DAEDALUS: a model to optimize social and economic activity while containing SARS-CoV-2 transmission

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Abstract

There is a trade-off between the economic, social and health outcomes in the management of a pandemic. DAEDALUS integrates a dynamic epidemiological model of SARS-CoV-2 transmission with a multi-sector economic model, reflecting sectoral heterogeneity in transmission and complex supply chains. The model identifies mitigation strategies that optimize economic production while constraining infections so that hospital capacity is not exceeded but allowing essential services, including much of the education sector, to remain active. The model differentiates closures by economic sector, keeping those sectors open that contribute little to transmission but much to economic output and those that produce essential services as intermediate or final consumption products. In an illustrative application to 63 sectors in the United Kingdom, the model achieves an economic gain of between £161bn (24%) and £193bn (29%) compared to a blanket

lockdown of non-essential activities over six months, depending on spare hospital capacity. Although it has been designed for SARS-CoV-2, DAEDALUS is sufficiently flexible to be applicable to pandemics with different epidemiological characteristics.

Introduction

The SARS-CoV-2 pandemic has galvanized debates on how to maintain economic and educational activities whilst reducing the spread of infection. Until vaccination coverage reaches a sufficiently high level, many countries need to implement non-pharmaceutical interventions (NPIs) to keep infections under control. Closures of schools and businesses deemed non-essential for day-to-day life are highly effective in reducing transmission, but they are associated with high economic and social costs [1, 2, 3, 4], and they are crude interventions if implemented as blanket policies across the whole economy. Economic activities differ greatly in the infection risk that they pose to both workers and consumers, in their potential to implement effective social distancing measures and in the contributions they make to Gross Domestic Product (GDP). It is vital to model how lockdowns can be fine-tuned to prevent health services from being overwhelmed, whilst minimizing the economic costs associated with business closures and the social costs associated with the closure of educational institutions.

DAEDALUS is an integrated economic-epidemiological model that computes the optimal trajectory of selective opening and closing of economic sectors that maximizes GDP while keeping infections under control. DAEDALUS provides concrete policy guidance on a smart opening/closure strategy differentiated by economic sectors. Changes to the economic configuration can be made at discrete time points over the projection horizon – here, we provide an example application to 63 sectors in the United Kingdom and assume a six-month horizon with three such decision points at 0, 2 and 4 months. With a few changes to the epidemiological and economic parameters, DAEDALUS can be applied to any country and respiratory pandemic that requires mitigation measures. Before this study, there was very little evidence on how to optimally design lockdown policies during pandemics. DAEDALUS necessarily rests on many assumptions, but it provides urgently-needed guidance to policy makers on how to design policies that balance key societal objectives.

Results

There are large variations in physical proximity by occupation type [5]. At the core of DAEDALUS lies the insight that relatively contact-light sectors which employ fewer workers carry less infections back into the community when they are open compared to more contact-intensive sectors with more workers (see figure 6). Partial or full opening and closing of a sector leads to changes in the sector's active workforce, and disease transmission in the workplace, during transport and in the community. It also changes the sector's associated contribution to the economy, in the form of gross value added (GVA). GVA is the value of a sector's output minus the value of intermediate inputs, i.e. the products from other sectors that are used in production. GDP is the sum of all sectors' GVA.

DAEDALUS calculates the GDP-maximizing set of sector closures over a chosen projection horizon, whilst containing daily hospital occupancy of COVID-19 patients within the maximum spare emergency hospital capacity ($\underline{H}$). Constraints on closures are applied to each sector to ensure essential services are maintained. To account for interdependencies between sectors, we require that, in producing a sector's final outputs, the intermediate inputs required from other sectors are available. Otherwise, a sector that is nominally opened may not be able to function properly if its supply chain is interrupted [6, 7]. Finally, we constrain the effective reproductive number (R_t) at the end of the projection horizon to be less than or equal to 1, denoted $R_{end} \leq 1$, to ensure that residual infections do not surge rapidly just beyond the intervention period.

For illustration, we apply DAEDALUS to the United Kingdom (UK). We obtained data on the interdependencies between 63 economic sectors from the most recent UK Input-Output (IO) table from 2016 [8] - for an illustrative excerpt from the table for the education sector, see table S1. We use recent data on the workforce [9] and on those working-from-home [10]. We specify a lower bound to production that allows demand for essential goods and services to be met, informed by empirical data on economic activity during the UK's first stringent lockdown in March-May 2020 [11]. The upper bound is given by the level of pre-pandemic production and assumes that the demand for goods and services does not exceed pre-pandemic levels.

We use a deterministic Susceptible-Exposed-Infectious-Removed (SEIR) model of SARS-CoV-2 transmission to project the spread of infection in the workplace, the education sector, households, travel and the community as sectors are opened and closed to varying degrees. The SEIR model accommodates sectoral and age heterogeneity in risk of infection via three contact matrices: worker-to-worker, consumer-to-worker and the community. Worker-to-worker contact rates are derived from a French social contact survey [12] and most epidemiological parameters are obtained from an existing model fitted to UK data (table S4) [13]. A scalar multiplier δ is used to capture the combined dampening impact of NPIs other than business closures that reduce transmission risk on contact. NPIs may include physical social distancing in social and work environments, test-and-trace interventions, shielding of vulnerable persons, travel restrictions and limits to social gatherings.

For the application, we calibrate the epidemiological model via a least-squares fit to English hospital occupancy data from 20th March to 30th June 2020 [14] by varying four parameters: the basic reproductive number R_0; the effectiveness of the UK's first lockdown captured by the parameter δ_{LD}; the epidemic start time and lockdown onset. Transmissibility is calculated from the fitted basic reproductive number R_0 and pre-lockdown contact patterns using the next-generation eigenvalue method [15].

We calculate the GDP, total disease prevalence and hospital occupancy for five scenarios over a six month projection horizon (September 2020 – February 2021):

- Scenario A (maximum GDP): maximize GDP subject to the above constraints where education, like any other sector, may be fully or partly closed;
- Scenario B (education open): maximize GDP as in scenario A, but the education sector remains open at or above 80% of the pre-pandemic level (less than 100% to account for NPIs such as online teaching at universities);
- Scenario LDA (lockdown): lockdown of all sectors (education included), allowing for only essential production, as reported for the UK during the first lockdown in March-May 2020, the most stringent lockdown period. LDA results in the lowest attainable infections at high economic costs, and yields lower bounds on infections and GDP;
- Scenario LDB (lockdown except education): as in LDA, except that the education sector remains operational at 80%;

- Scenario FO (fully open): all sectors are fully open for six months. The $\underline{H}$ and $R_{end} \leq 1$ constraints are disregarded but NPIs and voluntary behaviour changes are captured by δ. FO results in the highest GDP but at the cost of high infections and deaths; it yields upper bounds on infections and GDP.

Outcomes from scenarios A and B provide the schedule of sector closures that maximizes GDP, subject to the respective constraints, whilst LDA, LDB and FO are benchmark scenarios.

Maximizing GDP

The strategy that maximizes GDP while keeping hospital occupancy within constraints (Scenario A) allows for the closure of all economic sectors, including education. If emergency hospital capacity for COVID-19 patients is constrained at $\underline{H} = 18,000$, the optimal solution lets infections increase in September and October, then from November imposes increasingly stringent economic closures to remain within the epidemiological constraints (Figure 1A, figures S1A and S2A for alternative hospital capacity constraints $\underline{H} = 12,000$ and $\underline{H} = 24,000$). This strategy of GDP maximization results in the partial closure of the education sector (Figures 1B, S1B, S2B), with activity at 48% of pre-pandemic activity in November-February (table S5), assuming $\underline{H} = 18,000$. If $\underline{H} = 12,000$, then the education sector needs to close even more (86%, 54%, 48%) but if $\underline{H} = 24,000$, then less stringent closure is required in November-December (56%) and January-February (53%). Some other sectors require closure under any $\underline{H}$. Educational activities are likely chosen for closure because they contribute to transmission but have relatively little impact on short-term GDP, as measured in national accounts. Our analysis considers economic production over six months and not any longer-term economic benefits of keeping schools and universities open, which are likely substantial.

The GDP achieved by Scenario A is £865bn over six months ($\underline{H} = 18,000$), 31% higher than the £660bn of a blanket lockdown (Scenario LDA), but slightly lower than the £889bn achieved with a fully-open economy (Scenario FO). However, FO results in high incidence and deaths. FO also means that over 90,000 COVID-19 patients would require hospital treatment at the projected peak in February, compared to 18,000 patients under Scenario A.

Maximizing GDP subject to keeping education activities operational

The conventional measures of GVA used in IO tables significantly underestimate the contribution of the education sector to national prosperity [16], so it is important to treat it as a special case. Scenario LDB requires all but essential activity to close except for the education sector. In LDB, maximum hospital occupancy stays well below $\underline{H} = 12,000$ (Figure 3B) but is still higher than LDA, in which the education sector is closed more (Figure 3A). LDB causes more infections than LDA because the education sector is contact intensive.

Scenario B seeks out a differentiated sectoral closure strategy that maximizes GDP, and therefore results in less economic loss than LDB, while requiring education to remain at least 80% open. In this scenario, infections (and hospital occupancy and deaths) are allowed to increase between September-December towards the hospital capacity (Figures 2 $\underline{H} = 18,000$, S3 $\underline{H} = 12,000$ and S4 $\underline{H} = 24,000$), but then more stringent economic closures are imposed in January and February to satisfy the constraint on R_t at the end of the projection horizon. If $\underline{H} = 18,000$, education is the only sector required to partially close for the whole intervention period, almost at the 80% lower level specified (table S6). In January-February, five additional key sectors are mainly targeted: accommodation & food services (with almost complete closure at 8%), creative, arts & entertainment and sports, amusement & recreation (both 39%), membership organizations and other personal services - which includes hairdressing and beauty treatments (both 40%), and a few other sectors. If $\underline{H} = 12,000$, partial closures of the key sectors are required earlier, from November onwards. If $\underline{H} = 24,000$, closures for education, accommodation & food, sports & recreation, membership organizations and personal services are similar as for $\underline{H} = 18,000$, but creative, arts & entertainment can stay almost completely open throughout.

The economic output achieved when following a strategy that optimizes GDP while the education sector is operational is estimated to be £854bn over six months ($\underline{H} = 18,000$, Figure 3B), a gain of £184bn (27%) over the £670bn associated with a blanket lockdown of all sectors except education (Scenario LDB). The gain would be £161bn (24%) at $\underline{H} = 12,000$, and £193bn (29%) at $\underline{H} = 24,000$. The maximum GDP is lower for the 'education open' B scenarios compared to the 'GDP-maximizing' A scenarios (Figures 3A and 3B). The difference between the two reflects the GDP losses associated with keeping educational services active, which amounts to £11bn (£865bn − £854bn) for $\underline{H} = 18,000$. The loss between scenarios A and B is significantly higher at £31bn if $\underline{H} = 12,000$, and lower at £5bn if $\underline{H} = 24,000$. This loss occurs because demanding that the education sector remains open requires the closure of other sectors that make greater nominal GVA contributions, to compensate for the increase in transmission caused by education.

