Investigating duration and intensity of Covid-19 social-distancing strategies

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Abstract

The exponential character of the recent Covid-19 outbreak requires a change in strategy from containment to mitigation. Meanwhile, most countries apply social distancing with the objective to keep the number of critical cases below the capabilities of the health care system. Due to the novelty and rapid spread of the virus, an a priori assessment of this strategy was not possible. In this study, we present a model-based systems analysis to assess the effectiveness of social distancing measures in terms of intensity and duration of application. Results show a super-linear scaling between intensity (percent contact reduction) and required duration of application to have an added value (lower fatality rate). This holds true for an effective reproduction of $R > 1$ and is reverted for $R < 1$. If R is not reduced below 1, secondary effects of required long-term isolation are likely to unravel the added value of disease mitigation. If an extinction is not feasible, we recommend moderate social-distancing that is well balanced against capability limits of national health-care systems.

Introduction

This article is written in mid-April 2020 where globally the number of confirmed COVID-19 cases is above 2.5 million resulting in over 170,000 deaths [1]. Due to these large numbers, the initial approach of containment, i.e. tracing contacts of patients with laboratory-confirmed infection [2], is not applicable anymore and may even have unintended consequences of hampering effective healthcare delivery [3]. Instead, the majority of countries decided to use community interventions, like cancellation of events, general social distancing and travel restrictions [4].

These community mitigation measures reduce transmission, hence flatten the curve and push the peak of new infections further into the future which eventually helps preventing an epidemic peak that overwhelms health-care systems [5]. Numerous studies support this strategy [3] [4] [6] [7]. There is no doubt that this is the right course of action to protect the lives of many vulnerable patients. Nevertheless, considering the basic reproduction of Covid-19 as well as the considerable variation of regional availability of intensive care [8], drastic interventions are needed to push new infections below the maximum capabilities of national health care systems. This is also evident from the actions taken by European countries who implemented interventions including the closure of schools and universities, banning of mass gatherings, and most recently, widescale social distancing including local and national lockdowns [9]. Applied in the long-term, school closure and home confinement will negatively affect children's health [10] and the global economy, to name only two big drawbacks of these measures. In this light, it is of particular interest, for what duration these exceptional interventions must remain in place. According to recent estimates, we are probably at least 1 year to 18 month away from large-scale vaccine production [5]. Independent of the time it takes to develop a vaccine, the epidemic spread will also come to an end, if sufficient people have been infected to establish herd immunity. Studies on the effectiveness of the concept of disease mitigation with the objective to establish herd immunity shows some potential in the case of pandemic influenza [11].

In this study, we present an exploratory and model-based systems analysis that is aimed at investigating the application of social distancing strategies to Covid-19. Specific objectives of this research are: 1) to investigate the effectiveness of contact reduction policies with respect to intensity and duration and 2) to estimate the amount of time to establish herd immunity by considering the national health care systems of Austria and Sweden, which are very different in terms of critical care capabilities. A detailed description of model equations, assumptions as well as uncertainty of currently available data are presented in the following section. Data uncertainty is addressed by the analysis of alternative scenario runs to enhance robustness of model results. In a concluding section, we compare our results to similar studies, discuss current limitations of data availability and give recommendations based on exploratory results.

Method

Adapted SIR model

The current scenario of novel pathogen emergence includes considerable uncertainty [12]. This means that a reliable scientific evidence base on Covid-19 is yet to be established. Under these preconditions, the use of models for exploratory rather than predictive purposes is more appropriate [13]. Accordingly, the simulation model presented in this study was designed to identify and systematically explore important qualitative behavior of this dynamic system that remains unchanged irrespective of parameter variations. An adaptation of the popular susceptible-infected-recovered (SIR) model turned out to be most suitable for this purpose (see Fig. 1). In order to meet the specific requirements of a simulation model on Covid-19 mitigation, the structure of the original model was adapted accordingly. For instance, pathological findings of Covid-19 indicate that there is a considerable number of cases that develop mild or no symptoms [14]. To account for this characteristic, we separated the infected population into those that are asymptomatic and those that are not, which in the latter case leads to isolation or hospitalization. The asymptomatic infected get resistant without prior isolation.

Exponential growth in numbers of infected poses a challenge to health care facilities. In Italy, specialists are already considering denying life-saving care to the sickest and giving priority to those patients most likely to survive [15]. This will inevitably cause potentially avoidable deaths. In the model, deaths caused by a lack of intensive care is considered independently.

