-8 and 35-54 for Late Lockdown and between weeks 3-8 and 35-44 for Early Lockdown. *Standard Policies 3 and 4* follow the same rules as *Standard Policies 1 and 2* except with the postponement of 75% of electives.

For all policies, we run the different epidemiological scenarios, namely: Baseline (Early and Late Lockdown), Best-Case (Early and Late Lockdown) and Worst-Case scenario (Early and Late Lockdown).

G1. Simulation Model

We develop a simulation model over a 52-week planning-horizon to replicate the *Standard Policies* and compare their outcomes against those of the *Optimized Schedule*.

The simulation model admits patients to hospital according to a rule-based system, by which patients are admitted to hospital according to their order of priority as determined pre-pandemic; in addition to this, they account for the postponement of a fraction of elective admissions over given weeks of the planning horizon. For each scenario, we implement a postponement of "x%" elective admissions during the weeks in which the *Standard Policy* is activated. Patients for which their elective procedures are postponed remain in the queue awaiting admission at the earliest possible time according to a FIFO rule. We look at two values for "x%", namely 100% (in *Standard Policies 1 and 2*) and 75% (in *Standard Policies 3 and 4*). In addition, during the weeks in which the *Standard Policy* is on, CC is prioritized for non-frail patients (emergency and elective) belonging to each patient group.

G1.1 Model Inputs

At the beginning of the time horizon ($t = 0$) we have as inputs the total available resources and an initial stock of patients comprising of patients hospitalized at $t = 0$ in CC and G&A, and elective patients awaiting admission. We aggregate patients by disease type and severity states, allowing for enough differentiation to closely reflect the individual patient characteristics. For each subgroup, we also have information detailing their resource requirements, transition probabilities, and frailty proportions. The transition probabilities represent the evolution of a patient's condition (reflected by their severity state) once admitted to hospital, while the frailty proportions for each group are used for prioritizing access to CC for non-frail patients during the time periods that the resources are rationed. For $t > 0$, based on the scenario we are investigating (e.g., reproduction number, Late versus Early Lockdown), we observe new exogenous inflows of patients. Moreover, for each *Standard Policy* that is implemented, we have as input the time period in which the *Policy* is activated.

G1.2 Model Assumptions

We impose the following assumptions on the simulation model:

(i) If an incoming emergency patient is denied access to hospital due to shortage of beds in G&A at a particular time period, we assume that the patient dies if no more emergcncy capacity is created (Upper Bound case) or the patient is seen in extra emergency capacity created by the government (Lower Bound case).

(ii) The non-frail prioritization rule during the weeks in which the policy is activated applies only to new incoming patients requiring CC. That is, if a patient is in CC the week before the *Standard Policy* is turned on (week 2) and this patient again requires CC in the week that the *Standard Policy* is turned on (week 3), this patient will not be removed from CC even though he may be frail.

(iii) During the weeks in which the *Standard Policy* is on, non-frail patients are prioritized for access to CC. However, if beds are available once all the non-frail patients have been admitted to CC, the remaining beds are allocated to frail patients.

(iv) With regards to access to resources, a patient already in hospital has higher priority over incoming patients. That is, no patient already admitted in hospital is removed from hospital to make space for an incoming patient.

G1.3 Model Implementation

At the beginning of each week/time period *t* (where $0 \leq t \leq T$), all resources are available to the model. First, patients currently in hospital from the previous week, transition from their state in week $t - 1$ to their current state in week t. The transition occurs according to a Markov Chain which uses the transition probabilities of the subgroup that the patient belongs to. If a patient recovers (i.e., transitions to "H" state), he/she is removed from the system. If a patient dies (i.e., transitions to "D" state), the corresponding YLL is updated and the patient is removed from the system. For any other transition, patients are moved or allowed to stay on in the ward where they require care and the resources required in the current week are updated accordingly. Once all the patients have transitioned, we check if the resource requirement in CC for the current week exceeds the resource availability in CC. If this is the case, we choose uniformly among patients needing CC and move them to G&A (G*) until the resources in CC are no longer over-utilized. By design, we always have enough resources in G&A to accommodate patients already in hospital from previous weeks.

We next make admissions decisions regarding the patients in need of emergency care arising from the inflows (of standard emergencies as well as patients in need of emergency care as a result of waiting for elective care) in the current week. We first handle the emergency patients requiring CC, followed by those requiring G&A. Our handling of these patients depends on whether the *Standard Policy* is on/off in the current week.