Role of Hospital Capacity

Hospital capacity plays an important role in the trade-offs in DAEDALUS, and acts as a continuous constraint over the entire projection horizon. The optimal solutions under the B scenarios keep hospital occupancy closer to capacity in the later months, while occupancy steadily increases under the A scenarios. This has different implications for hospitals, with total bed days over the intervention period varying between 1.4m (B) and 1.5m (A) for $\underline{H} = 18,000$ (table S7). Sector closures can be less stringent if decision makers are prepared to let the level of infections (and hospitalizations and deaths) increase and to invest in additional emergency hospital capacity. The gain in GDP for Scenario B when hospital capacity is increased from 12,000 to 18,000 is £23bn over six months, and £9bn for an increase from 18,000 to 24,000 (Figure 3B). This gain occurs because the increase by 6,000 beds allows for a more open economy (Figures S3B, 2B, S4B). Over winter 2020/21, the UK actually managed to increase capacity to nearly 40,000 beds by cancelling many elective surgeries, using private hospital capacity, deploying retired medical and nursing staff, constructing field hospitals and re-organizing care. Such interventions are costly. It most likely also required rationing healthcare among patients requiring life-saving intensive hospital care.

We can also quantify the GVA loss that can be averted by increasing hospital capacity across the economic sectors that require partial closure. Given its relatively high contribution to transmission compared to GVA, the education sector frequently operates at 80% for the optimal solutions under any $\underline{H}$. For the other sectors, there are gains associated with increasing hospital capacity (Figure 4, table S8). If $\underline{H} = 12,000$, the GVA loss for accommodation & food services amounts to about £15.5bn under Scenario B, and for retail about £6.9bn. If hospital capacity was increased to $\underline{H} = 24,000$, the GVA loss for accommodation & food would be reduced to £9.8bn, and for retail to zero. If we allow infections and hospitalizations to increase, there will be more deaths, which are implicit in the level of hospital capacity chosen by decision-makers.

Sensitivity Analyses

The projections assume that other NPIs (social distancing, test-and-trace, etc.) are relatively stringent, effectively implemented and well adhered to. The fitted value is $\delta_{LD} = 0.57$, which reflects the reduction in R_t achieved by NPIs during the UK's first stringent lockdown. We allow for about 27% less stringency in NPIs by setting $\delta = 0.72$ in all scenarios. In sensitivity analyses, we find that small increases in δ ranging from 0.73 to 0.76 for Scenario B ($\underline{H} = 18,000$) result in much stricter closures required to satisfy the epidemiological constraints (tables S9 vs S6) and a substantial associated GVA loss (figure 5, table S8). Weak NPIs translate into economic losses because stricter closures are required to keep within hospital capacity. For $\delta = 0.76$, sectors with high GVA losses are accommodation & food services with GVA losses of £21.5bn, and retail and wholesale trades with combined losses of £12.9bn. There is no feasible solution for $\delta = 0.78$ if hospital occupancy is constrained at 18,000 or below. This demonstrates that it is impossible to keep the economy even minimally operational and maximum hospital occupancy below 18,000 if other NPIs are weakly implemented. Effectively, a society that accepts more stringent NPIs is rewarded with a higher GDP and fewer infections. There is a four-way trade-off between GDP, infections (and deaths), hospital capacity and social liberties.

The projections are also sensitive to assumptions on contact rates in the community and the education sector (figure S5). We varied contact rates by 5% standard deviation around their sector-specific means, assuming contact rates are independently and normally distributed. We find that much of the uncertainty in projected hospital occupancy arises from contact rates in the community and education sector, rather than the other economic sectors.

We also assume that the proportion of workers homeworking stays constant at sector-specific values observed over the first lockdown. If we decrease these proportions by 20% of their original values, resulting in fewer workers homeworking (figure S6), hospital occupancy increases from a peak occupancy of 18,000 to approximately 38,000 (Scenario A) and 40,000 (Scenario B).

Children may be less susceptible to infection than adults [17, 18, 19], although evidence is conflicting [20, 21]. We evaluated the outcomes for scenario B ($\underline{H} = 18,000$) if children under the age of 16 have 50% lower susceptibility to infection than adults. After refitting DAEDALUS, we find that schools make a somewhat lower contribution to transmission dynamics (figure S7). Stringency of education closures can be reduced while still keeping within constraints; other key sectors recommended for closure are the same.

We evaluate outcomes when changes to the economic configuration are allowed every month instead of two months (figure S8). The gain in GDP is modest (£843 million, table S8) and may not justify the upheaval associated with more frequent changes in policy.

We also explore the sensitivity of our findings to decreasing labour productivity, by re-estimating scenario B with $\underline{H} = 18,000$ assuming that the least productive workers are laid off first. We find that this leads to a modest increase in GDP of £15bn (see figure S9). We also explore the impact of waning immunity, but the impact is small over the six-month projection horizon considered here (figure S10). Lastly, an extended projection horizon of 12 months results in an approximate doubling of GDP (figure S11), but little change to the first 6 months of the optimal solution.

Discussion

We have developed DAEDALUS, a model that calculates optimal differentiated sectoral closure strategies, whereby certain economic sectors are partially closed over a given period and changes are possible at regular time points. In an example application, we show that a smart closure strategy results in a GDP gain of between £161bn (24%) and £193bn (29%) over six months (depending on spare hospital capacity) compared to a blanket lockdown of all non-essential services. Differentiated closures that keep hospital occupancy below different capacity thresholds (between 12,000 and 24,000) throughout the period are compared with a fully open economy, which is projected to cause over 90,000 COVID-19 patients requiring hospital care at its peak, more than double the peak occupancy of UK hospitals during winter 2020/21 at nearly 40,000. Activities that require partial closure in different months are accommodation & food services (including restaurants and bars), retail, creative and arts, entertainment, sports, amusement, recreation, and activities of membership organizations. To achieve the same outcomes, sectoral closures need to be much stricter if adherence to other NPIs such as social distancing is weaker. Decision makers can reoptimize for a new intervention period before the end of projection horizon if objectives change or new data become available.

The pandemic has greatly advanced the field of economic epidemiology, and there are now many studies that model the trade-off between the economic and public health impacts of COVID-19 [22]. Among those, a number of studies evaluate alternative control strategies on economic output and health outcomes with integrated macroeconomic-epidemiological models, for example [6, 23, 24, 7, 25, 26, 27, 28, 29], with some studies modelling in more detail the impact on productivity of individuals [30, 31, 32] or on consumption, labour force participation [33] and investment decisions [34] and how those propagate through a macro-economic model. Other studies focus on international trade [35, 36, 7]. Most studies simplify the economy by either considering an abstract measure of aggregate economic output, or by allocating sectors into two categories (e.g. high/low transmission, or essential/non-essential). Two studies [6, 7] model interdependencies between sectors, which allows impact projections of differentiated lockdown strategies, as done in DAEDALUS. Most studies employ simplified epidemiological models that do not consider disease latency, asymptomatic infection, or age-structured severity, all of which are important for realistic projections. Models are generally not fitted to the actual pandemic trajectory, limiting their usefulness for informing policy, with the exception of two studies [25, 26]. And while many studies investigate combined epidemiological and economic effects of lockdown policies, most fall short of calculating impact on GVA by sector. In contrast, we have developed an integrated model, differentiated by economic sectors, which poses the decision makers' problem as an optimal control model with both discrete and continuous constraints and discrete decision points. This allows us to give numerical outputs that can guide decisions about which sectors to open, and to what extent.

Our analysis has important limitations. We use contact data classified by the economic sector of employment of respondents [12]. The survey uses a high-level classification of 10 economic sectors and we need to attribute uniform rates to the subsectors for our application. Although the data are likely representative of many high-income countries, they would ideally be tailored directly to the country and sectors under scrutiny. DAEDALUS relies on IO tables that are only produced periodically, and that may not reflect recent changes in the economy. In line with usual IO methodology, we assume Leontief production functions with constant returns to scale [37] but relax this assumption in sensitivity analyses. With heterogeneous sectors, it will always be the case that partial opening of a sector may be able to focus on subsectors that are highly productive or have low reliance on inputs from other sectors that remain closed. However, policymakers may find it difficult to formulate granular opening/closure policies focusing on economic activities within sectors and instead be forced towards blanket sectoral policies. A further concern is that – with constraints on supplies – some producers may change to alternative suppliers. However, relatively fixed production processes mean that there is likely to be limited scope for changing the sector in which the supplies are produced. Producers may instead seek to solve supply chain problems by importing inputs for which there are domestic shortages. We have built in certain flexibility in production processes by allowing some tolerance in maximum and minimum levels of economic activity. This also accounts for seasonality of production in some economic sectors, which we do not consider otherwise.

We make no allowance for changes in prices or demand for final products. To some extent, if demand changes for a sector's produce are expected and can be quantified, this can be incorporated by imposing an exogenous change to the relevant economic constraint. More generally, behaviour may change over the course of the pandemic, with impact on demand for goods and services, supply chains, labour supply, and more. This may be the prevailing impact of the pandemic in an unmitigated scenario, when infections spike to very high levels. There is very little data on such impacts, therefore our unmitigated scenario does not consider behaviour change. We also do not model the effect of vaccinations, or increased transmissibility of new SARS-CoV-2 variants, but they can readily be considered in future iterations [13]. Similarly, we do not model changes to investments, assuming that these are mid- to long-term impacts. Lastly and importantly, we have made only rudimentary efforts to adjust for NPIs put in place to reduce transmission risk and voluntary behavior change. The major challenge is identifying the likely nature and magnitude of changes in demand, NPIs and behavior in the absence of available data, although estimates may be forthcoming as evidence from countries' experiences becomes available.

Faced with a recession of historic magnitude, we need to quantify difficult trade-offs that enable policymakers to minimize societal harm. This requires novel economic-epidemiological models that incorporate transmission dynamics as constraints [38], such as the one we present here. To the extent that data and modelling resources permit, DAEDALUS seeks to address the policy challenge of how to keep educational institutions functioning, the economy as open as possible, and the pandemic controlled so that health services are not overwhelmed. While the precise monthly economic configurations identified by our study are sensitive to the stringency of other NPIs, the recommended priority list of sectors to keep open proved robust to sensitivity analyses. As new data and policy concerns emerge, we are confident that DAEDALUS can form an important basis for future development of economic-epidemiological models.

Methods

The mathematical structure of DAEDALUS consists of two integrated parts: the economic model and the epidemiological model (see Figure 6). The economic model organizes the economy into sectors. This gives rise to a set of economic constraints that reflect the interdependencies between sectors. These are set out alongside a set of epidemiological constraints, which are modelled using a compartmental disease transmission model. We assume that the government can implement restrictions to non-essential economic activity to limit both the damage to the economy and the spread of infection. For the purposes of exposition, we assume that the objective is to return as closely as possible to the economy as it was before the arrival of the epidemic, without consideration of possible permanent changes to firm structures, production processes or consumer demand that may be caused by the epidemic.