The calculation of population quantities in respective compartments (S, IU, RA, II, D, DL and R) is in line with the logic of the standard SIR model. Initially everyone in the total population t_p is susceptible. The number of susceptible is reduced over time by infections i

$$i = i_r c_{ui} \quad , \tag{1}$$

where i_r is the infection rate (rate of contacts between uninfected and infected that result in infections) and c_{ui} is the number of contacts between infected and uninfected,

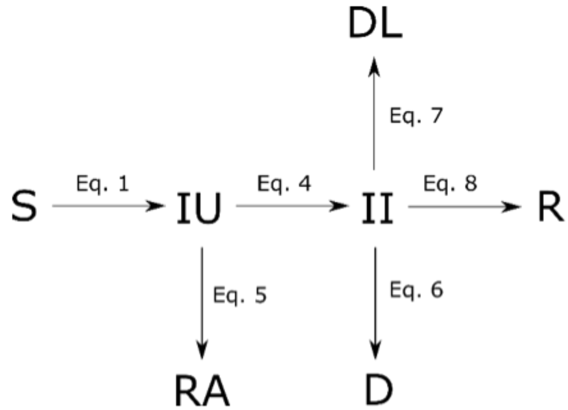

Fig 1. Schematic diagram of the adapted SIR model: susceptible (S), infected - infection unknown (IU), infected in isolation (II), resistant (R), resistant asymptomatic (RA), deaths (D), deaths caused by lack of ICU (DL), compare equations 1 - 8

which is calculated as

$$c_{ui} = IU\frac{c_d S_t}{t_p} \tag{2}$$

where c$_d$ is the personal contacts per day, S_t is the susceptible at time t and IU is the number of unknown infections. To take account for a lower infection rate of asymptomatic infected, the unknown infections IU in equation 2 is substituted by

$$IU_c = IU(1 - a_f + a_f a_p) \tag{3}$$

with IU_c being the unknown infected corrected for asymptomatic infected, a_f the fraction of asymptomatic among infected and a_p the asymptomatic population's potential to infect.

The flows from compartment IU - i.e. asymptomatic cases getting resistant r_A and isolation of symptomatic infected i_{so} –are calculated by

$$i_{so} = IU\frac{1 - a_f}{i_t} \quad , \tag{4}$$

$$r_A = IU\frac{a_f}{d_a} \quad . \tag{5}$$

Parameter i_t is the time between infection and isolation and d_a is the duration of asymptomatic infection. The flows from compartment II are given by

$$d = II\frac{CFR}{d_s} \quad , \tag{6}$$

$$d_l = \begin{cases} \frac{ICU_d - ICU_s}{d_s} & \text{if } ICU_d > ICU_s \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$r = \frac{II}{d_s} \tag{8}$$

where parameter d_s is the duration of distinct symptomatic sickness, CFR is the case fatality rate and ICU_d and ICU_s is the intensive care demand and supply respectively.

The intensive care demand ICU_d is calculated by taking the critical fraction of infected in isolation II. The fraction of infected who are admitted to intensive care are denoted as c_f (see Table 1).

Model inputs and exploration

Despite the novelty of Covid-19, the body of literature on key parameters like basic reproduction, case fatality rates and proportion of asymptomatic cases is quite substantial and growing. The wide range of suggested parameter values, however, poses a considerable challenge to model parametrization. For instance, estimates of the basic reproduction number R0 vary within a range from 1.4 [16] to 4.71 [17]. Part of this variation is explained by geographic variation of population densities and social habits. Moreover, there is uncertainty in the percentage of asymptomatic cases. The outbreak in a smaller isolated population is an opportunity to derive representative numbers by applying comprehensive and repeated laboratory testing. One such example is the outbreak of Covid-19 on board of the Diamond Princess cruise ship. However, given that most of the passengers were 60 years and older, the nature of the age distribution may lead to underestimation of asymptomatic cases if older individuals tend to experience more symptoms [18]. In a normal population higher ratios of up to 50% asymptomatic carriers of Covid-19 are expected ([19]). The question whether or not asymptomatic carriers are able to infect others is still controversial (e.g. [20]).

The severity of the disease does also play an important role in estimating the ratio of critically ill patients who need intensive care. According to Chinese statistics, 5% of positively tested patients are admitted to intensive care [21]. This number was adopted by the World Health Organization [22] and other studies (e.g. [23]), whereas national statistics show significant deviations; e.g. 9 to 11% in Italy [15] and 2.2% in Austria [24]. A potential explanation for these considerable differences is that in Italy a lot of the older population were infected [25].

