Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand

Neil M Ferguson, Daniel Laydon, Gemma Nedjati-Gilani, Natsuko Imai, Kylie Ainslie, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Zulma Cucunubá, Gina Cuomo-Dannenburg, Amy Dighe, Ilaria Dorigatti, Han Fu, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Lucy C Okell, Sabine van Elsland, Hayley Thompson, Robert Verity, Erik Volz, Haowei Wang, Yuanrong Wang, Patrick GT Walker, Caroline Walters, Peter Winskill, Charles Whittaker, Christl A Donnelly, Steven Riley, Azra C Ghani.

On behalf of the Imperial College COVID-19 Response Team

WHO Collaborating Centre for Infectious Disease Modelling
MRC Centre for Global Infectious Disease Analysis
Abdul Latif Jameel Institute for Disease and Emergency Analytics
Imperial College London

Correspondence: neil.ferguson@imperial.ac.uk

Summary

The global impact of COVID-19 has been profound, and the public health threat it represents is the most serious seen in a respiratory virus since the 1918 H1N1 influenza pandemic. Here we present the results of epidemiological modelling which has informed policymaking in the UK and other countries in recent weeks. In the absence of a COVID-19 vaccine, we assess the potential role of a number of public health measures – so-called non-pharmaceutical interventions (NPIs) – aimed at reducing contact rates in the population and thereby reducing transmission of the virus. In the results presented here, we apply a previously published microsimulation model to two countries: the UK (Great Britain specifically) and the US. We conclude that the effectiveness of any one intervention in isolation is likely to be limited, requiring multiple interventions to be combined to have a substantial impact on transmission.

Two fundamental strategies are possible: (a) mitigation, which focuses on slowing but not necessarily stopping epidemic spread – reducing peak healthcare demand while protecting those most at risk of severe disease from infection, and (b) suppression, which aims to reverse epidemic growth, reducing case numbers to low levels and maintaining that situation indefinitely. Each policy has major challenges. We find that that optimal mitigation policies (combining home isolation of suspect cases, home quarantine of those living in the same household as suspect cases, and social distancing of the elderly and others at most risk of severe disease) might reduce peak healthcare demand by 2/3 and deaths by half. However, the resulting mitigated epidemic would still likely result in hundreds of thousands of deaths and health systems (most notably intensive care units) being overwhelmed many times over. For countries able to achieve it, this leaves suppression as the preferred policy option.

We show that in the UK and US context, suppression will minimally require a combination of social distancing of the entire population, home isolation of cases and household quarantine of their family members. This may need to be supplemented by school and university closures, though it should be recognised that such closures may have negative impacts on health systems due to increased

absenteeism. The major challenge of suppression is that this type of intensive intervention package – or something equivalently effective at reducing transmission – will need to be maintained until a vaccine becomes available (potentially 18 months or more) – given that we predict that transmission will quickly rebound if interventions are relaxed. We show that intermittent social distancing – triggered by trends in disease surveillance – may allow interventions to be relaxed temporarily in relative short time windows, but measures will need to be reintroduced if or when case numbers rebound. Last, while experience in China and now South Korea show that suppression is possible in the short term, it remains to be seen whether it is possible long-term, and whether the social and economic costs of the interventions adopted thus far can be reduced.

Introduction

The COVID-19 pandemic is now a major global health threat. As of 16th March 2020, there have been 164,837 cases and 6,470 deaths confirmed worldwide. Global spread has been rapid, with 146 countries now having reported at least one case.

The last time the world responded to a global emerging disease epidemic of the scale of the current COVID-19 pandemic with no access to vaccines was the 1918-19 H1N1 influenza pandemic. In that pandemic, some communities, notably in the United States (US), responded with a variety of non-pharmaceutical interventions (NPIs) - measures intended to reduce transmission by reducing contact rates in the general population[1]. Examples of the measures adopted during this time included closing schools, churches, bars and other social venues. Cities in which these interventions were implemented early in the epidemic were successful at reducing case numbers while the interventions remained in place and experienced lower mortality overall[1]. However, transmission rebounded once controls were lifted.

Whilst our understanding of infectious diseases and their prevention is now very different compared to in 1918, most of the countries across the world face the same challenge today with COVID-19, a virus with comparable lethality to H1N1 influenza in 1918. Two fundamental strategies are possible[2]:

(a) Suppression. Here the aim is to reduce the reproduction number (the average number of secondary cases each case generates), R, to below 1 and hence to reduce case numbers to low levels or (as for SARS or Ebola) eliminate human-to-human transmission. The main challenge of this approach is that NPIs (and drugs, if available) need to be maintained – at least intermittently - for as long as the virus is circulating in the human population, or until a vaccine becomes available. In the case of COVID-19, it will be at least a 12-18 months before a vaccine is available[3]. Furthermore, there is no guarantee that initial vaccines will have high efficacy.