In DAEDALUS, the economy affects transmission through contacts occurring in the workplace: the more a sector is open, the greater the number of infections (everything else equal). DAEDALUS explicitly models a feedback to the economy: to control infections, hospitalizations and deaths, policy makers mandate closures of economic sectors. DAEDALUS has been developed to offer practical policy advice during the SARS-CoV-2 pandemic by modelling a highly complex and continuously evolving epidemiological/economic system. As many aspects of the pandemic are highly uncertain, including the epidemiological parameters, DAEDALUS should be re-calibrated and re-optimized whenever relevant information becomes available. For this reason DAEDALUS should only be used for short term projections (roughly 3 to 6 months), as medium to long term projections are highly speculative. If we were to extend the model to a one year projection horizon, the projections for the first few months would be very similar to those for the short term projections - compare Figures 2 and S11.

The population is divided into four age groups: pre-school-age 0-4, school-age 5-19, working-age 20-64, and retired-age 65+. All groups belong to the "community". Adults aged 20-64 may belong both to the community and the labor force if they are working in one of the economic sectors, as employed or self-employed workers, and if their economic sector is open for production. Adults aged 20-64 who are not in the labor force, or registered as unemployed, belong to the community only. The N economic sectors ($N = 63$ for the UK application) and four community groups play different roles in DAEDALUS. The productive sectors are engaged both in economic production and in the spread of infection, while the four community groups contribute only to the spread of infection. In the pre-pandemic world, the N economic sectors are fully operational and the final (consumption) product of each sector i contributes to the country's GDP, as represented by its GVA, including exports. In addition to final products for domestic consumption or export, sectors also create products that are used as intermediate inputs by other sectors in creating their own final products.

A model of the economy

Economies are complex systems of interdependent production processes. Each economic sector produces both intermediate inputs, used in the production processes of other sectors, and end products for final consumption by households, governments and non-profit organizations. The flows of intermediate products between sectors are represented by a matrix Z. The components z_{ij} of Z indicate the monetary value of flows from sector i used as inputs to the production process of sector j. Column j of matrix Z indicates all the inputs used in the production process of sector j, and row i indicates all the products of sector i used as inputs by the other sectors. Therefore, the monetary value of total production of sector y_i can be represented by the N relationship $y_i = \sum_{j=1}^{N} z_{ij} + f_i$, which sums inputs produced for other sectors and final demand f_i by sector i. Let $a_{ij} = z_{ij}/y_j$ be the fraction of output of sector i used in sector j so that

$$y_i = \sum_{j=1}^{N} a_{ij} y_j + f_i, \quad i = 1, \ldots, N.$$

Final demand comprises final consumption, gross fixed capital formation and changes in inventories and exports. We assume throughout that the demand for final consumption is constant during the pandemic but that inventories can increase in response to overproduction. This can be justified by the short-term projection horizon of DAEDALUS, as well as by the fact that changes in consumption patterns have occurred mostly within each sector as, for example, the shift from in-person grocery or clothes shopping to online shopping. Of course, there are sectors like hospitality and travel that have seen a sharp decrease in output but experience has shown that with the removal of restrictions, they are quickly recovering to pre-pandemic levels of activity.

Intersectoral flows of products are derived from Input-Output (IO) tables, see the data section for more detail. By solving this system of N equations in N unknowns, one can determine the (equilibrium) output of each sector y_i^* for $i = 1, \ldots, N$ in the pre-pandemic world. Let $y_i^* = \frac{y_i^*}{w_i^*} w_i^* = g_i w_i^*$, where w_i^* is the pre-pandemic workforce of sector i and $g_i = y_i^*/w_i^*$ is the output per worker (labour productivity) of sector $i = 1, \ldots, N$ in a given period. For simplicity, we assume that a_{ij} (interdependence between sectors), g_i (labour productivity) and final consumption are constant and held at pre-pandemic values.

DAEDALUS can also be extended to allow for a nonlinear effect of labour on sector output. For example, we could assume that $y_i = g_i w_i^{\alpha_i}$, $0 < \alpha_i \leq 1$, where α_i is the elasticity of output with respect to labour in sector i. This allows for decreasing returns to labour. Notice that this increases the number of parameters of the model needing to be calibrated. In sensitivity analyses, we have set $\alpha_i = 0.59$ uniformly for all sectors, informed by [39] (assuming profit maximization so that the elasticity of output with respect to labour is equal to labour productivity). We find that the conclusions are qualitatively similar to the constant productivity case in the short-run framework considered (compare Figures 2 and S9). The main scenarios considered in this analysis are therefore based on the model with constant labor productivity.

We assume that government policy can influence the proportion $x_i^{min} \leq x_i \leq 1$ of individuals working in each sector in each decision period. When $x_i = 1$, sector i is fully open and productive at pre-pandemic levels and when $x_i = x_i^{min}$, sector i is closed except for the provision of essential goods and services. To allow for uncertainty regarding the observed lockdown values x_i^{LD}, we use 80% of the lockdown values, i.e. $x_i^{min} = 0.8 x_i^{LD}$. This effectively imposes a lower bound constraint on all scenarios that - with some flexibility - allows essential services to operate. In the UK application, the lockdown production x_i^{LD} was obtained via a survey conducted as part of the monthly GDP calculation by the ONS [40]. We applied the same value of high-level sectors to all subsectors due to lack of more detailed data. The effective number of workers in each period in sector i is $w_i = x_i w_i^*$.

By controlling the proportion of individuals working in each sector and in each period, policy makers can keep the pandemic under control because infections in the workplace (between workers and between workers and customers) are reduced. However, by partially closing a sector, such policies also reduce the GVA contribution of each sector. During each period in the pandemic, the achieved output is $y_i = g_i \; w_i$. This implies that in DAEDALUS, the effect of the pandemic works through the reduction in the number of workers, and not reduced labor productivity. Therefore, even if labor productivity remains unchanged, $x_i^{min} y_i^* \leq g_i w_i \leq y_i^*$, $i = 1, \ldots, N$, because closures of sectors reduce the number of individuals who work.

Note that this is equivalent to assuming that infections and deaths do not affect productivity. In the application to COVID-19, we believe this is justified by the fact that COVID-19 disproportionately affects older individuals, who belong to the retired-age group. Only a small proportion of the working population is actually affected by the disease at any given time; moreover, there is little and conflicting empirical evidence regarding the impact of the pandemic on labour productivity [41]. To demonstrate the low prevalence of disease in workers in the UK, Figure S12 shows the percentage of working-age symptomatic infections, hospitalizations and deaths by economic sector over the course of the first wave for Scenario B. The percentage of workers with symptomatic infections is less than 1% of all workers and the percentage of hospitalized workers is less than 0.1% of all workers, even in the worst-affected sector at the peak in April. The cumulative percentage of deaths among workers in each sector is negligible, if the retired are excluded. It is therefore unlikely that COVID-19-related sickness and death is impacting productivity in a mitigated pandemic.

We assume that the decision maker has an outlook over a specific intervention horizon into the future (six months in the UK application). Decisions on the economic configuration are made at specific time points during the intervention horizon, the decision points. In the UK application, this is at the beginning of every two-month period. The objective is to keep the economy as active as possible over the intervention horizon without breaching hospital capacity. Precisely, at each decision point $\tau = 0, 1, 2, \ldots, T$ over the intervention horizon, the decision maker decides how much each sector is open in the next period. The decision maker chooses $x_i^{min} \leq x_{i\tau} \leq 1$, for $i = 1, \ldots, N$. The objective in each period is to maximise an objective-function based on the GDP.

The domestic economy must be balanced over the intervention period. All necessary domestic intermediate inputs required by a sector must be available. That is

$$\sum_{\tau=0}^{T} \left(g_i w^* x_{i\tau} - \sum_{j=1}^{N} a_{ij} x_{j\tau} g_j w^* \right) \geq T f_i^{min} = T \left(g_i w^* x_i^{min} - \sum_{j=1}^{N} a_{ij} x_j^{min} g_j w^* \right).$$

This requires each sector to produce at least enough to satisfy the intermediate needs of other sectors that are open, plus essential consumption. The pandemic has likely led to changes in production processes in some sectors compared to the pre-pandemic world due to several factors, most notably disruptions in global supply chains [42, 43]. To allow for some flexibility in the economic configuration due to these factors, we do allow "excess" production of intermediate and final products - that is, over the intervention horizon, there is the opportunity for inventory or additional export if supply exceeds demand. Output is however bounded by pre-pandemic levels in any period, i.e. $x_{i\tau} \leq 1$.

Certain sub-sectors, such as parts of healthcare, education and agriculture, may be considered essential services that must remain open regardless of the consequences for disease transmission. We may also want to allow some sectors, such as healthcare, to expand beyond pre-pandemic levels. Keeping certain sectors at specified level of production can be introduced via additional constraints to the optimization. In the UK application, we constrain healthcare to operate at at least the observed lockdown values (x_i^{LD}) in all scenarios and education to operate at 80% of pre-pandemic values in some scenarios.

A model of the epidemic

The partial or full opening of a sector increases the number of actively working adults. For most workers, working requires contact with colleagues and consumers, and there is therefore a risk of transmission amongst the workforce, between workforce and consumers, and onward transmission to the general population when working adults move between economic sectors and the community. Furthermore, for some sectors, there is increased transmission associated with contacts between consumers, e.g. the hospitality sector. DAEDALUS is sensitive to the different circumstances experienced by the workers and consumers associated with each sector.

At each time step of the epidemiological model t, the individuals in each economic sector and the four community groups are divided into mutually exclusive "epidemiological" groups: susceptible, exposed (infected but not yet infectious), asymptomatic infectious, symptomatic infectious, hospitalized, recovered, and dead. The number of individuals in each of these groups who are also member of sector i at time t are denoted respectively by $S_i(t)$, $E_i(t)$, $I_i^{asym}(t)$, $I_i^{sym}(t)$, $H_i(t)$, $R_i(t)$, and $D_i(t)$, for $i = 1, \ldots, N + 4$. Note that for each group i and time t, the total population of each group is the sum of the epidemiological groups:

$$w_i(t) = S_i\,(t) + E_i\,(t) + I_i^{asym}\,(t) + I_i^{sym}\,(t) + H_i\,(t) + R_i\,(t) + D_i\,(t)\,,$$

for all $t \in [t_\tau, t_{\tau+1})$, and all decision points $\tau = 0, \ldots, T$ at the start of each period. In each period $[t_\tau, t_{\tau+1})$, $\tau = 0, \ldots, T$ over the intervention horizon, the population of the epidemiological groups within each sector i change following a compartmental SEIR model for all sectors $i = 1, \ldots, N+4$. The force of infection (FOI) on sector i, $\lambda_i\,(t)$, and system of Ordinary Differential Equations (ODEs) are given as follows

$$\begin{aligned}
\dot{S}_i\,(t) &= -S_i\,(t)\,\lambda_i\,(t) + \nu R_i\,(t)\\
\dot{E}_i\,(t) &= S_i\,(t)\,\lambda_i\,(t) - \sigma E_i\,(t)\\
\lambda_i\,(t) &= \beta\delta \sum_{j=1}^{N+4} M_{ij} \frac{I_j\,(t)}{w_j}\\
I_i\,(t) &= r I_i^{asym}\,(t) + I_i^{sym}\,(t)\\
\dot{I}_i^{asym}\,(t) &= \sigma\,(1 - p_{sym})\,E_i\,(t) - \gamma_1 I_i^{asym}\,(t)\\
\dot{I}_i^{sym}\,(t) &= \sigma p_{sym} E_i\,(t) - \gamma_2 I_i^{sym}\,(t) - h_i I_i^{sym}\,(t)\\
\dot{H}_i\,(t) &= h_i I_i^{sym}\,(t) - \gamma_3 H_i\,(t) - \mu_i H_i\,(t)\\
\dot{D}_i\,(t) &= \mu_i H_i\,(t)\\
\dot{R}_i\,(t) &= \gamma_1 I_i^{asym}\,(t) + \gamma_2 I_i^{sym}\,(t) + \gamma_3 H_i\,(t) - \nu R_i\,(t)\,.
\end{aligned}$$