The specific age distributions of affected communities may also show some biasing effect on estimated case fatality rates. Another factor that contributes to regional differences in case fatality is the occupation or over-occupation of available intensive care beds (ICU beds). In a few instances, national critical care capabilities are exceeded by the number of critically ill patients (e.g. Italy and France), which drastically elevates fatality rates. By contrast, the true case fatality rates are lower if theoretically all cases were found by testing the entire population. Accordingly, a lower case fatality rate (CFR) was reported by countries who were effective in extensive testing and maintaining the prevalence of critical cases below critical care capabilities like South Korea [26]. A higher CFR was reported by countries who refrain from extensive testing and/or are overwhelmed by the pace of new infections like Iran, Italy and others [27]. In the model, we use the more reliable South Korean figures and simulate the additional fatalities due to the critical care limit based on capability limits of national critical care units (see Eq. 6 and Eq. 7).

Among the parameters in Table 1, the basic reproduction number R0 is the only parameter without explicit representation in the model equations. This parameter is the number of secondary cases, which an infected person produces in a completely susceptible population [31]. In the model, R0 is defined as the arithmetic product of i_t the time between infection and isolation, c_d the personal contacts per day and i_r the infection rate.

In response to the outbreak of an epidemic disease, changes in contact behavior diminish the reproduction. We refer to this modified reproduction as effective reproduction number R. In model scenarios where contact behavior is not constant, effective reproduction is denoted as R_t.

The choice of appropriate scenarios is based on parameter uncertainty and model sensitivity. Sensitivity analysis indicate a linear response in model output to variations in CFR and c_f, and interestingly non-linear effects in response to variations in R, a_f and a_p. Accordingly, the latter variables were selected as scenario parameters (see Table 2).

Dependent on the research objectives 1 and 2 (see Introduction); prolonged and

Table 1. Model parameters

Nr	Parameters	uncertainty	Value(s)
1	basic reproductive numbers (R0)	high	1.4 [16] 2.1 [28] 3.2 [29]
2	percentage of infected population that are asymptomatic (a_f)	high	17.9% [18] 50% [19]
3	asymptomatic population's potential to infect (a_p)	high	50% [30] 100%
4	number of available ICU beds/100000 inhabitants	medium	AUT 21.8 SWE 5.8 [8]
5	duration of distinct symptomatic sickness (d_s)	medium	7 days [14]
6	duration of asymptomatic infection (d_a)	medium	14 days (assumed to be similiar to symptomatic)
7	initial infected population of total population (I_{ini})	model input	10^{-6}
8	inital susceptible population (I_S)	model input	everyone
9	ratio of confirmed cases need intensive care (c_f)	high	5% [21] 2.2% [24]
10	case fatality rate (c_{fr})	high	0.7% [26]
11	social contact reduction in percent (c_r)	model input	
12	duration of precautionary measures (d_m)	model input	

intermittent social distancing [16] was applied in respective scenarios (see Table 2). Whereas prolonged social distancing is defined by constants c_r and d_m , intermittent social distancing is implemented by dynamic adaptation of contact reduction c_r during simulation runtime dependent on the amount of ICU beds available. If more than 70% of ICU beds are vacant, measures are loosened, whereas measures are tightened in case less than 30% of ICU beds are available. The adjustment in measures is made based on a linear function that gradually removes a complete lockdown (no social contact at all) within 5 days and vice versa.

Results and discussion

Effectiveness of contact reduction

An increase in asymptomatic cases will overall increase the potential of the infected population to infect susceptible people, i.e. increase the basic reproduction R0. This is due to the extended duration asymptomatic cases remain undetected and thus infectious. The reduction of potentially infective contacts has the opposite effect and thus diminishes R0.

Moreover, the simulation shows that a lowering of the effective reproduction number

Table 2. Scenario runs: N.B.Low, medium and high R0 from Table 1 were adjusted for asymptomatic infections in respective scenarios

Nr	Scenario name	Parameters	Type
1	symptomatic, high basic reproduction	a_f=17.9%, a_p=50%, R0=3.51	prolonged
2	symptomatic, medium basic reproduction	a_f=17.9%, a_p=50%, R0=2.3	prolonged
3	symptomatic, low basic reproduction	a_f=17.9%, a_p=50%, R0=1.53	prolonged
4	asymptomatic, high basic reproduction	a_f=50%, a_p=100%, R0=4.8	prolonged
5	asymptomatic, medium basic reproduction	a_f=50%, a_p=100%, R0=3.15	prolonged
6	asymptomatic, low basic reproduction	a_f=50%, a_p=100%, R0=2.1	prolonged
7	medium basic reproduction, high need for intensive care, Austria	a_f=17.9%, a_p=50%, R0=2.3, ICU_s=21.8, c_f=5%	intermittent
8	medium basic reproduction, high need for intensive care, Sweden	a_f=17.9%, a_p=50%, R0=2.3, ICU_s=5.8, c_f=5%	intermittent
9	high basic reproduction, high need for intensive care, Austria	a_f=50%, a_p=100%, R0=3.15, ICU_s=21.8, c_f=5%	intermittent
10	high basic reproduction, high need for intensive care, Sweden	a_f=50%, a_p=100%, R0=3.15, ICU_s=5.8, c_f=5%	intermittent
11	low basic reproduction, low need for intensive care (Felix Austria)	a_f=17.9%, a_p=50%, R0=1.53, ICU_s=21.8, c_f=2.2%	intermittent

