# The Global Impact of COVID-19 and Strategies for Mitigation and Suppression

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## Summary

The world faces a severe and acute public health emergency due to the ongoing COVID-19 global pandemic. How individual countries respond in the coming weeks will be critical in influencing the trajectory of national epidemics. Here we combine data on age-specific contact patterns and COVID-19 severity to project the health impact of the pandemic in 202 countries. We compare predicted mortality impacts in the absence of interventions or spontaneous social distancing with what might be achieved with policies aimed at mitigating or suppressing transmission. Our estimates of mortality and healthcare demand are based on data from China and high-income countries; differences in underlying health conditions and healthcare system capacity will likely result in different patterns in low income settings.

We estimate that in the absence of interventions, COVID-19 would have resulted in 7.0 billion infections and 40 million deaths globally this year. Mitigation strategies focussing on shielding the elderly (60% reduction in social contacts) and slowing but not interrupting transmission (40% reduction in social contacts for wider population) could reduce this burden by half, saving 20 million lives, but we predict that even in this scenario, health systems in all countries will be quickly overwhelmed. This effect is likely to be most severe in lower income settings where capacity is lowest: our mitigated scenarios lead to peak demand for critical care beds in a typical low-income setting outstripping supply by a factor of 25, in contrast to a typical high-income setting where this factor is 7. As a result, we anticipate that the true burden in low income settings pursuing mitigation strategies could be substantially higher than reflected in these estimates.

Our analysis therefore suggests that healthcare demand can only be kept within manageable levels through the rapid adoption of public health measures (including testing and isolation of cases and wider social distancing measures) to suppress transmission, similar to those being adopted in many countries at the current time. If a suppression strategy is implemented early (at 0.2 deaths per 100,000 population per week) and sustained, then 38.7 million lives could be saved whilst if it is initiated when death numbers are higher (1.6 deaths per 100,000 population per week) then 30.7 million lives could be saved. Delays in implementing strategies to suppress transmission will lead to worse outcomes and fewer lives saved.

We do not consider the wider social and economic costs of suppression, which will be high and may be disproportionately so in lower income settings. Moreover, suppression strategies will need to be maintained in some manner until vaccines or effective treatments become available to avoid the risk of later epidemics. Our analysis highlights the challenging decisions faced by all governments in the coming weeks and months, but demonstrates the extent to which rapid, decisive and collective action now could save millions of lives.

## 1. Introduction

The COVID-19 pandemic is now a major global health threat, with 332,930 cases and 14,510 deaths confirmed worldwide as of the 23rd March 2020[1]. Since the initial identification of the virus in China, global spread has been rapid, with 182 of 202 countries having reported at least one case. The experience in countries to date has emphasised the intense pressure that a COVID-19 epidemic places on national health systems, with demand for intensive care beds and mechanical ventilators rapidly outstripping their availability in even relatively highly resourced settings[2]. This has potentially profound consequences for resource-poor settings, where the quality and availability of healthcare and related resources (such as oxygen) is typically poorer[3].

There remain large uncertainties in the underlying determinants of the severity of COVID-19 infection and how these translate across settings. However, clear risk factors include age, with older people more likely to require hospitalisation and to subsequently die as a result of infection[4], and underlying co-morbidities including hypertension, diabetes and coronary heart disease serving to exacerbate symptoms[5]. Both the age-profile and the distribution of relevant co-morbidities are likely to vary substantially by country, region and economic status, as will age-specific contact patterns and social mixing. Variation in these factors between countries will have material consequences for transmission and the associated burden of disease by modifying the extent to which infection spreads to the older, more vulnerable members of society.

To help inform country strategies in the coming weeks, we provide here summary statistics of the potential impact of mitigation and suppression strategies in all countries across the world. These illustrate the need to act early, and the impact that failure to do so is likely to have on local health systems. It is important to note that these are not predictions of what is likely to happen; this will be determined by the action that governments and countries take in the coming weeks and the behaviour changes that occur as a result of those actions.

## 2. Demographics and Income Status

Figure 1 summarises two of the demographic and societal factors which are likely to determine the burden of COVID-19 in different countries. First, there is a strong correlation between the gross domestic product (GDP, a measure of the strength of the economy) of a country and its underlying demography (Figure 1A). Higher income countries tend to have the oldest populations; lower income countries in contrast have a much smaller proportion of the population who are above 65 and therefore within the age interval currently observed to be at particularly high risk of mortality from COVID-19[4]. However, we note that these populations also have very different underlying co-morbidities, including a high burden of infectious diseases in low-income (LIC) and low-middle income countries (LMIC) and both infectious and chronic diseases in middle-income countries (MIC). In addition, the burden of many infectious diseases is in young children who may therefore be more at risk than has been observed in China or Europe. The risk profile for COVID-19 could therefore be very different in some low-income settings from that observed to date in China, Europe and North America.