(b) Mitigation. Here the aim is to use NPIs (and vaccines or drugs, if available) not to interrupt transmission completely, but to reduce the health impact of an epidemic, akin to the strategy adopted by some US cities in 1918, and by the world more generally in the 1957, 1968 and 2009 influenza pandemics. In the 2009 pandemic, for instance, early supplies of vaccine were targeted at individuals with pre-existing medical conditions which put them at risk of more severe disease[4]. In this scenario, population immunity builds up through the epidemic, leading to an eventual rapid decline in case numbers and transmission dropping to low levels.

The strategies differ in whether they aim to reduce the reproduction number, R, to below 1 (suppression) – and thus cause case numbers to decline – or to merely slow spread by reducing R, but not to below 1.

In this report, we consider the feasibility and implications of both strategies for COVID-19, looking at a range of NPI measures. It is important to note at the outset that given SARS-CoV-2 is a newly emergent virus, much remains to be understood about its transmission. In addition, the impact of many of the NPIs detailed here depends critically on how people respond to their introduction, which is highly likely to vary between countries and even communities. Last, it is highly likely that there would be significant spontaneous changes in population behaviour even in the absence of government-mandated interventions.

We do not consider the ethical or economic implications of either strategy here, except to note that there is no easy policy decision to be made. Suppression, while successful to date in China and South Korea, carries with it enormous social and economic costs which may themselves have significant impact on health and well-being in the short and longer-term. Mitigation will never be able to completely protect those at risk from severe disease or death and the resulting mortality may therefore still be high. Instead we focus on feasibility, with a specific focus on what the likely healthcare system impact of the two approaches would be. We present results for Great Britain (GB) and the United States (US), but they are equally applicable to most high-income countries.

Methods

Transmission Model

We modified an individual-based simulation model developed to support pandemic influenza planning[5,6] to explore scenarios for COVID-19 in GB. The basic structure of the model remains as previously published. In brief, individuals reside in areas defined by high-resolution population density data. Contacts with other individuals in the population are made within the household, at school, in the workplace and in the wider community. Census data were used to define the age and household distribution size. Data on average class sizes and staff-student ratios were used to generate a synthetic population of schools distributed proportional to local population density. Data on the distribution of workplace size was used to generate workplaces with commuting distance data used to locate workplaces appropriately across the population. Individuals are assigned to each of these locations at the start of the simulation.

Transmission events occur through contacts made between susceptible and infectious individuals in either the household, workplace, school or randomly in the community, with the latter depending on spatial distance between contacts. Per-capita contacts within schools were assumed to be double those elsewhere in order to reproduce the attack rates in children observed in past influenza pandemics[7]. With the parameterisation above, approximately one third of transmission occurs in the household, one third in schools and workplaces and the remaining third in the community. These contact patterns reproduce those reported in social mixing surveys[8].

We assumed an incubation period of 5.1 days[9,10]. Infectiousness is assumed to occur from 12 hours prior to the onset of symptoms for those that are symptomatic and from 4.6 days after infection in those that are asymptomatic with an infectiousness profile over time that results in a 6.5-day mean generation time. Based on fits to the early growth-rate of the epidemic in Wuhan[10,11], we make a baseline assumption that R_0=2.4 but examine values between 2.0 and 2.6. We assume that symptomatic individuals are 50% more infectious than asymptomatic individuals. Individual infectiousness is assumed to be variable, described by a gamma distribution with mean 1 and shape parameter α=0.25. On recovery from infection, individuals are assumed to be immune to re-infection in the short-term. Evidence from the Flu Watch cohort study suggests that re-infection with the same strain of seasonal circulating coronavirus is highly unlikely in the same or following season (Prof Andrew Hayward, personal communication).

Infection was assumed to be seeded in each country at an exponentially growing rate (with a doubling time of 5 days) from early January 2020, with the rate of seeding being calibrated to give local epidemics which reproduced the observed cumulative number of deaths in GB or the US seen by 14th March 2020.