flattens the curve and delays the peak of new infections, whereas an increase has the opposite effect (see Fig. 2). Consequently, social distancing flattens the curve of daily infections, while higher proportions of asymptomatic cases elevate the peak.

This flattening effect can be expressed analytically. The daily infections resemble a

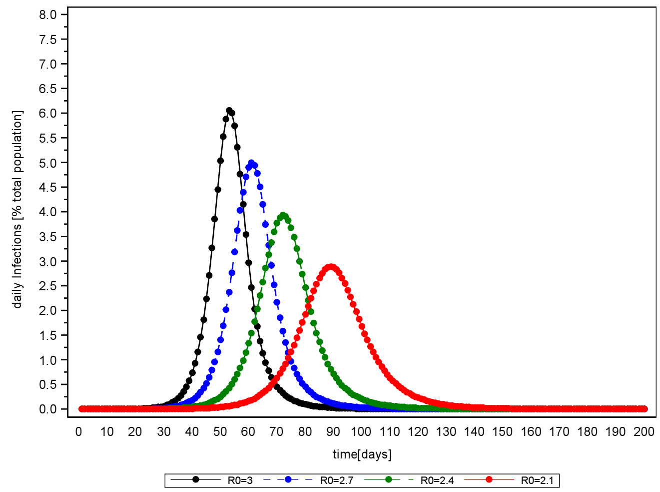

Fig 2. Delay effect of mitigation interventions

normal distribution, which is defined by a mean μ (days between outbreak and peak of daily infections) and a standard deviation σ. A lower R will lead to a higher μ (see Fig. 3) and a broader distribution σ (see Fig. 4). Additionally, the number of initial infected people reduces μ (see Fig. 5), whereas σ is independent of it.

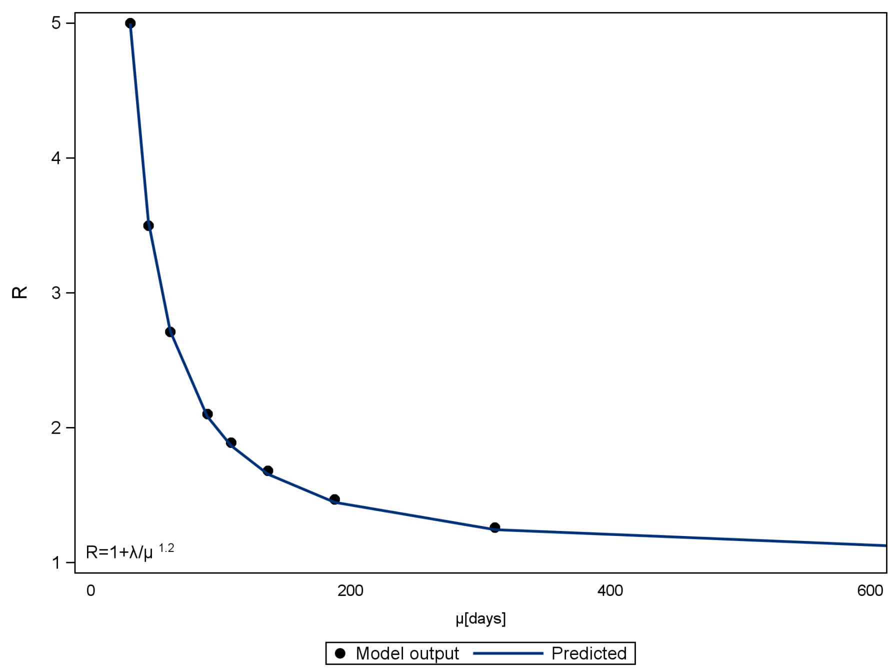

Fig 3. Relationship between effective reproduction R and peak occurrence μ in days after disease outbreak. The parameter λ is calculated to 238

These non-linear relationships have an important impact on the effectiveness of interventions. Social contact reduction and associated reduction in R push new infections further into the future. Hence, the more intense the social distancing