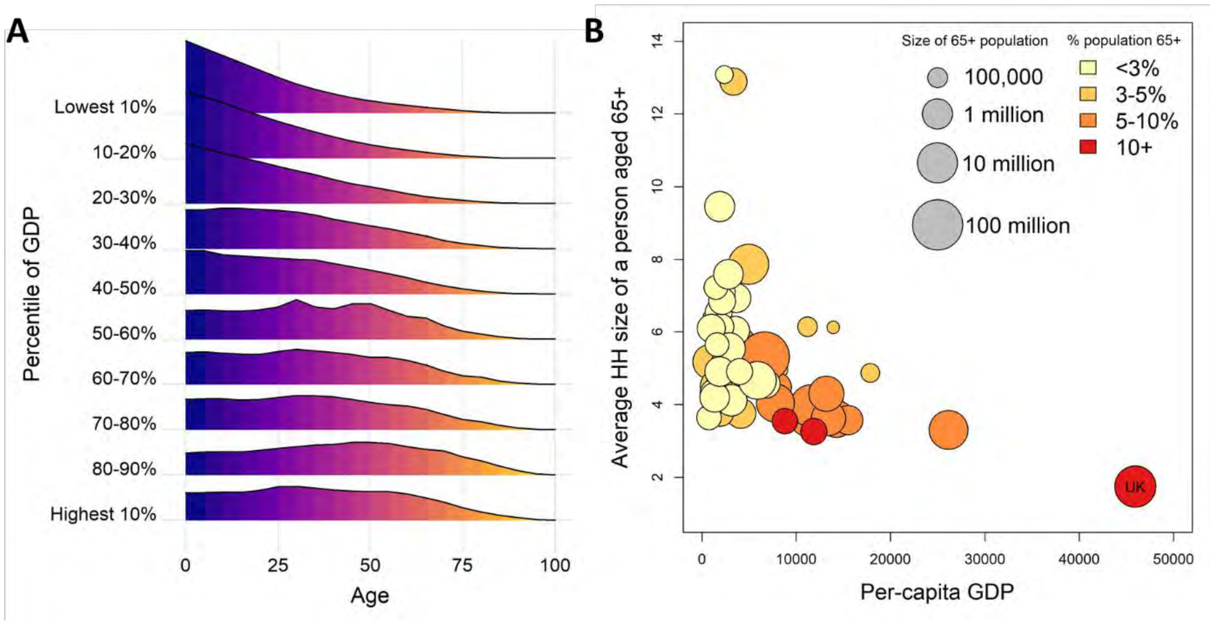


**Figure 1: Demographic, societal and mixing patterns relevant to COVID-19 transmission and burden across different countries. A. Aggregated demographic patterns within 2020 World Population Prospects (WPP) projections across countries within each 2018 World Bank (WB) GDP pre-capita decile. B. Average Household size within Demographic Health Surveys (DHS) of individuals aged 65 and over by 2018 WB GDP per-capita. For reference, the average household size of contacts in the UK is also provided.**

The household is a key context for COVID-19 transmission[6]. The average size of households that have a resident over the age of 65 years is substantially higher in countries with lower income (Figure 1B) compared with middle- and high-income countries, increasing the potential for spread generally but also specifically to this particularly vulnerable age-group. Contact patterns between age-groups also differ by country; in high-income settings contact patterns tend to decline steeply with age. This effect is more moderate in middle-income settings and disappears in low-income settings (Figure 2), indicating that elderly individuals in these settings (LICs and MICs) maintain higher contact rates with a wide range of age-groups compared to elderly individuals in high-income countries (HICs). These contact patterns influence the predicted COVID-19 infection attack rate across age-groups (Figure 2) with higher attack rates in the elderly predicted in low-income settings compared to high-income settings and middle-income settings showing intermediate patterns.

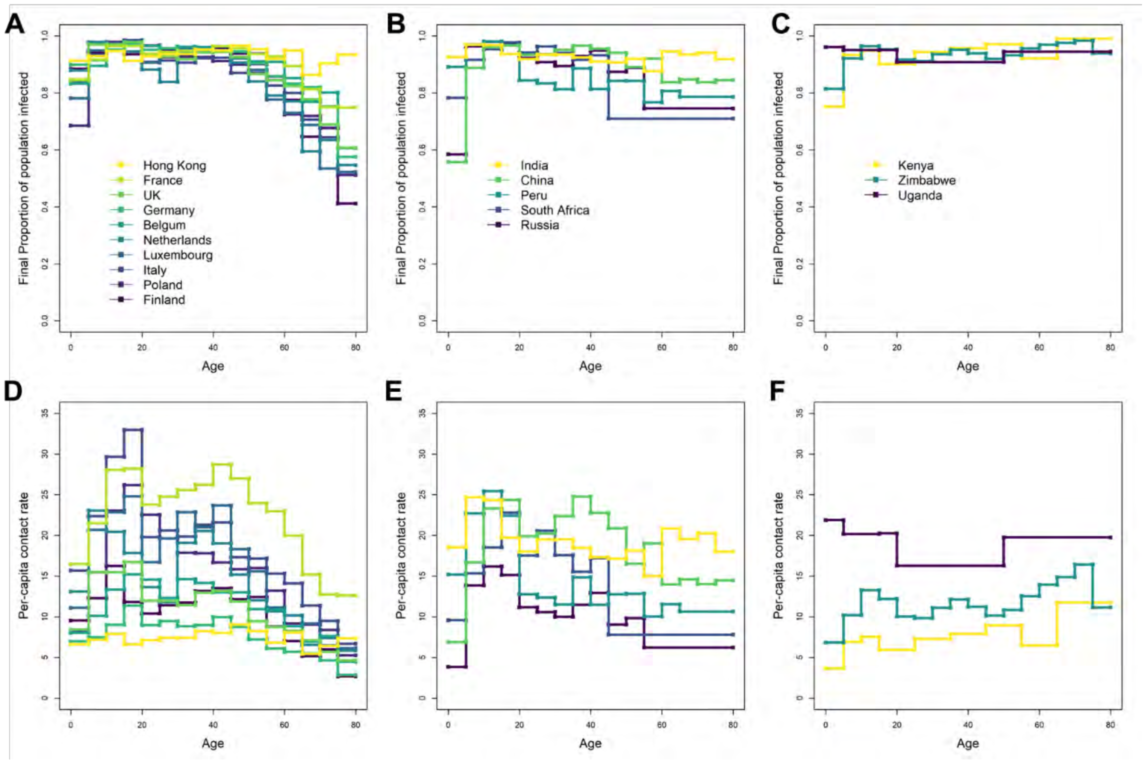


**Figure 2: Age-stratified COVID-19 attack rates based upon surveys of age-stratified contact patterns within all-age samples. A-C show estimates of the final attack rate (proportion infected) by age for $R_0 = 2.4$ for contact patterns from surveys in high income, upper middle income and lower middle income/lower income respectively. D-F show the estimated per-capita rates of contact within these surveys adjusted for national-level demography.**