Disease Progression and Healthcare Demand

Analyses of data from China as well as data from those returning on repatriation flights suggest that 40-50% of infections were not identified as cases[12]. This may include asymptomatic infections, mild disease and a level of under-ascertainment. We therefore assume that two-thirds of cases are sufficiently symptomatic to self-isolate (if required by policy) within 1 day of symptom onset, and a mean delay from onset of symptoms to hospitalisation of 5 days. The age-stratified proportion of infections that require hospitalisation and the infection fatality ratio (IFR) were obtained from an analysis of a subset of cases from China[12]. These estimates were corrected for non-uniform attack rates by age and when applied to the GB population result in an IFR of 0.9% with 4.4% of infections hospitalised (Table 1). We assume that 30% of those that are hospitalised will require critical care (invasive mechanical ventilation or ECMO) based on early reports from COVID-19 cases in the UK, China and Italy (Professor Nicholas Hart, personal communication). Based on expert clinical opinion, we assume that 50% of those in critical care will die and an age-dependent proportion of those that do not require critical care die (calculated to match the overall IFR). We calculate bed demand numbers assuming a total duration of stay in hospital of 8 days if critical care is not required and 16 days (with 10 days in ICU) if critical care is required. With 30% of hospitalised cases requiring critical care, we obtain an overall mean duration of hospitalisation of 10.4 days, slightly shorter than the duration from hospital admission to discharge observed for COVID-19 cases internationally[13] (who will have remained in hospital longer to ensure negative tests at discharge) but in line with estimates for general pneumonia admissions[14].

Table 1: Current estimates of the severity of cases. The IFR estimates from Verity et al.[12] have been adjusted to account for a non-uniform attack rate giving an overall IFR of 0.9% (95% credible interval 0.4%-1.4%). Hospitalisation estimates from Verity et al.[12] were also adjusted in this way and scaled to match expected rates in the oldest age-group (80+ years) in a GB/US context. These estimates will be updated as more data accrue.

Age-group (years)	% symptomatic cases requiring hospitalisation	% hospitalised cases requiring critical care	Infection Fatality Ratio
0 to 9	0.1%	5.0%	0.002%
10 to 19	0.3%	5.0%	0.006%
20 to 29	1.2%	5.0%	0.03%
30 to 39	3.2%	5.0%	0.08%
40 to 49	4.9%	6.3%	0.15%
50 to 59	10.2%	12.2%	0.60%
60 to 69	16.6%	27.4%	2.2%
70 to 79	24.3%	43.2%	5.1%
80+	27.3%	70.9%	9.3%

Non-Pharmaceutical Intervention Scenarios

We consider the impact of five different non-pharmaceutical interventions (NPIs) implemented individually and in combination (Table 2). In each case, we represent the intervention mechanistically within the simulation, using plausible and largely conservative (i.e. pessimistic) assumptions about the impact of each intervention and compensatory changes in contacts (e.g. in the home) associated with reducing contact rates in specific settings outside the household. The model reproduces the intervention effect sizes seen in epidemiological studies and in empirical surveys of contact patterns. Two of the interventions (case isolation and voluntary home quarantine) are triggered by the onset of symptoms and are implemented the next day. The other four NPIs (social distancing of those over 70 years, social distancing of the entire population, stopping mass gatherings and closure of schools and universities) are decisions made at the government level. For these interventions we therefore consider surveillance triggers based on testing of patients in critical care (intensive care units, ICUs). We focus on such cases as testing is most complete for the most severely ill patients. When examining mitigation strategies, we assume policies are in force for 3 months, other than social distancing of those over the age of 70 which is assumed to remain in place for one month longer. Suppression strategies are assumed to be in place for 5 months or longer.

Table 2: Summary of NPI interventions considered.

Label	Policy	Description
CI	Case isolation in the home	Symptomatic cases stay at home for 7 days, reducing non-household contacts by 75% for this period. Househ contacts remain unchanged. Assume 70% of househo comply with the policy.
HQ	Voluntary home quarantine	Following identification of a symptomatic case in the household, all household members remain at home for days. Household contact rates double during t quarantine period, contacts in the community reduce 75%. Assume 50% of household comply with the policy
SDO	Social distancing of those over 70 years of age	Reduce contacts by 50% in workplaces, increase house contacts by 25% and reduce other contacts by 7 Assume 75% compliance with policy.
SD	Social distancing of entir population	All households reduce contact outside household, schoo workplace by 75%. School contact rates unchang workplace contact rates reduced by 25%. Househ contact rates assumed to increase by 25%.
PC	Closure of schools and universities	Closure of all schools, 25% of universities remain op Household contact rates for student families increase b 50% during closure. Contacts in the community increas 25% during closure.