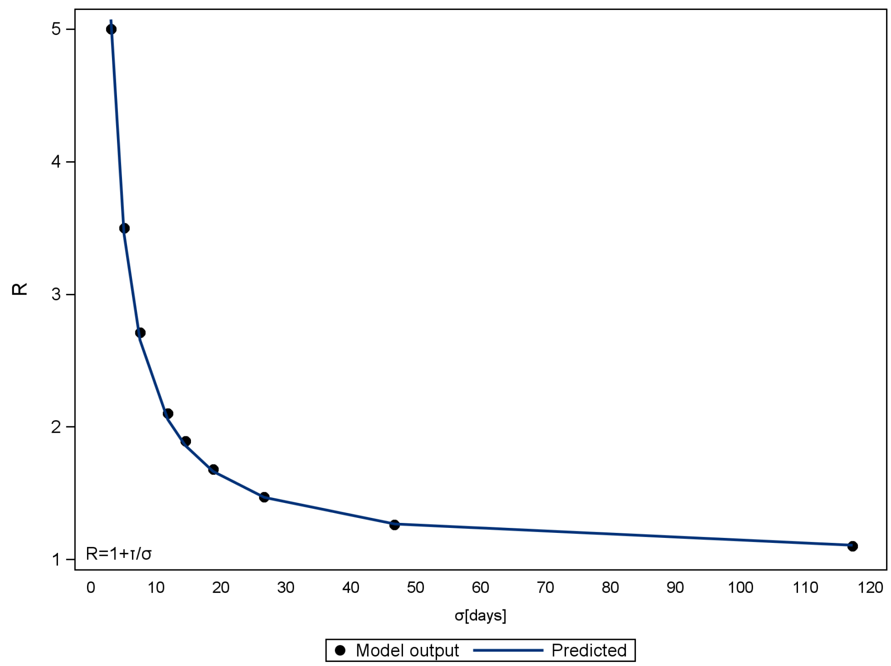

Fig 4. Relationship between effective reproduction R and standard deviation σ. The parameter τ is calculated to 12.46

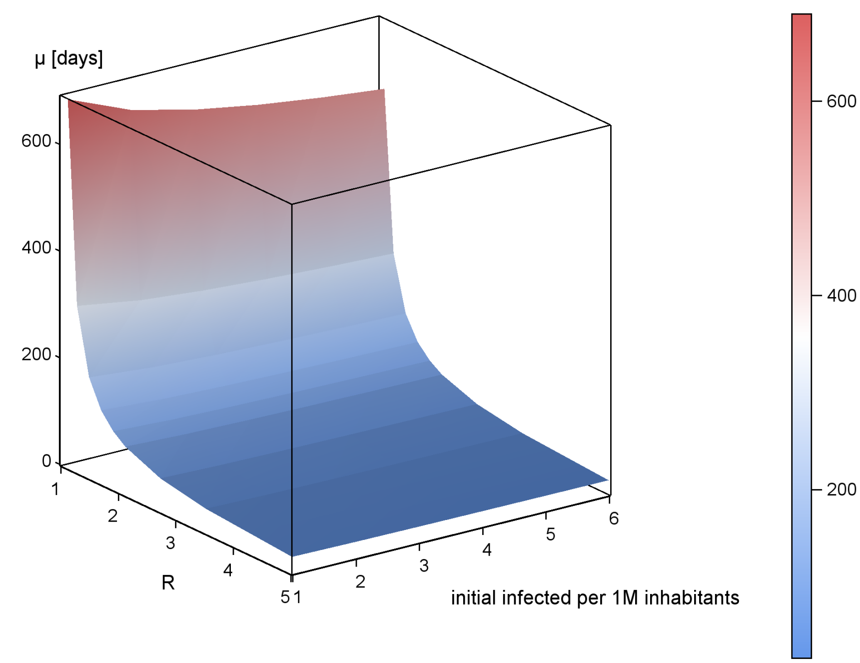

Fig 5. Relationship between effective reproduction, peak occurrence (μ) and number of infected at model initialization

measures in terms of contact reduction, the longer the duration needs to be to have an added value; i.e. a relatively lower fatality rate. In other words, the harder you break, the longer it takes.

For instance, 40% contact reduction needs to be applied for additional 600 days to outperform a 30% contact reduction in scenario 2 (see Fig. 6). The lower the basic reproduction in the scenarios, the larger the time lag associated with an intensification of social distancing (see Fig. 6, scenarios 1, 2, 4, 5 and 6). This is in line with above-mentioned relationships that show increased effects of R on μ and σ with lower R.