(i) *When the Standard Policy is on:* The non-frail patients from each patient subgroup are prioritized for access to CC. If not enough resources in CC are available to accommodate all non-frail patients requiring CC, we employ uniform sampling to choose non-frail patients across subgroups that are admitted to CC for the current week. The remaining patients are allocated G&A, where they evolve according to a new set of transition probabilities (G*). However, if space remains available in CC once all the non-frail patients have been accommodated in CC, the remaining resources are uniformly distributed amongst the frail patients belonging to the different subgroups. The remaining frail patients (if any) are moved to G&A (G*). Finally, we admit patients that require G&A. If resources in G&A are short, we once again employ uniform sampling across subgroups to admit patients to G&A. Any emergency patients denied admission to G&A are assumed to either die if no more emergency capacity is created (Upper Bound case) or to be seen in extra emergency capacity created by the government (Lower Bound case).

(ii) *When the Standard Policy is off:* In these weeks, the mechanism for admissions remains the same as in the weeks when the *Standard Policy* is on, except that the patients are not prioritized by frailty for access to CC.

Finally, we make decisions regarding the elective admissions for the current week. The patients are first added to the waiting queue (which may be empty) corresponding to their subgroups. Subsequently, the patients are admitted from the queue in a FIFO rule. That is, we first admit patients who entered the waiting queue at an earlier point in time before admitting patients who entered the queue at a later time.

(i) *When the Standard Policy is on:* In these weeks, we postpone x% of electives. That is, we can only admit up to (100 - x)% of the electives given that there is sufficient space available. Moreover, in these weeks, CC is prioritized for non-frail patients belonging to each subgroup. The number of patients admitted in the current week are thus driven by the *Standard Policy* and the availability of resources. The number of patients admitted from each subgroup is proportional to the fraction of the total waiting patients belonging to that particular subgroup.

(ii) *When the Standard Policy is off:* In these weeks, we admit as many elective patients as can be accommodated in CC and G&A subject to availability of resources. As in (i), the number of patients admitted from each subgroup is proportional to the fraction of the total waiting patients belonging to that particular subgroup.

G1.4 Model Outputs

At each time period, for each subgroup of patients we track the following:

(i) Number of elective and emergency admissions made, and the associated costs
(ii) Contribution to YLL as a result of patients dying
(iii) Emergency patients denied admission to hospital
(iv) The beds utilized in CC and G&A (differentiated by those that require G&A and those that required CC but were moved to G&A because of insufficient beds in CC).

Appendix H: Simulation & Scenarios for Optimized Schedule and Standard Policies

Table H. Constraints and assumptions for each scenario and simulation

Simulation	Scenario Name	X% Cancellation of Electives, Policy Description	Reproduction Number (R_t)/Lockdown month	Capacity	Emergency Care-Seeking Behavior
Optimized Schedule	Baseline Early Lockdown	N/A	1.1/Dec	Normal	Normal
	Baseline Late Lockdown	N/A	1.1/Feb	Normal	Normal
	Best-Case Early Lockdown	N/A	1.1/Dec	Expanded	Reduced
	Best-Case Late Lockdown	N/A	1.1/Feb	Expanded	Reduced
	Worst-Case Early Lockdown	N/A	1.2/Dec	Normal	Normal
	Worst-Case Late Lockdown	N/A	1.2/Feb	Normal	Normal
Standard Policy 1	Baseline Early Lockdown	100%, on over weeks 3-8	1.1/Dec	Normal	Normal
	Baseline Late Lockdown	100%, on over weeks 3-8	1.1/Feb	Normal	Normal
	Best-Case Early Lockdown	100%, on over weeks 3-8	1.1/Dec	Expanded	Reduced
	Best-Case Late Lockdown	100%, on over weeks 3-8	1.1/Feb	Expanded	Reduced
	Worst-Case Early Lockdown	100%, on over weeks 3-8	1.2/Dec	Normal	Normal
	Worst-Case Late Lockdown	100%, on over weeks 3-8	1.2/Feb	Normal	Normal
Standard Policy 2	Baseline Early Lockdown	100%, on/off with thresholds	1.1/Dec	Normal	Normal
	Baseline Late Lockdown	100%, on/off with thresholds	1.1/Feb	Normal	Normal
	Best-Case Early Lockdown	100%, on/off with thresholds	1.1/Dec	Expanded	Reduced
	Best-Case Late Lockdown	100%, on/off with thresholds	1.1/Feb	Expanded	Reduced
	Worst-Case Early Lockdown	100%, on/off with thresholds	1.2/Dec	Normal	Normal
	Worst-Case Late Lockdown	100%, on/off with thresholds	1.2/Feb	Normal	Normal
Standard Policy 3	Baseline Early Lockdown	75%, on over weeks 3-8	1.1/Dec	Normal	Normal
	Baseline Late Lockdown	75%, on over weeks 3-8	1.1/Feb	Normal	Normal
	Best-Case Early Lockdown	75%, on over weeks 3-8	1.1/Dec	Expanded	Reduced
	Best-Case Late Lockdown	75%, on over weeks 3-8	1.1/Feb	Expanded	Reduced
	Worst-Case Early Lockdown	75%, on over weeks 3-8	1.2/Dec	Normal	Normal