## 3. Healthcare Availability

Figure 3 summarises our estimates of healthcare capacity in different settings. Hospital bed capacity is strongly correlated with the income status of countries (Figure 3B); LICs have the fewest hospital beds per 1000 population (1.24 beds per 1000 population on average) and HICs the highest (4.82 beds per 1000 population on average). Lower and upper middle-income countries (LMIC/UMICs) fall between these two extremes (2.08 and 3.41 beds per 1000 population on average, respectively). We find that the percentage of hospital beds that are in intensive care units (ICU) is lowest in LICs (1.63 on average) and highest in HICs (3.57) with LMICs and UMICs falling in-between (2.38 and 3.32 respectively) (Figure 3C). Note that our estimates of the ICU capacity in HICs are drawn almost exclusively from a recent review of ICU capacity in Asian countries[7] and are not necessarily reflective of ICU capacity in HICs worldwide.

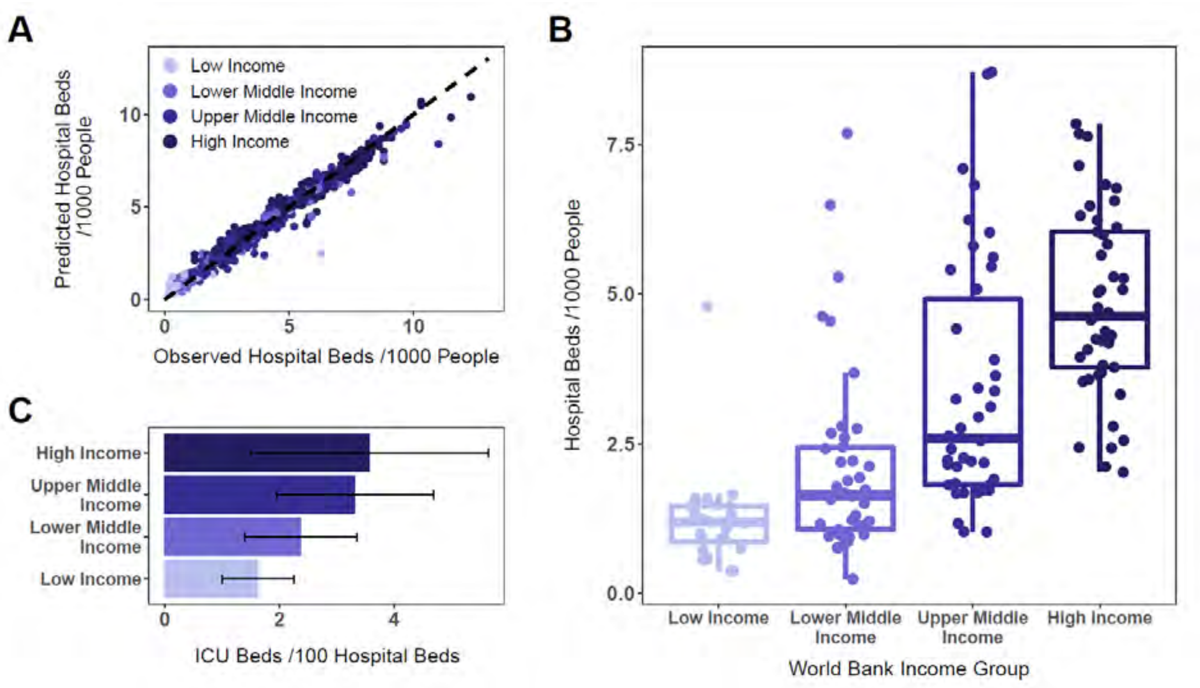


**Figure 3: Estimates of Hospital Bed and ICU Capacity, Stratified by World Bank Income Group. Data on hospital beds per 1000 population were modelled using covariates from the World Bank, and data on ICU capacity collated using a systematic review. (A) Comparison of model prediction and empirically observed numbers of hospital beds per 1000 population. Each point represents a country, with the x-axis indicating the observed number of hospital beds per 1000 population for that country, and the y-axis indicating the model predicted number of hospital beds per 1000 population. Colouring of the points indicates which World Bank income strata the country belongs to. (B) Boxplots of the number of hospital beds per 1000 population, stratified by World Bank income group. The points here are the modelled estimates of hospital beds per 1000 population obtained from the boosted regression tree model. (C) Results from a systematic review describing the percentage of all hospital beds that are in ICUs, stratified by World Bank income group. Error bars indicate the 95% confidence interval of the mean.**

## 4. Burden of Disease

We considered the likely scale of four potential scenarios:

A) An unmitigated epidemic – a scenario in which no action is taken.

B) Mitigation including population-level social distancing – we assessed the maximum reduction in the final scale of the epidemic that can be achieved through a uniform reduction in the rate at which individuals contact one another, short of complete suppression.

C) Mitigation including enhanced social distancing of the elderly – as (B) but with individuals aged 70 years old and above reducing their social contact rates by 60%.

D) Suppression –we explore different epidemiological triggers (deaths per 100,000 population) for the implementation of wide-scale intensive social distancing (modelled as a 75% reduction in interpersonal contact rates) with the aim to rapidly suppress transmission and minimise near-term cases and deaths. For these scenarios we do not produce final size estimates but illustrate their impact in representative settings.

We note that each of these strategies would be, in practice, accompanied by surveillance to test and isolate all identified cases and their household members as rapidly as possible to reduce onward transmission.