Given the trade-offs associated with required long-term lockdown, the effectiveness of additional social distancing decreases with R close to 1. The secondary effects of lock down have not been modelled, but it is speculated that reductions in social contacts will increase mortality (e.g. social isolation and homicide; obesity and cardiovascular diseases etc.) making moderate contact reduction more adequate.

Interestingly, if social distancing is intense enough to drop R below one, a further increase in intensity removes the pandemic earlier (see Fig. 6, scenario 3). This is contrary to the case of $R > 1$ where the effectiveness of more intense measures is in danger to be unraveled by the super-linear increase in duration.

The curve flattening effect of social contact reduction also explains why drastic contact reduction may cause more deaths than mild contact reduction, if measures are applied for too short time. In the worst case, intense social distancing will hardly have any effect (see Fig. 7).

Duration to establish herd immunity

Intensity and duration are also closely related in the intermittent social distancing and herd immunity scenario (see Fig. 8). The strategic objective in this scenario is to keep the demand for ICU beds within the bounds of ICU supply until herd immunity is established.

Independent of what values the policy thresholds have (see section Model inputs and exploration), the demand for the ICU beds behaves like a damped oscillation (see Fig. 8). This is explained by the delay in the system, diminishing number of susceptible people and the negative feedback between number of available ICU beds and social contacts.

In the early phase of the outbreak, the number of patients exceeds the number of available ICU beds due to high reproduction potentials. Higher basic reproduction R0 results in additional over-occupation of ICU capabilities (see Fig. 8, scenario 9 and 10).

Moreover, the variation of the constant of availability of intensive care brings about a shift in the time needed to achieve the strategic objective of herd immunity (compare Sweden and Austria in Fig. 8). This relationship exhibits an almost linear scaling. Independent of national health care capabilities, results show that social distancing and herd immunity strategies require extraordinary endurance.

This is also the case under more favorable conditions. In Austria, for instance, it is estimated that only 2.2% of confirmed cases are admitted to ICU [24]. Combined with Austria's high performance health care system and low effective reproduction, the time to establish herd immunity is still estimated to be about 2 years (see Fig. 9). Given that the ICU beds are also needed for patients other than Covid-19, an even longer period has to be expected.

Conclusion

In this article, we used methods of exploratory systems simulation to assess the effectiveness of social distancing measures in the mitigation of Covid-19. The simulated