The first equation specifies the rate of decrease in susceptible individuals as proportional to the stock of susceptible individuals and the force of infection $\lambda_i\,(t)$, which is the rate at which susceptible individuals acquire the infection. The second equation states that the number of exposed individuals increases by the same amount the susceptible individuals decrease minus a fraction of the stock of individuals already exposed, which progress to become infectious. The change in number of infectious individuals, whether asymptomatic or symptomatic, is assumed proportional to the number of exposed individuals and the number of individuals exiting the compartments is assumed proportional to the stock of infected. Transmission from asymptomatic individuals is reduced by a factor r relative to symptomatic individuals. A fraction of those infected are hospitalized and a fraction of those hospitalized die, while the others recover. Note that hospitalizations arise from symptomatic infections only, and never from asymptomatic infections. We also do not model transmission from hospitalized cases. Similarly, our model allows only for deaths after hospitalization. The last equation describes the number of recovered individuals as a fraction of the individuals infected and hospitalized. Transmissibility β is calibrated to a target R_0 (the basic reproductive number is the expected number of cases directly generated by one case in a population where all individuals are susceptible to infection). Calibration is based on pre-lockdown contact patterns and the next-generation operator eigenvalue method [44]. Emergence of variants with higher (or lower) transmissibility would require re-calibration to an updated R_0. The model allows for waning immunity, represented by the common term in the first and last equations, with immunity loss rate ν.

In addition to the partial or full closure of economic sectors, workplace-related disease transmission can also be suppressed by working-from-home, although the ability for home-working will vary by economic sector. Workers who work-from-home are exposed to (and contribute to) transmission only in the community. In DAEDALUS, workers who are able to work-from-home are modelled through a sector-dependent proportional reduction in the sector-dependent contact rates, which are used to construct the contact matrices M_{ij} (see section on Contact Matrices below). The sector-dependent proportion of workers able to work-from-home is assumed constant across the projection horizon.

At the start of each period $[t_\tau, t_{\tau+1})$, $\tau = 0, ..., T$, the economic and the epidemiological groups get re-matched. We denote the limit of the various epidemiological groups as t tends to t_τ from the from the left as $S_i(t_\tau^-)$, $E_i(t_\tau^-)$, $I_i^{asym}(t_\tau^-)$, $I_i^{sym}(t_\tau^-)$, $H_i(t_\tau^-)$, $R_i(t_\tau^-)$ and $D_i(t_\tau^-)$. These variables are given at time t_τ^- for all for $i = 1, \ldots, N+4$ from their past developments.

At time t_τ^-, the number of workers of sector i who are working is determined by the extent to which sector i is allowed to open and given by $x_{i\tau-1}w_i^*$, and the number of workers who are not working by $(1 - x_{i\tau-1})w_i^*$. Although this is the same number as at the start of the period, the composition of the population in the epidemiological groups has changed according to the system of ODEs above. Choosing $x_{i\tau}$ changes the initial values of the transmission model at the start of each period $[t_\tau, t_{\tau+1})$, $\tau = 0,\ ...,\ T$. We now make clear how this is done.

At time t_τ, the government's decision variables change from $x_{i\tau-1}$ to $x_{i\tau}$. The active workers in sector i at time t_τ are

$$x_{i\tau}w_i^* = x_{i\tau-1}w_i^* + (x_{i\tau} - x_{i\tau-1})\, w_i^*.$$

If $x_{i\tau} - x_{i\tau-1} = 0$, nothing changes for sector i and production is the same compared to the previous period.

If $x_{i\tau} - x_{i\tau-1} < 0$, then the sector's production is reduced compared to the previous period. The number of those working in sector i decreases and $(x_{i\tau} - x_{i\tau-1})\, w_i^*$ of them join the group of non-working adults for that period. Hence, $x_{i\tau}w_i^* = \frac{x_{i\tau}}{x_{i\tau-1}}(x_{i\tau-1}w_i^*)$. We assume that each epidemiological group in sector i is reduced by the same amount $\frac{x_{i\tau}}{x_{i\tau-1}}$. The remaining fraction $1 - \frac{x_{i\tau}}{x_{i\tau-1}}$ is added to the corresponding epidemiological group of the non-working adults for period $[t_\tau, t_{\tau+1})$ at time t_τ.

If $x_{i\tau} - x_{i\tau-1} > 0$, then the sector's production is increased compared to the previous period. The number of those working in sector i increases with $(x_{i\tau} - x_{i\tau-1})\, w_i^*$ and some or all of those workers who did not work the previous period now join sector i. The number of individuals in group $N+4$ changes at time t_τ, so it will be indexed by τ. The fraction

$$\chi_{i\tau} = \frac{(x_{i\tau} - x_{i\tau-1})\, w_i^*}{w_{N+4}\left(t_\tau^-\right)}$$

of $w_{N+4}(t_\tau^-)$ enters sector i at the start of period $[t_\tau, t_{\tau+1})$. So, assuming all non-working adults have the same chance of being employed in sector i, the initial values of the transmission model for the N productive sectors for the period $[t_\tau, t_{\tau+1})$ are

$$S_i(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} S_i(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ S_i(t_\tau^-) + \chi_{i\tau} S_{N+4}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

$$E_i(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} E_i(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ E_i(t_\tau^-) + \chi_{i\tau} E_{N+4}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

$$I_i^{asym}(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} I_i^{asym}(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ I_i^{asym}(t_\tau^-) + \chi_{i\tau} I_{N+4}^{asym}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

$$I_i^{sym}(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} I_i^{sym}(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ I_i^{sym}(t_\tau^-) + \chi_{i\tau} I_{N+4}^{sym}(t_\tau^-) & x_{i\tau} > x_{i\tau-1} \end{cases}$$

$$H_i(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} H_i(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ H_i(t_\tau^-) + \chi_{i\tau} H_{N+4}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

$$R_i(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} R_i(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ R_i(t_\tau^-) + \chi_{i\tau} R_{N+4}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

$$D_i(t_\tau) = \begin{cases} \frac{x_{i\tau}}{x_{i\tau-1}} D_i(t_\tau^-) & x_{i\tau} < x_{i\tau-1} \\ D_i(t_\tau^-) + \chi_{i\tau} D_{N+4}(t_\tau^-) & x_{i\tau} > x_{i\tau-1}, \end{cases}$$

for $i = 1, ..., N$. The values for each epidemiological group vary depending on whether production is increased or decreased in the respective period. Notice that when we move workers between working and non-working groups, we assume that we move the same proportion of all epidemiological groups, including the infected, the hospitalized and the dead. This accounts for reduced transmission due to absence. For pre-school children, school-children and retired individuals, the dynamics of the epidemic continue from the end values reached in the previous period. That is, $S_i(t_\tau^+) = S_i(t_\tau^-)$, $E_i(t_\tau) = E_i(t_\tau^-)$, $I_i^{asym}(t_\tau) = I_i^{asym}(t_\tau^-)$, $I_i^{sym}(t_\tau) = I_i^{sym}(t_\tau^-)$, $H_i(t_\tau) = H_i(t_\tau^-)$, $D_i(t_\tau) = D_i(t_\tau^-)$ for $i = N+1, N+2, N+3$.

For the non-working adults, the initial conditions at t_τ capture the fact that the productive sectors are partially closed and that a fraction of the workers may become temporarily non-working adults at t_τ, $\tau = 0, \ ..., \ T$:

$$S_{N+4}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) S_{N+4}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) S_i\left(t_\tau^-\right),$$

$$E_{N+4}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) E_{N+4}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) E_i\left(t_\tau^-\right),$$

$$I_{N+4}^{asym}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) I_{N+4}^{asym}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) I_i^{asym}\left(t_\tau^-\right),$$

$$I_{N+4}^{sym}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) I_{N+4}^{sym}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) I_i^{sym}\left(t_\tau^-\right),$$

$$H_{N+4}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) H_{N+4}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) H_i\left(t_\tau^-\right),$$

$$R_{N+4}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) R_{N+4}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) R_i\left(t_\tau^-\right),$$

$$D_{N+4}(t_\tau) = \left(1 - \sum_{i:x_{i\tau}-x_{i\tau-1}>0} \chi_{i\tau}\right) D_{N+4}\left(t_\tau^-\right) + \sum_{i:x_{i\tau}-x_{i\tau-1}<0} \left(1 - \frac{x_{i\tau}}{x_{i\tau-1}}\right) D_i\left(t_\tau^-\right).$$

Let $H(t)$ be the number of individuals in the country who are hospitalized at each t, which is the sum of the individuals in each productive sector and in the community who are hospitalized

$$H(t) = \sum_{i=1}^{N+4} H_i(t),$$

and let $\underline{H}$ be the country's hospital capacity - which for simplicity is assumed constant over the intervention horizon. The first epidemiological constraint demands that the number hospitalized does not exceed capacity at any one time. That is,

$$H\left(t\right) \leq \underline{H}$$

for all t.

The second epidemiological constraint requires $R_{end} \leq 1$. This is the effective reproductive number at the end of the projection period, considering all infections, immunity and mitigation over the course of the simulation (for calculation of R_{end}, see section Epidemiological Parameters and Calibration). This is to ensure that the epidemic is under control at the end of the planning horizon, leaving a manageable "legacy" for future periods.

Linking economics and epidemiology

The objective of DAEDALUS is to maximize the GDP of the country, as represented by the sum the GVA created by the sectors of the economy that are operational - either wholly or in part. The sum of the GVA (i.e. GDP) is maximized subject to the constraints that hospital capacity is not breached at any point in time, and the global effective reproductive number (R_t) is less than or equal to one at the end of the optimization horizon, i.e. $R_{end} \leq 1$. This leaves the country in a reasonable position with respect to incidence and hospitalizations. If required, a subsequent optimization can be implemented as new data become available, policy objectives change or we approach the end of the intervention horizon.