	Worst-Case Late Lockdown	75%, on over weeks 3-8	1.2/Feb	Normal	Normal
Standard Policy 4	Baseline Early Lockdown	75%, on/off with thresholds	1.1/Dec	Normal	Normal
	Baseline Late Lockdown	75%, on/off with thresholds	1.1/Feb	Normal	Normal
	Best-Case Early Lockdown	75%, on/off with thresholds	1.1/Dec	Expanded	Reduced
	Best-Case Late Lockdown	75%, on/off with thresholds	1.1/Feb	Expanded	Reduced
	Worst-Case Early Lockdown	75%, on/off with thresholds	1.2/Dec	Normal	Normal
	Worst-Case Late Lockdown	75%, on/off with thresholds	1.2/Feb	Normal	Normal

Appendix I: Results - Figures and Tables

Table I1. Health economic metrics (costs and years of life lost) for *Optimized Schedule* and *Standard Policy* scenarios

	Scenario	Total Cost (£ millions) Lower Bound	Total Cost (£ millions) Upper Bound	Unit Cost (£) Lower Bound	Unit Cost (£) Upper Bound	Total YLL (x 1,000) Lower Bound	Total YLL (x 1,000) Upper Bound	Unit YLL Lower Bound	Unit YLL Upper Bound
Optimized Schedule	Baseline Early Lockdown	23,173	23,180	2,593	2,593	5,113	5,129	0.57	0.57
	Baseline Late Lockdown	23,260	23,268	2,594	2,594	5,350	5,365	0.60	0.60
	Best-Case Early Lockdown	20,458	20,458	2,452	2,452	4,313	4,313	0.52	0.52
	Best-Case Late Lockdown	20,525	20,525	2,454	2,454	4,548	4,548	0.54	0.54
	Worst-Case Early Lockdown	23,197	23,204	2,595	2,596	6,063	6,078	0.68	0.68
	Worst-Case Late Lockdown	22,876	23,151	2,594	2,625	7,266	7,803	0.82	0.88
Standard Policy 1	Baseline Early Lockdown	23,586	23,611	2,629	2,632	5,432	5,687	0.61	0.63
	Baseline Late Lockdown	23,377	23,401	2,641	2,643	5,669	5,918	0.64	0.67
	Best-Case Early Lockdown	20,506	20,506	2,456	2,456	4,375	4,375	0.52	0.52
	Best-Case Late Lockdown	20,573	20,573	2,458	2,458	4,599	4,599	0.55	0.55
	Worst-Case Early Lockdown	22,922	22,974	2,667	2,673	6,581	7,130	0.77	0.83
	Worst-Case Late Lockdown	22,543	23,097	2,679	2,744	7,864	13,694	0.93	1.63
Standard Policy 2	Baseline Early Lockdown	23,586	23,611	2,629	2,632	5,432	5,687	0.61	0.63
	Baseline Late Lockdown	23,143	23,170	2,649	2,652	5,644	5,929	0.65	0.68
	Best-Case Early Lockdown	20,506	20,506	2,456	2,456	4,375	4,375	0.52	0.52
	Best-Case Late Lockdown	20,578	20,578	2,459	2,459	4,608	4,608	0.55	0.55
	Worst-Case Early Lockdown	22,642	22,700	2,678	2,685	6,534	7,142	0.77	0.84
	Worst-Case Late Lockdown	22,284	22,856	2,689	2,758	7,823	13,846	0.94	1.67
Standard Policy 3	Baseline Early Lockdown	23,584	23,614	2,629	2,632	5,423	5,732	0.60	0.64
	Baseline Late Lockdown	23,441	23,468	2,638	2,641	5,670	5,951	0.64	0.67
	Best-Case Early Lockdown	20,495	20,495	2,455	2,455	4,388	4,388	0.53	0.53
	Best-Case Late Lockdown	20,562	20,562	2,457	2,457	4,639	4,639	0.55	0.55
	Worst-Case Early Lockdown	23,001	23,065	2,663	2,670	6,552	7,229	0.76	0.84
	Worst-Case Late Lockdown	22,641	23,196	2,674	2,739	7,857	13,687	0.93	1.62
	Baseline Early Lockdown	23,584	23,614	2,629	2,632	5,423	5,732	0.60	0.64