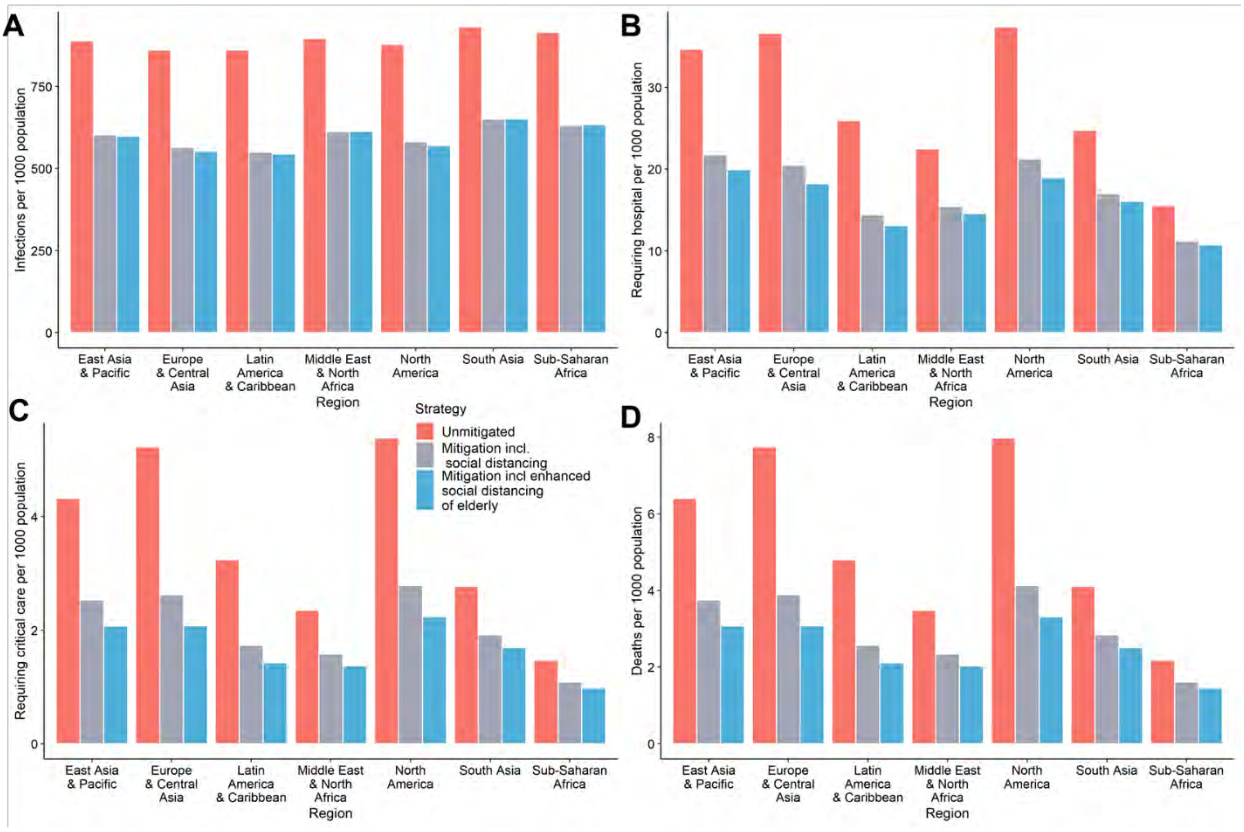


**Figure 4. Estimated total number of infections (A), individuals requiring hospitalisation (B) and critical care (c) and deaths (D) in unmitigated and mitigated scenarios by World Bank region.**

Figures 4 and 5 summarise these results across World Bank geographic regions and income statuses. The accompanying Excel spreadsheet gives these results for individual countries. Our estimated impact of an unmitigated scenario in the UK and the USA for a reproduction number, $R_0$ , of 2.4 (490,000 deaths and 2,180,000 deaths respectively) closely matches the equivalent scenarios using more sophisticated microsimulations (510,000 and 2,200,000 deaths respectively)[8]. On the basis of the observed three-day doubling time in the incidence of deaths across Europe, we here use a central estimate of $R_0$ to 3.0 and investigate scenarios with $R_0$ between 2.4 and 3.3. Globally, we estimate that a completely unmitigated COVID-19 epidemic would lead to 7.0 (range 6.4-7.2) billion infections for a basic reproduction number,

$R_0$, of 3.0 (range 2.4-3.3). Applying estimates of the age-specific IFR from China[4], this could result in 40 (range 35-42) million deaths.

Despite higher rates of contact across older age-groups, we predict a lower incidence of severe disease, hospitalisation and deaths in lower income settings. This is driven by the younger average age of these populations. It is important to note, however, that these estimates assume no substantive difference in general health/co-morbidity prevalence between Chinese and other populations. Furthermore, the standard of medical care available is likely to vary markedly between settings and be substantially lower within lower-income countries (Figure 3). Neither assumption is likely to hold in practice and as such mortality in unmitigated and mitigated epidemics in LMIC and LIC is likely to be substantially higher.

If mitigation including enhanced social distancing is pursued, for an $R_0$ of 3.0, we estimate a maximum reduction in infections in the range 30-38% (median 33%) and a range of reduction in mortality between 19%-55% (median 39%) representing 16 million lives saved for $R_0$=3 (assuming the mortality patterns observed in China). These optimal reductions in transmission and burden were achieved with a range of reductions in the overall rate of social contact between 40.0%- 44.9% (median 43.9%), with this range increasing to 42.9%-47.9% (median 46.9%) for an $R_0$ of 3.3 and decreasing to (34.3%-37.3%, median 36.9%) for an $R_0$ of 2.4.