Results

In the (unlikely) absence of any control measures or spontaneous changes in individual behaviour, we would expect a peak in mortality (daily deaths) to occur after approximately 3 months (Figure 1A). In such scenarios, given an estimated R_0 of 2.4, we predict 81% of the GB and US populations would be infected over the course of the epidemic. Epidemic timings are approximate given the limitations of surveillance data in both countries. The epidemic is predicted to be broader in the US than in GB and to peak slightly later. This is due to the larger geographic scale of the US, resulting in more distinct localised epidemics across states (Figure 1B) than seen across GB. The higher peak in mortality in GB is due to the smaller size of the country and its older population compared with the US. In total, in an unmitigated epidemic, we would predict approximately 510,000 deaths in GB and 2.2 million in the US, not accounting for the potential negative effects of health systems being overwhelmed on mortality.

Figure 1: Unmitigated epidemic scenarios for GB and the US. (A) Projected deaths per day per 100,000 population in GB and US. (B) Case epidemic trajectories across the US by state.

For an uncontrolled epidemic, we predict critical care bed capacity would be exceeded as early as the second week in April, with an eventual peak in ICU or critical care bed demand that is over 30 times greater than the maximum supply in both countries (Figure 2).

The aim of mitigation is to reduce the impact of an epidemic by flattening the curve, reducing peak incidence and overall deaths (Figure 2). Since the aim of mitigation is to minimise mortality, the interventions need to remain in place for as much of the epidemic period as possible. Introducing such interventions too early risks allowing transmission to return once they are lifted (if insufficient herd immunity has developed); it is therefore necessary to balance the timing of introduction with the scale

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of disruption imposed and the likely period over which the interventions can be maintained. In this scenario, interventions can limit transmission to the extent that little herd immunity is acquired leading to the possibility that a second wave of infection is seen once interventions are lifted.

Figure 2: Mitigation strategy scenarios for GB showing critical care (ICU) bed requirements. The black line shows the unmitigated epidemic. The green line shows a mitigation strategy incorporating closure of schools and universities; orange line shows case isolation; yellow line shows case isolation and household quarantine; and the blue line shows case isolation, home quarantine and social distancing of those aged over 70. The blue shading shows the 3-month period in which these interventions are assumed to remain in place.

Table 3 shows the predicted relative impact on both deaths and ICU capacity of a range of single and combined NPIs interventions applied nationally in GB for a 3-month period based on triggers of between 100 and 3000 critical care cases. Conditional on that duration, the most effective combination of interventions is predicted to be a combination of case isolation, home quarantine and social distancing of those most at risk (the over 70s). Whilst the latter has relatively less impact on transmission than other age groups, reducing morbidity and mortality in the highest risk groups reduces both demand on critical care and overall mortality. In combination, this intervention strategy is predicted to reduce peak critical care demand by two-thirds and halve the number of deaths. However, this "optimal" mitigation scenario would still result in an 8-fold higher peak demand on critical care beds over and above the available surge capacity in both GB and the US.

Stopping mass gatherings is predicted to have relatively little impact (results not shown) because the contact-time at such events is relatively small compared to the time spent at home, in schools or workplaces and in other community locations such as bars and restaurants.

Overall, we find that the relative effectiveness of different policies is insensitive to the choice of local trigger (absolute numbers of cases compared to per-capita incidence), R_0 (in the range 2.0-2.6), and varying IFR in the 0.25%-1.0% range.

Table 3. Mitigation options for GB. Relative impact of NPI combinations applied nationally for 3 months in GB on total deaths and peak hospital ICU bed demand for different choices of cumulative ICU case count triggers. The cells show the percentage reduction in peak ICU bed demand for a variety of NPI combinations and for triggers based on the absolute number of ICU cases diagnosed in a county per week. PC=school and university closure, CI=home isolation of cases, HQ=household quarantine, SD=social distancing of the entire population, SDOL70=social distancing of those over 70 years for 4 months (a month more than other interventions). Tables are colour-coded (green=higher effectiveness, red=lower). Absolute numbers are shown in Table A1.

	Trigger (cumulative ICU cases)	PC	CI	CI_HQ	CI_HQ_SD	CI_SD	CI_HQ_SDOL70	PC_CI_HQ_SDOL70
R_0=2.4 Peak beds	100	14%	33%	53%	33%	53%	67%	69%
	300	14%	33%	53%	34%	57%	67%	71%
	1000	14%	33%	53%	39%	64%	67%	77%
	3000	12%	33%	53%	51%	75%	67%	81%
R_0=2.2 Peak beds	100	23%	35%	57%	25%	39%	69%	48%
	300	22%	35%	57%	28%	43%	69%	54%
	1000	21%	35%	57%	34%	53%	69%	63%
	3000	18%	35%	57%	47%	68%	69%	75%
R_0=2.4 Total deaths	100	2%	17%	31%	13%	20%	49%	29%
	300	2%	17%	31%	14%	23%	49%	29%
	1000	2%	17%	31%	15%	26%	50%	30%
	3000	2%	17%	31%	19%	30%	49%	32%
R_0=2.2 Total deaths	100	3%	21%	34%	9%	15%	49%	19%
	300	3%	21%	34%	9%	17%	49%	20%
	1000	4%	21%	34%	11%	21%	49%	22%
	3000	4%	21%	34%	15%	27%	49%	24%