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	Baseline Late Lockdown	23,289	23,323	2,643	2,647	5,663	6,015	0.64	0.68
	Best-Case Early Lockdown	20,495	20,495	2,455	2,455	4,388	4,388	0.53	0.53
Standard Policy 4	Best-Case Late Lockdown	20,565	20,565	2,457	2,457	4,614	4,614	0.55	0.55
	Worst-Case Early Lockdown	22,748	22,808	2,673	2,681	6,585	7,212	0.77	0.85
	Worst- Case Late Lockdown	22,443	23,012	2,682	2,750	7,813	13,800	0.93	1.65

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Table I2. ICER calculations comparing *Optimized Schedule* and *Standard Policy* scenarios

	Upper Bound			Lower Bound		
Scenario Comparisons	**Incremental YLG**	**Incremental Costs**	**ICER (£ per YLG)**	**Incremental YLG**	**Incremental Costs**	**ICER (£ per YLG)**
Optimization vs Policy 1						
Baseline Early lockdown	558,662	-£413,446,875	Optimization Dominates	319,402	-£430,376,814	Optimization Dominates
Baseline Late lockdown	552,940	-£116,389,685	Optimization Dominates	319,747	-£132,725,591	Optimization Dominates
Best-Case Early Lockdown	61,454	-£47,596,452	Optimization Dominates	61,454	-£47,596,452	Optimization Dominates
Best-Case Late Lockdown	50,750	-£47,642,231	Optimization Dominates	50,750	-£47,642,231	Optimization Dominates
Worst-Case Early Lockdown	1,051,544	£275,091,690	£262	518,162	£230,349,858	£445
Worst-Case Late Lockdown	5,891,608	£333,374,507	£57	597,895	£54,170,589	£91
Optimization vs Policy 2						
Baseline Early lockdown	558,662	-£413,446,875	Optimization Dominates	319,402	-£430,376,814	Optimization Dominates
Baseline Late lockdown	563,403	£117,991,402	£209	294,776	£98,605,639	£335
Best-Case Early Lockdown	61,454	-£47,596,452	Optimization Dominates	61,454	-£47,596,452	Optimization Dominates
Best-Case Late Lockdown	60,114	-£53,050,302	Optimization Dominates	60,114	-£53,050,302	Optimization Dominates
Worst-Case Early Lockdown	1,063,271	£554,618,584	£522	471,048	£504,227,425	£1,070
Worst-Case Late Lockdown	6,043,843	£591,540,040	£98	556,905	£294,550,683	£529
Optimization vs Policy 3						
Baseline Early lockdown	603,207	-£411,545,947	Optimization Dominates	309,949	-£433,623,646	Optimization Dominates
Baseline Late lockdown	586,021	-£180,357,312	Optimization Dominates	320,614	-£199,556,768	Optimization Dominates
Best-Case Early Lockdown	75,133	-£37,030,951	Optimization Dominates	75,133	-£37,030,951	Optimization Dominates
Best-Case Late Lockdown	90,410	-£36,955,969	Optimization Dominates	90,410	-£36,955,969	Optimization Dominates
Worst-Case Early Lockdown	1,150,318	£195,800,775	£170	489,658	£138,855,856	£284
Worst-Case Late Lockdown	5,884,363	£235,303,123	Optimization Dominates	591,657	-£45,143,878	Optimization Dominates
Optimization vs Policy 4						
Baseline Early lockdown	603,207	-£411,545,947	Optimization Dominates	309,949	-£433,623,646	Optimization Dominates
Baseline Late lockdown	650,031	-£28,844,180	Optimization Dominates	313,334	-£55,015,902	Optimization Dominates
Best-Case Early Lockdown	75,133	-£37,030,951	Optimization Dominates	75,133	-£37,030,951	Optimization Dominates
Best-Case Late Lockdown	65,521	-£40,120,334	Optimization Dominates	65,521	-£40,120,334	Optimization Dominates
Worst-Case Early Lockdown	1,133,252	£448,788,642	£396	521,911	£396,138,396	£759
Worst-Case Late Lockdown	5,997,639	£432,669,881	£72	546,779	£139,210,355	£255

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Table I3. Patient flow and capacity metrics for *Optimized Schedule* and *Standard Policy* scenarios