For a single period, we assume decision variables $x_{j\tau}$ that indicate the proportion of each sector j that is operational in period τ and therefore take the value between x_j^{min} and 1. A partial opening $x_{j\tau}$ of sector j in period τ creates an output for sector j equal to $x_{j\tau}\ g_j w_j^*$. In order to calculate the GVA for sector j, we need to subtract the value of the intermediate products used by sector j, which are given by $\sum_{i=1}^{N} a_{ij} x_{j\tau}\ g_j w_j^*$. Considering the interdependency of the economic sectors, the hospital capacity and the transmission constraint specified above, DAEDALUS maximises the objective function

$$\max \sum_{j=1}^{N}\sum_{\tau=0}^{T} x_{j\tau} g_j w_j^* \left(1 - \sum_{i=1}^{N} a_{ij}\right)$$

subject to

$$\begin{aligned}
&H\left(t\right) \leq \underline{H} \\
&R_{end} \leq 1 \\
&\sum_{\tau=0}^{T}\left(g_i w^* x_{i\tau} - \sum_{j=1}^{N} a_{ij} x_{j\tau} g_j w^*\right) \geq T f_i^{min} \\
&x_i^{min} \leq x_{i\tau} \leq 1, i = 1, \ldots, N, \tau = 0, \ldots, T
\end{aligned}$$

where $g_j w_j^* \left(1 - \sum_{i=1}^{N} a_{ij}\right)$ is the pre-pandemic GVA associated with sector j. The first two constraints are the epidemiological constraints, namely that total hospital occupancy does not exceed the static hospital capacity $\underline{H}$ and that the global effective reproductive number at the end of the intervention horizon R_{end} is less than or equal to one, which set upper limits on hospitalizations and transmission. Constraints three and four represent economic constraints. Constraint three reflects the need for a sector to produce at least enough to satisfy essential consumption and the intermediate needs of other sectors that are open in period τ, and constraint four to produce no more than the maximum level produced before the pandemic.

Note that DAEDALUS could be modified to maximise a different objective function other than GDP, depending on government priorities. Alternative objectives functions could, for example, account for GDP as well as the value of life years lost, or unemployment. Supplementary figures S16-S17 show economic configurations and trajectories when maximizing employment, and when maximizing GDP less life-years lost monetized with a value-of-statistical life approach. Moreover, further constraints could be added, requiring for example that a sector (in our case education) to be open to a certain degree.

Computation

The multiperiod DAEDALUS model has substantial computational demands. The number of decision variables is the product of the number of periods and the number of sectors under consideration (in the application here, $63 \times T$). The number of linear (economic) constraints is $2 \times 63 \times T$ because they are applied to each time period. For a scenario where certain sectors are open, there are additional constraints, one for each sector and period. Although fewer in number, the two epidemiological constraints are much more computationally demanding, with the hospital occupancy constraint operating continuously throughout the projection horizon. Optimizations use 'Global search' with derivative-based base algorithm "fmincon" in MATLAB's "global optimization" toolbox [45].

Application of DAEDALUS to the UK

We now illustrate how DAEDALUS can be applied to a specific country (here the UK), and what data are required.

Economic Data

IO tables are central to DAEDALUS. They have been the subject of well-developed analytic frameworks represented in national accounts, most of which derive from the 1993 United Nations System of National Accounts [46]. IO tables describe how products (and primary inputs) are used to produce further products and satisfy final demand. They depict inter-sector relationships within an economy, showing how output from one economic sector may become an input to another sector. Column entries typically represent inputs to a sector, while row entries represent outputs from a given sector. Inputs and outputs are represented in monetary terms, not physical units. The value of all flows is represented in 'basic' prices, which exclude the margins secured by producers [37]. Each column of the table shows the value of inputs to each sector and each row represents the value of each sector's outputs [37]. This format therefore shows how dependent each sector is on every other sector, both as a customer of outputs from other sectors and as a supplier of inputs. In this application, we consider 63 sectors (obtained from a 64-sector IO table [8]), combining real estate services (sector 44) with imputed rents of owner-occupied dwellings (sector 45) because separate data were not available.

Most sectors use both imported and domestically-produced intermediate inputs from other sectors to produce their own goods and services. DAEDALUS considers only the impact of domestic production on SARS-CoV-2 transmission and assumes imports necessary for production continue to be available.

The calculation of IO matrices is a major undertaking, so they are produced only periodically. The last full estimates for the UK economy refer to the calendar year 2016 [8] and we are therefore constrained to using these estimates in our application. We assume a Leontief production function [37] for each sector (in main specification), so that the proportionate contributions of inputs from other sectors, the workforce and value-added remain unchanged whatever its level of operations.

The information obtained from the IO table for the UK is summarized in table S10. The first three columns list the high- mid- and low-level sector designations. The fifth column shows the workforce of each sector as headcount, obtained from the ONS [10]. We assume the workforce to be constant at pre-pandemic levels over the intervention horizon, although a certain proportion of the workforce may not work in any given period (non-active) depending on the extent to which a sector is closed. The total output of each sector is measured at basic prices in million of pounds. The output includes the value of intermediate products and services used by the respective sector in production. The GVA of a sector is obtained by subtracting intermediate products from total output, including exports. GVA is measured in £ million; this denotes the value of all products and/or services that the sector adds to the economy over and above the intermediate products used in production. For the optimization, we convert the annual GVA into a monthly value by dividing the annual value by 12. This makes the simplifying assumption that the sector in the pre-pandemic world produces the same amount each period. Therefore, the GVA for sector j in the period τ is $x_{j\tau} g_j w_j^* \left(1 - \sum_{i=1}^{N} a_{ij}\right)$.

The penultimate column of table S10 gives the sectors' use of intermediate products as a percentage of their overall output (intermediate use excludes use of imports and taxes less subsidies on products). A higher value indicates that the sector has greater reliance on other sectors; for our analysis, this implies that opening this sector is necessarily associated with greater opening of other sectors as well. The final column presents provision of intermediate products (row totals) as a percentage of total output, indicating the sector's reliance on other sectors as consumers, rather than final consumers (intermediate provision excludes exports and gross capital formation). The value of opening this relies heavily on other sectors being open to purchase its products and services. In summary, low values in the last two columns describe sectors that are relatively self-reliant and can be opened and closed with less consideration of activity levels in other sectors.

Table S11 provides changes in production and working-from-home during the first lockdown period in the UK between March and May 2020 for the ONS Standard Industry Classification (SIC) sections and divisions. These values provide important parameters for the economic model. Evidence on the productivity of home working during the pandemic is inconclusive. Empirical studies have found a decrease [47, 48], no change [49] or an increase in work productivity [50, 51, 48]. We therefore assume that the productivity of individuals working-from-home is not affected, i.e. it does not negatively affect the GVA contribution of the corresponding sector, and that the proportion of workers working-from-home during the lockdown in spring 2020 in the UK stays constant over the projection horizon [10].

Contact Matrices

Contact matrices define the mean number of contacts per day reported between groups of individuals and are important components of the SEIR model. They feature explicitly in the force of infection (FOI) term, denoted by M_{ij}, and are based on contact survey data [44]. There exists an extensive literature deriving coefficients for heterogeneous mixing with respect to age and geography. However, few studies estimated contacts structures with respect to economic sector. For the purpose of this study, we account for the heterogeneity in contact rates between sectors. We synthesize a contact matrix based on a contact survey conducted in 2012 in France [12]. While more recent contact surveys have been conducted, to our knowledge, this is the only survey that includes sector-specific and work-related information of respondents. The industry sectors as reported by the respondents of the French survey were translated to the industry sectors of the UK IO table (table S13). Due to lack of more detailed data, we had to use the same contact rate for all subsectors.

We constructed a contact matrix M as the sum of 3 matrices: A (community contacts), B (worker-to-worker contacts) and C (consumer-to-worker contacts, see tables S2-S3 and detailed explanation of contact matrices in Methods S1, p. 49ff). Opening of sectors, including hospitality and education, increases transmissions as informed by contact rates in matrices B and C. Workers and consumers carry infection back into the community, which increases transmission as informed by rates in A. Refining the matrices A, B and C in this study is fundamental to estimating DAEDALUS.

Community contacts (matrix A) are any contacts made that are unrelated to the workplace. This includes contacts in the household, during travel to and from the workplace and non-work-related travel, outside spaces, leisure activities (e.g. meeting friends), retail outlets (e.g. supermarkets), and contacts made in the hospitality or service sectors. When sectors are partially or fully opened, we account for additional transmission risk from contacts between consumers in matrix A. As such, in addition to household contacts, contacts are being made when consuming products or services from specific sectors. Opening the hospitality sector, for example, will increase the community transmission as consumers meet in pubs and restaurants. The contact rates show the average contact rate for the community. The columns of the community matrix A are weighted by the size of the workforce (measured in headcounts) in each sector. The value of row sums depends on the extent to which given sectors are open. If all economic sectors were fully closed the total contact is reduced to roughly 40% of total contact when all sectors are open.

Students are 'consumers' of education services. In the education sector, we account for the number of contacts between students going to school or university. School contacts are estimated separately in two age groups (pre-school age: $0-4$; school age: $5-18$). Similarly, hospitality consumer contacts are estimated considering age-heterogeneity in hospitality contacts. See table S3 for the age-adjusted average number of contacts in the education and hospitality sectors. Opening of schools and universities will affect the row sum of the school-age children group. The community contact rates were adjusted so that the mean rate across all age groups is equal to 3.5, as taken from survey data [12].

Worker-to-worker contacts (matrix B) describes the at-work contacts in sectors, i.e. the number of contacts per day reported by an individual actively working in the same sector (table S2). Here "actively working" refers to one period, i.e. two months in our application. Matrix B is diagonal owing to lack of data regarding between-sector contacts. Worker-worker contacts are defined by those contacts recorded to have happened at work and frequently (reported as a contact made almost every day). At work contacts at low frequency are classified as worker-consumer contacts. At-home working is considered, and community contact rates apply for contacts between working household member. We assume that transport contacts only add to the infection risk if the sector is open and the workers travel to and from their workplace.

Consumer-to-worker contacts (matrix C) describes contacts experienced by workers from consumers. As for A, the columns are weighted by sector population, though the row sums are sector specific. Contacts experienced by workers from consumers are defined by those contacts recorded to have happened at work less frequently than every day (i.e. recorded as a few times a week, a few times a month, a few times a year or less often, or for the first time). We account for a reduction in transmission risk due to NPIs or working from home via a reduction in effective contact rates. Furloughed and unemployed workers are considered as non-working. For a technical description as to how the contact matrices are constructed, please see the Supplementary Material.

Epidemiological Parameters and Calibration

For our application, we calibrate the following four parameters of DAEDALUS to English hospital occupancy data from the Office for National Statistics from 20th February to 31st July 2020 [14]: the basic reproductive number R_0; effectiveness of lockdown δ_{LD}; epidemic start time t_0 and lockdown onset t_{LD}. Model projections are then made using population data for the UK, in order to be consistent with the economic model.

The modifier parameter δ is a multiplicative factor applied to the transmission parameter β to capture the dampening impact of NPIs (other than economic closures) and individuals' behavior on transmission, as represented by R_t. The modifier captures the combined effect of NPIs that are difficult to estimate empirically, including social distancing in social and work environments, facemasks, testing-and-tracing, shielding of the vulnerable, travel restrictions and limits to social gatherings. The interventions may be government-mandated or adopted by individuals voluntarily. We use the calibrated value δ_{LD} of the modifier over the lockdown period as an upper bound estimate of the impact of NPI's. For all projections, we adjust the modifier to reflect less stringent NPIs and weaker compliance in the post-lockdown period.