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Given that mitigation is unlikely to be a viable option without overwhelming healthcare systems, suppression is likely necessary in countries able to implement the intensive controls required. Our projections show that to be able to reduce R to close to 1 or below, a combination of case isolation, social distancing of the entire population and either household quarantine or school and university closure are required (Figure 3, Table 4). Measures are assumed to be in place for a 5 month duration. Not accounting for the potential adverse effect on ICU capacity due to absenteeism, school and university closure is predicted to be more effective in achieving suppression than household quarantine. All four interventions combined are predicted to have the largest effect on transmission (Table 4). Such an intensive policy is predicted to result in a reduction in critical care requirements from a peak approximately 3 weeks after the interventions are introduced and a decline thereafter while the intervention policies remain in place. While there are many uncertainties in policy effectiveness, such a combined strategy is the most likely one to ensure that critical care bed requirements would remain within surge capacity.

Figure 3: Suppression strategy scenarios for GB showing ICU bed requirements. The black line shows the unmitigated epidemic. Green shows a suppression strategy incorporating closure of schools and universities, case isolation and population-wide social distancing beginning in late March 2020. The orange line shows a containment strategy incorporating case isolation, household quarantine and population-wide social distancing. The red line is the estimated surge ICU bed capacity in GB. The blue shading shows the 5 month period in which these interventions are assumed to remain in place. (B) shows the same data as in panel (A) but zoomed in on the lower levels of the graph. An equivalent figure for the US is shown in the Appendix.

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Adding household quarantine to case isolation and social distancing is the next best option, although we predict that there is a risk that surge capacity may be exceeded under this policy option (Figure 3 and Table 4). Combining all four interventions (social distancing of the entire population, case isolation, household quarantine and school and university closure) is predicted to have the largest impact, short of a complete lockdown which additionally prevents people going to work.

Once interventions are relaxed (in the example in Figure 3, from September onwards), infections begin to rise, resulting in a predicted peak epidemic later in the year. The more successful a strategy is at temporary suppression, the larger the later epidemic is predicted to be in the absence of vaccination, due to lesser build-up of herd immunity.

Given suppression policies may need to be maintained for many months, we examined the impact of an adaptive policy in which social distancing (plus school and university closure, if used) is only initiated after weekly confirmed case incidence in ICU patients (a group of patients highly likely to be š • š • Æ • Œ š] v ^ } is relaxed when ICU case incidence falls below a certain ^ } ((_ š Z Œ • Z } o (Figure 4). Case-based policies of home isolation of symptomatic cases and household quarantine (if adopted) are continued throughout.

Such policies are robust to uncertainty in both the reproduction number, R_0 (Table 4) and in the severity of the virus (i.e. the proportion of cases requiring ICU admission; not shown). Table 3 illustrates that suppression policies are best triggered early in the epidemic, with a cumulative total of 200 ICU cases per week being the latest point at which policies can be triggered and still keep peak ICU demand below GB surge limits in the case of a relatively high R_0 value of 2.6. Expected total deaths are also reduced for lower triggers, though deaths for the policies considered are much lower than for an uncontrolled epidemic. The right panel of Table 4 shows that social distancing (plus school and university closure, if used) need to be in force for the majority of the 2 years of the simulation, but that the proportion of time these measures are in force is reduced for more effective interventions and for lower values of R_0. Table 5 shows that š } š o š Z • Œ Œ µ Á] š Z ; o } Á Œ ^ } however, this also leads to longer periods during which social distancing is in place. Peak ICU demand v š Z ‰ Œ } ‰ } Œ š] } v } (š] u • }] o] • š v] v P] •] v ‰ o Œ v } š ((