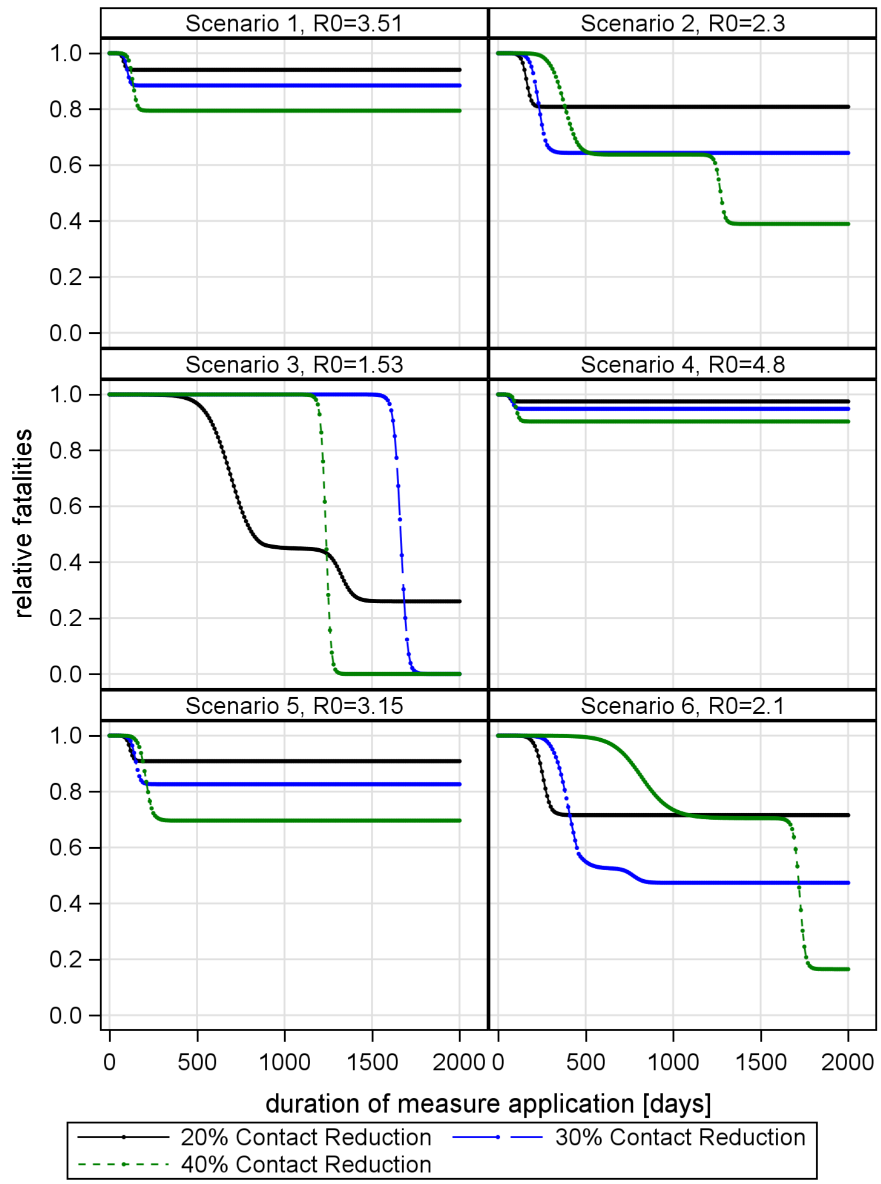

Fig 6. Relative fatality rates (1 = fatalities without intervention) plotted against social contact reduction in percent and duration of measure application

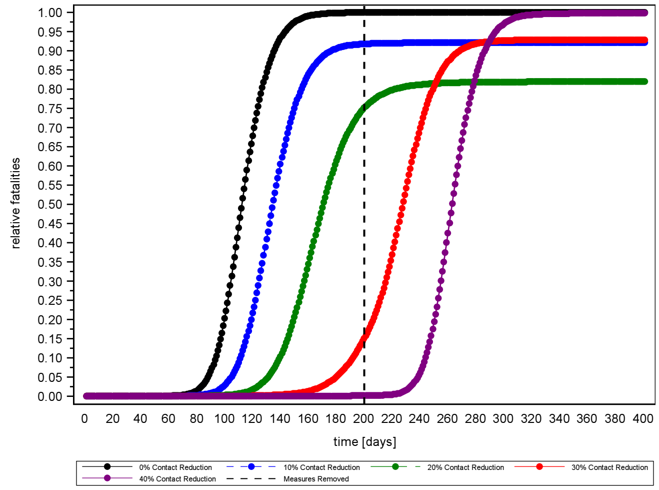

Fig 7. Relative fatality rates (1 = fatalities without intervention) in Scenario 2, R0=2.3 with constant duration (200 days) and varying intensity of contact reduction

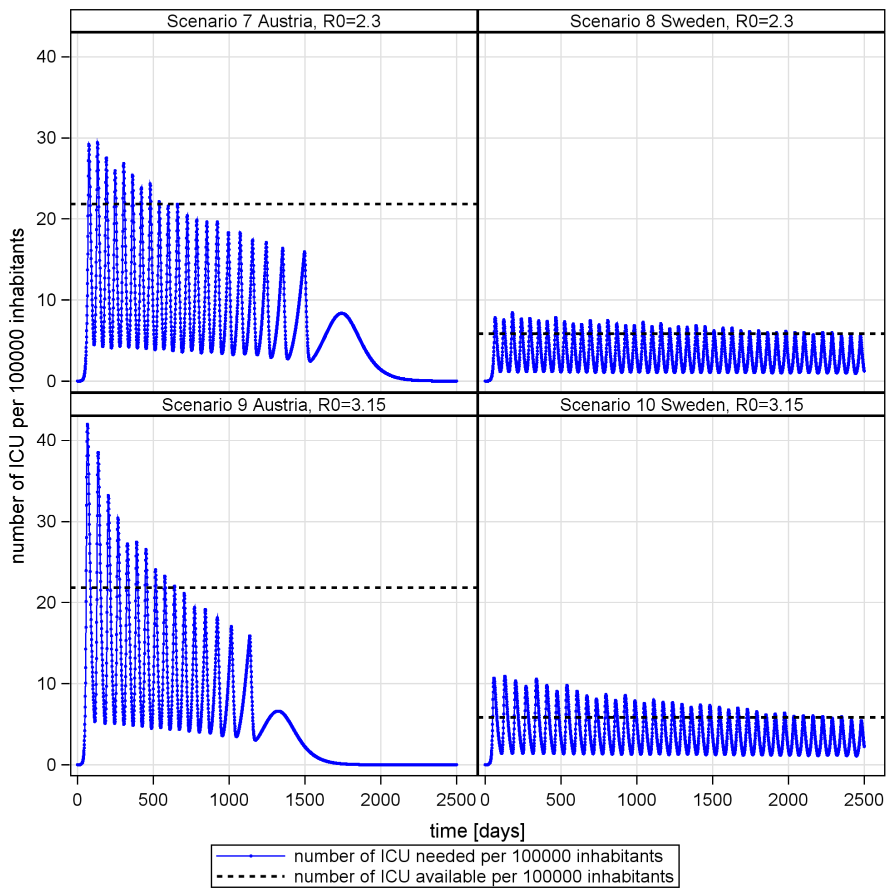

Fig 8. Policy based mitigation of new infections to meet capabilities of national health care systems