Additional parameter estimates are aligned with Imperial College's Real-time Model [52]. Given our interest in short-term projections, we set the waning paramter ν at zero in the main specification. However, we explore the impact of waning immunity ($\nu = 1/1095$ days^{-1} following [53], $\nu = 1/365$ days^{-1} and $\nu = 1/240$ days^{-1}) in sensitivity analyses and find that it affects the later part of the projection, but overall the impact is small (compare Figures 2 and S10). A full list of DAEDALUS's parameters is given in table S4. Transitions between epidemiological compartments are governed by rates and we therefore assume exponentially-distributed periods for serial interval, time to hospitalization and hospital stay. We output all epidemiological variables, including disease prevalence, hospital occupancy and cumulative deaths. These quantities then inform our epidemiological constraints and our comparison between model scenarios.

The global effective reproductive number at the end of the last decision period R_{end} is of particular importance, as it is the second epidemiological constraint in the optimization. We use the eigenvalue approach to calculate R_0 and R_{end} following the standard approach for populations with host heterogeneities [44, 15] (box 3.1, p. 60 in the former). All sectors and non-working groups have specific reproductive numbers, but it is assumed that incidence increases at the same exponential rate (i.e. the dynamics become slaved) from a certain point after the initial seeding, i.e. the start of the pandemic. R_{end} for the entire population lies between the values calculated for each group and will generally be greater than the weighted average because we assume that individuals belonging to certain groups are more likely to interact with each other than with individuals belonging to other groups (assortative mixing). We calculate R_0 and R_{end} from the distribution of infection across groups in the region of slaved dynamics, where the behaviour is independent of the initial seeds. This slaved distribution provides a natural weighting for the number of secondary cases generated by a primary case in each group.

Supplementary figures S13-S17 show additional sensitivities, comparing optimal solutions over different time horizons, increasing NPI modifiers over the mitigation period, and optimising with respect to different objective functions.

Hospital Capacity

Hospital capacity is an important parameter in DAEDALUS because it constrains the optimization. At any point in time, the number of hospitalized patients with COVID-19 must not exceed the number of available beds. We do not distinguish between critical care and general & acute beds for simplicity, instead summing them for an estimate of total hospital capacity. Treatment options and patient characteristics are changing over the course of the pandemic, and chosen parameters may have to be reviewed over time. For the UK application, we make three alternative assumptions on emergency spare hospital capacity available for the treatment of COVID-19 patients (see table S12).

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Author Contribution

DH, PCS, KH, GF, PD and PC conceived and designed the work; DH and PD undertook and KH, PCS, GF, PD, PC, RJ, MP and SB contributed to the analysis and interpretation of data; DH and PD created new software used in the work; KH wrote the first draft of the paper and PCS, DH, GF, MP, RJ and PD substantially revised it; SB, PD, ABH, PW, MM, PJW, ACG, and NMF contributed to interpretation of the data and substantially revised the paper. All authors have approved the submitted version and have agreed to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated, resolved, and the resolution documented in the literature.

Data Availability and Code

All data used in this study are publicly available, and references are provided in the method sections of the main manuscript or the supplement. The computer code is available on Github (https://github.com/j-idea/DAEDALUS-an-integrated-epidemiological-economic-model).

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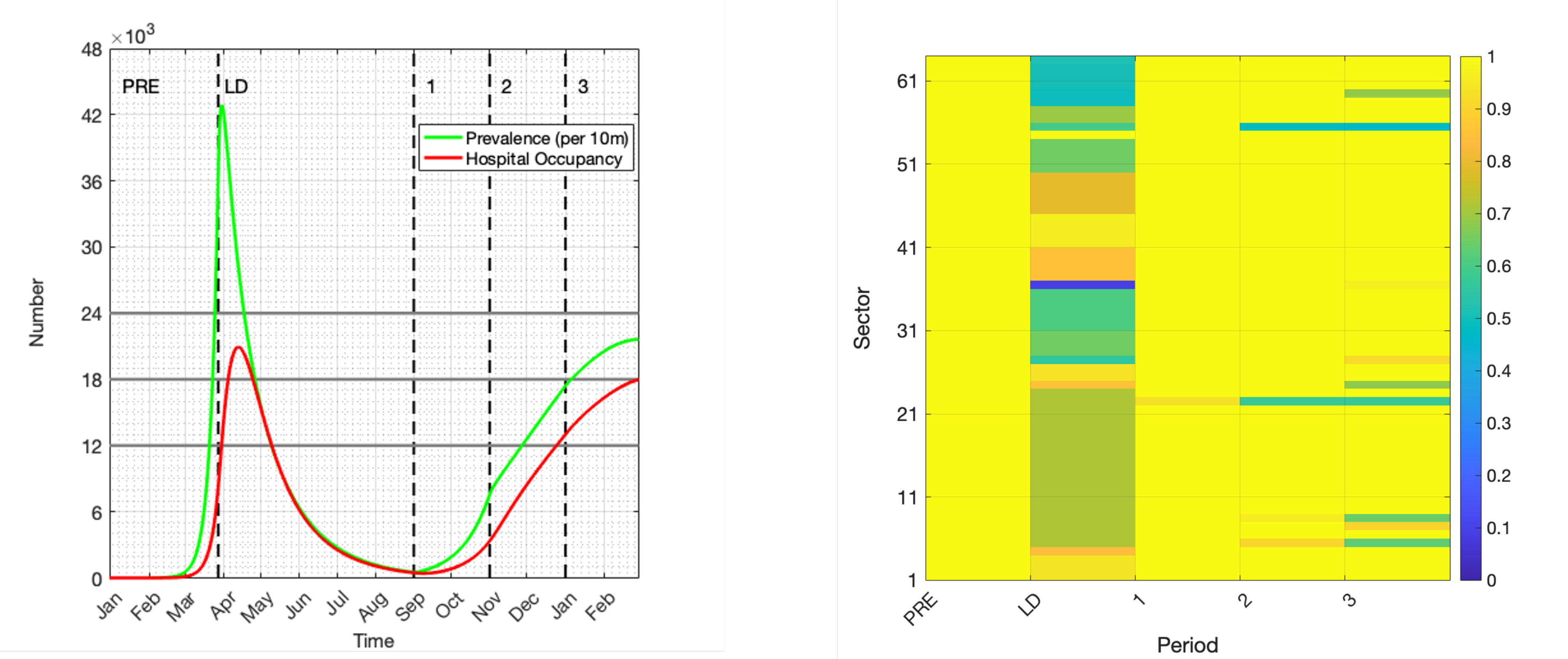

Figure 1: Optimal economic configuration under scenario A (GDP maximization), hospital capacity 18,000 beds. (A) Projected prevalence and hospital occupancy (B) Economic configuration across 63 sectors. GDP over six months £865bn.

Notes: Scenario A maximizes GDP via successive bi-monthly opening and closing of 63 sectors over a six-months intervention period, subject to epidemiological and economic constraints; any economic sector including education may close to 80% of observed minimum levels during the UK's first lockdown (March–May 2020), but not lower, in order to sustain essential services; (A) shows projected daily infection prevalence per 10 million population and daily hospital occupancy from January to February; emergency hospital capacity for the treatment of COVID-19 patients is constrained at 18,000 beds (2nd grey line from below); (B) illustrates the optimal economic configurations (extent of bi-monthly sector closures) under Scenario A GDP maximization; sector divisions are listed on the vertical axis (see table S4 for sector descriptions), and months on the horizontal axis; PRE is the pre-pandemic period, LD is the first lockdown March–May 2020 in the UK, based on available data for closures of higher-level sector categories; period 1 is September-October, period 2 is November-December, period 3 is January-February; openings vary between fully open as pre-pandemic (yellow, 1) to closed (blue, 0); scenario recommends partial closure of education sector (See table S3).

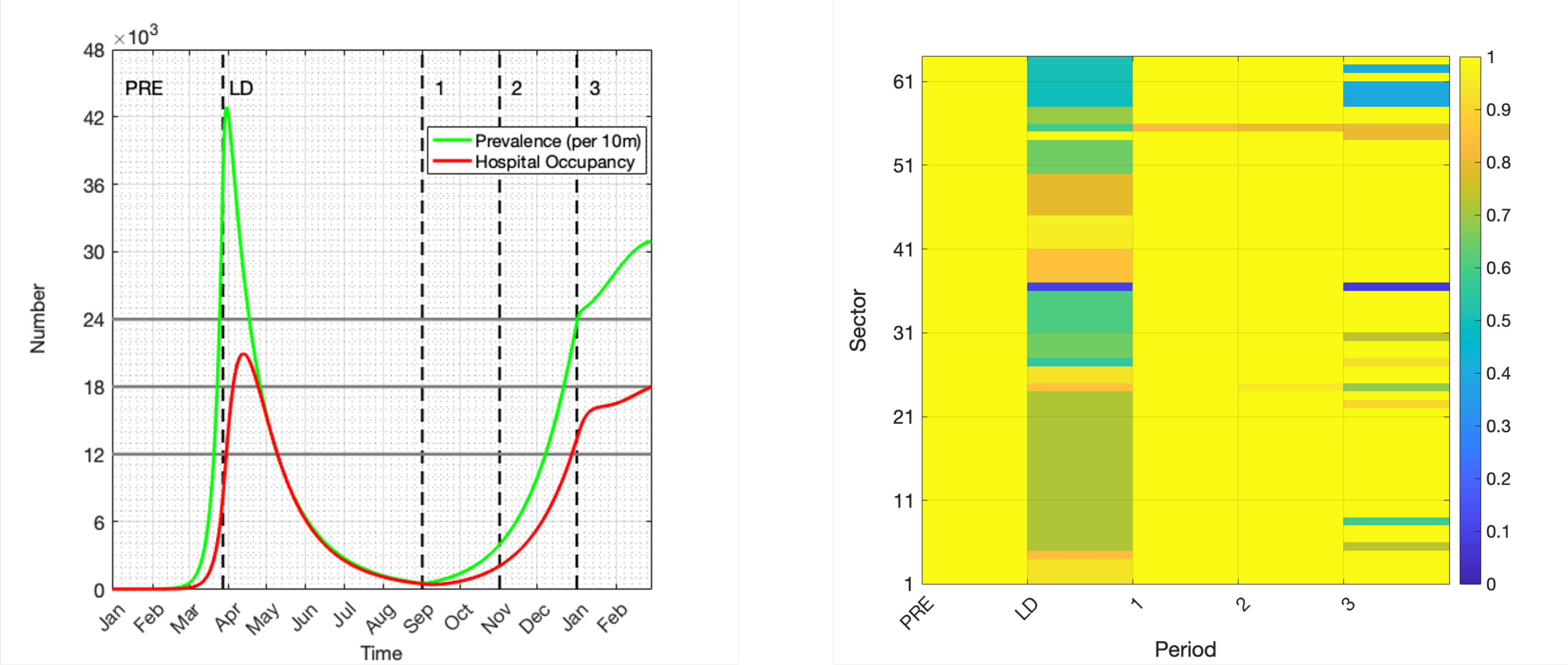

Figure 2: Optimal economic configuration under scenario B (education open), hospital capacity 18,000 beds. (A) Projected prevalence and hospital occupancy (B) Economic configuration across 63 sectors. GDP over six months £854bn.