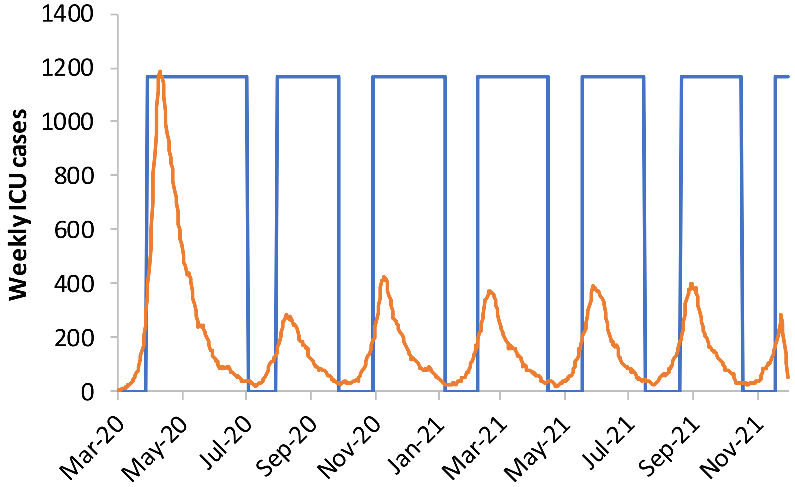

Figure 4: Illustration of adaptive triggering of suppression strategies in GB, for R_0=2.2, a policy of all four interventions considered, an "on" trigger of 100 ICU cases in a week and an "off" trigger of 50 ICU cases. The policy is in force approximate 2/3 of the time. Only social distancing and school/university closure are triggered; other policies remain in force throughout. Weekly ICU incidence is shown in orange, policy triggering in blue.

Table 4. Suppression strategies for GB. Impact of three different policy option (case isolation + home quarantine + social distancing, school/university closure + case isolation + social distancing, and all four interventions) on the total number of deaths seen in a 2-year period (left panel) and peak demand for ICU beds (centre panel). Social distancing and school/university closure are triggered at a national level when weekly numbers of new COVID-19 cases diagnosed in ICUs exceed the thresholds listed under "On trigger" and are suspended when weekly ICU cases drop to 25% of that trigger value. Other policies are assumed to start in late March and remain in place. The right panel shows the proportion of time after policy start that social distancing is in place. Peak GB ICU surge capacity is approximately 5000 beds. Results are qualitatively similar for the US.

		Total deaths				Peak ICU beds				Proportion of time with SD in place		
R_0	On Trigger	Do nothing	CI_HQ_SD	PC_CI_SD	PC_CI_HQ_SD	Do nothing	CI_HQ_SD	PC_CI_SD	PC_CI_HQ_SD	CI_HQ_SD	PC_CI_SD	PC_CI_HQ_SD
2	60	410,000	47,000	6,400	5,600	130,000	3,300	930	920	96%	69%	58%
	100	410,000	47,000	9,900	8,300	130,000	3,500	1,300	1,300	96%	67%	61%
	200	410,000	46,000	17,000	14,000	130,000	3,500	1,900	1,900	95%	66%	57%
	300	410,000	45,000	24,000	21,000	130,000	3,500	2,200	2,200	95%	64%	55%
	400	410,000	44,000	30,000	26,000	130,000	3,800	2,900	2,700	94%	63%	55%
2.2	60	460,000	62,000	9,700	6,900	160,000	7,600	1,200	1,100	96%	82%	70%
	100	460,000	61,000	13,000	10,000	160,000	7,700	1,600	1,600	96%	80%	66%
	200	460,000	64,000	23,000	17,000	160,000	7,700	2,600	2,300	89%	76%	64%
	300	460,000	65,000	32,000	26,000	160,000	7,300	3,500	3,000	89%	74%	64%
	400	460,000	68,000	39,000	31,000	160,000	7,300	3,700	3,400	82%	72%	62%
2.4	60	510,000	85,000	12,000	8,700	180,000	11,000	1,200	1,200	87%	89%	78%
	100	510,000	87,000	19,000	13,000	180,000	11,000	2,000	1,800	83%	88%	77%
	200	510,000	90,000	30,000	24,000	180,000	9,700	3,500	3,200	77%	82%	74%
	300	510,000	94,000	43,000	34,000	180,000	9,900	4,400	4,000	72%	81%	74%
	400	510,000	98,000	53,000	39,000	180,000	10,000	5,700	4,900	68%	81%	71%
2.6	60	550,000	110,000	20,000	12,000	230,000	15,000	1,500	1,400	68%	94%	85%
	100	550,000	110,000	26,000	16,000	230,000	16,000	1,900	1,800	67%	93%	84%
	200	550,000	120,000	39,000	30,000	230,000	16,000	3,600	3,400	62%	88%	83%
	300	550,000	120,000	56,000	40,000	230,000	17,000	5,500	4,700	59%	87%	80%
	400	550,000	120,000	71,000	48,000	230,000	17,000	7,100	5,600	56%	82%	76%