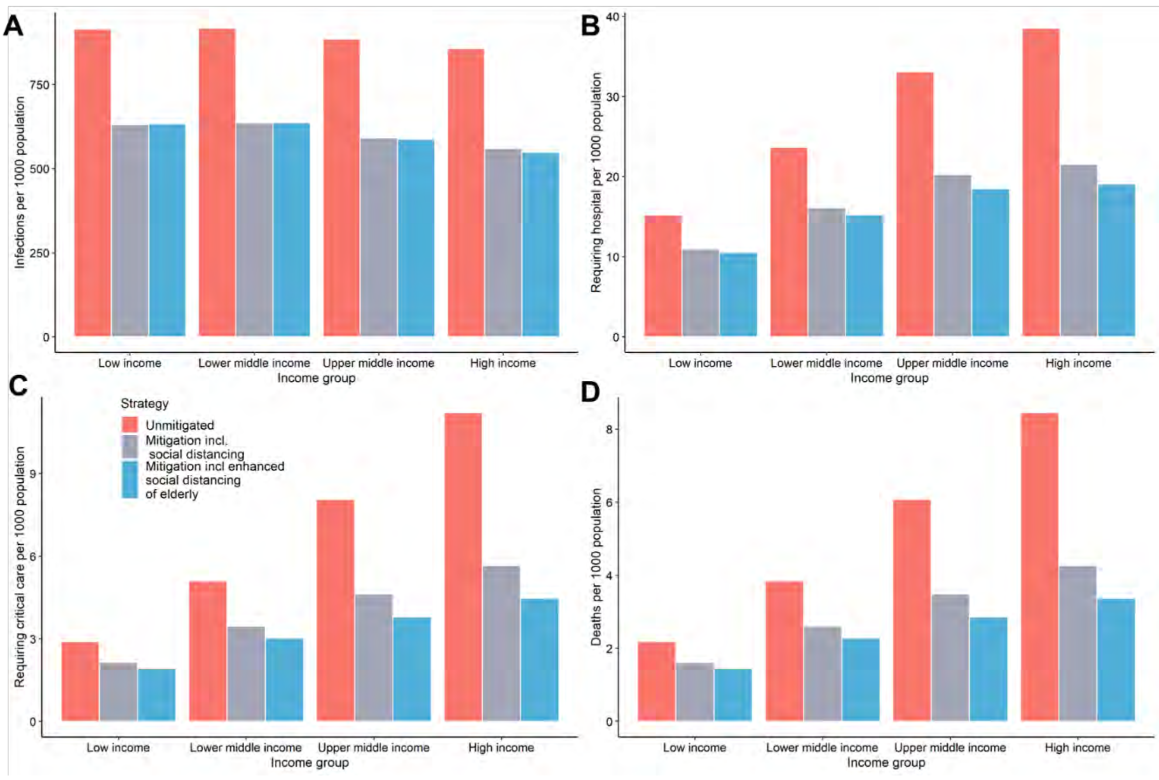


**Figure 5 Estimated total number of infections (A), individuals requiring hospitalisation (B) and critical care (c) and deaths (D) in unmitigated and mitigated scenarios by World Bank income group.**

Combining mitigation with enhanced social distancing of elderly individuals is predicted to result in higher overall mortality reductions of 23%-67% (median 49%), representing 20 million lives saved for $R_0$=3. However, these strategies are predicted to have lower proportional impact in lower income settings compared to higher income settings due primarily to lower-income settings possessing a far smaller proportion of elderly individuals. (Figure 1B and Figure 2).

The resulting reduction in burden under optimal mitigation is predicted to substantially reduce the gap between demand for hospital beds and capacity (Figures 6E-H). However, demand for critical care is still predicted to vastly exceed capacity in all countries (here, modelled using demographics and contact patterns for a representative LIC, LMIC, UMIC and HIC) under all mitigation scenarios considered. Although we predict lower demand for critical care in lower income settings due to their younger populations, this is likely to be offset by a much lower level of supply: for our mitigation scenario including population-level social distancing, peak demand for critical care in our simulation for a typical LIC outstrips demand by a factor of 25.4, whereas for the equivalent simulation in a typical HIC this factor was 7.0 (typical LMIC and UMIC produced factors of over-demand of 16.4 and 10.86 respectively). The impact of a lack of adequate care for more severe cases of COVID-19 in these scenarios is difficult to quantify but is likely to significantly increase overall mortality. As a result, we anticipate that those countries pursuing mitigation, lower-income settings are likely to experience a higher degree of excess mortality due to health system failure – this is a factor not currently captured in our projections of total deaths.