		Patient Flows (x 1,000)							Hospital Capacity			
	Scenario	Total Elective Admissions	Total Emergency Admissions	Total Admissions	Waiting Patients	Admission Denials (Total)	COVID Emergency Admissions	Non-COVID Emergency Admissions	Idle Capacity G&A (%)	Idle Capacity CC (%)	Average Elective Occupancy in G&A (%)	Average Elective Occupancy in CC (%)
Optimized Schedule	Baseline Early Lockdown	2,205	6,733	8,938	1,531	2	179	6,554	1.63	1.90	10.82	21.83
	Baseline Late Lockdown	2,229	6,740	8,969	1,521	2	200	6,540	1.04	1.91	10.93	20.59
	Best-Case Early Lockdown	3,868	4,476	8,345	0	0	182	4,294	31.78	18.02	15.76	26.68
	Best-Case Late Lockdown	3,869	4,496	8,365	0	0	202	4,294	31.32	16.32	15.76	26.69
	Worst-Case Early Lockdown	2,156	6,782	8,939	1,600	2	249	6,533	0.01	1.91	10.37	17.77
	Worst-Case Late Lockdown	2,021	6,798	8,820	1,745	74	311	6,487	0	3.06	9.57	21.94
Standard Policy 1	Baseline Early Lockdown	2,154	6,816	8,970	1,488	9	181	6,635	0.36	1.55	10.08	16.04
	Baseline Late Lockdown	2,014	6,839	8,853	1,625	8	201	6,638	0.35	1.40	9.48	14.85
	Best-Case Early Lockdown	3,850	4,500	8,350	0	0	182	4,318	31.69	22.56	15.46	22.09
	Best-Case Late Lockdown	3,850	4,520	8,370	0	0	202	4,318	31.20	21.14	15.47	22.10
	Worst-Case Early Lockdown	1,702	6,893	8,595	1,923	19	251	6,643	0.36	1.45	7.99	11.88
	Worst-Case Late Lockdown	1,600	6,816	8,416	2,022	196	329	6,487	0.36	1.41	7.58	11.73
Standard Policy 2	Baseline Early Lockdown	2,154	6,816	8,970	1,488	9	181	6,635	0.36	1.55	10.08	16.04
	Baseline Late Lockdown	1,891	6,844	8,735	1,743	10	201	6,642	0.78	1.44	8.95	14.83
	Best-Case Early Lockdown	3,850	4,500	8,350	0	0	182	4,318	31.69	22.56	15.46	22.09
	Best-Case Late Lockdown	3,842	4,528	8,369	1	0	202	4,325	31.42	21.96	15.21	20.83

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	Worst-Case Early Lockdown	1,556	6,898	8,454	2,062	21	250	6,648	1.02	1.74	7.33	10.85
	Worst-Case Late Lockdown	1,471	6,817	8,288	2,145	202	329	6,488	0.96	1.70	6.99	11.08
Standard Policy 3	Baseline Early Lockdown	2,159	6,812	8,971	1,485	10	181	6,631	0.26	0.92	10.18	16.91
	Baseline Late Lockdown	2,052	6,835	8,887	1,591	9	201	6,634	0.26	0.92	9.67	15.94
	Best-Case Early Lockdown	3,860	4,490	8,350	0	0	182	4,307	31.75	21.61	15.55	23.25
	Best-Case Late Lockdown	3,860	4,510	8,370	0	0	202	4,307	31.30	19.90	15.55	23.07
	Worst-Case Early Lockdown	1,756	6,883	8,638	1,876	23	250	6,633	0.26	0.92	8.25	12.34
	Worst-Case Late Lockdown	1,659	6,809	8,468	1,970	196	329	6,479	0.26	0.90	7.87	12.48
Standard Policy 4	Baseline Early Lockdown	2,159	6,812	8,971	1,485	10	181	6,631	0.26	0.92	10.18	16.91
	Baseline Late Lockdown	1,978	6,834	8,812	1,663	12	201	6,633	0.54	0.98	9.37	15.41
	Best-Case Early Lockdown	3,860	4,490	8,350	0	0	182	4,307	31.75	21.61	15.55	23.25
	Best-Case Late Lockdown	3,857	4,513	8,370	0	0	202	4,311	31.33	20.52	15.48	22.74
	Worst-Case Early Lockdown	1,616	6,893	8,509	2,007	21	250	6,642	0.71	0.97	7.66	12.57
	Worst- Case Late Lockdown	1,560	6,810	8,369	2,065	200	329	6,481	0.69	0.98	7.42	12.14