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On trigger	Off trigger as proportion of on trigger	Total deaths CI_HQ_SD	PC_CI_SD	PC_CI_HQ_S
60	0.25	85,000	12,000	8,700
	0.5	85,000	15,000	10,000
	0.75	85,000	14,000	11,000
100	0.25	87,000	19,000	13,000
	0.5	87,000	20,000	15,000
	0.75	88,000	21,000	16,000
200	0.25	90,000	30,000	24,000
	0.5	92,000	36,000	27,000
	0.75	94,000	40,000	30,000
300	0.25	94,000	43,000	34,000
	0.5	97,000	48,000	37,000
	0.75	99,000	52,000	39,000
400	0.25	98,000	53,000	39,000
	0.5	100,000	61,000	46,000
	0.75	100,000	65,000	51,000

Discussion

As the COVID-19 pandemic progresses, countries are increasingly implementing a broad range of responses. Our results demonstrate that it will be necessary to layer multiple interventions, regardless of whether suppression or mitigation is the overarching policy goal. However, suppression will require the layering of more intensive and socially disruptive measures than mitigation. The choice of interventions ultimately depends on the relative feasibility of their implementation and their likely effectiveness in different social contexts.

Disentangling the relative effectiveness of different interventions from the experience of countries to date is challenging because many have implemented multiple (or all) of these measures with varying degrees of success. Through the hospitalisation of all cases (not just those requiring hospital care), China in effect initiated a form of case isolation, reducing onward transmission from cases in the household and in other settings. At the same time, by implementing population-wide social distancing, the opportunity for onward transmission in all locations was rapidly reduced. Several studies have estimated that these interventions reduced R to below 1.[15] In recent days, these measures have begun to be relaxed. Close monitoring of the situation in China in the coming weeks will therefore help to inform strategies in other countries.

Overall, our results suggest that population-wide social distancing applied to the population as a whole would have the largest impact; and in combination with other interventions – notably home isolation of cases and school and university closure – has the potential to suppress transmission below the threshold of R=1 required to rapidly reduce case incidence. A minimum policy for effective suppression is therefore population-wide social distancing combined with home isolation of cases and school and university closure.

To avoid a rebound in transmission, these policies will need to be maintained until large stocks of vaccine are available to immunise the population – which could be 18 months or more. Adaptive hospital surveillance-based triggers for switching on and off population-wide social distancing and school closure offer greater robustness to uncertainty than fixed duration interventions and can be adapted for regional use (e.g. at the state level in the US). Given local epidemics are not perfectly synchronised, local policies are also more efficient and can achieve comparable levels of suppression to national policies while being in force for a slightly smaller proportion of the time. However, we estimate that for a national GB policy, social distancing would need to be in force for at least 2/3 of the time (for R_0=2.4, see Table 4) until a vaccine was available.

However, there are very large uncertainties around the transmission of this virus, the likely effectiveness of different policies and the extent to which the population spontaneously adopts risk reducing behaviours. This means it is difficult to be definitive about the likely initial duration of measures which will be required, except that it will be several months. Future decisions on when and for how long to relax policies will need to be informed by ongoing surveillance.

The measures used to achieve suppression might also evolve over time. As case numbers fall, it becomes more feasible to adopt intensive testing, contact tracing and quarantine measures akin to the strategies being employed in South Korea today. Technology – such as mobile phone apps that šŒ l v]v]À]µo[•]vš Œ š]}v• Á]šZ }šZŒ %}%o]v š – might allow such a policy to be more effective and scalable if the associated privacy concerns can be overcome. However, if intensive NPI packages aimed at suppression are not maintained, our analysis suggests that transmission will rapidly rebound, potentially producing an epidemic comparable in scale to what would have been seen had no interventions been adopted.

Long-term suppression may not be a feasible policy option in many countries. Our results show that the alternative relatively short-term (3-month) mitigation policy option might reduce deaths seen in the epidemic by up to half, and peak healthcare demand by two-thirds. The combination of case isolation, household quarantine and social distancing of those at higher risk of severe outcomes (older individuals and those with other underlying health conditions) are the most effective policy combination for epidemic mitigation. Both case isolation and household quarantine are core epidemiological interventions for infectious disease mitigation and act by reducing the potential for onward transmission through reducing the contact rates of those that are known to be infectious (cases) or may be harbouring infection (household contacts). The WHO China Joint Mission Report suggested that 80% of transmission occurred in the household,[16] although this was in a context where interpersonal contacts were drastically reduced by the interventions put in place. Social distancing of high-risk groups is predicted to be particularly effective at reducing severe outcomes given the strong evidence of an increased risk with age[12,16] though we predict it would have less effect in reducing population transmission.