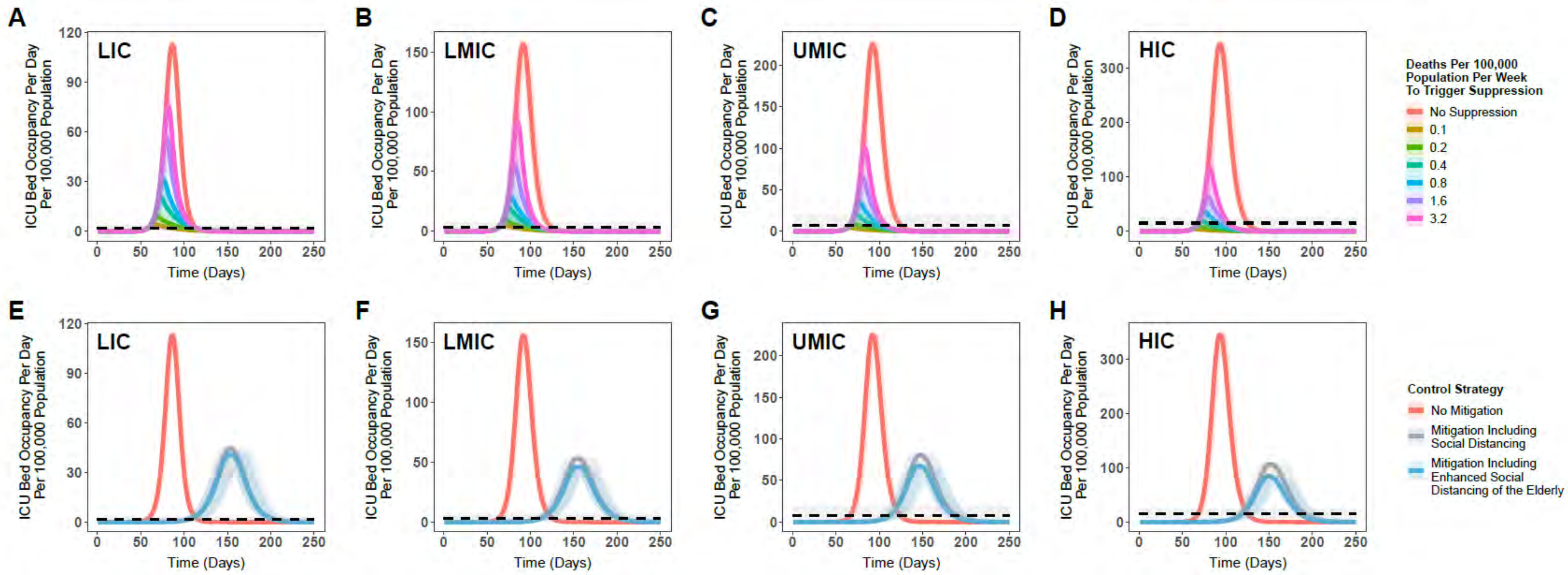


**Figure 6: The impact of various control strategies in representative settings. Using an age-structured SEIR model along with demographies and contact patterns representative of LIC, LMIC, UMIC and HIC countries (columns left to right) the impact of different control strategies was. ICU bed occupancy per day per 100,000 population is shown in all figures. The top row shows impact of suppression (triggered at times dependent on when the rate of deaths per week increases beyond certain defined thresholds) and the bottom row shows mitigation (involving either mitigation involving general social distancing across the whole population or mitigation involving whole population social distancing as well as enhanced social distancing of the elderly)**

**Table 1: Estimated impact of suppression strategies. The impact on infections and deaths over 250 days for two different suppression strategies triggered according to different thresholds for mortality incidence (0.2 and 1.6 deaths per 100,000 population per week).**

| | **Unmitigated Scenario** | | **Suppression at 0.2 deaths per 100,000 population per week** | | **Suppression at 1.6 deaths per 100,000 population per week** | |
|---|---|---|---|---|---|---|
| | **Infections** | **Deaths** | **Infections** | **Deaths** | **Infections** | **Deaths** |
| East Asia & Pacific | 2,117,131,000 | 15,303,000 | 92,544,000 | 442,000 | 632,619,000 | 3,315,000 |
| Europe & Central Asia | 801,770,000 | 7,276,000 | 61,578,000 | 279,000 | 257,706,000 | 1,397,000 |
| Latin America & Caribbean | 566,993,000 | 3,194,000 | 45,346,000 | 158,000 | 186,595,000 | 729,000 |
| Middle East & North Africa | 419,138,000 | 1,700,000 | 30,459,000 | 113,000 | 152,262,000 | 594,000 |
| North America | 326,079,000 | 2,981,000 | 17,730,000 | 92,000 | 90,529,000 | 520,000 |
| South Asia | 1,737,766,000 | 7,687,000 | 111,703,000 | 475,000 | 629,164,000 | 2,693,000 |
| Sub-Saharan Africa | 1,044,858,000 | 2,483,000 | 110,164,000 | 298,000 | 454,968,000 | 1,204,000 |
| Total | 7,013,734,000 | 40,624,000 | 469,523,000 | 1,858,000 | 2,403,843,000 | 10,452,000 |

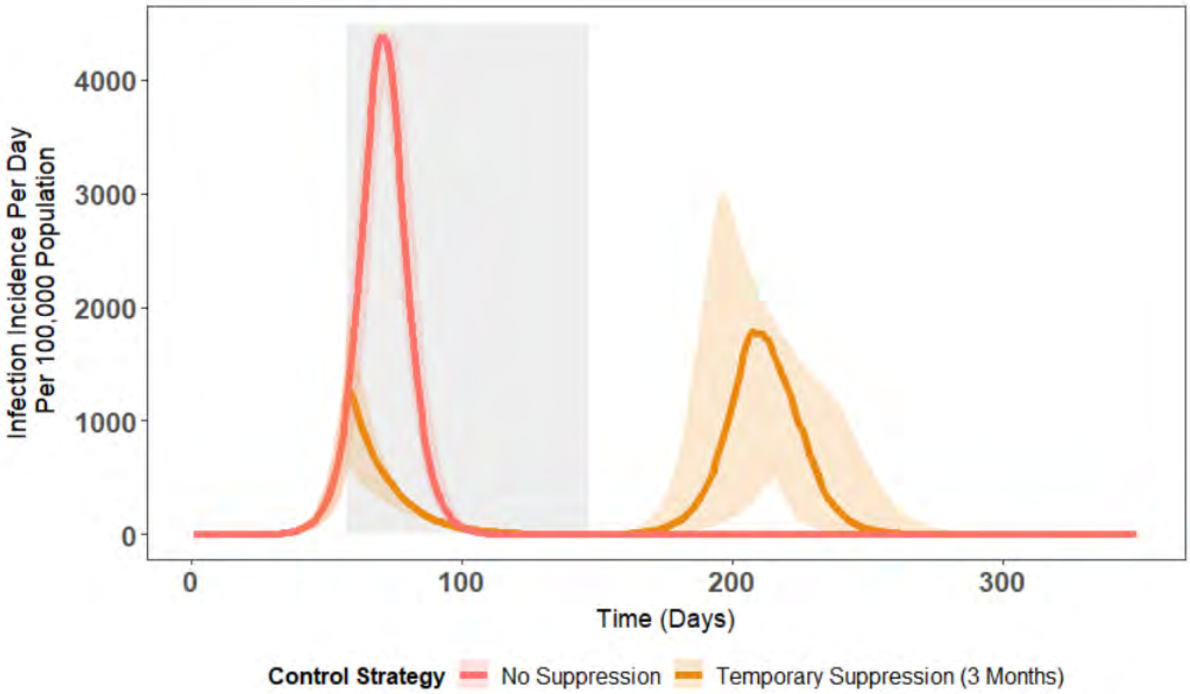


**Figure 7: The impact of temporary suppression on infection incidence in a representative lower income setting. In this example, suppression is maintained for 3 months but is then stopped and contact patterns are assumed to return to previous levels.**