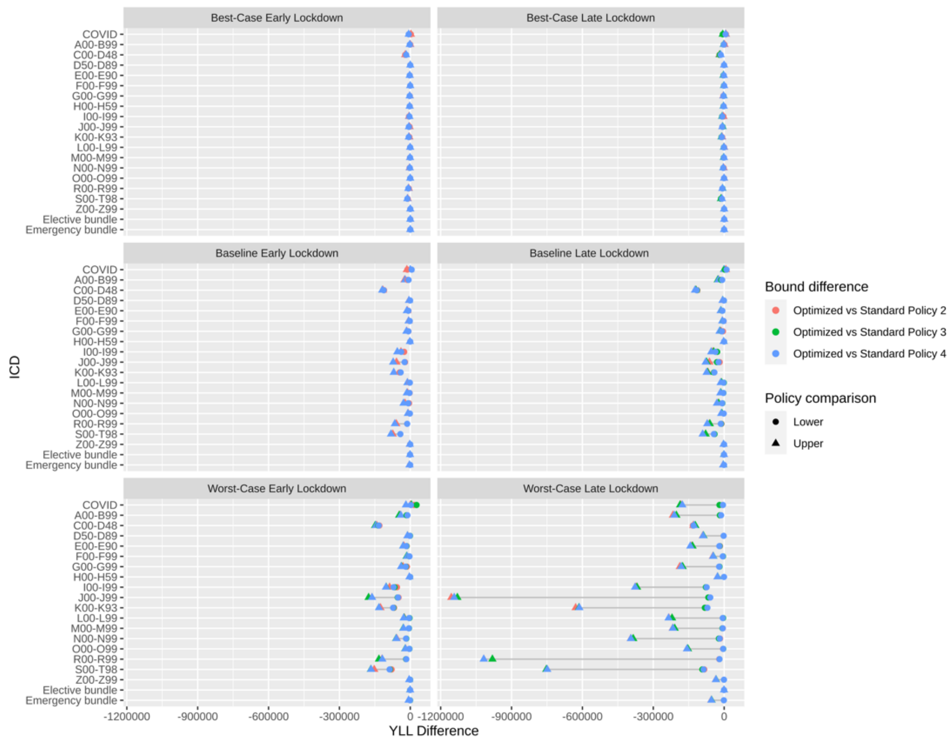


Figure I1. Comparison of *Standard Policies 2-4* with the *Optimized Schedule* for Years of Life Lost (YLL) The difference in YLL for all admissions under *Standard Poli*cies and *Optimized Schedule* ($YLL_{OPT} - YLL_{SP}$) over the 52-week planning horizon.

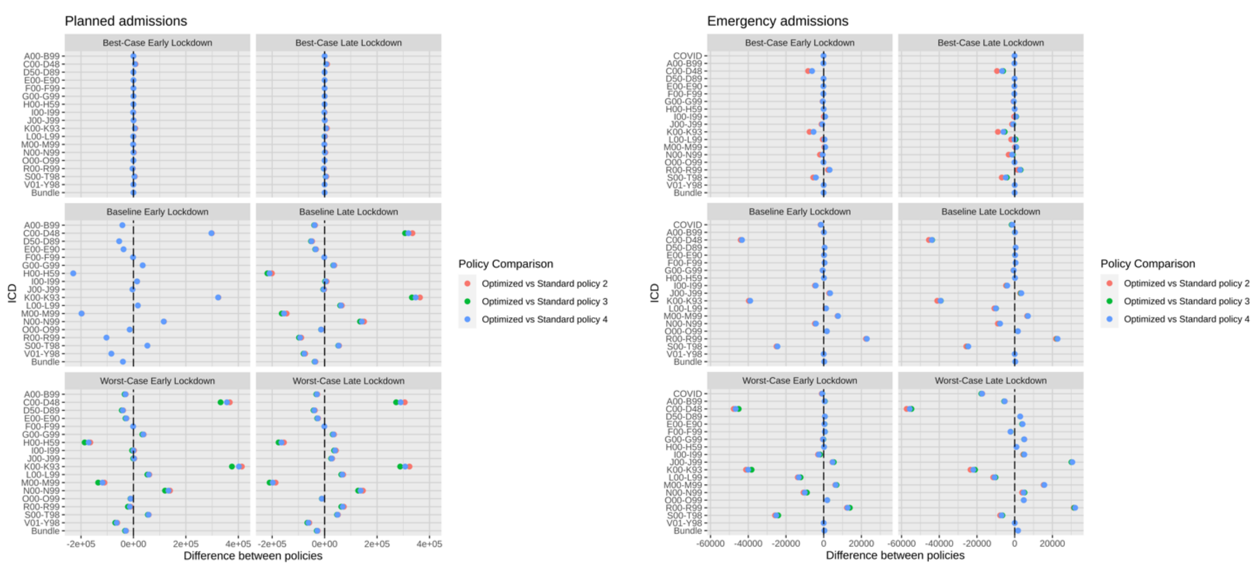


Figure I2. Difference in Elective and Emergency Admissions between Optimized Schedule for Standard Policies 2-4, by ICD. $Difference = Admissions_{OPT} - Admissions_{SP}$.