Notes: Scenario B optimizes GDP via successive bi-monthly opening and closing of 63 sectors over a six-months intervention period, subject to epidemiological and economic constraints; any economic sector except for education may close to 80% of observed minimum levels; education is constrained to stay operational at or above 80% of pre-pandemic production levels; (B) optimal economic configuration targets several sectors for partial closure (see table S3).

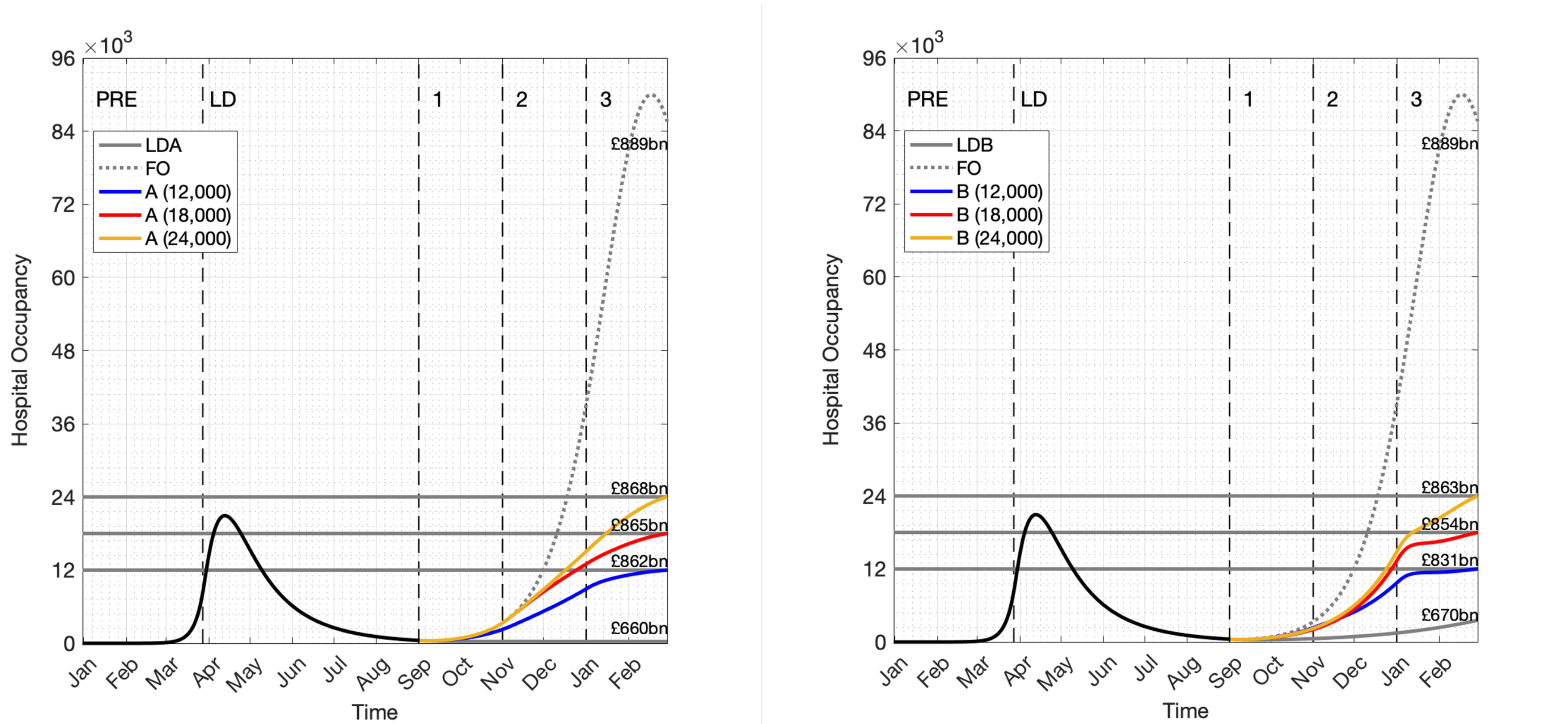

Figure 3: Projected hospital occupancy and GDP for all scenarios and hospital capacity constraints. (A) Scenarios A (GDP maximization), LDA, FO; (B) Scenarios B (education open), LDB, FO

Notes: In scenario FO, all sectors are open at pre-pandemic levels; in all scenarios including FO, stringent NPIs and self-protective behavior reduce transmission; three grey horizontal lines represent alternative $\underline{H}$; aggregate GDP over six months; (A) Scenarios A: any economic sector -including education - may close to 80% of observed minimum levels; LDA: all economic sectors close to observed minima. (B) Scenarios B: education sector is operational at 80% throughout and all other sectors may close to observed minima; LDB: all economic sectors close to observed minima except for the education sector which is operational at 80%.

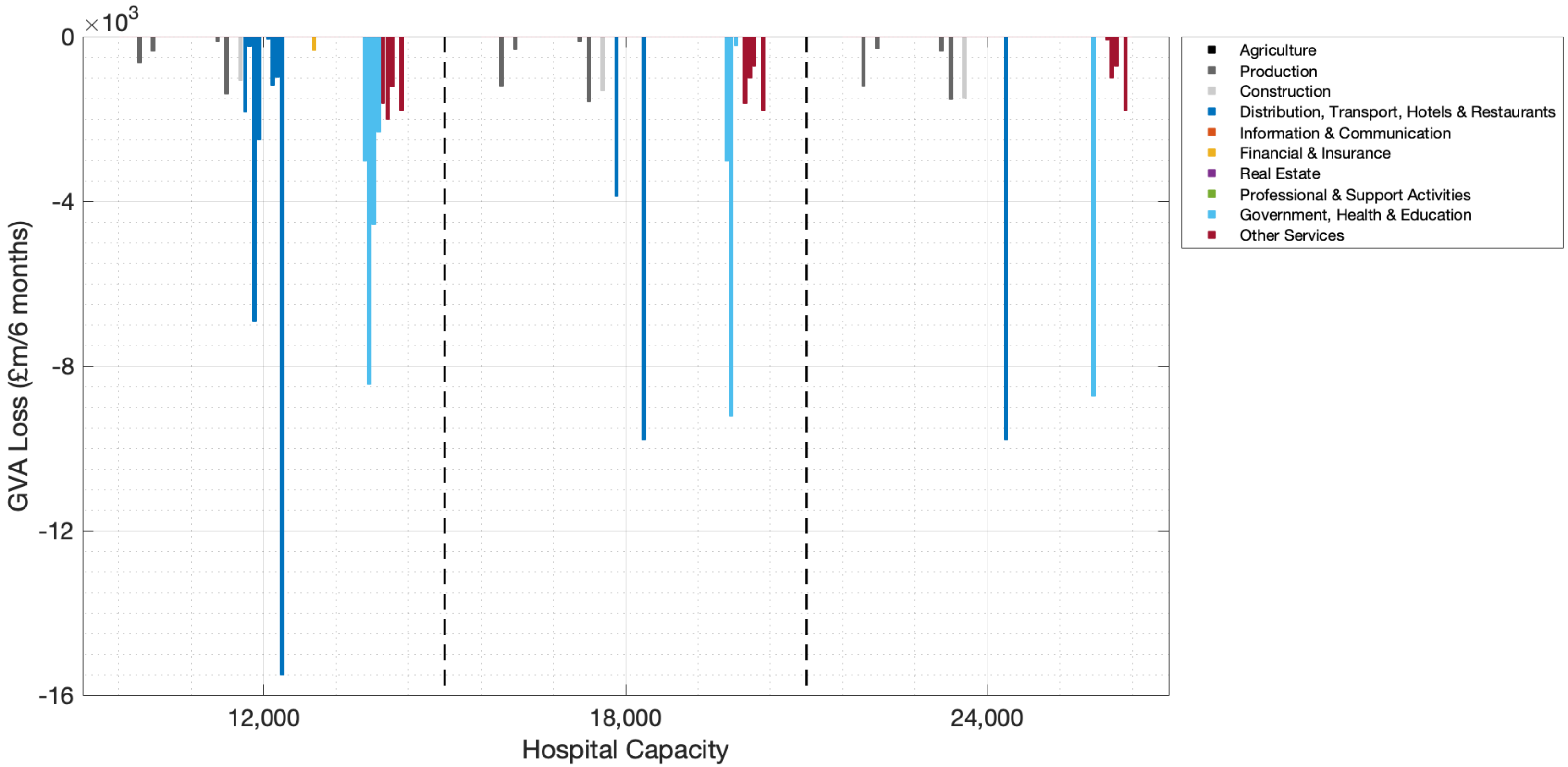

Figure 4: Loss in Gross Value Added under scenario B (education open), September to February. Gross Value Added (GVA) loss over six months for sectors selected for partial closure by Scenario B, compared to FO (fully open), under three assumptions on maximum hospital capacity.

Notes: $\underline{H}$=12,000: Dark grey sectors from 'Agriculture' are 5 'Manufacture of food products, beverages and tobacco products', 8 'Manufacture of paper and paper products'; lighter grey sectors from 'Production' are 22 'Manufacture of furniture; other manufacturing', 24 'Electricity, gas, steam and air conditioning supply'; light grey sector is 'Construction'; dark blue sectors from 'Distribution, transport, hotels and restaurants' from left to right are 28 'Wholesale and retail trade and repair of motor vehicles and motorcycles', 29 'Wholesale trade, except of motor vehicles and motorcycles', 30 'Retail trade, except of motor vehicles and motorcycles' (loss of £6.9bn), 31 'Land transport and transport via pipelines', 33 'Air transport', 34 'Warehousing and support activities for transportation', 35 'Postal and courier activities', 36 'Accommodation and food service activities' (loss of £15.5bn); yellow sector from 'Financial & Insurance' is 43 'Activities auxiliary to financial services and insurance activities'; light blue sectors from 'Government, health & education' from left to right are 55 'Public administration and defence; compulsory social security', 56 'Education' (loss of £9.2bn), 57 'Human health activities' (loss of £4.6bn), 58 'Social work activities'; dark red sectors from 'Other services' from left to right are 59 'Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities, gambling and betting activities', 60 'Sports activities and amusement and recreation activities', 61 'Activities of membership organisations', 63 'Other personal service activities'.

$\underline{H}$=18,000: Dark grey sectors from 'Agriculture' are 5 'Manufacture of food products, beverages and tobacco products', 8 'Manufacture of paper and paper products'; lighter grey sectors from 'Production' are 22 'Manufacture of furniture; other manufacturing', 24 'Electricity, gas, steam and air conditioning supply'; light grey sector is 'Construction'; dark blue sectors from 'Distribution, transport, hotels and restaurants' from left to right are 30 'Retail trade, except of motor vehicles and motorcycles' (£3.9bn), 36 'Accommodation and food service activities' (£9.8bn); light blue sectors from 'Government, health & education' from left to right are 55 'Public administration and defence; compulsory social security', 56 'Education' (loss of £9.2bn); dark red sectors from 'Other services' from left to right are 59 'Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities', 60 'Sports activities and amusement and recreation activities', 61 'Activities of membership organisations' 63 'Other personal service activities'.