Even extensive suppression (Figures 6A-D & Table 1), triggered when weekly rate of deaths per 100,000 reaches a given threshold, is predicted to result in critical care demand being exceeded unless suppression is triggered at an early stage of the epidemic in a country. Additionally, the impact of a trigger based upon number of deaths for suppression and its ability to prevent the epidemic exceeding ICU bed capacity differs between settings. Triggering suppression based on deaths or death rates is less sensitive in LICs and LMICs - the younger populations in these settings mean that by the time a certain death rate threshold is reached, they have typically accrued a higher number of cases (and by extension, ICU capacity has already been overwhelmed).

Given these results, the only approaches that can avert health system failure in the coming months are likely to be the intensive social distancing measures currently being implemented in many of the most affected countries, preferably combined with high levels of testing. These approaches are likely to have the largest impact when implemented early (Figure 6, Table 1). It is however important to consider the sustainability of such measures. As illustrated in Figure 7, these interventions will likely need to be maintained at some level in tandem alongside high levels of surveillance and rapid case isolation to avoid the potential for resurgent epidemics.

It is important to note that we do not quantify the wider societal and economic impact of such intensive suppression approaches; these are likely to be substantial. Nor do we quantify the potentially different societal and economic impact of mitigation strategies. Moreover, for countries lacking the infrastructure capable of implementing technology-led suppression maintenance strategies such as those currently being pursued in Asia[6,9], and in the absence of a vaccine or other effective therapy (as well as the possibility of resurgence), careful thought will need to be given to pursuing such strategies in order to avoid a high risk of future health system failure once suppression measures are lifted.

The results presented here illustrate the potential impact of the COVID-19 pandemic globally. Our analyses give insight into possible trajectories and the impact of measures that can help reduce the spread of the virus based on the experience of countries affected early in the outbreak. However, at the current time, it is not possible to predict with any certainty the exact number of cases for any given country or the precise mortality and disease burden that will result. A full understanding of both will only be available retrospectively.

This analysis highlights the challenging decisions faced by all governments in the coming weeks and months. However, our counterfactual of an unmitigated pandemic clearly demonstrates the extent to which rapid, decisive and collective action can prevent billions of infections and save millions of lives globally.

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## 5. Methods

### Patterns of contact, demography and household size across the World

Population sizes and age distributions by country were taken from the 2020 World Population Prospects, the 27th round of the official United Nations population estimates prepared by the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (available here: https://population.un.org/wpp/). Estimates of household size and the age of members of each household were extracted from The Demographic and Health Surveys (DHS) Program using the rDHS package[10]; data from a total of 59 LMIC countries with surveys conducted since 2010 were extracted. In addition, we extracted equivalent household information for the United Kingdom as a representative HIC[11].

Patterns of contact across different populations and countries were drawn from several sources, including previously published estimates of mixing from a number of HICs [12] and a recent systematic review of social contact surveys including MICs and LMICs [13]. Additional data were obtained from surveys included in the socialmixR package (https://github.com/sbfnk/socialmixr), as well as references identified through either the reference lists of included surveys, or through informal searches of Web of Science and PubMed. We identified data from 18 countries. Ten were from HIC settings, with 8 (Belgium, Finland, Germany, Italy, Luxembourg, Netherlands, Poland and the United Kingdom) from the POLYMOD social mixing study[12], and two further surveys from France[14] and Hong Kong[15]. Five surveys were identified in UMIC settings: China[16], India[17], Peru[18], Russia[19] and South Africa[20]. Two surveys were identified in LMIC settings: Kenya[21] and Zimbabwe[22]. One survey was undertaken in a LIC: Uganda[23]. Contact matrices were adjusted to give symmetric age-specific contact rates for each country.

As Figure 2 shows, contact patterns measured within Western Europe suggest attack rates are likely to decline substantially by age. For Hong Kong, the only non-European HIC setting for which contact data were identified, contact rates did not decline sufficiently at older ages to produce a similar decline, which may suggest this is not a consistent trait across all high-income countries. However, we identified additional surveys in the literature from Hong Kong[24] and Japan[25] where contact rates did appear to decline more substantially with age but were not available in readily downloadable format. Our projections for UMIC settings showed declines in projected attack rates by age, though to a lesser extent than HIC settings. Meanwhile the limited data from LMIC did not result in substantial declines in attack rate by age.

Given the sparse availability of contact data, we used representative patterns for countries which do not have survey data. For the USA and Canada we used the UK survey data. For other European and Central Asian countries (with available data from Russia also indicating substantial declines in attack rates in older ages – Figure 2B), as well as countries previously classified as advanced economies by the International Monetary Fund[26], we used the patterns from the European survey producing the median final attack rate within individuals aged 70 and above (the Netherlands POLYMOD survey[12]). Countries from Latin America and the Caribbean were assigned mixing patterns from the Peruvian survey; those from South Asia, mixing patterns from the Indian survey; those from East Asia, mixing patterns from the Chinese survey; those from sub-Saharan Africa, mixing patterns from the Zimbabwean survey (with the exception of South Africa which was assigned patterns from the Chinese survey); whilst those in the Middle-East and North Africa were assigned patterns from the Chinese survey if they were high or upper-middle income and from the Zimbabwean survey if they were low or lower-middle income. These contact patterns, alongside country-specific demography were then used to provide estimation of number of Infections and deaths, demand for health care in an unmitigated pandemic and the impact of control measures for a given basic reproduction number.