We predict that school and university closure will have an impact on the epidemic, under the assumption that children do transmit as much as adults, even if they rarely experience severe disease[12,16]. We find that school and university closure is a more effective strategy to support epidemic suppression than mitigation; when combined with population-wide social distancing, the effect of school closure is to further amplify the breaking of social contacts between households, and thus supress transmission. However, school closure is predicted to be insufficient to mitigate (never mind supress) an epidemic in isolation; this contrasts with the situation in seasonal influenza epidemics, where children are the key drivers of transmission due to adults having higher immunity levels[17,18].

The optimal timing of interventions differs between suppression and mitigation strategies, as well as depending on the definition of optimal. However, for mitigation, the majority of the effect of such a strategy can be achieved by targeting interventions in a three-month window around the peak of the epidemic. For suppression, early action is important, and interventions need to be in place well before healthcare capacity is overwhelmed. Given the most systematic surveillance occurs in the hospital context, the typical delay from infection to hospitalisation means there is a 2 to 3-week lag between interventions being introduced and the impact being seen in hospitalised case numbers, depending on whether all hospital admissions are tested or only those entering critical care units. In the GB context, this means acting before COVID-19 admissions to ICUs exceed 200 per week.

Perhaps our most significant conclusion is that mitigation is unlikely to be feasible without emergency surge capacity limits of the UK and US healthcare systems being exceeded many times over. In the most effective mitigation strategy examined, which leads to a single, relatively short epidemic (case isolation, household quarantine and social distancing of the elderly), the surge limits for both general ward and ICU beds would be exceeded by at least 8-fold under the more optimistic scenario for critical care requirements that we examined. In addition, even if all patients were able to be treated, we predict there would still be in the order of 250,000 deaths in GB, and 1.1-1.2 million in the US.

In the UK, this conclusion has only been reached in the last few days, with the refinement of estimates of likely ICU demand due to COVID-19 based on experience in Italy and the UK (previous planning estimates assumed half the demand now estimated) and with the NHS providing increasing certainty around the limits of hospital surge capacity.

We therefore conclude that epidemic suppression is the only viable strategy at the current time. The social and economic effects of the measures which are needed to achieve this policy goal will be profound. Many countries have adopted such measures already, but even those countries at an earlier stage of their epidemic (such as the UK) will need to do so imminently.

Our analysis informs the evaluation of both the nature of the measures required to suppress COVID-19 and the likely duration that these measures will need to be in place. Results in this paper have informed policymaking in the UK and other countries in the last weeks. However, we emphasise that is not at all certain that suppression will succeed long term; no public health intervention with such disruptive effects on society has been previously attempted for such a long duration of time. How populations and societies will respond remains unclear.

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Appendix

Figure A1: Suppression strategy scenarios for US showing ICU bed requirements. The black line shows the unmitigated epidemic. Green shows a suppression strategy incorporating closure of schools and universities, case isolation and population-wide social distancing beginning in late March 2020. The orange line shows a containment strategy incorporating case isolation, household quarantine and population-wide social distancing. The red line is the estimated surge ICU bed capacity in US. The blue shading shows the 5-month period in which these interventions are assumed to remain in place. (B) shows the same data as in panel (A) but zoomed in on the lower levels of the graph.

Table A1. Mitigation options for GB. Absolute impact of NPI combinations applied nationally for 3 months in the UK on total deaths and peak hospital ICU bed demand for different choices of cumulative ICU case count triggers. The cells show peak bed demand and total deaths for a variety of NPI combinations and for triggers based on the absolute number of ICU cases diagnosed in a county per week. PC=school and university closure, CI=home isolation of cases, HQ=household quarantine, SD=large-scale general population social distancing, SDOL70=social distancing of those over 70 years for 4 months (a month more than other interventions). Tables are colour-coded (green= higher effectiveness, red=lower).

	Trigger (cumulative ICU cases)	PC	CI	CI_HQ	CI_HQ_SD	CI_SD	CI_HQ_SDOL70	PC_CI_HQ_SDOL70
R0=2.4 Peak beds	100	156	122	85	123	85	61	57
	300	157	122	85	121	78	60	53
	1000	158	122	85	111	65	60	42
	3000	161	122	85	89	45	60	35
R0=2.2 Peak beds	100	125	105	70	120	98	50	83
	300	125	105	70	115	92	50	75
	1000	126	105	70	106	76	49	59
	3000	132	105	70	86	51	49	40
R0=2.4 Total deaths	100	501	421	349	443	406	258	363
	300	499	421	349	440	393	259	360
	1000	498	421	349	432	375	257	356
	3000	498	421	349	415	354	258	347
R0=2.2 Total deaths	100	451	367	308	423	395	238	373
	300	448	367	308	419	384	236	369
	1000	445	367	308	412	366	234	360
	3000	445	367	308	396	340	234	351

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