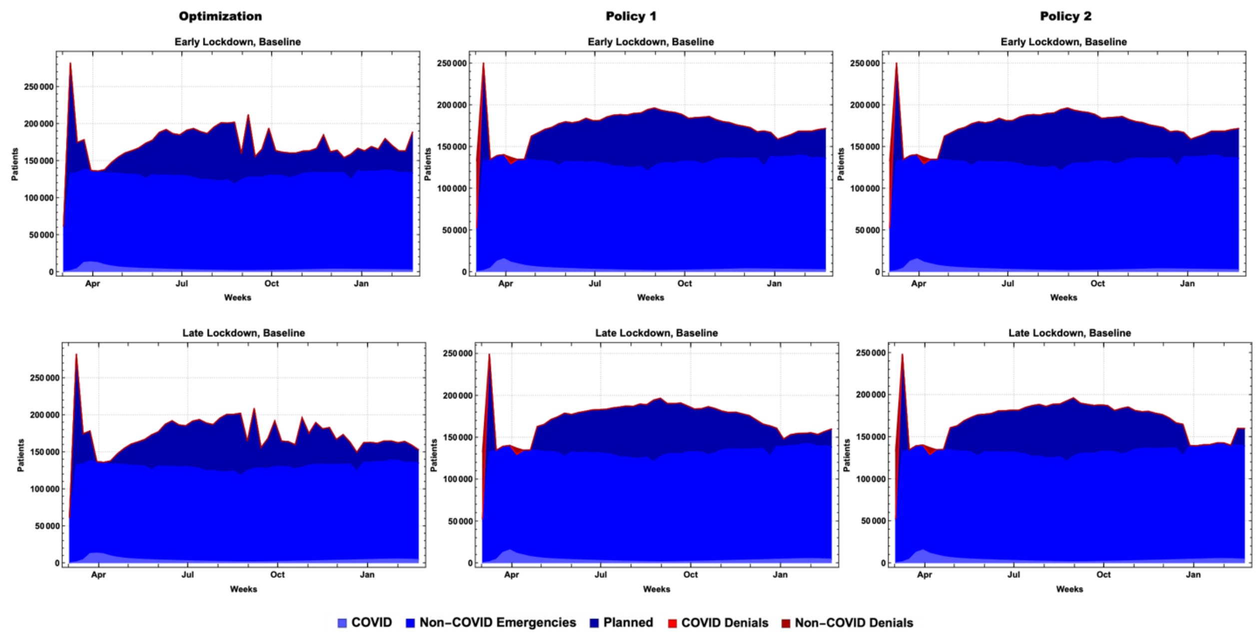
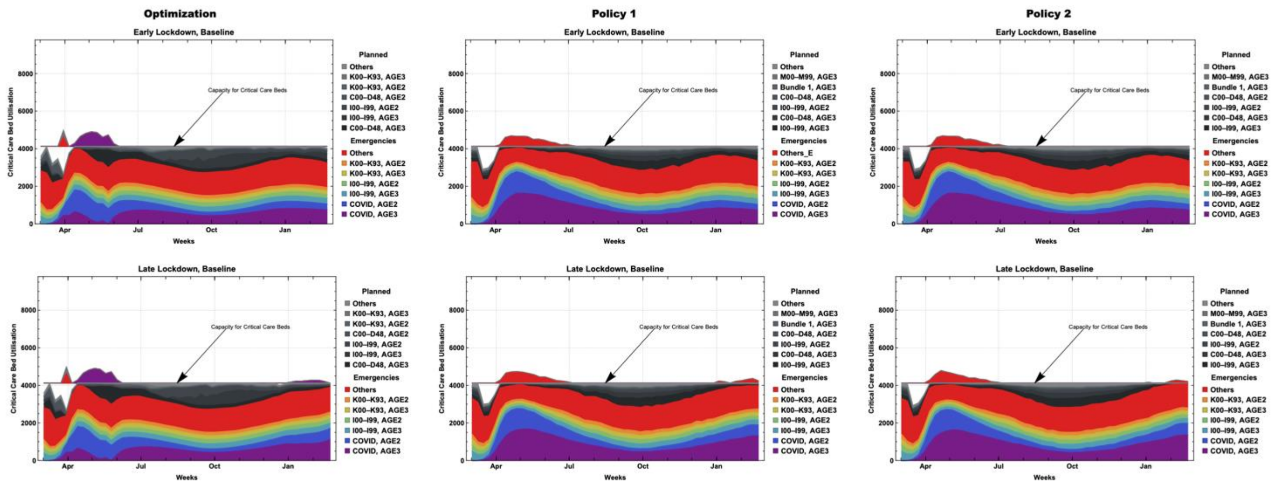
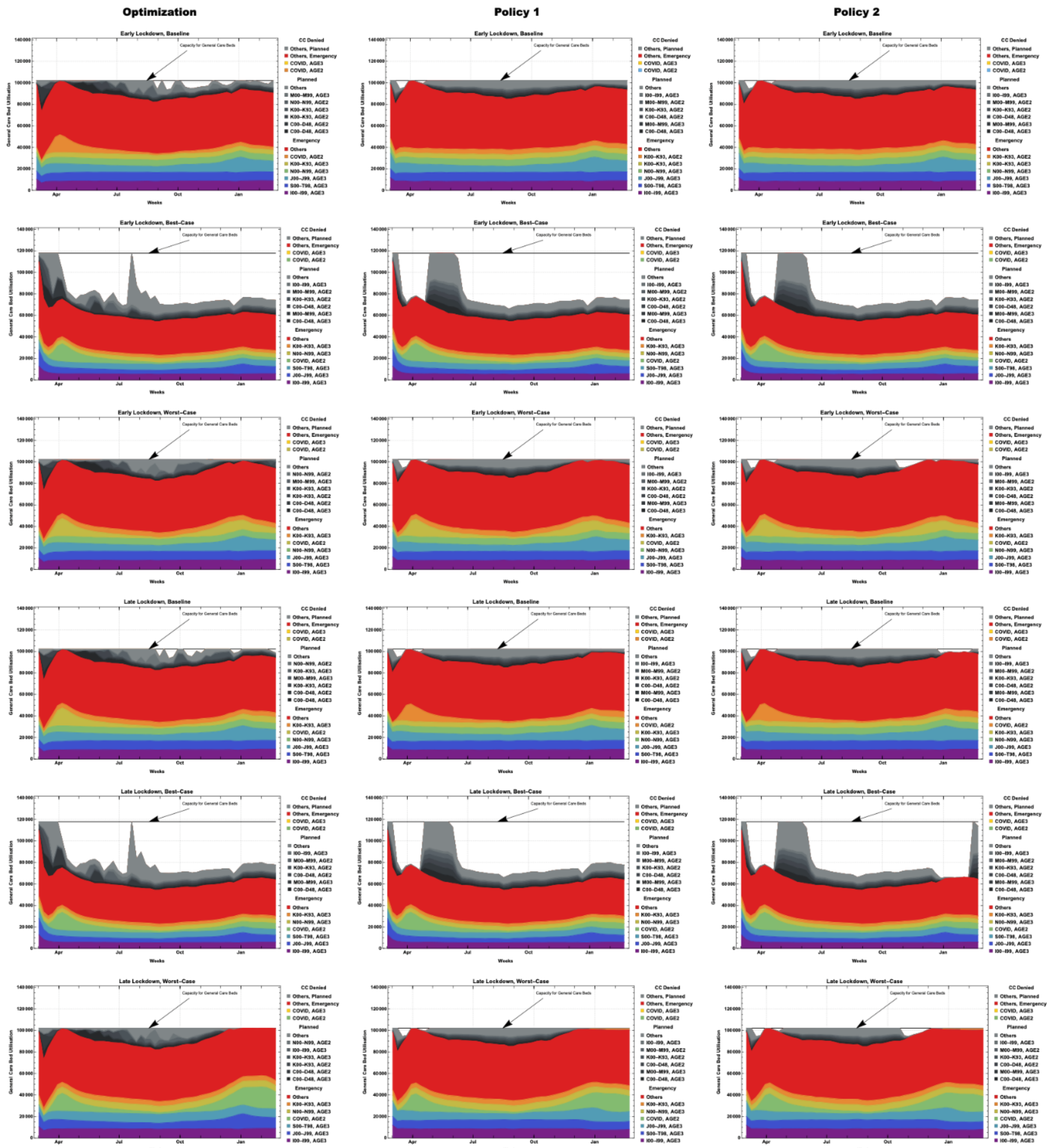


Figure I3. Comparison of admissions and admission denials between *Standard Policy* and *Optimization* scenarios for Baseline scenarios with Early and Late Lockdown



Bundle 1 includes ICD codes A00-B99, E00-E90, F00-F99, H60-H95, O00-O99, P00-P96 and Q00-Q99. Age 1, 2 and 3 correspond to age brackets <25, 25-64 and 64+ respectively.

Figure I4. Comparing CC bed utilisation between *Optimized Schedule* and *Standard Policy* scenarios for Baseline scenarios with Early and Late Lockdown



Age 1, 2 and 3 correspond to age brackets <25, 25-64 and 64+ respectively.

Figure I5. Comparison of G&A bed utilization between *Optimized Schedule* and *Standard Policy* scenarios for Baseline, Best-Case and Worst-Case scenarios

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