We calculated the final epidemic size generated from an age-structured Susceptible-Infected-Recovered model incorporating both the demographic structure of the population and the rates of contact between different individuals across different age groups[27]. This numerical solution replicates the total number of infected individuals derived from our simulation models for the UK and USA[8]. Final epidemic sizes by age where then generated using a central $R_0$ value of 3.0, with uncertainty range between 2.4 and 3.3. This value of $R_0$ was chosen as it results in a 3-day doubling time, consistent with current observations in Europe.

To estimate the demand for health services and overall mortality, we use age-specific estimates of the hospitalisation rate and infection fatality ratio (IFR) obtained from our previous analysis of data from China[4]. Hence, we make the strong assumption that similar levels of medical care to that provided in China are available elsewhere. We also implicitly assume that mortality patterns do not vary given the different co-morbidities. These assumptions may mean that our results may overestimate mortality in some HICs and under-estimate it in some lower income countries.

For each country we estimated the potential maximum benefits from mitigation through a policy of social distancing within the general population. We identified the minimum final size of the epidemic produced by a uniform proportional reduction in social contacts across age categories conditional on this final size achieving a level of herd immunity that would be sufficient to prevent a second wave following the relaxation of the policy and a subsequent return to the levels of social contact prior to the pandemic. In a similar manner, we also assessed the maximum impact of a policy where in addition to overall social distancing, individuals 70 years old and above reduce their social contacts by a substantially larger proportion, here modelled as 60% ("shielding").

To model the impact of these scenarios on the dynamics of likely healthcare demand over time we used an age-structured stochastic Susceptible-Exposed-Infected-Recovered (SEIR) model parameterised to match best estimates of key parameters determining the dynamics of spread of COVID-19. The exposed category was modelled as two separate compartments to produce a gamma-distributed incubation period of mean 4.58 days and standard deviation

3.24 days. A single compartment was used for the infectious compartment, yielding an exponentially distributed infectious period with mean 2.09 days. An $R_0$ of 3.0 was used for all scenarios explored and presented in this report. Integration with country-specific demographies and patterns of contact between age-groups then enabled setting-specific estimation of the incidence of new infections over time. This incidence of new infections over time is then converted to the incidence of infections requiring hospitalisation and/or critical care. Both the probability that an infected person requires hospitalisation and whether they also require critical care increase with age, matching estimates given in[8]. We assume a delay of 5 days between symptom onset (assumed here to be when individuals progress from the Exposed to the Infectious compartment) and hospitalisation and that hospitalised individuals require a hospital bed for 8 days. If critical care is also required, we assume that individuals remain in hospital and occupy a critical bed for a further 8 days, yielding a total hospital stay of 16 days. Any mortality associated with COVID-19 is assumed to occur 21 days after symptom onset. These parameters are based on our current best understanding of the likely progression and severity of COVID-19.

Using this model, we replicated the “unmitigated”, “mitigation including social distancing” and “mitigation including enhanced social distancing of the elderly” scenarios from the final size analysis. For the “mitigation including social distancing scenario”, contact rates were reduced by a factor determined through our minimum final size calculations described above. For the “mitigation including enhanced social distancing of the elderly” scenario, contact rates were reduced uniformly across age groups less than 70 and then a further, more extreme reduction (60%) applied to the 70-75 and 75+ age groups.

We also explored the impact of more rigorous social distancing approaches aimed at immediate suppression of transmission. We looked at 6 suppression scenarios in which the timing of policy implementation varied according to when the weekly death rate per 100,000 population exceeds a certain threshold (here, either 0.1, 0.2, 0.4, 0.8, 1.6 or 3.2 deaths per week per 100,000 population) – the effects of widespread transmission suppression were modelled as a uniform reduction in contact rates by 75%, applied across all age-groups.

**Hospital bed capacity estimation**

Data on the number of hospital beds per 1,000 population were available from the World Bank (https://data.worldbank.org/indicator?tab=all) for 201 countries (66 High Income, 58 Upper Middle Income, 47 Lower Middle Income and 30 Low Income). However, many of these records were not recent (earlier than 2015). We therefore use a boosted regression tree-based modelling approach to generate contemporary estimates of hospital beds per 1,000 population using the following covariates: maternal mortality (per 100,000 live births), access to electricity (% of population), population aged 0-14 years (% of population), pupil-teacher ratio in secondary school, rural population (% of population), domestic government health expenditure (% of GDP), infant mortality (per 1,000 live births), the proportion of children enrolled in secondary school, geographical region and income group (with the latter two covariates categorised according to the World Bank's definitions). The model was fitted using the statistical software R and the dismo package, with tree complexity of 12, bag fraction of 0.65, and a learning rate of 0.001. 10-fold cross-validation was implemented to check overfitting, and the model found to predict well both training and held-out (test) datasets.

**Review of Intensive Care Unit Capacity**

These data were derived from 3 resources. We extracted data from a previously conducted systematic review of ICU capacity in low-income countries[28], as well as a more recently published review of ICU capacity across Asia[7]. In addition to this, we also carried out a systematic review to identify further references containing information on ICU bed capacity in Lower- and Middle-Income Countries. Web of Science was searched on Friday 13th March using the search terms ("critical care" OR "intensive care" OR "ICU" OR "CCU") AND capacity AND (country name) where country name refers to 1 of the 138 countries classified as LMIC by the World Bank. This search yielded 174 results, with 30 texts retained after Abstract screening, and 20 of these retained following screening of the full text. Due to the requirement for contemporary estimates, balanced by the comparative paucity of data for ICU capacity compared to hospital beds, we excluded papers earlier than 2000. These resources provided a total of 57 data points describing the number of ICU beds per 100 hospital beds across countries belonging to the World Bank's 4 income strata (LIC, LMIC, UMIC and HIC).

## 6. Appendix data sources

Data on global unmitigated, mitigated and suppression scenarios: Imperial-College-COVID19-Global-unmitigated-mitigated-suppression-scenarios.xlsx

## 7. References


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