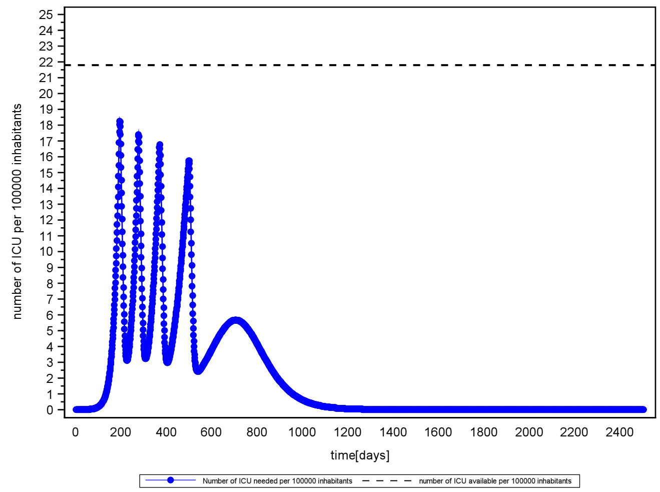

Fig 9. Mitigation and herd immunity strategy in a high performance health care system (Scenario 11 Austria, R0=1.53) and low rates of ICU admissions (2.2% of confirmed infected)

behavior is governed by a non-linear relationship between the intensity of applied measures (i.e. expressed as reduction of social contacts) and delay in the peak of new infections. As a consequence of this delay, measure intensity scales super-linearly with the required duration of application to show added value; i.e. a relatively lower fatality rate. Given the large scale of temporal delay (up to multiple years for a 10% increment of additional contact reduction), secondary effects of long-term social isolation such as psychological distress, depression [32], and increased mortality [33] are likely to unravel the added value of disease mitigation. This holds true for effective reproduction numbers above one. Below this threshold, more intense measure applications are associated with earlier termination of viral spread.

In the absence of a vaccination, mitigation strategies are crucial to keep the number of severe and critical cases below the capabilities of the health care system. If the use of mitigation interventions is well balanced against capability limits, the time required to establish herd immunity linearly scales with available capabilities of the health care system (defined by the number of ICU beds in the simulation). Other important factors are the reproduction number and the severity of the disease (expressed by the fraction of cases that need ICU admission). Depending on the calibration of those factors, it is estimated that herd immunity on a national level will be established in more than 2 years from now. This is in line with an agent-based simulation study by [34], who indicate a duration of 2 years and 4 months for the Netherlands. According to a deterministic simulation by [16] in the United States the epidemic could last into 2022 under current critical care capabilities.

It is important to mention that assumptions and policies implemented in models are not exactly reproducible in reality. For instance, Bock et al. [35] argue that mitigation measures imposed by state authorities can hardly be fine-tuned enough to hit the narrow feasible interval of epidemiologically relevant parameters with which a successful mitigation is possible. Given those constraints, as well as trade-offs associated with required long-term lockdown, we conclude that the success of a strategy based on social distancing, delay and herd immunity is unrealistic under known preconditions. According to [35], an extinction strategy implemented by intense countermeasures seems promising. This is supported by our low effective reproduction scenario ($R < 1$). If an extinction is not feasible, the intensity of social-distancing measures is determined by the capability limits of national health care systems. However, taking into consideration the identified relationship between intensity and required duration of measure application, social-distancing interventions should be as moderate as possible. To date, a more differentiated assessment of alternative countermeasures such as the selective isolation of vulnerable individuals or approaches of contact tracing and isolation are limited by data scarcity and in part data inconsistency.

For instance, there is little reliable information about age-stratified asymptomatic ratios. There is also few studies on secondary effects of social distancing and isolation in the case of a global pandemic. Up until now, the impact of country-based measures has hardly been empirically assessed by methods of inferential statistics. While such studies will shed light on important system dependencies, large-scale investment into health care and medical research is essential to spawn game-changing innovation such as the development of vaccines, drugs and affordable test kits.

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