$\underline{H}$=24,000: Dark grey sectors from 'Agriculture' are 5 'Manufacture of food products, beverages and tobacco products', 7 'Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials', 8 'Manufacture of paper and paper products'; lighter grey sectors from 'Production' are 22 'Manufacture of furniture; other manufacturing', 24 'Electricity, gas, steam and air conditioning supply'; light grey sector is 'Construction'; dark blue sector from 'Distribution, transport, hotels and restaurants' is 36 'Accommodation and food service activities' (£9.8bn); light blue sector from 'Government, health & education' from left to right is 56 'Education' (loss of £8.7bn); dark red sectors from 'Other services' from left to right are 59 'Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities', 60 'Sports activities and amusement and recreation activities', 61 'Activities of membership organisations' 63 'Other personal service activities'.

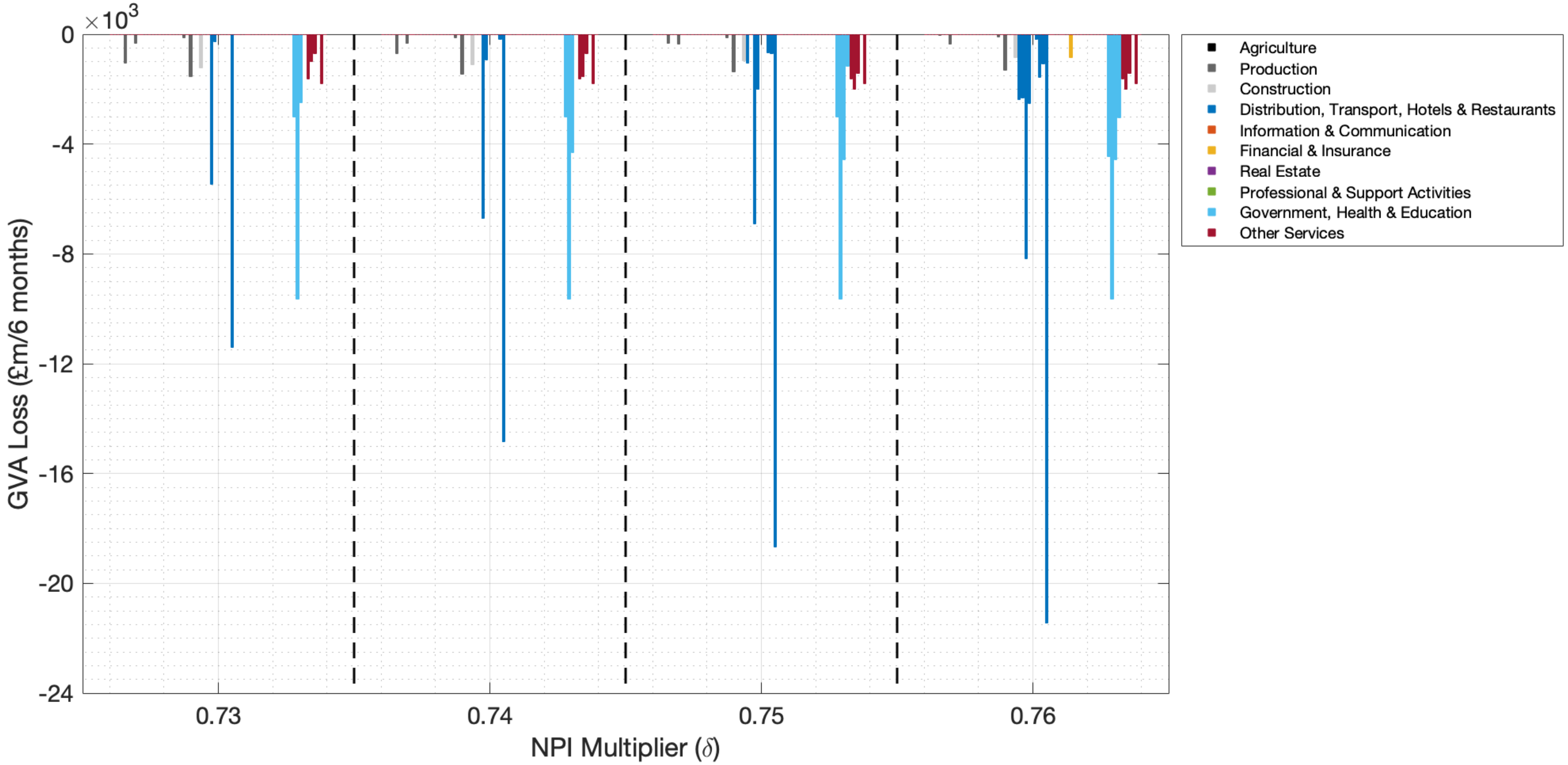

Figure 5: Alternative assumptions on stringency of other non-pharmaceutical interventions, Scenario B, September to February.
Aggregate GVA loss over six months of the sectors selected for closure by Scenario B (compared to FO) under alternative assumptions on the stringency of other NPIs and adherence from stronger (δ=0.73) to weaker (δ=0.76); calibrated value of δ for the first lockdown period is 0.57. Sectors with aggregate GVA losses above £4bn over 6 months are dark blue sectors 30 'Retail trade, except of motor vehicles and motorcycles', and 36 'Accommodation and food service activities', and light blue sector 56 'Education'. For δ=0.74 and above, in addition light blue sector 57 'Human health activities' has GVA losses above £4bn. For δ=0.76, in addition light blue sector 55 'Public administration and defence; compulsory social security' has GVA losses above £4bn.

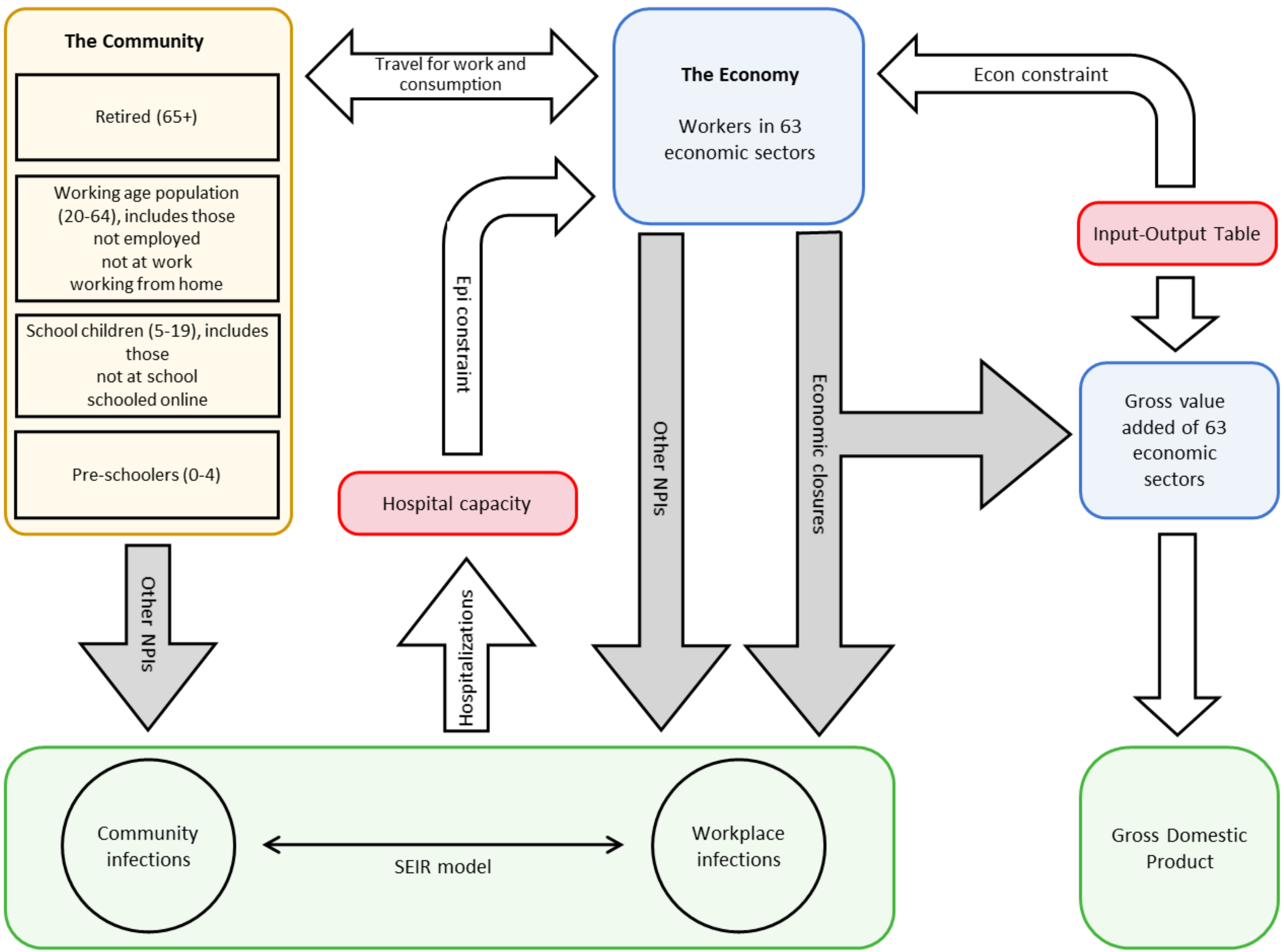

Figure 6: Structure of DAEDALUS

Notes to figure 6: DAEDALUS models economic exchange and infection transmission within the community, the economy, during travel, and between these places. The community consists of individuals who are not employed, workers during their leisure time and when working from home, school children and students during their leisure time and when attending school online. The economy consist of workers in 63 economic sectors, including the education sector. There is an exchange between the community and the economy, via workers travelling between home and workplaces, students traveling to educational institutions, and individuals consuming goods and services. Transmission of infections in the community, at workplaces, in educational institutions, while consuming goods and services and travelling is modelled via a deterministic compartmental SEIR model. This determines the number of infected individuals seeking hospital treatment. Contact rates vary by age group and by economic sectors. Complex supply chains and inter-dependencies between sectors are represented by a static input-output table of 63 economic sectors. There are two constraints in the model to any policy that optimizes GDP while containing infections via economic closures: First, the interdependencies between sectors and the need for essential production, as given by the input-output table, limits the extent to which the economy can be closed. Second, the need to contain the number of hospital patients within the available hospital capacity limits the extend to which the economy can be opened. The government has two levers to reduce infections: Economic closures (or lockdowns) of economic activity not essential to day-to-day life, and other NPIs including social distancing guidance, limits to social contacts, test-and-trace interventions, and others: First, policy makers can mandate the partial or full closure of non-essential economic production of some or all of the 63 economic sectors. This reduces workplace infections because workers and/or students stay in the community and do not travel and spend time at workplaces, which has a dampening effect to community infections. However, closures reduces sectors' economic production because not all workers can work from home; this results in less economic output (measured by sectoral Gross Value Added, or GVA) and a reduction in short-term GDP, compared to pre-pandemic production. The second lever to reduce infections is the implementation of other NPIs, for example social distancing mandates, facemasks, test-and-trace interventions, and more. These reduce transmission of infection but have no impact on economic production. In the optimization, economic closures keep hospitalizations within the available hospital capacity, while maximizing GDP.